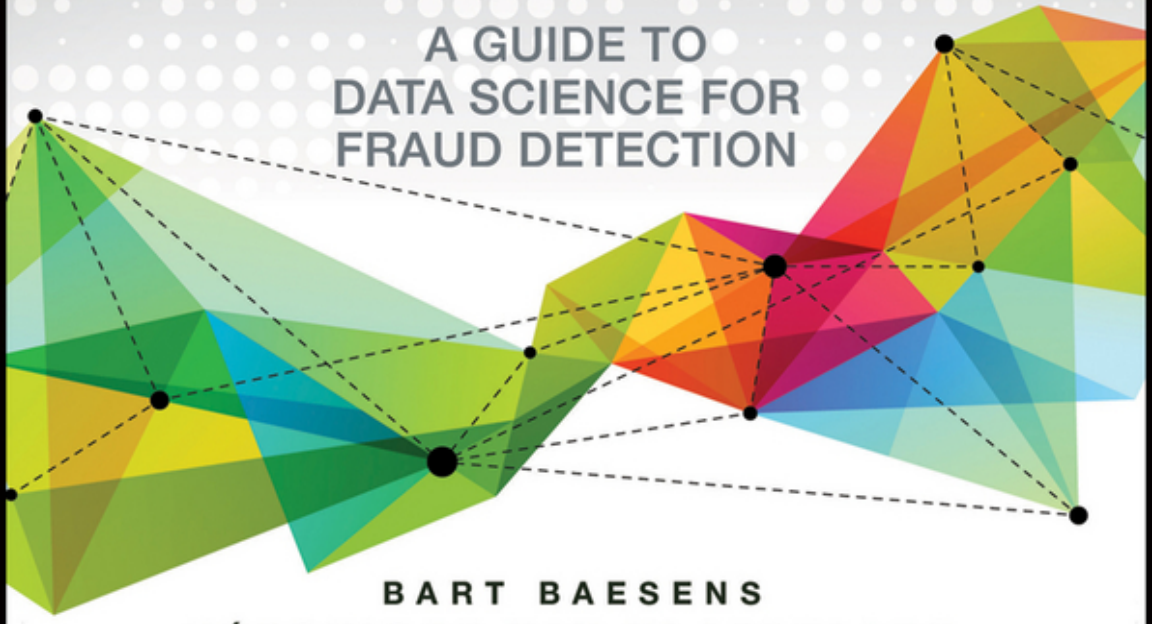
FRAUD ANALYTICS

USING DESCRIPTIVE, PREDICTIVE, AND SOCIAL NETWORK TECHNIQUES

A GUIDE TO DATA SCIENCE FOR FRAUD DETECTION



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Fraud Analytics Using Descriptive, Predictive, and Social Network Techniques

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Published by John Wiley & Sons, Inc., Hoboken, New Jersey.
Published simultaneously in Canada.

Library of Congress Cataloging-in-Publication Data:

Baesens, Bart.
Fraud analytics using descriptive, predictive, and social network techniques : a guide to data science for fraud detection / Bart Baesens, Veronique Van Vlasselaer, Wouter Verbeke.
pages cm. — (Wiley & SAS business series)
Includes bibliographical references and index.
ISBN 978-1-119-13312-4 (cloth) — ISBN 978-1-119-14682-7 (epdf) — ISBN 978-1-119-14683-4 (epub)
1. Fraud—Statistical methods. 2. Fraud—Prevention. 3. Commercial crimes—Prevention. I. Title.
HV6691.B34 2015
364.16' 3015195—dc23

2015017861

Cover Design: Wiley
Cover Image: ©iStock.com/aleksandarvelasevic

Printed in the United States of America

10 9 8 7 6 5 4 3 2 1

To my wonderful wife, Katrien, and kids, Ann-Sophie, Victor, and Hannelore.

To my parents and parents-in-law.

To my husband and soul mate, Niels, for his never-ending support.

To my parents, parents-in-law, and siblings-in-law.

To Luit and Titus.

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Foreword

Fraud will always be with us. It is linked both to organized crime and to terrorism, and it inflicts substantial economic damage. The perpetrators of fraud play a dynamic cat and mouse game with those trying to stop them. Preventing a particular kind of fraud does not mean the fraudsters give up, but merely that they change their tactics: they are constantly on the lookout for new avenues for fraud, for new weaknesses in the system. And given that our social and financial systems are forever developing, there are always new opportunities to be exploited.

This book is a clear and comprehensive outline of the current state-of-the-art in fraud-detection and prevention methodology. It describes the data necessary to detect fraud, and then takes the reader from the basics of fraud-detection data analytics, through advanced pattern recognition methodology, to cutting-edge social network analysis and fraud ring detection.

If we cannot stop fraud altogether, an awareness of the contents of this book will at least enable readers to reduce the extent of fraud, and make it harder for criminals to take advantage of the honest. The readers' organizations, be they public or private, will be better protected if they implement the strategies described in this book. In short, this book is a valuable contribution to the well-being of society and of the people within it.

Professor David J. Hand
Imperial College, London

Preface

It is estimated that a typical organization loses about 5 percent of its revenues due to fraud each year. In this book, we will discuss how state-of-the-art descriptive, predictive and social network analytics can be used to fight fraud by learning fraud patterns from historical data.

The focus of this book is not on the mathematics or theory, but on the practical applications. Formulas and equations will only be included when absolutely needed from a practitioner's perspective. It is also not our aim to provide exhaustive coverage of all analytical techniques previously developed but, rather, give coverage of the ones that really provide added value in a practical fraud detection setting.

Being targeted at the business professional in the first place, the book is written in a condensed, focused way. Prerequisite knowledge consists of some basic exposure to descriptive statistics (e.g., mean, standard deviation, correlation, confidence intervals, hypothesis testing), data handling (using for example, Microsoft Excel, SQL, etc.), and data visualization (e.g., bar plots, pie charts, histograms, scatter plots, etc.). Throughout the discussion, many examples of real-life fraud applications will be included in, for example, insurance fraud, tax evasion fraud, and credit card fraud. The authors will also integrate both their research and consulting experience throughout the various chapters. The book is aimed at (senior) data analysts, (aspiring) data scientists, consultants, analytics practitioners, and researchers (e.g., PhD candidates) starting to explore the field.

Chapter 1 sets the stage on fraud detection, prevention, and analytics. It starts by defining fraud and then zooms into fraud detection and prevention. The impact of big data for fraud detection and the fraud analytics process model are reviewed next. The chapter concludes by summarizing the key skills of a fraud data scientist.

Chapter 2 provides extensive discussion on the basic ingredient of any fraud analytical model: data! It introduces various types of

data sources and discusses how to merge and sample them. The next sections discuss the different types of data elements, visual exploration, Benford's law, and descriptive statistics. These are all essential tools to start understanding the characteristics and limitations of the data available. Data preprocessing activities are also extensively covered: handling missing values, detecting and treating outliers, defining red flags, standardizing data, categorizing variables, weights of evidence coding, and variable selection. Principal component analysis is outlined as a technique to reduce the dimensionality of the input data. This is then further illustrated with RIDIT and PRIDIT analysis. The chapter ends by reviewing segmentation and the risks thereof.

Chapter 3 continues by exploring the use of descriptive analytics for fraud detection. The idea here is to look for unusual patterns or outliers in a fraud data set. Both graphical and statistical outlier detection procedures are reviewed first. This is followed by an overview of break-point analysis, peer group analysis, association rules, clustering, and one-class SVMs.

Chapter 4 zooms into predictive analytics for fraud detection. We start from a labeled data set of transactions whereby each transaction has a target of interest that can either be binary (e.g., fraudulent or not) or continuous (e.g., amount of fraud). We then discuss various analytical techniques to build predictive models: linear regression, logistic regression, decision trees, neural networks, support vector machines, ensemble methods, and multiclass classification techniques. A next section reviews how to measure the performance of a predictive analytical model by first deciding on the data set split-up and then on the performance metric. The class imbalance problem is also extensively elaborated. The chapter concludes by giving some performance benchmarks.

Chapter 5 introduces the reader to social network analysis and its use for fraud detection. Stating that the propensity to fraud is often influenced by the social neighborhood, we describe the main components of a network and illustrate how transactional data sources can be transformed in networks. In the next section, we elaborate on featurization, the process on how to extract a set of meaningful features from the network. We distinguish between three main types of features: neighborhood metrics, centrality metrics, and collective

inference algorithms. We then zoom into community mining, where we aim at finding groups of fraudsters closely connected in the network. By introducing multipartite graphs, we address the fact that fraud often depends on a multitude of different factors and that the inclusion of all these factors in a network representation contribute to a better understanding and analysis of the detection problem at hand. The chapter is concluded with a real-life example of social security fraud.

Chapter 6 deals with the postprocessing of fraud analytical models. It starts by giving an overview of the analytical fraud model lifecycle. It then discusses the traffic light indicator approach and decision tables as two popular model representations. This is followed by a set of guidelines to appropriately select the fraud sample to investigate. Fraud alert and case management are covered next. We also illustrate how visual analytics can contribute to the postprocessing activities. We describe how to backtest analytical fraud models by considering data stability, model stability, and model calibration. The chapter concludes by giving some guidelines about model design and documentation.

Chapter 7 provides a broader perspective on fraud analytics. We provide some guidelines for setting up and managing data quality programs. We zoom into privacy and discuss various ways to ensure appropriate access to both internal and external data. We discuss how analytical fraud estimates can be used to calculate both expected and unexpected losses, which can then help to determine provisioning and capital buffers. A discussion of total cost of ownership and return on investment provides an economic perspective on fraud analytics. This is followed by a discussion of in- versus outsourcing of analytical model development. We briefly zoom into some interesting modeling extensions, such as forecasting and text analytics. The potential and danger of the Internet of Things for fraud analytics is also covered. The chapter concludes by giving some recommendations for corporate fraud governance.

Acknowledgments

It is a great pleasure to acknowledge the contributions and assistance of various colleagues, friends, and fellow analytics lovers to the writing of this book. This book is the result of many years of research and teaching in analytics, risk management, and fraud. We first would like to thank our publisher, John Wiley & Sons, for accepting our book proposal less than one year ago.

We are grateful to the active and lively analytics and fraud detection community for providing various user fora, blogs, online lectures, and tutorials, which proved very helpful.

We would also like to acknowledge the direct and indirect contributions of the many colleagues, fellow professors, students, researchers, and friends with whom we collaborated during the past years.

Last but not least, we are grateful to our partners, parents, and families for their love, support, and encouragement.

We have tried to make this book as complete, accurate, and enjoyable as possible. Of course, what really matters is what you, the reader, think of it. Please let us know your views by getting in touch. The authors welcome all feedback and comments—so do not hesitate to let us know your thoughts!

Bart Baesens
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Wouter Verbeke
August 2015

Fraud Analytics Using Descriptive, Predictive, and Social Network Techniques

CHAPTER 1

Fraud: Detection, Prevention, and Analytics!

INTRODUCTION

In this first chapter, we set the scene for what's ahead by introducing fraud analytics using descriptive, predictive, and social network techniques. We start off by defining and characterizing fraud and discuss different types of fraud. Next, fraud detection and prevention is discussed as a means to address and limit the amount and overall impact of fraud. Big data and analytics provide powerful tools that may improve an organization's fraud detection system. We discuss in detail how and why these tools complement traditional expert-based fraud-detection approaches. Subsequently, the fraud analytics process model is introduced, providing a high-level overview of the steps that are followed in developing and implementing a data-driven fraud-detection system. The chapter concludes by discussing the characteristics and skills of a good fraud data scientist, followed by a scientific perspective on the topic.

FRAUD!

Since a thorough discussion or investigation requires clear and precise definitions of the subject of interest, this first section starts by defining fraud and by highlighting a number of essential characteristics. Subsequently, an explanatory conceptual model will be introduced that provides deeper insight in the underlying drivers of fraudsters, the individuals committing fraud. Insight in the field of application—or in other words, expert knowledge—is crucial for analytics to be successfully applied in any setting, and matters eventually as much as technical skill. Expert knowledge or insight in the problem at hand helps an analyst in gathering and processing the right information in the right manner, and to customize data allowing analytical techniques to perform as well as possible in detecting fraud.

The *Oxford Dictionary* defines fraud as follows:

> **Wrongful or criminal deception intended to result in financial or personal gain.**

On the one hand, this definition captures the essence of fraud and covers the many different forms and types of fraud that will be

discussed in this book. On the other hand, it does not very precisely describe the nature and characteristics of fraud, and as such, does not provide much direction for discussing the requirements of a fraud detection system. A more useful definition will be provided below.

Fraud is definitely not a recent phenomenon unique to modern society, nor is it even unique to mankind. Animal species also engage in what could be called *fraudulent activities*, although maybe we should classify the behavior as displayed by, for instance, chameleons, stick insects, apes, and others rather as *manipulative behavior* instead of fraudulent activities, since *wrongful* or *criminal* are human categories or concepts that do not straightforwardly apply to animals. Indeed, whether activities are *wrongful* or *criminal* depends on the applicable rules or legislation, which defines explicitly and formally these categories that are required in order to be able to classify behavior as being fraudulent.

A more thorough and detailed characterization of the multifaceted phenomenon of fraud is provided by Van Vlasselaer et al. (2015):

> **Fraud is an uncommon, well-considered, imperceptibly concealed, time-evolving and often carefully organized crime which appears in many types of forms.**

This definition highlights five characteristics that are associated with particular challenges related to developing a fraud-detection system, which is the main topic of this book. The first emphasized characteristic and associated challenge concerns the fact that fraud is ***uncommon***. Independent of the exact setting or application, only a minority of the involved population of cases typically concerns fraud, of which furthermore only a limited number will be known to concern fraud. This makes it difficult to both detect fraud, since the fraudulent cases are covered by the nonfraudulent ones, as well as to learn from historical cases to build a powerful fraud-detection system since only few examples are available.

In fact, fraudsters exactly try to blend in and not to behave different from others in order not to get noticed and to remain covered by nonfraudsters. This effectively makes fraud ***imperceptibly concealed***, since fraudsters do succeed in hiding by ***well considering*** and planning how

to precisely commit fraud. Their behavior is definitely not impulsive and unplanned, since if it were, detection would be far easier.

They also adapt and refine their methods, which they need to do in order to remain undetected. Fraud-detection systems improve and learn by example. Therefore, the techniques and tricks fraudsters adopt ***evolve in time*** along with, or better ahead of fraud-detection mechanisms. This cat-and-mouse play between fraudsters and fraud fighters may seem to be an endless game, yet there is no alternative solution so far. By adopting and developing advanced fraud-detection and prevention mechanisms, organizations do manage to reduce losses due to fraud because fraudsters, like other criminals, tend to look for the easy way and will look for other, easier opportunities. Therefore, fighting fraud by building advanced and powerful detection systems is definitely not a pointless effort, but admittedly, it is very likely an effort without end.

Fraud is often as well a ***carefully organized*** crime, meaning that fraudsters often do not operate independently, have allies, and may induce copycats. Moreover, several fraud types such as money laundering and carousel fraud involve complex structures that are set up in order to commit fraud in an organized manner. This makes fraud not to be an isolated event, and as such in order to detect fraud the context (e.g., the social network of fraudsters) should be taken into account. Research shows that fraudulent companies indeed are more connected to other fraudulent companies than to nonfraudulent companies, as shown in a company tax-evasion case study by Van Vlasselaer et al. (2015). Social network analytics for fraud detection, as discussed in Chapter 5, appears to be a powerful tool for unmasking fraud by making clever use of contextual information describing the network or environment of an entity.

A final element in the description of fraud provided by Van Vlasselaer et al. indicates the ***many different types of forms*** in which fraud occurs. This both refers to the wide set of techniques and approaches used by fraudsters as well as to the many different settings in which fraud occurs or economic activities that are susceptible to fraud. Table 1.1 provides a nonexhaustive overview and description of a number of *important* fraud types—*important* being defined in terms of frequency of occurrence as well as the total monetary value involved.

Table 1.1 Nonexhaustive List of Fraud Categories and Types

Credit card fraud	In credit card fraud there is an unauthorized taking of another's credit. Some common credit card fraud subtypes are counterfeiting credit cards (for the definition of counterfeit, see below), using lost or stolen cards, or fraudulently acquiring credit through mail (definition adopted from definitions.uslegal.com). Two subtypes can been identified, as described by Bolton and Hand (2002): (1) Application fraud, involving individuals obtaining new credit cards from issuing companies by using false personal information, and then spending as much as possible in a short space of time; (2) Behavioral fraud, where details of legitimate cards are obtained fraudulently and sales are made on a "Cardholder Not Present" basis. This does not necessarily require stealing the physical card, only stealing the card credentials. Behavioral fraud concerns most of the credit card fraud. Also, debit card fraud occurs, although less frequent. Credit card fraud is a form of identity theft, as will be defined below.
Insurance fraud	Broad category-spanning fraud related to any type of insurance, both from the side of the buyer or seller of an insurance contract. Insurance fraud from the issuer (seller) includes selling policies from nonexistent companies, failing to submit premiums and churning policies to create more commissions. Buyer fraud includes exaggerated claims (property insurance: obtaining payment that is worth more than the value of the property destroyed), falsified medical history (healthcare insurance: fake injuries), postdated policies, faked death, kidnapping or murder (life insurance fraud), and faked damage (automobile insurance: staged collision) (definition adopted from www.investopedia.com).
Corruption	Corruption is the misuse of entrusted power (by heritage, education, marriage, election, appointment, or whatever else) for private gain. This definition is similar to the definition of fraud provided by the Oxford Dictionary discussed before, in that the objective is personal gain. It is different in that it focuses on misuse of entrusted *power*. The definition covers as such a broad range of different subtypes of corruption, so does not only cover corruption by a politician or a public servant, but also, for example, by the CEO or CFO of a company, the notary public, the team leader at a workplace, the administrator or admissions-officer to a private school or hospital, the coach of a soccer team, and so on (definition adopted from www.corruptie.org).
Counterfeit	An imitation intended to be passed off fraudulently or deceptively as genuine. Counterfeit typically concerns valuable objects, credit cards, identity cards, popular products, money, etc. (definition adopted from www.dictionary.com).

(*continued*)

Table 1.1 (*Continued*)

Product warranty fraud	A product warranty is a type of guarantee that a manufacturer or similar party makes regarding the condition of its product, and also refers to the terms and situations in which repairs or exchanges will be made in the event that the product does not function as originally described or intended (definition adopted from www.investopedia.com). When a product fails to offer the described functionalities or displays deviating characteristics or behavior that are a consequence of the production process and not a consequence of misuse by the customer, compensation or remuneration by the manufacturer or provider can be claimed. When the conditions of the product have been altered due to the customer's use of the product, then the warranty does not apply. Intentionally wrongly claiming compensation or remuneration based on a product warranty is called product warranty fraud.
Healthcare fraud	Healthcare fraud involves the filing of dishonest healthcare claims in order to make profit. Practitioner schemes include: individuals obtaining subsidized or fully covered prescription pills that are actually unneeded and then selling them on the black market for a profit; billing by practitioners for care that they never rendered; filing duplicate claims for the same service rendered; billing for a noncovered service as a covered service; modifying medical records, and so on. Members can commit healthcare fraud by providing false information when applying for programs or services, forging or selling prescription drugs, loaning or using another's insurance card, and so on (definition adopted from www.law.cornell.edu).
Telecommunications fraud	Telecommunication fraud is the theft of telecommunication services (telephones, cell phones, computers, etc.) or the use of telecommunication services to commit other forms of fraud (definition adopted from itlaw.wikia.com). An important example concerns cloning fraud (i.e. the cloning of a phone number and the related call credit by a fraudster), which is an instance of superimposition fraud in which fraudulent usage is superimposed on (added to) the legitimate usage of an account (Fawcett and Provost 1997).
Money laundering	The process of taking the proceeds of criminal activity and making them appear legal. Laundering allows criminals to transform illegally obtained gain into seemingly legitimate funds. It is a worldwide problem, with an estimated $300 billion going through the process annually in the United States (definition adopted from legal-dictionary.thefreedictionary.com).
Click fraud	Click fraud is an illegal practice that occurs when individuals click on a website's click-through advertisements (either banner ads or paid text links) to increase the payable number of clicks to the advertiser. The illegal clicks could either be performed by having a person manually click the advertising hyperlinks or by using automated software or online bots that are programmed to click these banner ads and pay-per-click text ad links (definition adopted from www.webopedia.com).

Table 1.1 (*Continued*)

Identity theft	The crime of obtaining the personal or financial information of another person for the purpose of assuming that person's name or identity in order to make transactions or purchases. Some identity thieves sift through trash bins looking for bank account and credit card statements; other more high-tech methods involve accessing corporate databases to steal lists of customer information (definition adopted from www.investopedia.com).
Tax evasion	Tax evasion is the illegal act or practice of failing to pay taxes that are owed. In businesses, tax evasion can occur in connection with income taxes, employment taxes, sales and excise taxes, and other federal, state, and local taxes. Examples of practices that are considered tax evasion include knowingly not reporting income or underreporting income (i.e., claiming less income than you actually received from a specific source) (definition adopted from biztaxlaw.about.com).
Plagiarism	Plagiarizing is defined by *Merriam Webster*'s online dictionary as to steal and pass off (the ideas or words of another) as one's own, to use (another's production) without crediting the source, to commit literary theft, to present as new and original an idea or product derived from an existing source. It involves both stealing someone else's work and lying about it afterward (definition adopted from www.plagiarism.org).

In the end, fraudulent activities are intended to result in gains or benefits for the fraudster, as emphasized by the definition of fraud provided by the *Oxford Dictionary*. The potential, usually monetary, gain or benefit forms in the large majority of cases the basic driver for committing fraud.

The so-called fraud triangle as depicted in Figure 1.1 provides a more elaborate explanation for the underlying motives or drivers for

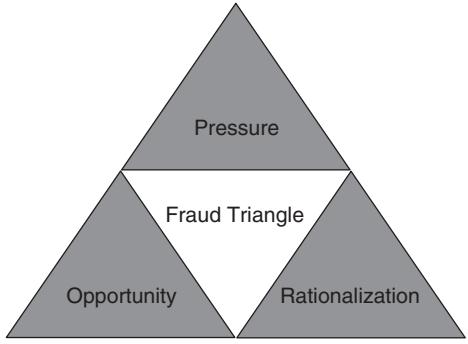

Figure 1.1 Fraud Triangle

committing occupational fraud. The fraud triangle originates from a hypothesis formulated by Donald R. Cressey in his 1953 book *Other People's Money: A Study of the Social Psychology of Embezzlement*:

> *Trusted persons become trust violators when they conceive of themselves as having a financial problem which is non-shareable, are aware this problem can be secretly resolved by violation of the position of financial trust, and are able to apply to their own conduct in that situation verbalizations which enable them to adjust their conceptions of themselves as trusted persons with their conceptions of themselves as users of the entrusted funds or property.*

This basic conceptual model explains the factors that together cause or explain the drivers for an individual to commit *occupational* fraud, yet provides a useful insight in the fraud phenomenon from a broader point of view as well. The model has three legs that together institute fraudulent behavior:

1. ***Pressure*** is the first leg and concerns the main motivation for committing fraud. An individual will commit fraud because a pressure or a problem is experienced of financial, social, or any other nature, and it cannot be resolved or relieved in an authorized manner.
2. ***Opportunity*** is the second leg of the model, and concerns the precondition for an individual to be able to commit fraud. Fraudulent activities can only be committed when the opportunity exists for the individual to resolve or relieve the experienced pressure or problem in an unauthorized but concealed or hidden manner.
3. ***Rationalization*** is the psychological mechanism that explains why fraudsters do not refrain from committing fraud and think of their conduct as acceptable.

An essay by Duffield and Grabosky (2001) further explores the motivational basis of fraud from a psychological perspective.

It concludes that a number of psychological factors may be present in those persons who commit fraud, but that these factors are also associated with entirely legitimate forms of human endeavor. And so fraudsters cannot be distinguished from nonfraudsters purely based on psychological characteristics or patterns.

Fraud is a social phenomenon in the sense that the potential benefits for the fraudsters come at the expense of the victims. These victims are individuals, enterprises, or the government, and as such society as a whole. Some recent numbers give an indication of the estimated *size* and the financial impact of fraud:

- A typical organization loses 5 percent of its revenues to fraud each year (www.acfe.com).
- The total cost of insurance fraud (non–health insurance) in the United States is estimated to be more than $40 billion per year (www.fbi.gov).
- Fraud is costing the United Kingdom £73 billion a year (National Fraud Authority).
- Credit card companies "lose approximately seven cents per every hundred dollars of transactions due to fraud" (Andrew Schrage, Money Crashers Personal Finance, 2012).
- The average size of the informal economy, as a percent of official GNI in the year 2000, in developing countries is 41 percent, in transition countries 38 percent, and in OECD countries 18 percent (Schneider 2002).

Even though these numbers are rough estimates rather than exact measurements, they are based on evidence and do indicate the importance and impact of the phenomenon, and therefore as well the need for organizations and governments to actively fight and prevent fraud with all means they have at their disposal. As will be further elaborated in the final chapter, these numbers also indicate that it is likely worthwhile to invest in fraud-detection and fraud-prevention systems, since a significant financial return on investment can be made.

The importance and need for effective fraud-detection and fraud-prevention systems is furthermore highlighted by the many different

forms or types of fraud of which a number have been summarized in Table 1.1, which is not exhaustive but, rather, indicative, and which illustrates the widespread occurrence across different industries and product and service segments. The broad fraud categories enlisted and briefly defined in Table 1.1 can be further subdivided into more specific subtypes, which, although interesting, would lead us too far into the particularities of each of these forms of fraud. One may refer to the further reading sections at the end of each chapter of this book, providing selected references to specialized literature on different forms of fraud. A number of particular fraud types will also be further elaborated in real-life case studies throughout the book.

FRAUD DETECTION AND PREVENTION

Two components that are essential parts of almost any effective strategy to fight fraud concern *fraud detection* and *fraud prevention*. Fraud detection refers to the ability to recognize or discover fraudulent activities, whereas fraud prevention refers to measures that can be taken to avoid or reduce fraud. The difference between both is clear-cut; the former is an ex post approach whereas the latter an ex ante approach. Both tools may and likely should be used in a complementary manner to pursue the shared objective, *fraud reduction*.

However, as will be discussed in more detail further on, preventive actions will change fraud strategies and consequently impact detection power. Installing a detection system will cause fraudsters to adapt and change their behavior, and so the detection system itself will impair eventually its own detection power. So although complementary, fraud detection and prevention are not independent and therefore should be aligned and considered a whole.

The classic approach to fraud detection is an *expert-based approach*, meaning that it builds on the experience, intuition, and business or domain knowledge of the fraud analyst. Such an expert-based approach typically involves a manual investigation of a suspicious case, which may have been signaled, for instance, by a customer complaining of being charged for transactions he did not do. Such a disputed transaction may indicate a new *fraud mechanism* to have been discovered or developed by fraudsters, and therefore requires

a detailed investigation for the organization to understand and subsequently address the new mechanism.

Comprehension of the fraud mechanism or pattern allows extending the fraud detection and prevention mechanism that is often implemented as a rule base or engine, meaning in the form of a set of If-Then rules, by adding rules that describe the newly detected fraud mechanism. These rules, together with rules describing previously detected fraud patterns, are applied to future *cases* or transactions and trigger an alert or signal when fraud is or may be committed by use of this mechanism. A simple, yet possibly very effective, example of a fraud detection rule in an insurance claim fraud setting goes as follows:

IF:

- Amount of claim is above threshold OR
- Severe accident, but no police report OR
- Severe injury, but no doctor report OR
- Claimant has multiple versions of the accident OR
- Multiple receipts submitted

THEN:

- Flag claim as suspicious AND
- Alert fraud investigation officer.

Such an expert approach suffers from a number of disadvantages. Rule bases or engines are typically expensive to build, since they require advanced manual input by the fraud experts, and often turn out to be difficult to maintain and manage. Rules have to be kept up to date and only or mostly trigger real fraudulent cases, since every signaled case requires human follow-up and investigation. Therefore, the main challenge concerns keeping the rule base lean and effective—in other words, deciding when and which rules to add, remove, update, or merge.

It is important to realize that fraudsters can, for instance by trial and error, learn the business rules that block or expose them and will devise inventive workarounds. Since the rules in the rule-based detection system are based on past experience, new emerging fraud patterns are not automatically flagged or signaled. Fraud is a dynamic

phenomenon, as will be discussed below in more detail, and therefore needs to be traced continuously. Consequently, a fraud detection and prevention system also needs to be continuously monitored, improved, and updated to remain effective.

An expert-based fraud-detection system relies on human expert input, evaluation, and monitoring, and as such involves a great deal of labor intense human interventions. An automated approach to build and maintain a fraud-detection system, requiring less human involvement, could lead to a more efficient and effective system for detecting fraud. The next section in this chapter will introduce several alternative approaches to expert systems that leverage the massive amounts of data that nowadays can be gathered and processed at very low cost, in order to develop, monitor, and update a high-performing fraud-detection system in a more automated and efficient manner. These alternative approaches still require and build on expert knowledge and input, which remains crucial in order to build an effective system.

EXAMPLE CASE

EXAMPLE CASE: EXPERT-BASED APPROACH TO INTERNAL FRAUD DETECTION IN AN INSURANCE CLAIM-HANDLING PROCESS

An example expert-based detection and prevention system to signal potential fraud committed by claim handling officers concerns the business process depicted in Figure 1.2, illustrating the handling of fire incident claims without any form of bodily injury (including death) (Caron et al. 2013). The process involves the following types of activities:

- Administrative activities
- Evaluation-related activities
- In-depth assessment by internal and external experts
- Approval activities
- Leniency-related activities
- Fraud investigation activities

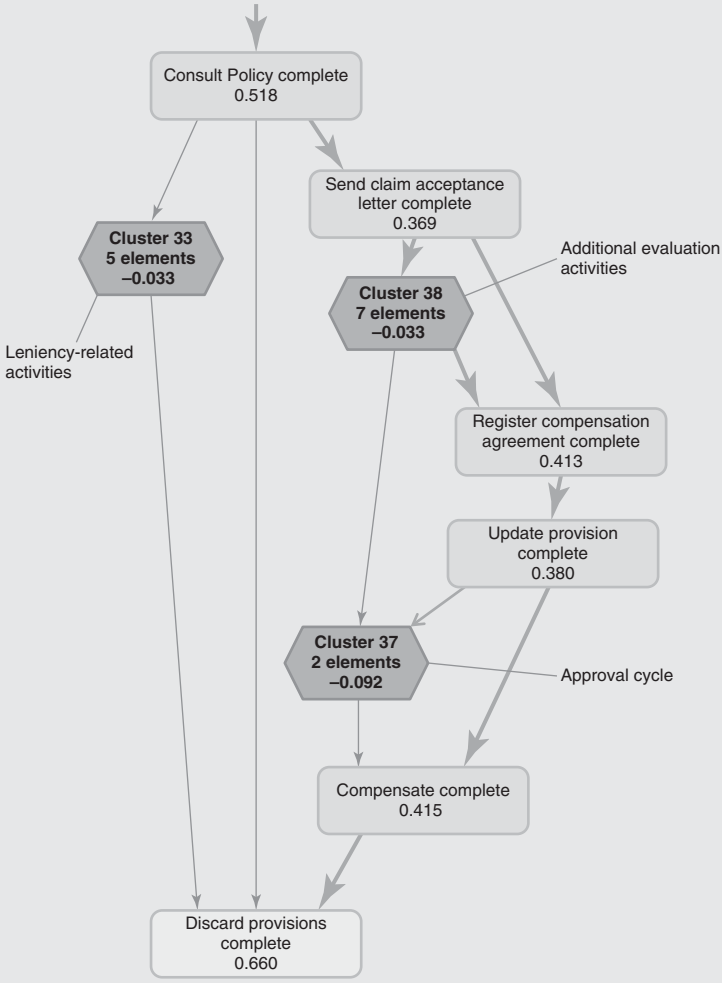

Figure 1.2 Fire Incident Claim-Handling Process

A number of harmful process deviations and related risks can be identified regarding these activities:

- Forgetting to discard provisions
- **Multiple partial compensations (exceeding limit)**

- **Collusion between administrator and experts**
- **Lack of approval cycle**
- Suboptimal task allocation
- Fraud investigation activities
- **Processing rejected claim**
- Forced claim acceptance, absence of a timely primary evaluation

Deviations marked in bold may relate to and therefore indicate fraud. By adopting business policies as a governance instrument and prescribing procedures and guidelines, the insurer may reduce the risks involved in processing the insurance claims. For instance:

Business policy excerpt 1 (customer relationship management related): If the insured requires immediate assistance (e.g., to prevent the development of additional damage), arrangements will be made for a single partial advanced compensation (maximum *x*% of expected covered loss).

- Potential risk: The expected (covered) loss could be exceeded through partial advanced compensations.

Business policy excerpt 2 (avoid financial loss): Settlements need to be approved.

- Potential risk: Collusion between the drafter of the settlement and the insured

Business policy excerpt 3 (avoid financial loss): The proposal of a settlement and its approval must be performed by different actors.

- Potential risk: A person might hold both the team-leader and the expert role in the information system.

Business policy excerpt 4 (avoid financial loss): After approval of the decision (settlement or claim rejection) no changes may occur.

- Potential risk: The modifier and the insured might collude.
- Potential risk: A rejected claim could undergo further processing.

Since detecting fraud based on specified business rules requires prior knowledge of the fraud scheme, the existence of fraud issues will be the direct result of either:

- An inadequate internal control system (controls fail to prevent fraud); or
- Risks accepted by the management (no preventive or corrective controls are in place).

Some examples of fraud-detection rules that can be derived from these business policy excerpts and process deviations, and that may be added to the fraud-detection rule engine are as follows:

Business policy excerpt 1:

- IF multiple advanced payments for one claim, THEN suspicious case.

Business policy excerpt 2:

- IF settlement was not approved before it was paid, THEN suspicious case.

Business policy excerpt 3:

- IF settlement is proposed AND approved by the same person, THEN suspicious case.

Business policy excerpt 4:

- IF settlement is approved AND changed afterward, THEN suspicious case.
- IF claim is rejected AND processed afterward (e.g., look for a settlement proposal, payment,… activity), THEN suspicious case.

BIG DATA FOR FRAUD DETECTION

When fraudulent activities have been detected and confirmed to effectively concern fraud, two types of measures are typically taken:

1. *Corrective measures,* that aim to resolve the fraud and correct the wrongful consequences—for instance by means of pursuing

restitution or compensation for the incurred losses. These corrective measures might also include actions to retrospectively detect and subsequently address similar fraud cases that made use of the same mechanism or loopholes in the fraud detection and prevention system the organization has in place.

2. *Preventive measures,* which may both include actions that aim at preventing future fraud by the caught fraudster (e.g., by terminating a contractual agreement with a customer, as well as actions that aim at preventing fraud of the same type by other individuals). When an expert-based approach is adopted, an example preventive measure is to extend the rule engine by incorporating additional rules that allow detecting and preventing the uncovered fraud mechanism to be applied in the future. A fraud case must be investigated thoroughly so the underlying mechanism can be unraveled, extending the available expert knowledge and allowing it to prevent the fraud mechanism to be used again in the future by making the organization more robust and less vulnerable to fraud by adjusting the detection and prevention system.

Typically, the sooner corrective measures are taken and therefore the sooner fraud is detected, the more effective such measures may be and the more losses can be avoided or recompensed. On the other hand, fraud becomes easier to detect the more time has passed, for a number of particular reasons.

When a fraud mechanism or *path* exists—meaning a loophole in the detection and prevention system of an organization—the number of times this path will be followed (i.e., the fraud mechanism used) grows in time and therefore as well the number of occurrences of this particular type of fraud. The more a fraud path is taken the more apparent it becomes and typically, in fact statistically, the easier to detect. The number of occurrences of a particular type of fraud can be expected to grow since many fraudsters appear to be repeat offenders. As the expression goes, "*Once a thief, always a thief.*" Moreover, a fraud mechanism may well be discovered by several individuals or the knowledge shared between fraudsters. As will be shown in Chapter 5 on social network analytics for fraud detection, certainly some types of fraud tend to

spread virally and display what are called social network effects, indicating that fraudsters share their knowledge on how to commit fraud. This effect, too, leads to a growing number of occurrences and, therefore, a higher risk or chance, depending on one's perspective, of detection.

Once a case of a particular type of fraud has been revealed, this will lead to the exposition of similar fraud cases that were committed in the past and made use of the same mechanism. Typically, a retrospective screening is performed to assess the size or impact of the newly detected type of fraud, as well as to resolve (by means of corrective measures, cf. supra) as much as possible fraud cases. As such, fraud becomes easier to detect the more time has passed, since more similar fraud cases will occur in time, increasing the probability that the particular fraud type will be uncovered, as well as because fraudsters committing repeated fraud will increase their individual risk of being exposed. The individual risk will increase the more fraud a fraudster commits for the same basic reason: The chances of getting noticed get larger.

A final reason why fraud becomes easier to detect the more time has passed is because better detection techniques are being developed, are getting readily available, and are being implemented and applied by a growing amount of organizations. An important driver for improvements with respect to detection techniques is *growing data availability*. The informatization and digitalization of almost every aspect of society and daily life leads to an abundance of available data. This so-called big data can be explored and exploited for a range of purposes including fraud detection (Baesens 2014), at a very low cost.

DATA-DRIVEN FRAUD DETECTION

Although classic, expert-based fraud-detection approaches as discussed before are still in widespread use and definitely represent a good starting point and complementary tool for an organization to develop an effective fraud-detection and prevention system, a shift is taking place toward data-driven or statistically based fraud-detection methodologies for three apparent reasons:

1. *Precision*. Statistically based fraud-detection methodologies offer an increased detection power compared to classic approaches.

By processing massive volumes of information, fraud patterns may be uncovered that are not sufficiently apparent to the human eye. It is important to notice that the improved power of data-driven approaches over human processing can be observed in similar applications such as credit scoring or customer churn prediction. Most organizations only have a limited capacity to have cases checked by an inspector to confirm whether or not the case effectively concerns fraud. The goal of a fraud-detection system may be to make the most optimal use of the limited available inspection capacity, or in other words to maximize the fraction of fraudulent cases among the inspected cases (and possibly in addition, the detected amount of fraud). A system with higher precision, as delivered by data-based methodologies, directly translates in a higher fraction of fraudulent inspected cases.

2. *Operational efficiency*. In certain settings, there is an increasing amount of cases to be analyzed, requiring an automated process as offered by data-driven fraud-detection methodologies. Moreover, in several applications, operational requirements exist, imposing time constraints on the processing of a case. For instance, when evaluating a transaction with a credit card, an almost immediate decision is required with respect to approve or block the transaction because of suspicion of fraud. Another example concerns fraud detection for customs in a harbor, where a decision has to be made within a confined time window whether to let a container pass and be shipped inland, or whether to further inspect it, possibly causing delays. Automated data-driven approaches offer such functionality and are able to comply with stringent operational requirements.
3. *Cost efficiency*. As already mentioned in the previous section, developing and maintaining an effective and lean expert-based fraud-detection system is both challenging and labor intensive. A more automated and, as such, more efficient approach to develop and maintain a fraud-detection system, as offered by data-driven methodologies, is preferred. Chapters 6 and 7 discuss the cost efficiency and return on investment of data-driven fraud-detection models.

An additional driver for the development of improved fraud-detection technologies concerns the growing amount of interest that fraud detection is attracting from the general public, the media, governments, and enterprises. This increasing awareness and attention for fraud is likely due to its large negative social as well as financial impact, and leads to growing investments and research into the matter, both from academia, industry, and government.

Although fraud-detection approaches have gained significant power over the past years by adopting potent statistically based methodologies and by analyzing massive amounts of data in order to discover fraud patterns and mechanisms, still fraud remains hard to detect. It appears the Pareto principle holds with respect to the required effort and difficulty of detecting fraud: It appears the principle of decreasing returns holds with respect to the required effort and so forth. In order to explain the *hardness* and complexity of the problem, it is important to acknowledge the fact that fraud is a dynamic phenomenon, meaning that its nature changes in time. Not only fraud-detection mechanisms evolve, but also fraudsters adapt their approaches and are inventive in finding more refined and less apparent ways to commit fraud without being exposed. Fraudsters probe fraud-detection and prevention systems to understand their functioning and to discover their weaknesses, allowing them to adapt their methods and strategies.

FRAUD-DETECTION TECHNIQUES

Indeed, fraudsters develop advanced strategies to cleverly cover their tracks in order to avoid being uncovered. Fraudsters tend to try and blend in as much as possible into the surroundings. Such an approach reminds of camouflage techniques as used by the military or by animals such as chameleons and stick insects. This is clearly no fraud by opportunity, but rather, is carefully planned, leading to a need for new techniques that are able to detect and address patterns that initially seem to comply with normal behavior, but in reality instigate fraudulent activities.

Detection mechanisms based on unsupervised learning techniques or descriptive analytics, as discussed in Chapter 3, typically aim at

finding behavior that *deviates* from *normal* behavior, or in other words at detecting anomalies. These techniques learn from historical observations, and are called unsupervised since they do not require these observations to be labeled as either a fraudulent or a nonfraudulent example case. An example of behavior that does not comply with *normal behavior* in a telecommunications subscription fraud setting is provided by the transaction data set with call detail records of a particular subscriber shown in Table 1.2 (Fawcett and Provost 1997). Remark that the calls found to be fraudulent (last column in the table indicating *bandit*) are not suspicious by themselves; however, they are deviating from normal behavior for this particular subscriber.

Outlier-detection techniques have great value and allow detecting a significant fraction of fraudulent cases. In particular, they might allow detecting fraud that is different in nature from historical fraud, or in other words fraud that makes use of new, unknown mechanisms resulting in a *novel fraud pattern*. These new patterns are not discovered by expert systems, and as such descriptive analytics may be a first

Table 1.2 Call Detail Records of a Customer with Outliers Indicating Suspicious Activity (deviating behavior starting at a certain moment in time) at the Customer Subscription (Fawcett and Provost 1997)

Date (m/d)	Time	Day	Duration	Origin	Destination	Fraud
1/01	10:05:01	Mon	13 mins	Brooklyn, NY	Stamford, CT	
1/05	14:53:27	Fri	5 mins	Brooklyn, NY	Greenwich, CT	
1/08	09:42:01	Mon	3 mins	Bronx, NY	White Plains, NY	
1/08	15:01:24	Mon	9 mins	Brooklyn, NY	Brooklyn, NY	
1/09	15:06:09	Tue	5 mins	Manhattan, NY	Stamford, CT	
1/09	16:28:50	Tue	53 sec	Brooklyn, NY	Brooklyn, NY	
1/10	01:45:36	Wed	35 sec	Boston, MA	Chelsea, MA	Bandit
1/10	01:46:29	Wed	34 sec	Boston, MA	Yonkers, MA	Bandit
1/10	01:50:54	Wed	39 sec	Boston, MA	Chelsea, MA	Bandit
1/10	11:23:28	Wed	24 sec	White Plains, NY	Congers, NY	
1/11	22:00:28	Thu	37 sec	Boston, MA	East Boston, MA	Bandit
1/11	22:04:01	Thu	37 sec	Boston, MA	East Boston, MA	Bandit

complementary tool to be adopted by an organization in order to improve its expert rule–based fraud-detection system.

Descriptive techniques however show to be prone to deception, exactly by the camouflage-like fraud strategies already discussed. Therefore, the detection system can be further improved by complementing it by a tool that is able to unmask fraudsters adopting a camouflage-like technique.

Therefore, in Chapter 4, a second type of techniques is introduced. Supervised learning techniques or predictive analytics aim to learn from historical information or observations in order to retrieve patterns that allow differentiating between normal and fraudulent behavior. These techniques exactly aim at finding silent alarms, the parts of their tracks that fraudsters cannot cover up. Supervised learners can be applied to predict or detect fraud as well as to estimate the amount of fraud.

Predictive analytics has limitations as well, probably the most important one being that they need historical examples to learn from (i.e., a labeled data set of historically observed fraud behavior). This reduces their detection power with respect to drastically different fraud types making use of new mechanisms or methods, and which have not been detected thus far and are therefore not included in the historical database of fraud cases from which the predictive model was learned. As already discussed, descriptive analytics may perform better with respect to detecting such new fraud mechanisms, at least if a new fraud mechanism leads to detectable deviations from *normality*. This illustrates the complementarity of supervised and unsupervised methods and motivates the use of both types of methods as complementary tools in developing a powerful fraud-detection and prevention system.

A third type of complementary tool concerns social network analysis, which further extends the abilities of the fraud-detection system by learning and detecting characteristics of fraudulent behavior in a network of linked entities. Social network analytics is the newest tool in our toolbox to fight fraud, and proofs to be a very powerful means as will appear from the discussion and presented case study

in Chapter 5. Social network analytics allows including an extra source of information in the analysis, being the relationships between entities, and as such may contribute in uncovering particular patterns indicating fraud.

It is important to stress that these three different types of techniques may complement each other since they focus on different aspects of fraud and are not to be considered as exclusive alternatives. An effective fraud-detection and prevention system will make use of and combine these different tools, which have different possibilities and limitations and therefore reinforce each other when applied in a combined setup. When developing a fraud-detection system, an organization will likely follow the order in which the different tools have been introduced; as a first step an expert-based rule engine may be developed, which in a second step may be complemented by descriptive analytics, and subsequently by predictive and social network analytics. Developing a fraud-detection system in this order allows the organization to gain expertise and insight in a stepwise manner, hereby facilitating each next step. However, the exact order of adopting the different techniques may depend on the characteristics of the type of fraud an organization is faced with.

FRAUD CYCLE

Figure 1.3 introduces the *fraud cycle*, and depicts four essential activities:

- **Fraud detection**: Applying detection models on new, unseen observations and assigning a fraud risk to every observation.
- **Fraud investigation**: A human expert is often required to investigate suspicious, flagged cases given the involved subtlety and complexity.
- **Fraud confirmation**: Determining *true* fraud label, possibly involving field research.
- **Fraud prevention**: Preventing fraud to be committed in the future. This might even result in detecting fraud even before the fraudster knows s/he will commit fraud, which is exactly the

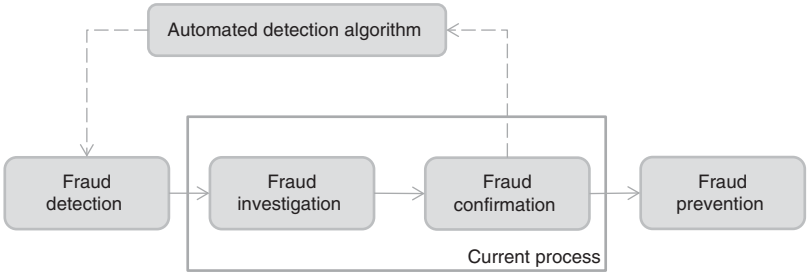

Figure 1.3 The Fraud Cycle

premise of the 1956 science fiction short story *Minority Report* by Philip K. Dick.

Remark the feedback loop in Figure 1.3 from the fraud confirmation activity toward the fraud-detection activity. Newly detected cases should be added (as soon as possible!) to the database of historical fraud cases, which is used to learn or induce the detection model. The fraud-detection model may not be retrained every time a new case is confirmed; however, a regular update of the model is recommendable given the dynamic nature of fraud and the importance of detecting fraud as soon as possible. The required frequency of retraining or updating the detection model depends on several factors:

- The volatility of the fraud behavior
- The detection power of the current model, which is related to the volatility of the fraud behavior
- The amount of (similar) confirmed cases already available in the database
- The rate at which new cases are being confirmed
- The required effort to retrain the model

Depending on the emerging need for retraining as determined by these factors, as well as possible additional factors, an automated approach such as reinforcement learning may be considered which continuously updates the detection model by learning from the newest observations.

EXAMPLE CASE

EXAMPLE CASE: SUPERVISED AND UNSUPERVISED LEARNING FOR DETECTING CREDIT CARD FRAUD

In order to fight fraud and given the abundant data availability, credit card companies have been among the early adopters of big data approaches to develop effective fraud-detection and prevention systems. A typical credit card transaction is registered in the systems of the credit card company by logging up to a hundred or more characteristics describing the details of a transaction. Table 1.3 provides for illustrative purposes a number of such characteristics or variables that are being captured (Hand 2007).

Table 1.3 Example Credit Card Transaction Data Fields

Transaction ID	Transaction type	Date of transaction
Time of transaction	Amount	Currency
Local currency amount	Merchant ID	Merchant category
Card issuer ID	ATM ID	Cheque account prefix

By logging this information over a period of time, a dataset is being created that allows applying descriptive analytics. This includes *outlier detection techniques,* which allow detecting abnormal or anomalous behavior and/or characteristics in a data set. So-called outliers may indicate suspicious activities, and may occur at the data item level or the data set level.

Figure 1.4 provides an illustration of outliers at the data item level, in this example transactions that deviate from the *normal* behavior by a customer. The scatter plot clearly shows three clusters of regular, frequently occurring *types* as characterized by the time and place dimension of transactions for one particular customer, as well as two deviating transactions marked in black. These outliers are suspicious and possibly concern fraudulent transactions, and therefore may be flagged for further human investigation.

An outlier at the data set level means that the behavior of a person or instance does not comply with the overall behavior. Figure 1.5 plots the age and income characteristics of customers as provided when applying for a credit card. The two outliers marked in black in the plot may indicate so-called subscription fraud (cf. Table 1.1, definition of credit card fraud), since these combinations of age and income strongly deviate from the *normal behavior*.

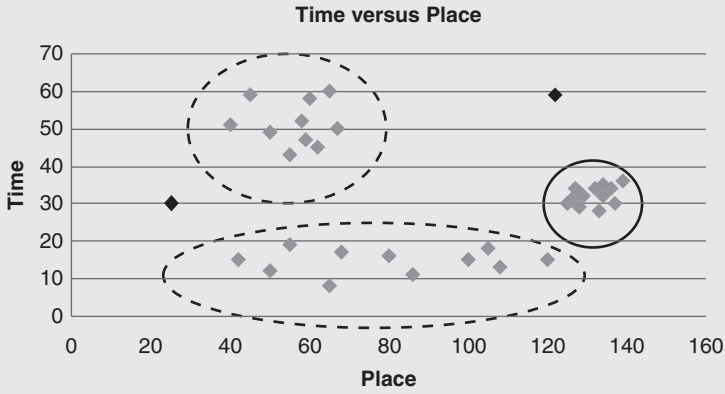

Figure 1.4 Outlier Detection at the Data Item Level

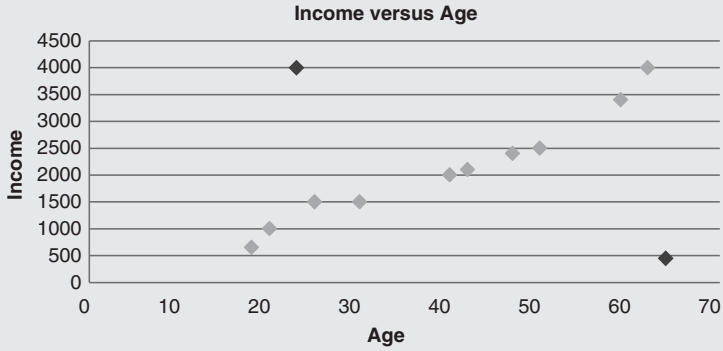

Figure 1.5 Outlier Detection at the Data Set Level

The addition of a field in the available transaction data set that indicates whether a transaction was fraudulent allows predictive analytics to be applied to yield a model predicting or classifying an instance as being fraudulent or not. As will be discussed in the next section as well as in Chapter 4, such models may be interpreted to understand the underlying credit card fraud behavior patterns that lead the model to predict whether a transaction might be fraudulent. Such patterns may be:

- Small purchase followed by a big one
- Large number of online purchases in a short period

- Spending as much as possible as quickly as possible
- Spending smaller amounts, spread across time

Such pattern may be harder to detect and concern advanced methods adopted by fraudsters and developed exactly to avoid detection.

THE FRAUD ANALYTICS PROCESS MODEL

Figure 1.6 provides a high-level overview of the analytics process model (Han and Kamber 2011; Hand, Mannila, and Smyth 2001; Tan, Steinbach, and Kumar 2005). As a first step, a thorough definition of the business problem is needed to be solved with analytics. Next, all source data must be identified that could be of potential interest. This is a very important step, as data are the key ingredient to any analytical exercise and the selection of data will have a deterministic impact on the analytical models that will be built in a subsequent step. All data will then be gathered in a staging area that could be a data mart or data warehouse. Some basic exploratory analysis can be considered here using for instance OLAP (online analytical processing, see Chapter 3) facilities for multidimensional data analysis (e.g., roll-up, drill down, slicing and dicing). This will be followed by a data-cleaning step to

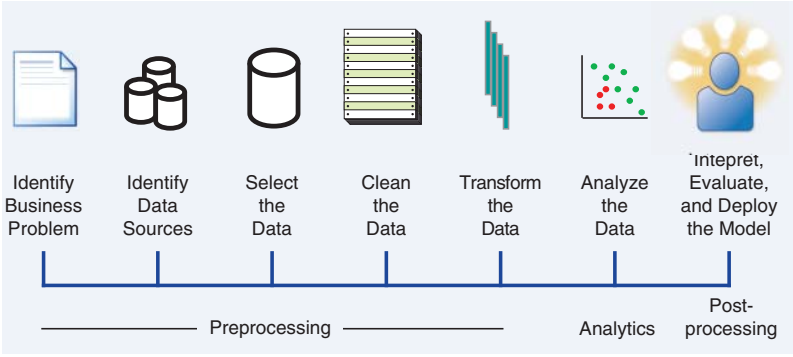

Figure 1.6 The Fraud Analytics Process Model

get rid of all inconsistencies, such as missing values and duplicate data. Additional transformations may also be considered, such as binning, alphanumeric to numeric coding, geographical aggregation, and so on. In the analytics step, an analytical model will be estimated on the preprocessed and transformed data. In this stage, the actual fraud-detection model is built. Finally, once the model has been built, it will be interpreted and evaluated by the fraud experts.

Trivial patterns that may be detected by the model, for instance similar to expert rules, are interesting as they provide some validation of the model. But of course, the key issue is to find the unknown yet interesting and actionable patterns (sometimes also referred to as knowledge diamonds) that can provide added insight and detection power. Once the analytical model has been appropriately validated and approved, it can be put into production as an analytics application (e.g., decision support system, scoring engine). Important to consider here is how to represent the model output in a user-friendly way, how to integrate it with other applications (e.g., detection and prevention system, risk engines), and how to make sure the analytical model can be appropriately monitored and backtested on an ongoing basis. These post-processing steps will be discussed in detail in Chapter 6.

It is important to note that the process model outlined in Figure 1.6 is iterative in nature in the sense that one may have to go back to previous steps during the exercise. For example, during the analytics step, the need for additional data may be identified, which may necessitate additional cleaning, transformation, and so on. The most time-consuming step typically is the data selection and preprocessing step, which usually takes around 80 percent of the total efforts needed to build an analytical model.

A fraud-detection model must be thoroughly evaluated before being adopted. Depending on the exact setting and usage of the model, different aspects may need to be assessed during evaluation in order to ensure the model to be acceptable for implementation. Table 1.4 reviews several key characteristics of *successful* fraud analytics models that may or may not apply, depending on the exact application.

A number of particular challenges may present themselves when developing and implementing a fraud-detection model, possibly leading to difficulties in meeting the objectives as expressed by the

Table 1.4 Key Characteristics of Successful Fraud Analytics Models

Statistical accuracy	Refers to the detection power and the correctness of the statistical model in flagging cases as being suspicious. Several statistical evaluation criteria exist and may be applied to evaluate this aspect, such as the hit rate, lift curves, AUC, etc. A number of suitable measures will be discussed in detail in Chapter 4. Statistical accuracy may also refer to statistical significance, meaning that the patterns that have been found in the data have to be real and not the consequence of coincidence. In other words, we need to make sure that the model generalizes well and is not overfitted to the historical data set.
Interpretability	When a deeper understanding of the detected fraud patterns is required, for instance to validate the model before it is adopted for use, a fraud-detection model may have to be interpretable. This aspect involves a certain degree of subjectivism, since interpretability may depend on the user's knowledge. The interpretability of a model depends on its format, which, in turn, is determined by the adopted analytical technique. Models that allow the user to understand the underlying reasons why the model signals a case to be suspicious are called white-box models, whereas complex incomprehensible mathematical models are often referred to as black-box models. It may well be in a fraud-detection setting that black-box models are acceptable, although in most settings some level of understanding and in fact validation which is facilitated by interpretability is required for the management to have confidence and allow the effective operationalization of the model.
Operational efficiency	Operational efficiency refers to the time that is required to evaluate the model, or in other words, the time required to evaluate whether a case is suspicious or not. When cases need to be evaluated in real time, for instance to signal possible credit card fraud, operational efficiency is crucial and is a main concern during model performance assessment. Operational efficiency also entails the efforts needed to collect and preprocess the data, evaluate the model, monitor and backtest the model, and reestimate it when necessary.
Economical cost	Developing and implementing a fraud-detection model involves a significant cost to an organization. The total cost includes the costs to gather, preprocess, and analyze the data, and the costs to put the resulting analytical models into production. In addition, the software costs, as well as human and computing resources, should be taken into account. Possibly also external data has to be bought to enrich the available in-house data. Clearly, it is important to perform a thorough cost-benefit analysis at the start of the project, and to gain insight in the constituent factors of the returns on investment of building an advanced fraud-detection system.
Regulatory compliance	Depending on the context there may be internal or organization-specific and external regulation and legislation that applies to the development and application of a model. Clearly, a fraud-detection model should be in line and comply with all applicable regulation and legislation, for instance with respect to privacy, the use of cookies in a web-browser, etc.

characteristics discussed in Table 1.4. A first key challenge concerns the dynamic nature of fraud. Fraudsters constantly try to beat detection and prevention systems by developing new strategies and methods. Therefore, adaptive analytical models and detection and prevention systems are required, in order to detect and resolve fraud as soon as possible. Detecting fraud as early as possible is crucial, as discussed before.

Clearly, it is also crucial to detect fraud as accurately as possible, and not to miss out on too many fraud cases, especially on fraud cases involving a large amount or financial impact. The cost of missing a fraudulent case or a fraud mechanism may be significant. Related to having good detection power is the requirement of having at the same time a low false alarm rate, since we also want to avoid harassing good customers and prevent accounts or transactions to be blocked unnecessarily.

In developing analytical models with good detection power and low false alarm rate, an additional difficulty concerns the skewedness of the data, meaning that we typically have plenty of historical examples of nonfraudulent cases, but only a limited number of fraudulent cases. For instance, in a credit card fraud setting, typically less than 0.5 percent of transactions are fraudulent. Such a problem is commonly referred to as a needle-in-a-haystack problem and might cause an analytical technique to experience difficulties in learning an accurate model. A number of approaches to address the skewedness of the data will be discussed in Chapter 4.

Depending on the exact application, also operational efficiency may be a key requirement, meaning that the fraud-detection system might only have a limited amount of time available to reach a decision and let a transaction pass or not. As an example, in a credit card fraud-detection setting the decision time has to be typically less than eight seconds. Such a requirement clearly impacts the design of the operational IT systems, but also the design of the analytical model. The analytical model should not take too long to be evaluated, and the information or the variables that are used by the model should not take too long to be gathered or calculated. Calculating trend variables in real time, for instance, may not be feasible from an operational perspective, since this is taking too much valuable time. This also

relates to the final challenge of dealing with the massive volumes of data that are available and need to be processed.

FRAUD DATA SCIENTISTS

Whereas in the previous section we discussed the characteristics of a good fraud-detection model, in this paragraph we will elaborate on the key characteristics of a good fraud data scientist from the perspective of the hiring manager. It is based on our consulting and research experience, having collaborated with many companies worldwide on the topic of big data, analytics, and fraud detection.

A Fraud Data Scientist Should Have Solid Quantitative Skills

Obviously, a fraud data scientist should have a thorough background in statistics, machine learning and/or data mining. The distinction between these various disciplines is getting more and more blurred and is actually not that relevant. They all provide a set of quantitative techniques to analyze data and find business relevant patterns within a particular context such as fraud detection. A data scientist should be aware of which technique can be applied when and how. He/she should not focus too much on the underlying mathematical (e.g., optimization) details but, rather, have a good understanding of what analytical problem a technique solves, and how its results should be interpreted. In this context, the education of engineers in computer science and/or business/industrial engineering should aim at an integrated, multidisciplinary view, with graduates formed in both the use of the techniques, and with the business acumen necessary to bring new endeavors to fruition. Also important is to spend enough time validating the analytical results obtained so as to avoid situations often referred to as data massage and/or data torture whereby data is (intentionally) misrepresented and/or too much focus is spent discussing spurious correlations. When selecting the optimal quantitative technique, the fraud data scientist should

take into account the specificities of the context and the problem or fraud-detection application at hand. Typical requirements for fraud-detection models have been discussed in the previous section and the fraud data scientist should have a basic understanding and feeling for all of those. Based on a combination of these requirements, the data scientist should be capable of selecting the best analytical technique to solve the particular business problem.

A Fraud Data Scientist Should Be a Good Programmer

As per definition, data scientists work with data. This involves plenty of activities such as sampling and preprocessing of data, model estimation and post-processing (e.g., sensitivity analysis, model deployment, backtesting, model validation). Although many user-friendly software tools are on the market nowadays to automate and support these tasks, every analytical exercise requires tailored steps to tackle the specificities of a particular business problem and setting. In order to successfully perform these steps, programming needs to be done. Hence, a good data scientist should possess sound programming skills (e.g., SAS, R, Python, etc.). The programming language itself is not that important as such, as long as he/she is familiar with the basic concepts of programming and knows how to use these to automate repetitive tasks or perform specific routines.

A Fraud Data Scientist Should Excel in Communication and Visualization Skills

Like it or not, analytics is a technical exercise. At this moment, there is a huge gap between the analytical models and the business users. To bridge this gap, communication and visualization facilities are key. Hence, data scientists should know how to represent analytical models and their accompanying statistics and reports in user-friendly ways using traffic-light approaches, OLAP (online analytical processing) facilities, If-then business rules, and so on. They should be capable of communicating the right amount of information without

getting lost into complex (e.g., statistical) details, which will inhibit a model's successful deployment. By doing so, business users will better understand the characteristics and behavior in their (big) data which will improve their attitude toward and acceptance of the resulting analytical models. Educational institutions must learn to balance, since many academic degrees form students who are skewed to either too much analytical or too much practical knowledge.

A Fraud Data Scientist Should Have a Solid Business Understanding

While this might be obvious, we have witnessed (too) many data science projects that failed because the respective analyst did not understand the business problem at hand. By "business" we refer to the respective application area. Several examples of such application areas of fraud-detection techniques were summarized in Table 1.1. Each of those fields has its own particularities that are important for a fraud data scientist to know and understand in order to be able to design and implement a customized fraud-detection system. The more aligned the detection system with the environment, the better its performance will be, as evaluated on each of the dimensions already discussed.

A Fraud Data Scientist Should Be Creative

A data scientist needs creativity on at least two levels. First, on a technical level, it is important to be creative with regard to feature selection, data transformation, and cleaning. These steps of the standard analytics process have to be adapted to each particular application, and often the "right guess" could make a big difference. Second, big data and analytics is a fast-evolving field. New problems, technologies, and corresponding challenges pop up on an ongoing basis. Moreover, also fraudsters are very creative and adapt their tactics and methods on an ongoing basis. Therefore, it is crucial that a fraud data scientist keeps up with these new evolutions and technologies and has enough creativity to see how they can create new opportunities.

Figure 1.7 summarizes the key characteristics and strengths constituting the ideal fraud data scientist profile.

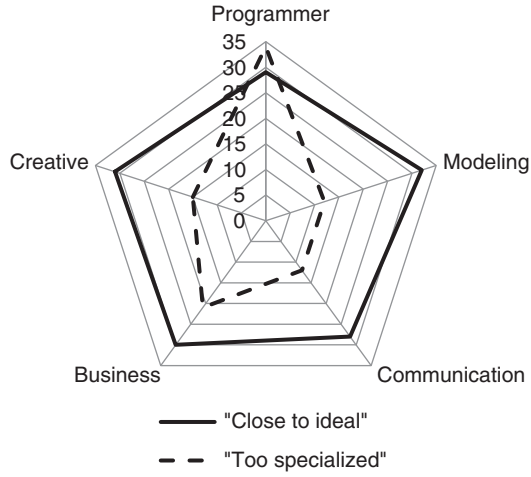

Figure 1.7 Profile of a Fraud Data Scientist

A SCIENTIFIC PERSPECTIVE ON FRAUD

To conclude this chapter, let's provide a scientific perspective about the research on fraud. Figure 1.8 shows a screenshot of the Web of Science statistics when querying all scientific publications between 1996 and 2014 for the key term *fraud*. It shows the total number of papers published each year, the number of citations and the top five most-cited papers.

A couple of conclusions can be drawn as follows:

- 6,174 scientific papers have been published on the topic of fraud during the period reported.
- The h-index is 44, implying that there are at least 44 papers with 44 citations on the topic of fraud.
- The number of publications is steadily increasing, which shows a growing interest from the academic community and research on the topic.
- The citations are exponentially growing, which is associated with the increasing number of publications.
- Two of the five papers mentioned study the use of analytics for fraud detection, clearly illustrating the growing attention in the field for data-driven approaches.

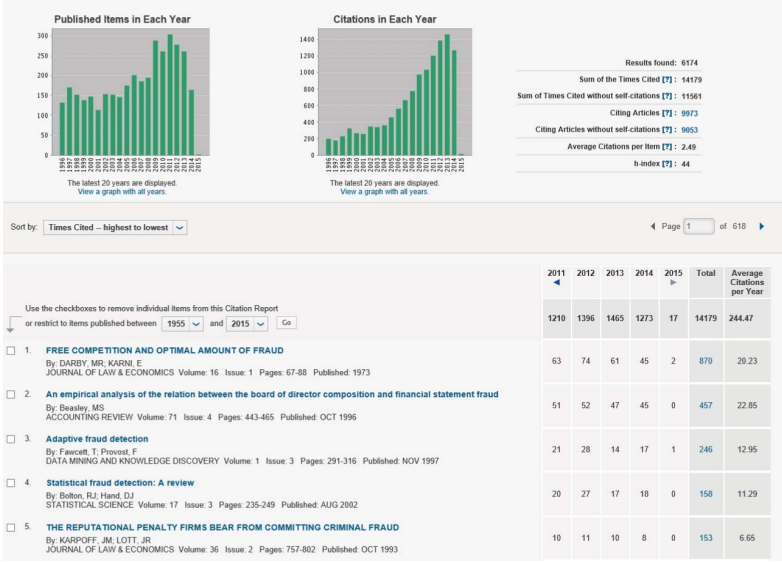

Figure 1.8 Screenshot of Web of Science Statistics for Scientific Publications on Fraud between 1996 and 2014

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CHAPTER 2

Data Collection, Sampling, and Preprocessing

INTRODUCTION

Data is a key ingredient for any analytical exercise. Hence, it is of key importance to thoroughly consider and list all data sources that are potentially of interest and relevant before starting the analysis. Large experiments as well as a broad experience in different fields indicate that when it comes to data, bigger is better (see de Fortuny, Martens, & Provost, 2013). However, real-life data can be (typically is) dirty because of inconsistencies, incompleteness, duplication, merging, and many other problems. Hence, throughout the analytical modeling steps, various data-filtering mechanisms will be applied to clean up and reduce the data to a manageable and relevant size. Worth mentioning here is the garbage in, garbage out (GIGO) principle, which essentially states that messy data will yield messy analytical models. Hence, it is of utmost importance that every data preprocessing step is carefully justified, carried out, validated, and documented before proceeding with further analysis. Even the slightest mistake can make the data totally unusable for further analysis and the results invalid and of no use whatsoever. In what follows, we will elaborate on the most important data preprocessing steps that should be considered during an analytical modeling exercise to build a fraud detection model. But first, let us have a closer look at what data to gather.

TYPES OF DATA SOURCES

Data can originate from a variety of different sources and provide different types of information that might be useful for the purpose of fraud detection, as will be further discussed in this section. Do remark that the provided mixed discussion of different sources and types of data concerns a *broad, non-exhaustive* and *non-mutually exclusive* categorization, respectively in the sense that the most prominent data sources and types of information as available in a typical organization are listed, but clearly not all possible data sources and types of information are discussed, and possibly some overlap exists between the enlisted categories.

Transactional data is a first important source of data. It consists of structured and detailed information capturing the key characteristics of a customer transaction (e.g., a purchase, claim, cash transfer, credit card payment). It is usually stored in massive OLTP (online transaction processing) relational databases. This data can also be summarized over longer time horizons by aggregating it into averages, (absolute or relative) trends, maximum or minimum values, etc. An important type of such aggregated transactional information in a fraud detection setting concern *RFM variables*, which stands for recency (R), frequency (F), and monetary (M) variables. RFM variables are often used for clustering in fraud detection, as will be discussed in Chapter 3, but are useful as well in a supervised learning setting as will be discussed in Chapter 4. RFM variables have been originally introduced in a marketing setting (Cullinan, 1977), but they clearly may also come in handy for fraud detection.

RFM variables can be operationalized in various ways. Let us take the example of credit card fraud detection. The recency can be measured in a continuous way such as how much time elapsed since the most recent transaction, or in a binary way such as was there a transaction made during the past day, week, month, and so on. The frequency can be quantified as the number of transactions per day, week, month, and so on. Similarly, the monetary variable can be quantified as the minimum, maximum, average, median, or most recent value of a transaction. Although these variables can be meaningful when interpreted individually (e.g., fraudsters make more frequent transactions than nonfraudsters), also their interaction can be very useful for fraud detection. For example, credit card fraudsters often try out a stolen credit card for a low amount to see whether it works, before making a big purchase, resulting in a recent and low monetary value transaction followed by a recent and high monetary value transaction. RFM variables can also prove their worth in an anti-money laundering context by considering recency, frequency, and amount of cash transfers between accounts, which possibly allows uncovering characteristic money laundering patterns. A final illustration concerns RFM variables which may be operationalized for insurance claim fraud

detection by constructing variables such as *time since previous claim*, *number of claims submitted in the previous twelve months*, and *total monetary amount of claims since subscription of insurance contract*.

Contractual, subscription, or account data may complement transactional data if a contractual relation exists, which is often the case for utilities such as gas, electricity, telecommunication, and so on. Examples of subscription data are the start date of the relation, information on subscription renewals, characteristics of a subscription such as type of services or products delivered, levels of service, cost of service, product guarantees and insurances, and so on. The moment when customers subscribe to a service offers a unique opportunity for organizations to get to know their customers. Unique in the sense that it may be the only time when a direct contact exists between an employee and the customer, either in person, over the phone, or online, and as such offers the opportunity for the organization to gather additional information that is nonessential to the contract but may be useful for purposes such as marketing but as well for fraud detection. Such information is typically stored in an account management or customer relationship management (CRM) database.

Subscription data may also be a source of **sociodemographic information**, since typically subscription or registration requires identification. Examples of socioeconomic characteristics of a population consisting of individuals are *age*, *gender*, *marital status*, *income level*, *education level*, *occupation*, *religion*, and so on. Although not very advanced or complex measures, sociodemographic information may significantly relate to fraudulent behavior. For instance, it appears that both gender as well as age is very often related to an individual's likelihood to commit fraud: female and older individuals are less likely to commit fraud than male and younger individuals. Similar characteristics can also be defined when the basic entities for which fraud is to be detected do not concern individuals but instead companies or organizations. In such a setting one rather speaks of slow-moving data dimensions, factual data or static characteristics. Examples include the address, year of foundation, industrial sector, activity type, and so on. These do not change over time at all or as often as do other characteristics such as turnover, solvency, number of employees, etc. These latter variables are examples of what we will call below behavioral information.

Several data sources may be consulted for retrieving sociodemographic or factual data, including subscription data sources as discussed above, and data poolers, survey data, and publicly available data sources as discussed below.

Nowadays, **data poolers** are getting more and more important in the industry. Examples are Experian, Equifax, CIFAS, Dun & Bradstreet, Thomson Reuters, etc. The core business of these companies is to gather data (e.g., sociodemographic information) in particular settings or for particular purposes (e.g., fraud detection, credit risk assessment, and marketing) and sell it to interested customers looking to enrich or extend their data sources. Additionally to selling data, these data poolers typically also build predictive models themselves and sell the output of these models as risk scores. This is a common practice in credit risk, for instance, in the United States the FICO score is a credit score ranging between 300 and 850 provided by the three most important credit data poolers or credit bureaus: Experian, Equifax and Transunion. Many financial institutions as well as commercial vendors that give credit to customers use these FICO scores either as their final internal model to assess creditworthiness, or to benchmark it against an internally developed credit scorecard to better understand the weaknesses of the latter. The use of generic, pre-defined fraud risk scores is not yet common practice, but may become possible in the near future.

Surveys are another source of data—that is, survey data. Such data are gathered by inquiring the target population by means of an *offline* (via mail, letter, etc.) or *online* (via phone call or the Internet, which offers different contact channels such as the organization's website, the online helpdesk, social media profiles such as Facebook, LinkedIn, or Twitter) survey. Surveys may aim at gathering sociodemographic data, but also behavioral information.

Behavioral information concerns any information describing the behavior of an individual or an entity in the particular context under research. Such data are also called fast-moving data or dynamic characteristics. Examples of behavioral variables include information with regards to preferences of customers, usage information, frequencies of events, trend variables, and so on. When dealing with organizations, examples of behavioral characteristics or dynamic

characteristics are *turnover*, *solvency*, *number of employees*, and so on. Marketing data results from monitoring the impact of marketing actions on the target population, and concerns a particular type of behavioral information.

Also, **unstructured data** embedded in text documents (e.g., emails, Web pages, claim forms) or multimedia content can be interesting to analyze. However, these sources typically require extensive preprocessing before they can be successfully included in an analytical exercise. Analyzing textual data is the goal of a particular branch of analytics, called text analytics. Given the high level of specialization involved, this book does not provide an extensive discussion of text mining techniques, although a brief introduction is provided in the final chapter of the book. For more information on this topic, one may refer to academic textbooks on the subject (Chakraborty, Murali, & Satish 2013).

A second type of unstructured information is **contextual or network information**, meaning the context of a particular entity. An example of such contextual information concerns relations of a particular type that exist between an entity and other entities of the same type or of another type. How to gather and represent such information, as well as how to make use of it will be described in detail in Chapter 5, which will focus on social network analytics for fraud detection.

Another important source of data is **qualitative, expert-based data**. An expert is a person with a substantial amount of subject matter expertise within a particular setting (e.g., credit portfolio manager, brand manager). The expertise stems from both common sense and business experience and it is important to elicit this knowledge as much as possible before the analytical model building exercise is started. It will allow steering the modeling in the right direction and interpret the analytical results from the right perspective. A popular example of applying expert-based validation is checking the univariate signs of a regression model. For instance, an example already discussed before concerns the observation that a higher age often results in a lower likelihood of being fraudulent. Consequently, a negative sign is expected when including age in a fraud prediction model

yielding the probability of an individual committing fraud. If this turns out not to be the case due to whatever reason (e.g., bad data quality, multicollinearity), the expert or business user will not be tempted to use the analytical model at all, since it contradicts prior expectations.

A final source of information concerns **publicly available** data sources that can provide for instance, **external information**. This is contextual information that is not related to a particular entity, such as macroeconomic data (GDP, inflation, unemployment, etc.), and weather observations. By enriching the data set with such information one may see for example how the model and the model outputs vary as a function of the state of the economy. Possibly fraud rates and total amounts of fraud increase during economic downturn periods, although no scientific evidence (or counter evidence, for that matter) of such an effect is, to our knowledge, available (yet) in the scientific literature. Also social media data from, for example, Facebook, Twitter, LinkedIn, and so on, and that are publicly available can be an important source of information. However, one needs to be careful in both gathering and using such data and make sure that local and international privacy regulations are respected at all times. Privacy concerns in a data analytics context will be discussed in the final chapter.

MERGING DATA SOURCES

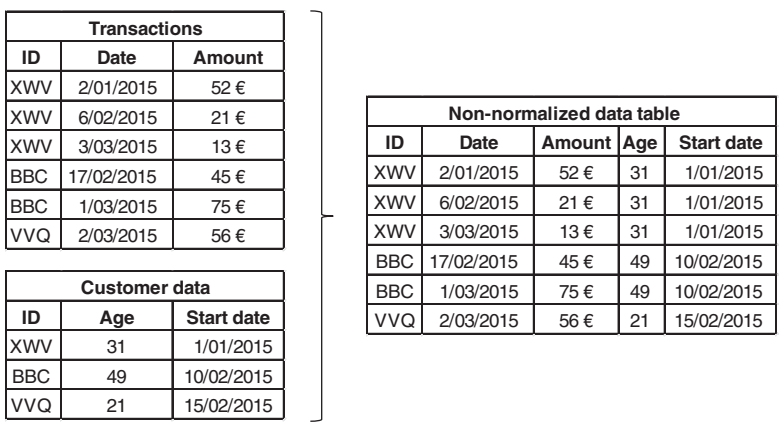
The application of both descriptive and predictive analytics typically requires or presumes the data to be presented in a single table containing and representing all the data in a structured manner. A structured data table allows straightforward processing and analysis. (Learning from multiple tables that are related—that is, learning directly from relational databases without merging the normalized tables—is a particular branch within the field of data mining called relational learning, and shares techniques and approaches with social network analytics as discussed in Chapter 5.)

Typically, the rows of a data table represent the basic entities to which the analysis applies (e.g., customers, transactions, enterprises, claims, cases). The rows are referred to as instances, observations, or

lines. The columns in the data table contain information about the basic entities. Plenty of synonyms are used to denote the columns of the data table, such as (explanatory) variables, fields, characteristics, attributes, indicators, features, and so on.

In order to construct the aggregated, non-normalized data table to facilitate further analysis, often several normalized source data tables have to be merged. Merging tables involves selecting information from different tables related to an individual entity, and copying it to the aggregated data table. The individual entity can be recognized and selected in the different tables by making use of ***keys***, which are attributes that have exactly been included in the table to allow identifying and relating observations from different source tables pertaining to the same entity. Figure 2.1 illustrates the process of merging two tables—that is, transactions data and customer data, into a single non-normalized data table by making use of the key attribute *ID*, which allows connecting observations in the transactions table with observations in the customer table. The same approach can be taken to merge as many tables as required, but clearly the more tables are merged, the more duplicate data might be included in the resulting table.

When merging data tables, it is crucial that no errors happen, so some checks should be applied to control the resulting table and to make sure that all information is correctly integrated.



Transactions

ID	Date	Amount
XWV	2/01/2015	52 €
XWV	6/02/2015	21 €
XWV	3/03/2015	13 €
BBC	17/02/2015	45 €
BBC	1/03/2015	75 €
VVQ	2/03/2015	56 €

Customer data

ID	Age	Start date
XWV	31	1/01/2015
BBC	49	10/02/2015
VVQ	21	15/02/2015

Non-normalized data table

ID	Date	Amount	Age	Start date
XWV	2/01/2015	52 €	31	1/01/2015
XWV	6/02/2015	21 €	31	1/01/2015
XWV	3/03/2015	13 €	31	1/01/2015
BBC	17/02/2015	45 €	49	10/02/2015
BBC	1/03/2015	75 €	49	10/02/2015
VVQ	2/03/2015	56 €	21	15/02/2015

Figure 2.1 Aggregating Normalized Data Tables into a Non-Normalized Data Table

SAMPLING

The aim of sampling is to take a subset of historical data (e.g., past transactions) and use that to build an analytical model. A first obvious question that comes to mind concerns the need for sampling. Obviously, with the availability of high-performance computing facilities (e.g., grid and cloud computing), one could also try to directly analyze the full data set. However, a key requirement for a good sample is that it should be representative for the future entities on which the analytical model will be run. Hence, the timing aspect becomes important since for instance transactions of today are more similar to transactions of tomorrow than transactions of yesterday. Choosing the optimal time window of the sample involves a trade-off between lots of data (and hence a more robust analytical model) and recent data (which may be more representative). The sample should also be taken from an average business period to get as accurate as possible a picture of the target population.

It speaks for itself that sampling bias should be avoided as much as possible. However, this is not always that straightforward. For instance, in a credit card context one may take a month's data as input, which will already result in a substantial amount of data to be processed. But which month is representative for future months? Clearly, customers may use their credit card differently during the month of December when buying gifts for the holiday period. When looking at this example more closely, we discover in fact two sources of bias or deviations from *normal* business periods. Credit card customers may spend more during this period, both in total as well as on individual products. Additionally, different types of products may be bought in different stores usually frequented by the customer.

Let us consider two concrete solutions to address such a seasonality effect or bias, although other solutions may exist. Since every month may in fact deviate from *normal*, if normal is defined as average, it could make sense to build separate models for different months, or for *homogeneous* time frames. This is a rather complex and demanding solution from an operational perspective, since multiple models have to be developed, run, maintained, and monitored.

Alternatively, a sample may be gathered by sampling observations over a period covering a full business cycle. Then only a single model has to be developed, run, maintained, and monitored, which may possibly come at a cost of reduced fraud detection power since less tailored to a particular time frame, yet clearly will be less complex and costly to operate.

The sample to be gathered as such depends on the choice that is made between these two alternative solutions in addressing potential sampling bias. This example illustrates the importance and direct impact of sampling, not in the least on the performance of the model that is built based on the gathered sample (i.e., the fraud detection power).

In stratified sampling, a sample is taken according to predefined strata. In a fraud detection context data sets are typically very skew (e.g., 99 percent nonfraudulent and 1 percent fraudulent transactions). When stratifying according to the target fraud indicator, the sample will contain exactly the same percentages of (non-) fraudulent transactions as in the original data. Additional stratification can be applied on predictor variables as well—for instance, in order for the number of observations across different product categories to closely resemble the real product transaction distribution. However, as long as no large deviations exist with respect to the sample and observed distribution of predictor variables, it will usually be sufficient to limit stratification to the target variable.

TYPES OF DATA ELEMENTS

It is important to appropriately consider the different types of data elements at the start of the analysis. The following types of data elements can be considered:

- Continuous data
  - These are data elements that are defined on an interval, which can be both limited and unlimited.
  - A distinction is sometimes made between continuous data with and without a natural zero value, and which are respectively referred to as *ratio* (e.g., amounts) and *interval* data

(e.g., temperature in degrees Celsius or Fahrenheit). In the latter case, you cannot make a statement like, "It is double or twice as hot as last month"; since the value zero has no meaning you cannot take the ratio of two values, hence explaining the name *ratio* data for data measured on a scale with a natural zero value. Most continuous data in a fraud detection setting concerns ratio data, since often we are dealing with amounts.

- Examples: amount of transaction; balance on savings account; (dis-) similarity index

- Categorical data
  - Nominal
    - These are data elements that can only take on a limited set of values with no meaningful ordering in between.
    - Examples: marital status; payment type; country of origin
  - Ordinal
    - These are data elements that can only take on a limited set of values with a meaningful ordering in between.
    - Examples: age coded as young, middle-aged, and old
  - Binary
    - These are data elements that can only take on two values.
    - Examples: daytime transaction (yes/no); online transaction (yes/no)

Appropriately distinguishing between these different data elements is of key importance to start the analysis when importing the data into an analytics tool. For example, if marital status would be incorrectly specified as a continuous data element, then the software would calculate its mean, standard deviation, and so on, which is obviously meaningless and may perturb the analysis.

VISUAL DATA EXPLORATION AND EXPLORATORY STATISTICAL ANALYSIS

Visual data exploration is a very important part of getting to know your data in an "informal" way. It allows gaining some initial insights

into the data, which can then be usefully adopted throughout the modeling stage. Different plots/graphs can be useful here. Pie charts are a popular example. A pie chart represents a variable's distribution as a pie, whereby each section represents the portion of the total percent taken by each value of the variable. Figure 2.2 represents a pie chart for a variable *payment type* with possible values *credit card*, *debit card*, or *cheque*. A separate pie chart analysis for the fraudsters and nonfraudsters indicates that for payment type *cheque* relatively more fraud occurs, which can be a very useful starting insight. Bar charts represent the frequency of each of the values (either absolute or relative) as bars. Other handy visual tools are histograms and scatter plots. A histogram provides an easy way to visualize the central tendency and to determine the variability or spread of the data. It also allows to contrast the observed data with standard known distributions (e.g., normal distribution). Scatter plots allow users to visualize one variable against another to see whether there are any correlation patterns in the data. Also, OLAP based multidimensional data analysis can be usefully adopted to explore patterns in the data (see Chapter 3).

A next step after visual analysis could be inspecting some basic statistical measurements such as averages, standard deviations, minimum, maximum, percentiles, confidence intervals, and so on. One could calculate these measures separately for each of the target classes (e.g., fraudsters versus nonfraudsters) to see whether there are any interesting patterns present (e.g., do fraudsters usually have a lower average age than nonfraudsters?).

BENFORD'S LAW

A both visual and numerical data exploration technique that is particularly interesting in a fraud detection setting relates to what is commonly known as Benford's law. This law describes the frequency distribution of the first digit in many real-life data sets and is shown in Figure 2.3. When comparing the expected distribution following Benford's law with the observed distribution in a data set, strong deviations from the expected frequencies may indicate the data to be suspicious and possibly manipulated. For instance, government aid or

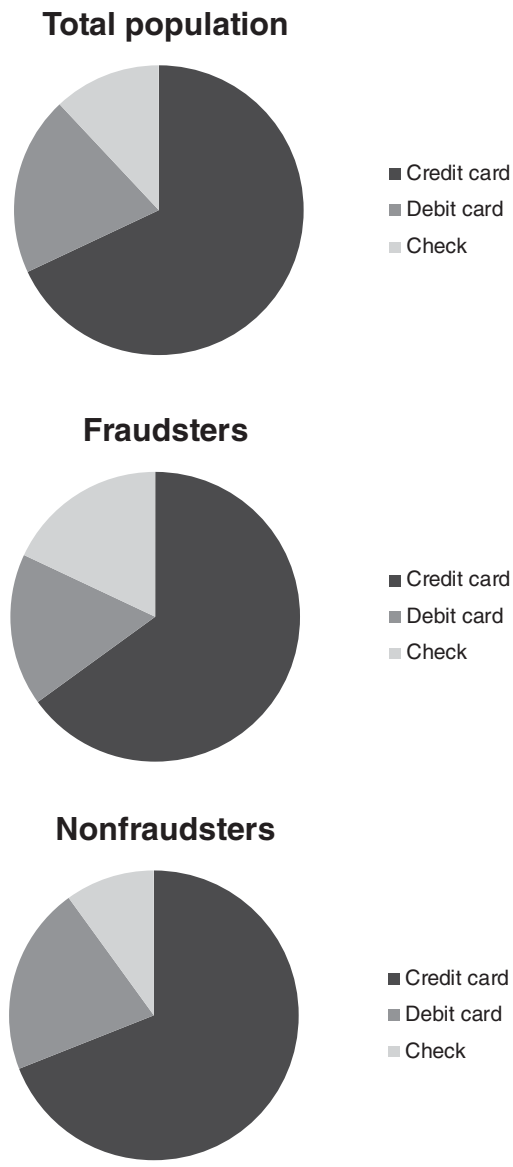


Figure 2.2 Pie Charts for Exploratory Data Analysis

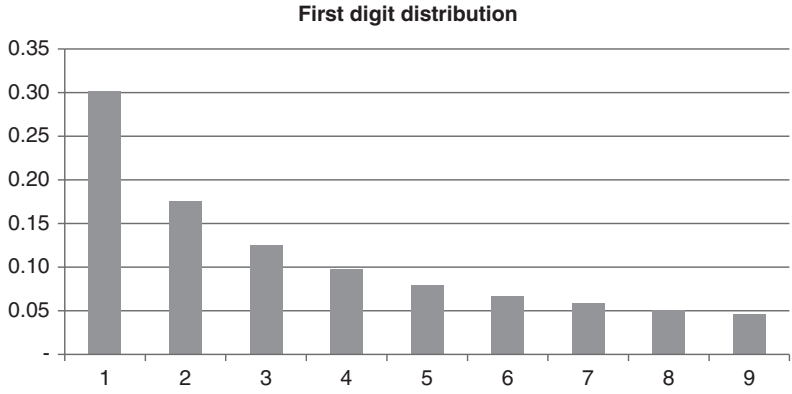


Figure 2.3 Benford's Law Describing the Frequency Distribution of the First Digit

support eligibility typically depends on whether the applicant meets certain requirements, such as an income below a certain threshold. Therefore, data may be tampered with in order for the application to comply with these requirements. It is exactly such types of fraud that are prone to detection using Benford's law, since the manipulated or made-up numbers will not comply with the expected observed frequency of the first digit as expressed by Benford's law.

The mathematical formula describing this law expresses the probability *P(d)* of the leading digit *d* to occur to be equal to:

$$P(d) = log_{10}\left(1 + \frac{1}{d}\right)$$

Benford's law can be used as a screening tool for fraud detection (Jamain 2001). It is a *partially negative rule*, like many other rules, meaning that if Benford's law is not satisfied, then it is probable that the involved data were manipulated and further investigation or testing is required. Conversely, if a data set complies with Benford's law, it can still be fraudulent. Note that Benford's law applies to a data *set*, meaning that a sufficient amount of numbers related to an individual case need to be gathered in order for Benford's law to be meaningful, which is typically the case when dealing with financial statements, for instance.

A deviation from Benford's law does not necessarily mean that the data have been tampered with. It may also attract the analyst's

attention toward data quality issues resulting from merging several data sets in a single structured data table, toward duplicate data, and so on. Hence, it may definitely be worthwhile for several purposes to control compliance with Benford's law during the data-preprocessing phase.

DESCRIPTIVE STATISTICS

Similar to Benford's law and in addition to the preparatory visual data exploration, several descriptive statistics might be calculated that provide basic insight or *feeling* for the data. Plenty of descriptive statistics exist to summarize or provide information with respect to a particular characteristic of the data, and therefore descriptive statistics should be assessed together—in support and completion of each other.

Basic descriptive statistics are the mean and median value of continuous variables, with the median value less sensitive to extreme values but then as well not providing as much information with respect to the full distribution. Complementary to the mean value, the variation or the standard deviation provide insight with respect to how much the data is spread around the mean value. Likewise, percentile values such as the 10, 25, 75, and 90 percentile, provide further information with respect to the distribution and as a complement to the median value.

Specific descriptive statistics exist to express the symmetry or asymmetry of a distribution, such as the *skewness* measure, as well as the peakedness or flatness of a distribution—for example, the *kurtosis* measure. However, the exact values of these measures are likely a bit harder to interpret than for instance the value of the mean and standard deviation. This limits their practical use. Instead, one could more easily assess these aspects by inspecting visual plots of the distributions of the involved variables.

When dealing with categorical variables, instead of the median and the mean value one may calculate the mode, which is the most frequently occurring value. In other words, the mode is the most typical value for the variable at hand. The mode is not necessarily unique, since multiple values can result in the same maximum frequency.

MISSING VALUES

Missing values can occur because of various reasons. The information can be nonapplicable. For example, when modeling amount of fraud for users, then this information is only available for the fraudulent accounts and not for the nonfraudulent accounts since it is not applicable there. The information can also be undisclosed. For example, a customer decided not to disclose his or her income because of privacy. Missing data can also originate because of an error during merging (e.g., typos in name or ID).

Some analytical techniques (e.g., decision trees) can deal directly with missing values. Other techniques need some additional preprocessing. The following are the most popular schemes to deal with missing values (Little and Rubin 2002).

- **Replace (Impute)**

  This implies replacing the missing value with a known value. For example, consider the example in Table 2.1. One could impute the missing credit bureau scores with the average or median of the known values. For marital status, the mode can then be used. One could also apply regression-based imputation whereby a regression model is estimated to model a target variable (e.g., credit bureau score) based on the other information available (e.g., age, income). The latter is more sophisticated, although the added value from an empirical viewpoint (e.g., in terms of model performance) is questionable.

- **Delete**

  This is the most straightforward option and consists of deleting observations or variables with lots of missing values. This, of course, assumes that information is missing at random and has no meaningful interpretation and/or relationship to the target.

- **Keep**

  Missing values can be meaningful. For example, a customer did not disclose his/her income because he/she is currently unemployed. This fact may have a relation with fraud and needs to be considered as a separate category.

Table 2.1 Dealing with Missing Values

ID	Age	Income	Marital Status	Credit Bureau Score	Fraud
1	34	1,800	?	620	Yes
2	28	1,200	Single	?	No
3	22	1,000	Single	?	No
4	60	2,200	Widowed	700	Yes
5	58	2,000	Married	?	No
6	44	?	?	?	No
7	22	1,200	Single	?	No
8	26	1,500	Married	350	No
9	34	?	Single	?	Yes
10	50	2,100	Divorced	?	No

As a practical way of working, one can first start with statistically testing whether missing information is related to the target variable or not (using, e.g., a Chi-squared test, see the section on categorization). If yes, then we can adopt the keep strategy and make a special category for it. If not, one can depending on the number of observations available, decide to either delete or impute.

OUTLIER DETECTION AND TREATMENT

Outliers are extreme observations that are very dissimilar to the rest of the population. Actually, two types of outliers can be considered:

- Valid observations, e.g., salary of boss is US$1,000,000
- Invalid observations, e.g., age is 300 years

Both are univariate outliers in the sense that they are outlying on one dimension. However, outliers can be hidden in unidimensional views of the data. Multivariate outliers are observations that are outlying in multiple dimensions. For example, Figure 2.4 gives an example of two outlying observations considering both the dimensions of income and age.

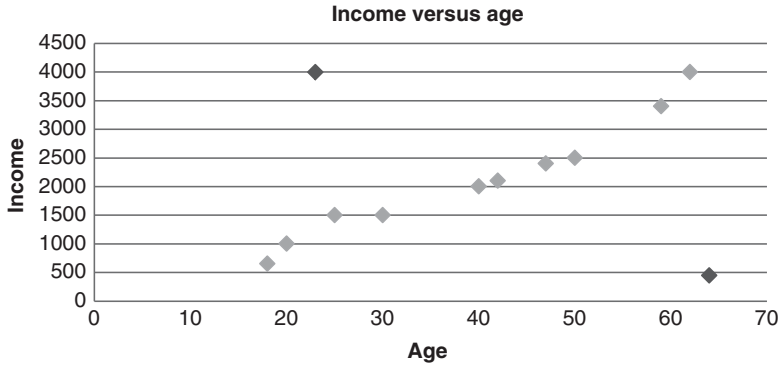


Figure 2.4 Multivariate Outliers

Two important steps in dealing with outliers are detection and treatment. A first obvious check for outliers is to calculate the minimum and maximum values for each of the data elements. Various graphical tools can be used to detect outliers. Histograms are a first example. Figure 2.5 presents an example of a distribution for age whereby the circled areas clearly represent outliers.

Another useful visual mechanism is a box plot. A box plot represents three key quartiles of the data: the first quartile (25 percent of the observations have a lower value), the median (50 percent of the observations have a lower value), and the third quartile (75 percent

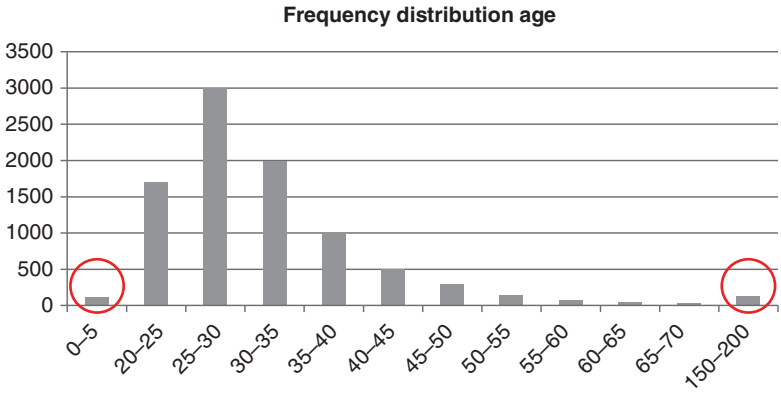


Figure 2.5 Histogram for Outlier Detection

of the observations have a lower value). All three quartiles are represented as a box. The minimum and maximum value are then also added unless they are too far away from the edges of the box. Too far away is then quantified as more than 1.5 × Interquartile Range (IQR = $Q_3 - Q_1$). Figure 2.6 gives an example of a box plot where three outliers can be seen.

Another way is to calculate *z*-scores, measuring how many standard deviations an observation lies away from the mean, as follows:

$$z_i = \frac{x_i - \mu}{\sigma},$$

where μ represents the average of the variable and σ its standard deviation. An example is given in Table 2.2. Note that, by definition, the *z*-scores will have a mean of zero and unit standard deviation.

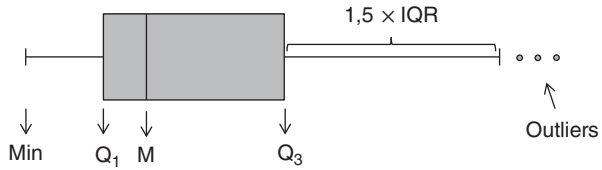


Figure 2.6 Box Plots for Outlier Detection

Table 2.2 *z*-Scores for Outlier Detection

ID	Age	*z*-Score
1	30	(30 – 40)/10 = –1
2	50	(50 – 40)/10 = +1
3	10	(10 – 40)/10 = –3
4	40	(40 – 40)/10 = 0
5	60	(60 – 40)/10 = +2
6	80	(80 – 40)/10 = +4
…		
	$\mu = 40$ $\sigma = 10$	$\mu = 0$ $\sigma = 1$

A practical rule of thumb, then, defines outliers when the absolute value of the *z*-score |*z*| is bigger than three. Note that the *z*-score relies on the normal distribution.

These methods all focus on univariate outliers. Multivariate outliers can be detected by fitting regression lines and inspecting the observations with large errors (using, e.g., a residual plot). Alternative methods are clustering or calculating the Mahalanobis distance. Note, however, that although potentially useful, multivariate outlier detection is typically not considered in many modeling exercises due to the typical marginal impact on model performance.

Some analytical techniques (e.g., decision trees, neural networks, SVMs) are fairly robust with respect to outliers. Others (e.g., linear/logistic regression) are more sensitive to them. Various schemes exist to deal with outliers. It highly depends on whether the outlier represents a valid or invalid observation. For invalid observations (e.g., age is 300 years), one could treat the outlier as a missing value using any of the schemes discussed in the previous section. For valid observations (e.g., income is US$1,000,000), other schemes are needed. A popular scheme is truncation/capping/winsorizing. One hereby imposes both a lower and upper limit on a variable and any values below/above are brought back to these limits. The limits can be calculated using the *z*-scores (see Figure 2.7), or the IQR (which is more robust than the *z*-scores) as follows:

Upper/Lower limit = $M \pm 3s$, with M = median and $s = \text{IQR}/(2 \times 0.6745)$ (Van Gestel and Baesens 2009). A sigmoid transformation ranging between 0 and 1 can also be used for capping as follows:

$$f(x) = \frac{1}{1 + e^{-x}}$$

In addition, expert-based limits based on business knowledge and/or experience can be imposed.

An important remark concerning outliers is the fact that not all invalid values are outlying and, as such, may go unnoted if not explicitly looked into. For instance, a clear issue exists when observing customers with values *gender* = *male* and *pregnant* = *yes*. Which value is invalid, either the value for gender or pregnant, cannot be determined, but it needs to be noted that both values are not outlying and therefore

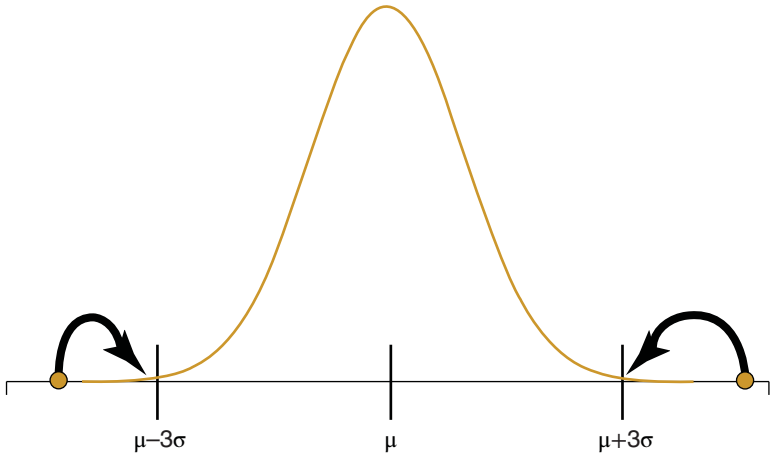


Figure 2.7 Using the *z*-Scores for Truncation

such a conflict will not be noted by the analyst unless some explicit precautions are taken. In order to detect particular invalid combinations, one may construct a set of rules that are formulated based on expert knowledge and experience (similar to a fraud detection rule engine in fact), which is applied to the data to check and alert for issues. In this particular context, a network representation of the variables may be of use to construct the rule set and reason upon relations that exist between the different variables, with links representing constraints that apply to the combination of variable values and resulting in rules added to the rule set.

RED FLAGS

An important remark with respect to outlier treatment is to be made, which particularly holds in a fraud detection setting. As discussed in the introductory chapter, fraudsters may be detected by the very fact that their behavior is different or deviant from nonfraudsters, although most likely only slightly or in a complex (multivariate) manner since they will cover their tracks to remain undetected. These deviations from *normality* are called *red flags* of fraud and are probably the most successful and widespread tool that is being used

to detect fraud. As discussed in Grabosky and Duffield (2001) in the broadest terms, the fundamental red flag of fraud is the anomaly, that is, a variation from predictable patterns of behavior or, simply, something that seems out of place. Some examples of red flags follow:

Tax evasion fraud red flags:

- An identical financial statement, since fraudulent companies copy financial statements of nonfraudulent companies to look less suspicious
- Name of an accountant is unique, since this might concern a nonexisting accountant

Credit card fraud red flags:

- A small payment followed by a large payment immediately after, since a fraudster might first check whether the card is still active before placing a bet
- Regular rather small payments, which is a technique to avoid getting noticed

Telecommunications-related fraud may be reflected in the following red-flag activities (Grabosky and Duffield 2001):

- Long-distance access followed by reverse call charges accepted from overseas
- High-volume usage over short periods before disconnection
- A large volume of calls where one call begins shortly after the termination of another
- The nonpayment of bills

Such red-flag activities are typically translated in expert rules and included in a rule engine as discussed in Chapter 1. When red flags and expert rules are defined, the reasoning behind the red flag or rule should be documented in order to inform the inspectors about the underlying reasons or causes of suspicion underlying the red flag that is raised, so they can focus their investigations on these causes for suspicion.

Descriptive or unsupervised learning techniques will be discussed in Chapter 3, including several approaches that aim at detecting such slight or complex deviations from regular behavior associated

with fraud. When handling valid outliers in the data set using the treatment techniques discussed before, we may impair in fact the ability of descriptive analytics in finding anomalous fraud patterns. Therefore, one should be extremely careful in treating valid outliers when applying unsupervised learning techniques to build a fraud detection model. This is true even when handling univariate outliers, since these might be not by themselves but in combination with other variables in a multivariate manner related to and as such be used to uncover fraud. Invalid outliers, on the contrary, can straightforwardly be treated as discussed above as missing values, preferably by including an indicator that the value was missing or even more precisely an invalid outlier. This allows users to test if there is any relation at all between an invalid value and fraud.

STANDARDIZING DATA

Standardizing data is a data preprocessing activity targeted at scaling variables to a similar range. Consider, for example, two variables gender (coded as 0/1) and income (ranging between 0 and US$1,000,000). When building logistic regression models using both information elements, the coefficient for income might become very small. Hence, it could make sense to bring them back to a similar scale. The following standardization procedures could be adopted:

- Min/Max standardization

$$X_{new} = \frac{X_{old} - \min(X_{old})}{\max(X_{old}) - \min(X_{old})}(newmax - newmin) + newmin,$$

  whereby newmax and newmin are the newly imposed maximum and minimum (e.g., 1 and 0).
- z-score standardization
  - Calculate the z-scores (see the previous section).
- Decimal scaling
  - Divide by a power of 10 as follows: $X_{new} = \frac{X_{old}}{10^n}$, with n the number of digits of the maximum absolute value.

Again, note that standardization is especially useful for regression-based approaches but is not needed for decision trees, for example.

CATEGORIZATION

Categorization (also known as coarse-classification, classing, grouping, or binning) can be done for various reasons. For categorical variables, it is needed to reduce the number of categories. Consider, for example, the variable *country of origin* having 50 different values. When this variable would be put into a regression model, one would need 49 dummy variables (50 – 1 because of the collinearity), which would necessitate the estimation of 49 parameters for only one variable. With categorization, one would create categories of values such that less parameters will have to be estimated and a more robust model is obtained.

For continuous variables, categorization may also be very beneficial. Consider, for example, the age variable and the observed amount of fraudulent cases as depicted in Figure 2.8. Clearly, there is a nonmonotonous relation between risk of fraud and age. If a nonlinear model (e.g., neural network, support vector machine) would be used, then the nonlinearity can be perfectly modeled. However, if a regression model would be used (which is typically more common because of its interpretability), then since it can only fit a line, it will miss out on the nonmonotonicity. By categorizing the variable into ranges, part of the nonmonotonicity can be taken into account in the regression. Hence, categorization of continuous variables can be useful to model nonlinear effects into linear models.

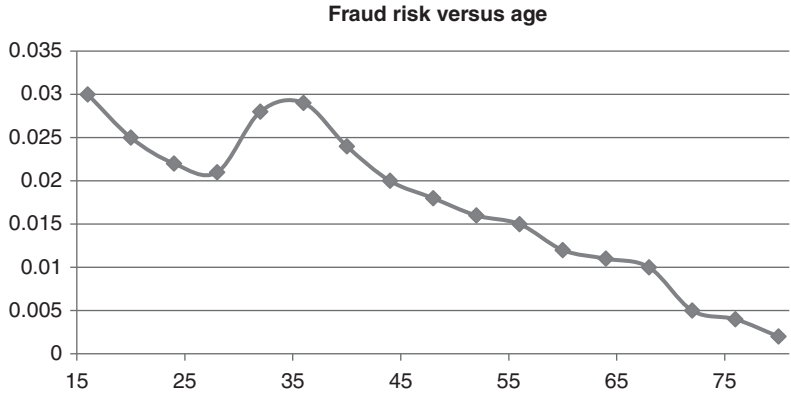


Figure 2.8 Default Risk Versus Age

Various methods can be used to do categorization. Two very basic methods are equal interval binning and equal frequency binning. Consider, for example, the income values 1,000, 1,200, 1,300, 2,000, 1,800, 1,400. Equal interval binning would create two bins with the same range, Bin 1: 1,000, 1,500 and Bin 2: 1,500, 2,000, whereas equal frequency binning would create two bins with the same number of observations as follows, Bin 1: 1,000, 1,200, 1,300, Bin 2: 1,400, 1,800, 2,000. However, both methods are quite basic and do not take into account a target variable (e.g., churn, fraud, credit risk).

Many analytics software tools have built-in facilities to do categorization using Chi-squared analysis. A very handy and simple approach (available in Microsoft Excel) is to use pivot tables. Consider the examples in Tables 2.3 and 2.4.

Table 2.3 Coarse Classifying the Product Type Variable

Customer ID	Age	Product Type	…	Fraud
C1	44	clothes		No
C2	20	books		No
C3	58	music		Yes
C4	26	clothes		No
C5	30	electro		Yes
C6	32	games		No
C7	48	books		Yes
C8	60	clothes		No
…				

Table 2.4 Pivot Table for Coarse Classifying the Product Type Variable

	Clothes	Books	Music	Electro	Games	…
Good	1,000	2,000	3,000	100	5,000	
Bad	500	100	200	80	800	
Odds	2	20	15	1.25	6.25	

One can then construct a pivot table and calculate the odds as follows:

We can then categorize the values based on similar odds. For example, category 1 (clothes, electro), category 2 (games), and category 3 (books and music).

Chi-squared analysis is a more sophisticated way to do coarse classification. Consider, for example, Table 2.5 for coarse classifying a variable *product type*.

Suppose we want three categories and consider the following options:

- Option 1: clothes; books and music; others
- Option 2: clothes; electro; others

Both options can now be investigated using Chi-squared analysis. The purpose hereby is to compare the empirically observed with the independence frequencies. For option 1, the empirically observed frequencies are depicted in Table 2.6.

The independence frequencies can be calculated as follows. The number of nonfraud observations given that the odds are the same as in the whole population is $6{,}300/10{,}000 \times 9{,}000/10{,}000 \times 10{,}000 = 5{,}670$. One then obtains Table 2.7.

Table 2.5 Coarse Classifying the Product Type Variable

Attribute	Clothes	Books	Music	Electro	Games	Movies	Total
No-fraud	6,000	1,600	350	950	90	10	9,000
Fraud	300	400	140	100	50	10	1,000
No-fraud: Fraud odds	20:1	4:1	2.5:1	9.5:1	1.8:1	1:1	9:1

Table 2.6 Empirical Frequencies Option 1 for Coarse Classifying Product Type

Attribute	Clothes	Books & Music	Others	Total
No-fraud	6,000	1,950	1,050	9000
Fraud	300	540	160	1,000
Total	6,300	2,490	1,210	10,000

Table 2.7 Independence Frequencies Option 1 for Coarse Classifying Product Type

Attribute	Clothes	Books & Music	Others	Total
No-fraud	5,670	2,241	1,089	9,000
Fraud	630	249	121	1,000
Total	6,300	2,490	1,210	10,000

The more the numbers in both tables differ, the less independence, hence better dependence and a better coarse classification. Formally, one can calculate the Chi-squared distance as follows:

$$\chi^2 = \frac{(6000-5670)^2}{5670} + \frac{(300-630)^2}{630} + \frac{(1950-2241)^2}{2241} + \frac{(540-249)^2}{249} + \frac{(1050-1089)^2}{1089} + \frac{(160-121)^2}{121} = 583$$

Likewise, for option 2, the calculation becomes:

$$\chi^2 = \frac{(6000-5670)^2}{5670} + \frac{(300-630)^2}{630} + \frac{(950-945)^2}{945} + \frac{(100-105)^2}{105} + \frac{(2050-2385)^2}{2385} + \frac{(600-265)^2}{265} = 662$$

So, based on the Chi-squared values, option 2 is the better categorization. Note that formally, one needs to compare the value with a Chi-squared distribution with $k-1$ degrees of freedom with k the number of values of the characteristic.

WEIGHTS OF EVIDENCE CODING

Categorization reduces the number of categories for categorical variables. For continuous variables, categorization will introduce new variables. Consider, for example, a regression model with age (four categories, so three parameters) and product type (five categories, so four parameters) characteristics. The model then looks as follows:

$$Y = \beta_0 + \beta_1 \text{Age}_1 + \beta_2 \text{Age}_2 + \beta_3 \text{Age}_3 + \beta_4 \text{Prod}_1 + \beta_5 \text{Prod}_2 + \beta_6 \text{Prod}_3 + \beta_7 \text{Prod}_4$$

Despite having only two characteristics, the model still needs eight parameters to be estimated. It would be handy to have a monotonic transformation $f(.)$ such that our model could be rewritten as follows:

$$Y = \beta_0 + \beta_1 f(\text{Age}_1, \text{Age}_2, \text{Age}_3) + \beta_2 f(\text{Prod}_1, \text{Prod}_2, \text{Prod}_3, \text{Prod}_4)$$

The transformation should have a monotonically increasing or decreasing relationship with Y. Weights-of-evidence coding is one example of a transformation that can be used for this purpose. This is illustrated in Table 2.8.

The WOE is calculated as: ln(Dist No-fraud/Dist Fraud). Because of the logarithmic transformation, a positive (negative) WOE means Dist No-fraud > (<) Dist Fraud. The WOE transformation thus implements a transformation monotonically related to the target variable.

The model can then be reformulated as follows:

$$Y = \beta_0 + \beta_1 WOE_{\text{age}} + \beta_2 WOE_{\text{product-type}}$$

This gives a more concise model than the model that we started this section with. However, note that the interpretability of the model becomes somewhat less straightforward when *WOE* variables are being used.

Table 2.8 Calculating Weights of Evidence (WOE)

Age	Count	Distr. Count	No-fraud	Distr No-fraud	Fraud	Distr Fraud	WOE
Missing	50	2.50%	42	2.33%	8	4.12%	–57.28%
18–22	200	10.00%	152	8.42%	48	24.74%	–107.83%
23–26	300	15.00%	246	13.62%	54	27.84%	–71.47%
27–29	450	22.50%	405	22.43%	45	23.20%	–3.38%
30–35	500	25.00%	475	26.30%	25	12.89%	71.34%
35–44	350	17.50%	339	18.77%	11	5.67%	119.71%
44+	150	7.50%	147	8.14%	3	1.55%	166.08%
	2,000		1,806		194		

VARIABLE SELECTION

Many analytical modeling exercises start with tons of variables, of which typically only a few actually contribute to the prediction of the target variable. For example, the average fraud model in fraud detection has somewhere between 10 and 15 variables. The key question is how to find these variables. Filters are a very handy variable selection mechanism. They work by measuring univariate correlations between each variable and the target. As such, they allow for a quick screening of which variables should be retained for further analysis. Various filter measures have been suggested in the literature. One can categorize them as depicted in Table 2.9.

The Pearson correlation ρ_P is calculated as follows:

$$\rho_P = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

It measures a linear dependency between two variables and always varies between -1 and $+1$. To apply it as a filter, one could select all variables for which the Pearson correlation is significantly different from 0 (according to the p-value), or for example, the ones where $|\rho_P| > 0.50$.

The Fisher score can be calculated as follows:

$$\frac{|\overline{X}_{G-}\overline{X}_B|}{\sqrt{s_G^2 + s_B^2}},$$

Table 2.9 Filters for Variable Selection

	Continuous Target (e.g., CLV, LGD)	Categorical Target (e.g., churn, fraud, credit risk)
Continuous variable	Pearson correlation	Fisher score
Categorical variable	Fisher score/ANOVA	Information value Cramer's V Gain/entropy

where $\overline{X}_G$ ($\overline{X}_B$) represents the average value of the variable for the non-fraudsters (fraudsters) and s_G^2 (s_B^2) the corresponding variances. High values of the Fisher score indicate a predictive variable. To apply it as a filter, one could, for example, keep the top 10 percent. Note that the Fisher score may generalize to a well-known analysis of variance (ANOVA) in case a variable has multiple categories.

The information value (IV) filter is based on weights of evidence and is calculated as follows:

$$IV = \sum_{i=1}^{k} (Dist\ Good_i - Dist\ Bad_i) \times WOE_i,$$

whereby k represents the number of categories of the variable. For the example discussed in Table 2.10, the calculation becomes as shown.

The following rules of thumb apply for the information value:

- <0.02: unpredictive
- 0.02 – 0.1: weak predictive
- 0.1 – 0.3: medium predictive
- +0.3: strong predictive

Note that the information value assumes that the variable has been categorized. It can actually also be used to adjust/steer the categorization so as to optimize the IV. Many software tools will provide

Table 2.10 Calculating the Information Value Filter Measure

Age	Count	Distr. Count	No-fraud	Distr No-fraud	Fraud	Distr Fraud	WOE	IV
Missing	50	2.50%	42	2.33%	8	4.12%	–57.28%	0,0103
18–22	200	10.00%	152	8.42%	48	24.74%	–107.83%	0,1760
23–26	300	15.00%	246	13.62%	54	27.84%	–71.47%	0,1016
27–29	450	22.50%	405	22.43%	45	23.20%	–3.38%	0,0003
30–35	500	25.00%	475	26.30%	25	12.89%	71.34%	0,0957
35–44	350	17.50%	339	18.77%	11	5.67%	119.71%	0,1568
44+	150	7.50%	147	8.14%	3	1.55%	166.08%	0,1095
Information Value								**0,6502**

interactive support to do this, whereby the modeler can adjust the categories and gauge the impact on the IV. To apply it as a filter, one can calculate the information value of all (categorical) variables and only keep those for which the IV > 0.1 or, for example, the top 10 percent.

Another filter measure based on Chi-squared analysis is Cramer's V. Consider, for example, the contingency table depicted in Table 2.11 for online/offline transaction versus nonfraud/fraud.

Similar to the example discussed in the section on categorization, the Chi-squared value for independence can then be calculated as follows:

$$\chi^2 = \frac{(500-480)^2}{480} + \frac{(100-120)^2}{120} + \frac{(300-320)^2}{320} + \frac{(100-80)^2}{80} = 10.41$$

This follows a Chi-squared distribution with $k - 1$ degrees of freedom, with k being the number of classes of the characteristic. The Cramer's V measure can then be calculated as follows:

$$Cramer's\ V = \sqrt{\frac{\chi^2}{n}} = 0.10,$$

with n the number of observations in the data set. Cramer's V is always bounded between 0 and 1 and higher values indicate better predictive power. As a rule of thumb, a cut-off of 0.1 is commonly adopted. One can then again select all variables where Cramer's V is bigger than 0.1, or consider, for example, the top 10 percent. Note that the Information Value and Cramer's V typically consider the same characteristics as most important.

Table 2.11 Contingency Table for Marital Status versus Good/Bad Customer

	Nonfraud	Fraud	Total
Offline	500	100	600
Online	300	100	400
Total	800	200	1000

Filters are very handy, as they allow reduction in the number of dimensions of the data set early in the analysis in a quick way. Their main drawback is that they work univariately and typically do not consider correlation between the dimensions individually, for example. Hence, a follow-up input selection step during the modeling phase will be necessary to further refine the characteristics. Also worth mentioning here is that other criteria may play a role in selecting variables, such as regulatory compliance and privacy issues. Note that different regulations may apply in different geographical regions and hence should be checked. Also operational issues could be considered. For example, trend variables could be very predictive but might require too much time to be computed in a real-time, online fraud detection environment.

PRINCIPAL COMPONENTS ANALYSIS

An alternative method for input or variable selection is principal component analysis, which is a technique to reduce the dimensionality of data by forming new variables that are linear composites of the original variables. These new variables describe the main components or dimensions that are present in the original data set, hence its name. The main dimensions may and often are different from the *imposed* measurement dimensions, and as such are obtained as a linear combination of those. Figure 2.9 provides a two-dimensional illustration of this. The two measurement dimensions represented by the *X* and *Y* axes do not adequately capture the actual dimensions or components present in the data. These are clearly situated in a 45-degree angle

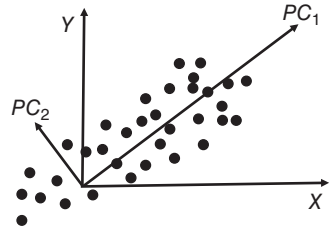


Figure 2.9 Illustration of Principal Component Analysis in a Two-Dimensional Data Set

compared to the X and Y dimensions and are described or captured by the two principal components PC_1 and PC_2.

The maximum number of new variables that can be formed or derived from the original data (i.e., the number of principal components) is equal to the number of original variables. However, when the aim is data reduction, then typically a reduced set of principal components is sufficient to replace the original larger set of variables, since most of the variance in the original set of variables will be explained by a limited number of principal components. In other words, most of the information that is contained in the large set of original variables typically can be summarized by a small number of new variables. To explain all the variance in the original data set, the full set of principal components is needed, but some of these will only account for a very small fraction of variance and therefore can be left out, leading to a reduced dimensionality or number of variables in the data set.

Example: A data set contains 80 financial ratio variables describing the financial situation or health of a firm, which may be indicative or relevant for detecting fraud. However, many of these financial ratios are typically strongly correlated. In other words, many of these ratios *overlap*, meaning that they basically express the same information. This may be explained by the fact that these ratios are derived from and summarize the same basic information. Therefore, one could prefer to combine or summarize the original large set of ratios by a reduced number of financial indices, as can be done by performing a principal component analysis.

Moreover, the new limited set of financial indices should preferably be uncorrelated, such they can be included in a fraud-detection model without causing the final model to become unstable. Correlation among the explanatory or predictor variables, which is called *multicollinearity*, may result in unstable models. The stability or robustness of a model refers to the stability of the exact values of the parameters of the model that are being estimated based on the sample of observations. If the values of these parameters heavily depend on the exact sample of observations used to induce the model, then the model is called unstable. The values of the parameters, in fact, express the relation between the explanatory or predictor variables and the dependent or target variable. When the exact relation differs strongly for

different samples of observations, then questions arise with respect to the exact nature and reliability of this presumed relation. When the explanatory variables included in a model are correlated, typically, the resulting model is unstable. Therefore, an input selection procedure is often performed—for example, using the filter approach discussed in the previous paragraph, or alternatively a new set of factors may be derived using principal component analysis to address this problem, since the resulting new variables (i.e., the principal components, will be uncorrelated among themselves).

Principal components are calculated by making use of the eigenvector decomposition (which will not be explained within the scope of this book; interested readers may refer to specialized literature on principal component analysis and eigenvector decomposition). Let $X_1, X_2, \ldots, X_p$ be the mean-corrected, standardized original variables, and $\Sigma = cov(X)$ the corresponding covariance matrix. Let $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$ be the p eigenvalues of Σ and $e_1, e_2, \ldots, e_p$ the corresponding eigenvectors. The principal components $PC_j, j = 1 \ldots p$, corresponding with and in fact replacing the variables $X_1, X_2, \ldots, X_p$ are then given by:

$$PC_j = \boldsymbol{e'_j X} = e_{j1}X_1 + e_{j2}X_2 + \cdots + e_{jp}X_p = \boldsymbol{X' e_j}$$

The eigenvectors express the importance of each of the original variables in the construction of the new variables. The eigenvectors determine how the original variables are combined into new variables, and in what proportions.

The observed variance in data set X that is explained by principal component PC_j is equal to the corresponding eigenvalue λ_j. The total variance or information in the data will not change and remain constant as the sum of the variances of the principal components—that is, the new variables—is equal to the sum of the variances of the original variables. Also note that the covariance or correlation between two principal components is equal to zero, $cov(PC_i, PC_j) = 0$ for $i \neq j$.

For each observation in the data set, the values for the new variables can be calculated. These values are called the PC scores and can be calculated by making use of the eigenvectors as weights on the mean-corrected data.

Example: A data set consists of two original variables X_1 and X_2, which we will replace by two principal components. The first step consists of calculating the two eigenvectors e_1 and e_2 of the covariance matrix Σ, which can be done straightforwardly using the available observations in the data set. As such, we get $e_1 = (e_{11}, e_{12}) = (0.562, 0.345)$ and $e_2 = (e_{21}, e_{22}) = (-0.345, 0.562)$. Subsequently, in a second step the PC scores for the two principal components (i.e., the two new variables) are calculated as a function of the original, mean-corrected, values (x_1, x_2):

$$PC_1 = e_{11}x_1 + e_{12}x_2 = 0.562x_1 + 0.345x_2$$

$$PC_2 = e_{21}x_1 + e_{22}x_2 = -0.345x_1 + 0.562x_2$$

Filling out the values x_1 and x_2 for the two original variables for each observation in the data set then gives the *new observations* with the values for the new variables.

How does the transformation of the two original variables in the above example lead to reducing the data set and to select inputs? By looking at the eigenvalues, one may decide about leaving out new variables. If in the above example the eigenvalue corresponding to PC_1 is significantly larger than the eigenvalue corresponding to PC_2 (i.e., if $\lambda_1 \gg \lambda_2$), then it can be decided to drop PC_2 from the further analysis.

Note from this simple example that replacing the original variables with a (reduced) set of uncorrelated principal components comes at a price—reduced interpretability. The principal component variables derived from the original set of variables cannot easily be interpreted, since they are calculated as a weighted linear combination of the original variables. In the previous example, only two original variables were combined into principal components, still allowing some interpretation of the resulting principal components. But when the analysis spans tens or even hundreds or thousands of variables, then any interpretation of the resulting components is clearly prohibited. As discussed in Chapter 1, in certain settings this might be unacceptable, since the analysts using the resulting model can no longer interpret it. However, when interpretability is no concern, then principal component analysis is a powerful data reduction tool that will yield a *better* model in terms of stability as well as predictive performance.

RIDITS

As an alternative to weights of evidence values, one may adopt another approach to assign numerical values to categorical ordinal variables, called RIDIT scoring, introduced by Bross (1958), who coined the term RIDIT in analogy to logit and probit. The following discussion of RIDITs and PRIDITs is based on a study by Brocket et al. (2002), who adopted and adapted RIDITs for fraud detection in an unsupervised setting.

The RIDIT scoring mechanism incorporates the ranked nature of responses, that is, categories of an ordinal categorical variable. Assume the different response categories are ordered in decreasing likelihood of fraud suspicion so that a higher categorical response indicates a lesser suspicion of fraud. In ranking the categories from high- to low-fraud risk, one may use expert input or historical observed fraud rates. The RIDIT score for a categorical response value i to variable t, with $\hat{p}_{tj}$ indicating the proportion of the population having value i for variable t, is then calculated as follows:

$$B_{ti} = \sum_{j<i} \hat{p}_{tj} - \sum_{j>i} \hat{p}_{tj} \; i = 1, 2, \ldots, k_t$$

The above formula transforms a set of categorical responses into a set of meaningful numerical values in the interval [–1,1], reflecting the relative abnormality of a particular response. Intuitively, the RIDIT score can be interpreted to be an adjusted or transformed percentile score.

Example: A binary response fraud indicator variable with value *yes* occurring for 10 percent of the cases and considered by experts more indicative of fraud than a value *no*, occurring for the other 90 percent of the cases, results in RIDIT scores $B_{t1}(\text{“}yes\text{”}) = -0.9$ and $B_{t2}(\text{“}no\text{”}) = 0.1$. For a similar binary fraud indicator with 50 percent of the cases having a value “yes” and 50 percent having a value “no,” the resulting RIDIT scores are $B_{t1}(\text{“}yes\text{”}) = -0.5$ and $B_{t2}(\text{“}no\text{”}) = 0.5$. This clearly indicates that a response “yes” on the first indicator variable is more abnormal or indicative of fraud than a response “yes” on the second indicator, and as such the transformation yields RIDIT scores that can be easily included in a quantitative model and make sense from an operational or expert perspective.

Also for ordinal categorical variables with more than two categorical values RIDIT scores can be calculated using the above formula. RIDIT scores may be used to replace the categorical fraud indicator values, and as such allow these categorical variables to be directly integrated in any numerical analysis for fraud detection.

Remark that for calculating RIDIT scores the actual target values do not have to be known, as required for weights of evidence calculation. Therefore, RIDIT scores can be used in an unsupervised learning setting and when no labeled historical observations are available.

PRIDIT ANALYSIS

PRIDIT analysis combines the two techniques described in the two previous paragraphs and results in overall fraud suspicion scores calculated from a set of ordinal categorical fraud indicators. As such, PRIDIT analysis may be used to assemble these indicators into a single variable that can be included in any further analysis. Alternatively, PRIDIT analysis can be used as a filter approach to reduce the number of indicator variables included in the further analysis, as well as the final outputted fraud suspicion score. Given the two first uses, we include PRIDIT analysis in this chapter although it could be considered an unsupervised learning technique for fraud detection as discussed in Chapter 3. The reader may refer to Brocket et al. (2002) for an extensive discussion regarding the mathematical derivation and interpretation of PRIDIT scores.

Assume that only a set of ordinal categorical fraud indicators is available, transformed into RIDIT scores as discussed in the above section. Let $F = (f_{it})$ denote the matrix of individual RIDIT variable scores for each of the variables $t = 1, 2, \ldots, m$, for each of the cases $i = 1, 2, \ldots, n$ to be analyzed and scored for fraud. A straightforward overall fraud suspicion score aggregating these individual RIDIT scores for the available fraud indicator variables can simply be calculated by summing all the individual RIDITs. We then get the PRIDIT score vector by multiplying the matrix F with a unity weight vector $W = (1, 1, \ldots, 1)'$, with the prime indicating the transposed vector, that is:

$$S = FW$$

Note that these simple aggregated suspicion scores are equally dependent on each of the indicator variables, since the weights in vector W, which determine the impact of an indicator on the resulting score are all set equal to one. However, clearly not every indicator is equally related to fraud and therefore serves as a predictor or warning signal of fraud. Hence, an effective overall suspicion score should not necessarily assign equal importance to each indicator, on the contrary. A smarter aggregation of the individual indicators assesses the relative importance and weighs the indicators accordingly when aggregating them into a single overall suspicion score.

The intuition underlying the calculation of PRIDIT scores is to adapt the weights according to the correlation or consistency between the individual RIDIT scores and the resulting overall score. Basically, PRIDIT scores assign higher weights to an individual fraud indicator variable if the RIDIT scores of this variable over all cases included in the analysis are in line with the resulting overall suspicion score. On the other hand, when a variable is less consistent with the overall score, then it receives a lower weight. As elaborated in Brocket et al. (2002), a meaningful set of weights can be obtained by calculating the first principal component, as discussed in a previous section, of the matrix $F'F$. The first principal component is the weight vector that is used in calculating the PRIDIT scores, assigning a relative importance to each indicator according to the intuitive consistency principle discussed in this paragraph.

The PRIDIT approach can as such be used for variable selection, since indicators receiving weights that are not significantly different from zero may be removed from the data set. Alternatively, similar to principal component analysis to variable reduction, the set of ordinal indicators aggregated into the PRIDIT score may be replaced by this score, depending on the purpose and setup of the analysis.

SEGMENTATION

Sometimes the data are segmented before the analytical modeling starts. A first reason for this could be strategic. For example, banks might want to adopt special strategies to specific segments of customers. It could also be motivated from an operational viewpoint.

For example, new customers must have separate models because the characteristics in the standard model do not make sense operationally for them. Segmentation could also be needed to take into account significant variable interactions. For example, if one variable strongly interacts with a number of others, it might be sensible to segment according to this variable.

The segmentation can be conducted using the experience and knowledge from a business expert, or it could be based on statistical analysis using, for example, decision trees (cf. infra), *k*-means clustering or self-organising maps (cf. infra).

Segmentation is a very useful preprocessing activity since one can now estimate different analytical models each tailored to a specific segment. However, one needs to be careful with it since, by segmenting, the number of analytical models to estimate will increase, which will obviously also increase the production, monitoring, and maintenance costs.

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CHAPTER 3

Descriptive Analytics for Fraud Detection

INTRODUCTION

Descriptive analytics or unsupervised learning aims at finding unusual anomalous behavior deviating from the average behavior or norm (Bolton and Hand 2002). This norm can be defined in various ways. It can be defined as the behavior of the average customer at a snapshot in time, or as the average behavior of a given customer across a particular time period, or as a combination of both. Predictive analytics or supervised learning, as will be discussed in the following chapter, assumes the availability of a historical data set with known fraudulent transactions. The analytical models built can thus only detect fraud patterns as they occurred in the past. Consequently, it will be impossible to detect previously unknown fraud. Predictive analytics can however also be useful to help explain the anomalies found by descriptive analytics, as we will discuss later.

When used for fraud detection, unsupervised learning is often referred to as anomaly detection, since it aims at finding anomalous and thus suspicious observations. In the literature, anomalies are commonly described as outliers or exceptions. One of the first definitions of an outlier was provided by Grubbs (1969), as follows:

> *"An outlying observation, or outlier, is one that appears to deviate markedly from other members of the sample in which it occurs."*

A first challenge when using unsupervised learning is to define the average behavior or norm. Typically, this will highly depend on the application field considered. Also the boundary between the norm and the outliers is typically not clear-cut. As said earlier, fraudsters will try to blend into the average or norm as good as possible, hereby substantially complicating their detection and the corresponding definition of the norm. Furthermore, the norm may change over time, so the analytical models built need to be continuously monitored and updated, possibly in real-time. Finally, anomalies do not necessarily represent fraudulent observations. Hence, the usage of unsupervised learning for fraud detection requires extensive follow-up and validation of the identified, suspicious observations.

Unsupervised learning can be useful for organizations that start doing fraud detection and thus have no labeled historical data set available. It can also be used in existing fraud models by uncovering new fraud mechanisms. This is especially relevant in environments where fraudsters are continuously adapting their strategies to beat the detection methods. A first example of this is credit card fraud whereby fraudsters continuously try out new ways of committing fraud. Another example is intrusion detection in a cyber-fraud setting. Supervised methods are based on known intrusion patterns, whereas unsupervised methods or anomaly detection can identify emerging cyber threats.

In this chapter, we will explore various unsupervised techniques to detect fraud.

GRAPHICAL OUTLIER DETECTION PROCEDURES

To detect one-dimensional outliers, a histogram or box plot can be used (see Chapter 2). Two-dimensional outliers can be detected using a scatter plot. The latter can also be extended to a three-dimensional setting, whereby spinning facilities can be handy to rotate the graph so as to facilitate finding the outliers. This is illustrated in Figure 3.1. The plot clearly shows three outliers marked by asterisks (*) representing claims with an unusually high amount, a high number of cars of the claimant, and a small number of days since the previous claim. Clearly, these claims are suspicious and should be further investigated.

Ideally, graphical methods should be complemented with multidimensional data analysis and online analytical processing (OLAP) facilities. Figure 3.2 shows an example of an OLAP cube representing the distribution or count of claims based on amount of claim, number of cars, and recency of previous claim. Once the cube has been populated from a data warehouse or transactional data source, the following OLAP operations can be performed:

- *Roll-up*: The idea here is to aggregate across one or more dimensions. An example of this is the distribution of amount of claim and recency aggregated across all number of cars (roll up of number of cars dimension). Another example is the distribution

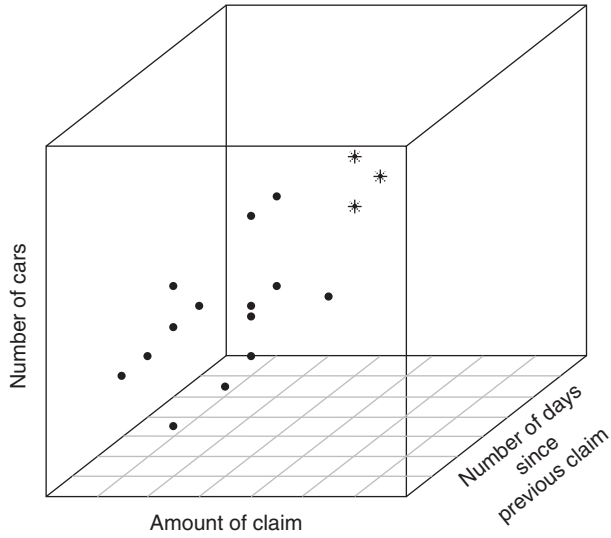


Figure 3.1 3D Scatter Plot for Detecting Outliers

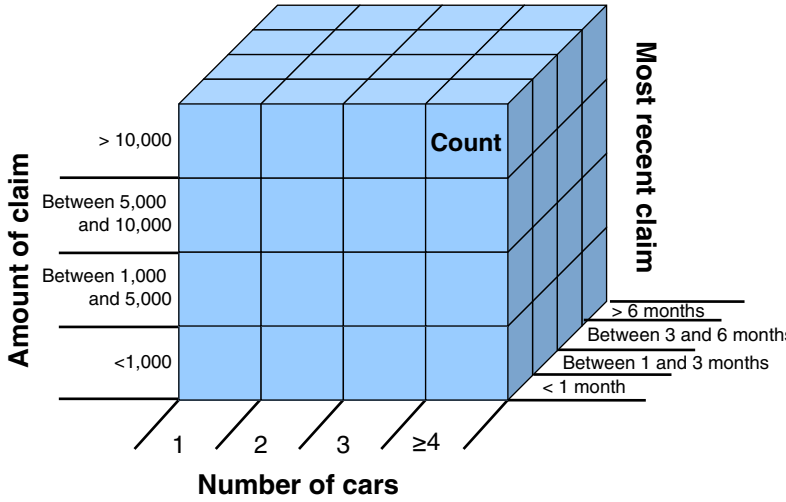


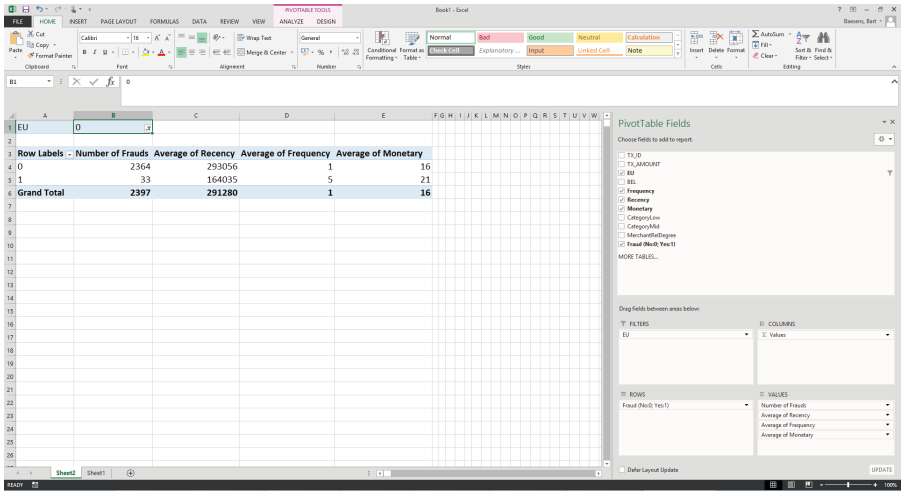
Figure 3.2 OLAP Cube for Fraud Detection

of amount of claim aggregated across all number of cars and all number of days since previous claim (roll up of number of cars and number of days since previous claim dimensions).

- *Drill-down*: This is the opposite of roll-up whereby more detail is asked for by adding another dimension to the analysis.
- *Slicing*: The idea here is to pick a slice along one of the dimensions. An example is to show the distribution of amount and recency for all claims where the claimant has more than or equal to four cars (slice along the number of cars dimension).
- *Dicing*: The idea here is to fix values for all the dimensions and create a sub-cube. An example is to show the distribution of amount, number of cars, and recency for all claims where amount is between 1,000 and 10,000, number of cars is two or three, and recency is between one and six months.

Many software tools are available to support OLAP analysis. They excel in offering powerful visualizations, sometimes even augmented with virtual reality technology for better detecting relationships in the data. OLAP tools will also typically implement pivot tables for multidimensional data analysis. Pivot tables allow analysts to summarize tabular data by cross-tabulating user specified dimensions using a drag and drop interface. This is illustrated in Figure 3.3 for a credit card fraud detection data set analyzed in Microsoft Excel. You can see that the data set has 2,397 observations with 2,364 nonfrauds and 33 frauds. The columns depict the average for the recency, frequency, and monetary (RFM) variables. Note that the data depicted has been filtered to non-EU transactions as depicted in the upper-left corner cell B2. From the results, it can be seen that when looking at non EU-transactions, fraudulent transactions have a lower average recency, higher average frequency, and higher average monetary value when compared to nonfraudulent transactions. These are very interesting starting insights to further explore fraud patterns in the data. The pivot table can be easily manipulated using the panel to the right. Other filters can be defined, columns and rows can be added, and descriptive statistics or summarization measures can be varied (e.g., count, minimum, maximum).

Graphical and OLAP methods are handy and easy to work with. They are ideal tools to explore the data and get preliminary insights.



Row Labels	Number of Frauds	Average of Recency	Average of Frequency	Average of Monetary
0	2364	293056	1	16
1	33	164035	5	21
Grand Total	**2397**	**291280**	**1**	**16**

Figure 3.3 Example Pivot Table for Credit Card Fraud Detection

However, they are less formal and only limited to a few dimensions. They require active involvement of the end-user in detecting the anomalies. In other words, the user should select the dimensions and decide on the OLAP routines to be performed. For a large dimensional data set, this may be a cumbersome exercise. Besides being used during preprocessing, OLAP facilities are getting more and more popular for model post-processing and monitoring, as we will discuss later.

STATISTICAL OUTLIER DETECTION PROCEDURES

A first well-known statistical outlier detection method is calculating the *z*-scores, as previously discussed in Chapter 2. Remember, observations for which the absolute value of the *z*-score is bigger than 3 can be considered as outliers. A more formal test is the Grubbs test, which is formulated as follows (see Grubbs 1950):

H_0: There are no outliers in the data set.

H_A: There is at least one outlier in the data set.

It starts by calculating the *z*-score for every observation. Let's say that the maximum absolute value of the observed *z*-scores equals *G*. The corresponding observation is then considered an outlier at significance level α if:

$$G > \frac{N-1}{\sqrt{N}} \sqrt{\frac{t^2_{\frac{\alpha}{2N}, N-2}}{N-2+t^2_{\frac{\alpha}{2N}, N-2}}},$$

where N represents the number of observations, and $t^2_{\frac{\alpha}{2N}, N-2}$ is the critical value of a Student's *t*-distribution with $N-2$ degrees of freedom and significance level equal to $\alpha/(2N)$. If an outlier is detected, it is removed from the data set and the test can be run again. The test can also be run for multivariate outliers whereby the *z*-score can be replaced by the Mahalanobis distance defined as follows:

$$\sqrt{(x-\overline{x})^t S^{-1}(x-\overline{x})},$$

where x represents the observation, $\overline{x}$ the mean vector, and S the covariance matrix. A key weakness of this test is that it assumes an underlying normal distribution, which is not always the case.

Other statistical procedures fit a distribution, or mixture of distributions (using, e.g., maximum likelihood or expectation-maximization procedures) and label the observations with small values for the probability density function as outliers.

Break-Point Analysis

Break-point analysis is an intra-account fraud detection method (Bolton and Hand, 2001). A break point indicates a sudden change in account behavior, which merits further inspection. The method starts from defining a fixed time window. This time window is then split into an old and new part. The old part represents the local model or profile against which the new observations will be compared. For example, in (Bolton and Hand 2001), the time window was set to 24 transactions whereby 20 transactions made up the local model, and 4 transactions were used for testing. A Student's *t*-test can be used to compare the averages of the new and old parts. Observations can then be ranked according to their value of the *t*-statistic. This is illustrated in Figure 3.4.

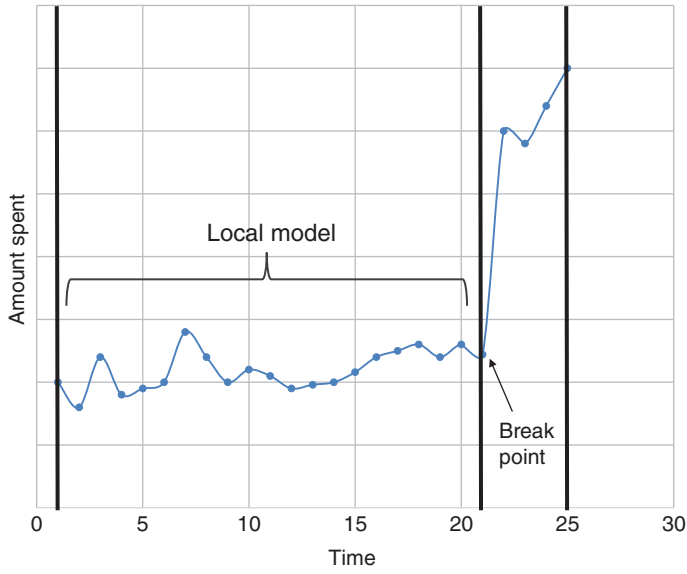


Figure 3.4 Break-Point Analysis

Peer-Group Analysis

Peer-group analysis was also introduced by Bolton and Hand (2001). A peer group is a group of accounts that behave similarly to the target account. When the behavior of the latter starts to deviate substantially from its peers, an anomaly can be signaled. Peer-group analysis proceeds in two steps. In step 1, the peer group of a particular account needs to be identified. This can be accomplished either by using prior business knowledge or in a statistical way.

For example, in an employee fraud context, people sharing similar jobs can be grouped as peers. Another example is healthcare fraud detection, whereby the aim is to detect fraudulent claim behavior of doctors across geographical regions. Suppose the target observation is a cardiologist in San Francisco; then its peers are defined as all other cardiologists in San Francisco. Statistical similarity metrics can also be used to define peers, but these are typically application specific. Popular examples here are Euclidean-based metrics (see, e.g., Bolton and Hand 2001; Weston et al. 2008). The number of peers should be carefully selected. It cannot be too small, or the method becomes too local and thus sensitive to noise, and also not too large, or the method becomes too global and thus insensitive to local important irregularities.

In step 2, the behavior of the target account is contrasted with its peers using a statistical test such a Student's *t*-test, or a distance metric such as the Mahalanobis distance, which works similar.

Let's work out an example in a credit card context. Assume our target account has the following time series:

$$y_1, y_2, \ldots . y_{n-1}, y_n$$

where y_i represents the amount spent at time (e.g., day or week) i. The aim is now to verify whether the amount spent at time n, y_n, is anomalous. We start by identifying the k peers of the target account. These are depicted in gray in the Table 3.1 below, whereby all accounts have been sorted according to their similarity to the target.

To see whether y_n is an outlier, a t-score can be calculated as follows:

$$\frac{y_n - \overline{x_{1:k,n}}}{s},$$

Table 3.1 Transaction Data Set for Peer-Group Analysis

$x_{m,1}$	$x_{m,2}$	…	$x_{m,n-1}$	$x_{m,n}$
…				
$x_{k,1}$	$x_{k,2}$		$x_{k,n-1}$	$x_{k,n}$
…				
$x_{2,1}$	$x_{2,2}$		$x_{2,n-1}$	$x_{2,n}$
$x_{1,1}$	$x_{1,2}$		$x_{1,n-1}$	$x_{1,n}$
$\boldsymbol{y_1}$	$\boldsymbol{y_2}$		$\boldsymbol{y_{n-1}}$	$\boldsymbol{y_n}$
…				

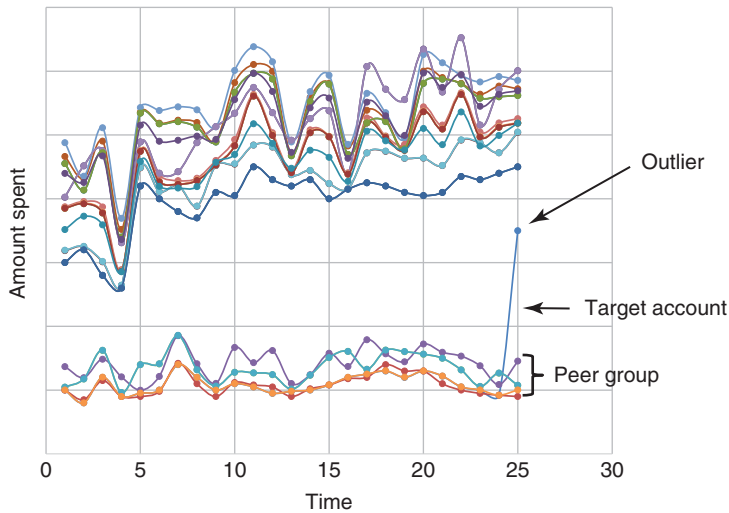


Figure 3.5 Peer-Group Analysis

where $\overline{x_{1:k,n}}$ represents the average of $x_{1,n}, \ldots, x_{k,n}$ and s the corresponding standard deviation. Although a Student's t-distribution can be used for statistical interpretation, it is recommended to simply order the observations in terms of their t-score and further inspect the ones with the highest scores. This is illustrated in Figure 3.5.

A key advantage of peer-group analysis when compared to breakpoint analysis is that it tracks anomalies by considering inter-account instead of intra-account behavior. For example, if one was to compare

transaction amounts for a particular account with previous amounts on that same account (intra-account), then the spending behavior during Christmas will definitely be flagged as anomalous. By considering peers instead (inter-account), this problem is avoided. It is important to note that both break-point and peer-group analysis will detect local anomalies rather than global anomalies. In other words, patterns or sequences that are not unusual in the global population might still be flagged as suspicious when they appear to be unusual compared to their local profile or peer behavior.

Association Rule Analysis

Association rules detect frequently occurring relationships between items (Agrawal, Imielinski et al. 1993). They were originally introduced in a market basket analysis context to detect which items are frequently purchased together. The key input is a transactions database D consisting of a transaction identifier and a set of items $\{i_1, i_2, \ldots, i_n\}$ selected from all possible items I. An association rule is then an implication of the form $X \rightarrow Y$, whereby $x \subset I$, $Y \subset I$ and $x \cap Y = \varnothing$. x is referred to as the rule antecedent whereas Y is referred to as the rule consequent. Examples of association rules could be:

- If a customer has a car loan and car insurance, then the customer has a checking account in 80 percent of the cases.
- If a customer buys spaghetti, then the customer buys red wine in 70 percent of the cases.
- If a customer visits web page A, then the customer will visit web page B in 90 percent of the cases.

It is hereby important to note that association rules are stochastic in nature. This means that they should not be interpreted as a universal truth, and are characterized by statistical measures quantifying the strength of the association. Furthermore, the rules measure correlational associations and should not be interpreted in a causal way.

In a fraud setting, association rules can be used to detect fraud rings in insurance. The transaction identifier then corresponds to a claim identifier and the items to the various parties involved such as the insured, claim adjuster, police officer and claim service provider

Table 3.2 Transactions Database for Insurance Fraud Detection

Claim Identifier	Parties Involved
1	insured A, police officer X, claim adjuster 1, auto repair shop 1
2	insured A, claim adjuster 2, police officer X
3	insured A, police officer Y, auto repair shop 1
4	insured A, claim adjuster 1, claim adjuster 1, police officer Y
5	insured B, claim adjuster 2, auto repair shop 2, police officer Z
6	insured A, auto repair shop 2, auto repair shop 1, police officer X
7	insured C, police officer X, auto repair shop 1
8	insured A, auto repair shop 1, police officer Z
9	insured A, auto repair shop 1, police officer X, claim adjuster 1
10	insured B, claim adjuster 3, auto repair shop 1

(e.g., auto repair shop, medical provider, home repair contractor, etc.). Let's consider an example of a transactions database as depicted in Table 3.2.

The goal is now to find frequently occurring relationships or association rules between the various parties involved in the handling of the claim. This will be solved using a two-step procedure. In step 1, the frequent item sets will be identified. The frequency of an item set is measured by means of its support, which is the percentage of total transactions in the database that contains the item set. Hence, the item set X has support s if $100 \times s$ percent of the transactions in D contain X. It can be formally defined as follows:

$$support(X) = \frac{number\ of\ transactions\ supporting\ (X)}{total\ number\ of\ transactions}$$

Consider the item set {insured A, police officer X, auto repair shop 1}. This item set occurs in transactions 1, 6, and 9 hereby giving a support of 3/10 or 30 percent. A frequent item set can now be defined as an item set of which the support is higher than a minimum value as specified by the data scientist (e.g., 10 percent). Computationally efficient procedures have been developed to identify the frequent item sets (Agrawal, Imielinski et al. 1993).

Once the frequent item sets have been found, the association rules can be derived in step 2. Multiple association rules can be defined based on the same item set. Consider the item set {insured *A*, police officer *X*, auto repair shop 1}. Example association rules could be:

If insured *A* **And** police officer X ⇒ auto repair shop 1

If insured *A* **And** auto repair shop 1 ⇒ police officer *X*

If insured *A* ⇒ auto repair shop 1 **And** police officer *X*

The strength of an association rule can be quantified by means of its confidence. The confidence measures the strength of the association and is defined as the conditional probability of the rule consequent, given the rule antecedent. The rule $X \Rightarrow Y$ has confidence c if 100×c percent of the transactions in *D* that contain *X* also contain *Y*. It can be formally defined as follows:

$$confidence\,(X \rightarrow Y) = P(Y|X) = \frac{support\,(X \cup Y)}{support(X)}$$

Consider the association rule "**If** insured A **And** police officer *X* ⇒ auto repair shop 1." The antecedent item set {insured A, police officer X} occurs in transactions 1, 2, 6, and 9. Out of these four transactions, three also include the consequent item set {auto repair shop 1}, which results into a confidence of three-fourths, or 75 percent. Again, the data scientist has to specify a minimum confidence in order for an association rule to be considered interesting.

Once all association rules have been found, they can be closer inspected and validated. In our example, the association "**If** insured A **And** police officer *X* ⇒ auto repair shop 1" does not necessarily imply a fraud ring, but it's a least worth the effort to further inspect the relationship between these parties.

CLUSTERING

Introduction

The aim of clustering is to split up a set of observations into segments such that the homogeneity within a segment is maximized (cohesive),

and the heterogeneity between segments is maximized (separated) (Everitt, Landau et al. 2010). Examples of applications in fraud detection include:

- Clustering transactions in a credit card setting
- Clustering claims in an insurance setting
- Clustering tax statements in a tax-inspection setting
- Clustering cash transfers in an anti-money laundering setting

Various types of clustering data can be used, such as customer characteristics (e.g., sociodemographic, behavioral, lifestyle, …), account characteristics, transaction characteristics, etc. A very popular sets of transaction characteristics used for clustering in fraud detection are the recency, frequency, and monetary (RFM) variables, as introduced in Chapter 2.

Note that besides structured information, also unstructured information such as emails, call records, and social media information might be considered. As always in analytics, it is important to carefully select the data for clustering. The more data the better, although care should be taken to avoid excessive amounts of correlated data by applying unsupervised feature selection methods. One very simple approach here is to simply calculate the Pearson correlation between each pair of data characteristics and only retain one characteristic in case of a significant correlation.

When used for fraud detection, a possible aim of clustering may be to group anomalies into small, sparse clusters. These can then be further analyzed and inspected in terms of their characteristics and potentially fraudulent behavior (see Figure 3.6).

Different types of clustering techniques can be applied for fraud detection. At a high level, they can be categorized as either hierarchical or nonhierarchical (see Figure 3.7).

Distance Metrics

As said, the aim of clustering is to group observations based on similarity. Hence, a distance metric is needed to quantify similarity. Various distance metrics have been introduced in the literature for both continuous and categorical data.

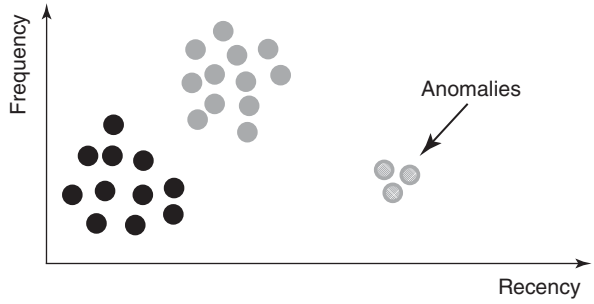


Figure 3.6 Cluster Analysis for Fraud Detection

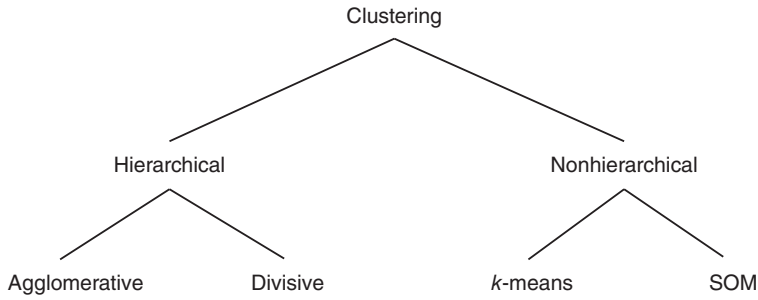


Figure 3.7 Hierarchical Versus Nonhierarchical Clustering Techniques

For continuous data, the Minkowski distance or L_p norm between two observations $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ can be defined as follows:

$$D(\boldsymbol{x}_i;\boldsymbol{x}_j) = \left(\sum_{k=1}^{n} \left|x_{ik} - x_{jk}\right|^p\right)^{1/p},$$

where n represents the number of variables. When p equals 1, the Minkowski distance is also referred to the Manhattan or City block distance. When p equals 2, the Minkowski distance becomes the well-known Euclidean distance. Both are illustrated in Figure 3.8. For the example depicted, the distance measures become:

$$\text{Euclidean} : \sqrt{(1500-1000)^2 + (10-5)^2}^{\sim} = 500$$

$$\text{Manhattan} : |1500-100| + |10-5| = 505$$

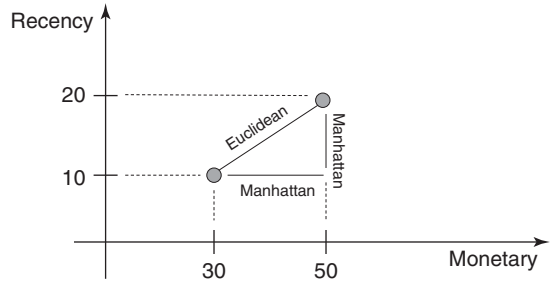


Figure 3.8 Euclidean Versus Manhattan Distance

From this example, it is clear that the amount variable clearly dominates the distance metric since it is measured on a larger scale than the recency variable. Hence, to appropriately take this into account, it is recommended to scale both variables to a similar range using any of the standardization procedures we discussed in Chapter 2. It is obvious that the Euclidean distance will always be shorter than the Manhattan distance. The Euclidean metric is the most popular metric used for quantifying the distance between continuous variables. Other less frequently used distance measures are based on the Pearson correlation or cosine measure.

Besides continuous variables, also categorical variables can be used for clustering. Let's first discuss the case of binary variables. These are often used in insurance fraud detection methods, which are typically based on a series of red-flag indicators to label a claim as suspicious or not. Assume we have the following data set with binary red-flag indicators.

	Poor Driving Record	Premium Paid in Cash	Car Purchase Information Available	Coverage Increased	Car Was Never Inspected or Seen
Claim 1	Yes	No	Yes	Yes	No
Claim 2	Yes	Yes	No	No	No
…					

A first way to calculate the distance or similarity between claim 1 and 2 is to use the simple matching coefficient (SMC), which simply

calculates the number of identical matches between the variable values as follows:

$$\text{SMC}(\text{Claim 1}, \text{Claim 2}) = 2/5.$$

A tacit assumption behind the SMC is that both states of the variable (Yes versus No) are equally important and should thus both be considered. Another option is to use the Jaccard index whereby the No-No match is left out of the computation as follows:

$$\text{Jaccard}(\text{Claim 1}, \text{Claim 2}) = 1/4.$$

The Jaccard index measures the similarity between both claims across those red flags that where raised at least once. It is especially useful in those situations where many red-flag indicators are available and typically only a few are raised. Consider, for example, a fraud-detection system with 100 red-flag indicators, of which on average 5 are raised. If you would use the simple matching coefficient, then typically all claims would be very similar since the 0–0 matches would dominate the count, hereby creating no meaningful clustering solution. By using the Jaccard index a better idea of the claim similarity can be obtained. The Jaccard index has actually been very popular in fraud detection.

Let's now consider the case of categorical variables with more than two values. Assume we have the following data in a medical insurance setting.

	Treatment Day	Distance between Clinic and Subject's Home	Type of Diagnosis	Risk Class	Claim Submitted by
Claim 1	Sunday	Medium	Severe	C	Phone
Claim 2	Wednesday	Medium	Life threatening	C	Email
…					

A first option here is to code the categorical variables as 0/1 dummies and apply the Manhattan or Euclidean distance metrics discussed earlier. However, this may be cumbersome in case of categorical variables with lots of values. Coarse classification might be considered to reduce the number of dummy variables, but, remember, since we don't

have a target variable in this unsupervised setting, it should be based on expert knowledge. Another option would be to use the simple matching coefficient (SMC) and count the number of identical matches. In our case, the SMC would become 2/5.

Many data sets will contain both continuous and categorical variables, which complicates the distance calculation. One option here is to code the categorical variables as 0/1 dummies and use a continuous distance measure. Another option is to use a (weighted) combination of distance measures, although this is less straightforward and thus less frequently used.

Hierarchical Clustering

Once the distance measures have been chosen, the clustering process can start. A first popular set of techniques are hierarchical clustering methods. Depending on the starting point of the analysis, divisive or agglomerative hierarchical clustering methods can be used. Divisive hierarchical clustering starts from the whole data set in one cluster, and then breaks this up in each time smaller clusters until one observation per cluster remains (right to left in Figure 3.9). Agglomerative

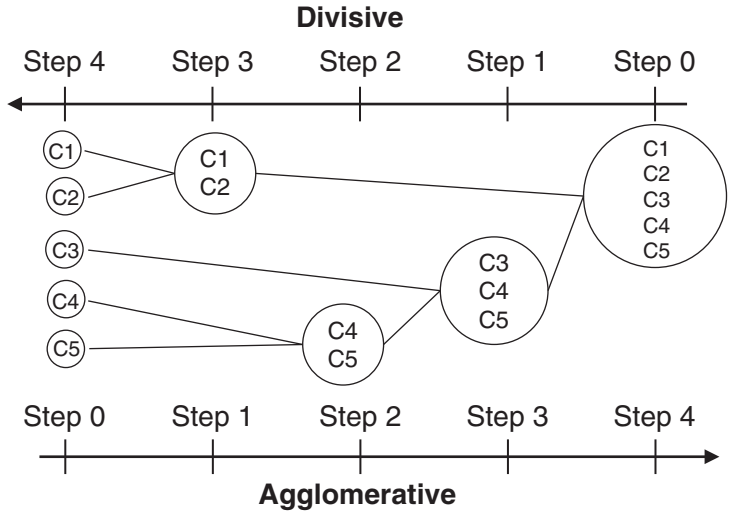


Figure 3.9 Divisive Versus Agglomerative Hierarchical Clustering

clustering works the other way around, and starts from each observation in one cluster, and then continues to merge the ones that are most similar until all observations make up one big cluster (left to right in Figure 3.9). The optimal clustering solution then lies somewhere in between the extremes to the left and right, respectively.

Although we have earlier discussed various distance metrics to quantify the distance between individual observations, we haven't talked about how to measure distances between clusters. Also here, various options are available, as depicted in Figure 3.10. The single linkage method defines the distance between two clusters as the smallest possible distance, or the distance between the two most similar objects. The complete linkage method defines the distance between two clusters as the biggest distance, or the distance between the two most dissimilar objects. The average linkage method calculates the average of all possible distances. The centroid method calculates the distance between the centroids of both clusters. Finally, Ward's distance between two clusters C_i and C_j is calculated as the difference between the total within cluster sum of squares for the two clusters separately, and the total within cluster sum of squares obtained from merging the clusters C_i and C_j into one cluster C_{ij}. It is calculated as follows:

$$D_{Ward}(C_i, C_j) = \sum_{x \in C_i} (x - c_i)^2 + \sum_{x \in C_j} (x - c_j)^2 - \sum_{x \in C_{ij}} (x - c_{ij})^2,$$

where c_i, c_j, c_{ij} is the centroid of cluster C_i, C_j, and C_{ij}, respectively.

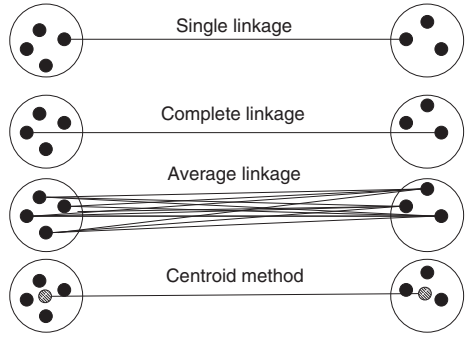


Figure 3.10 Calculating Distances between Clusters

In order to decide on the optimal number of clusters, one could use a dendrogram or screen plot. A dendrogram is a tree-like diagram that records the sequences of merges. The vertical (or horizontal scale) then gives the distance between two clusters amalgamated. One can then cut the dendrogram at the desired level to find the optimal clustering. This is illustrated in Figure 3.11 and Figure 3.12 for a birds clustering

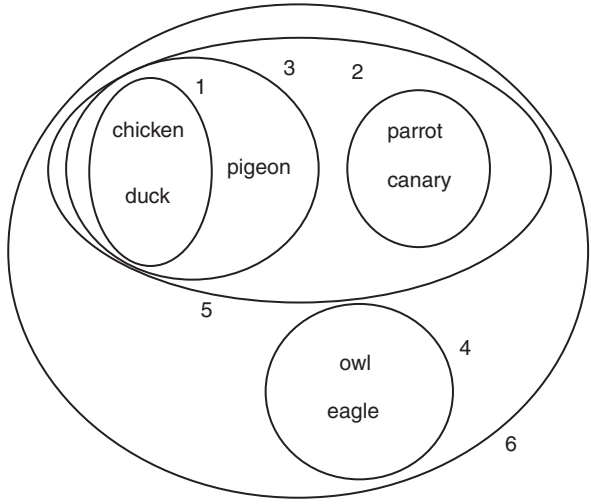


Figure 3.11 Example for Clustering Birds. The Numbers Indicate the Clustering Steps

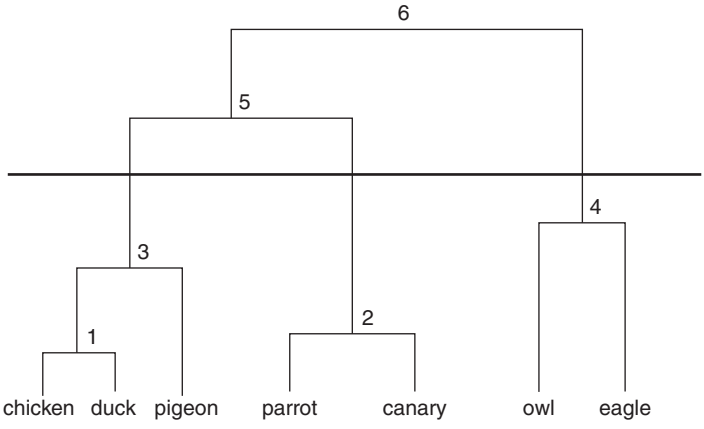


Figure 3.12 Dendrogram for Birds Example. The Thick Black Line Indicates the Optimal Clustering

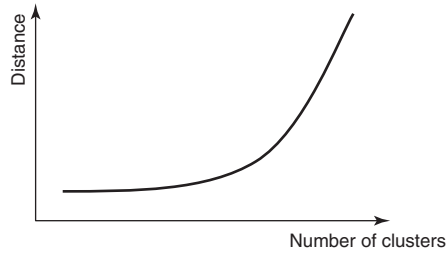


Figure 3.13 Scree Plot for Clustering

example. A scree plot is a plot of the distance at which clusters are merged. The elbow point then indicates the optimal clustering. This is illustrated in Figure 3.13.

A key advantage of hierarchical clustering is that the number of clusters does not need to be specified prior to the analysis. A disadvantage is that the methods do not scale very well to large data sets. Also, the interpretation of the clusters is often subjective and depends on the business expert and/or data scientist.

Example of Hierarchical Clustering Procedures

To illustrate the various hierarchical clustering procedures discussed, suppose we have a data set of seven observations, as depicted in Table 3.3. Figure 3.14 displays the corresponding scatter plot.

The output of the various hierarchical clustering procedures is depicted in Figure 3.15. As it can be observed, single linkage results

Table 3.3 Data Set for Hierarchical Clustering

	X	*Y*
A	4	4
B	5	4
C	7	5
D	8	5
E	11	5
F	2	7
G	1	3

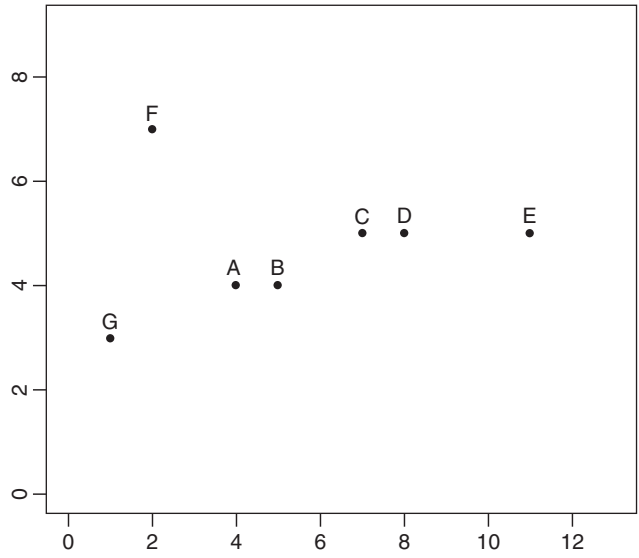


Figure 3.14 Scatter Plot of Hierarchical Clustering Data

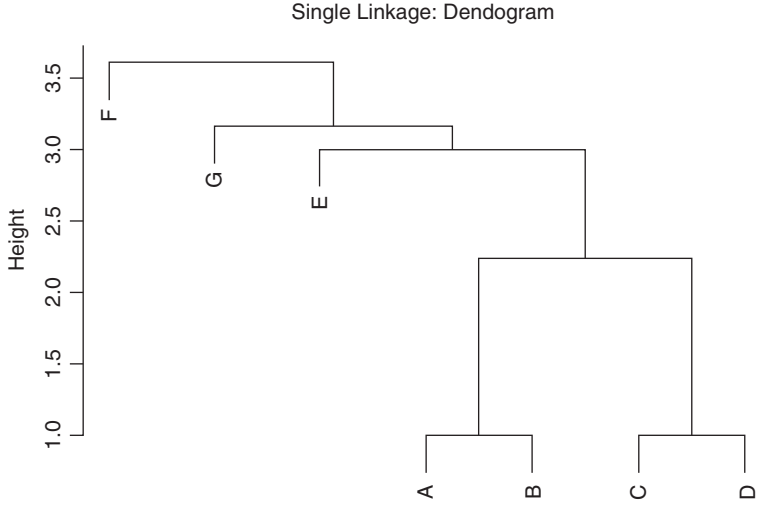


Figure 3.15 Output of Hierarchical Clustering Procedures

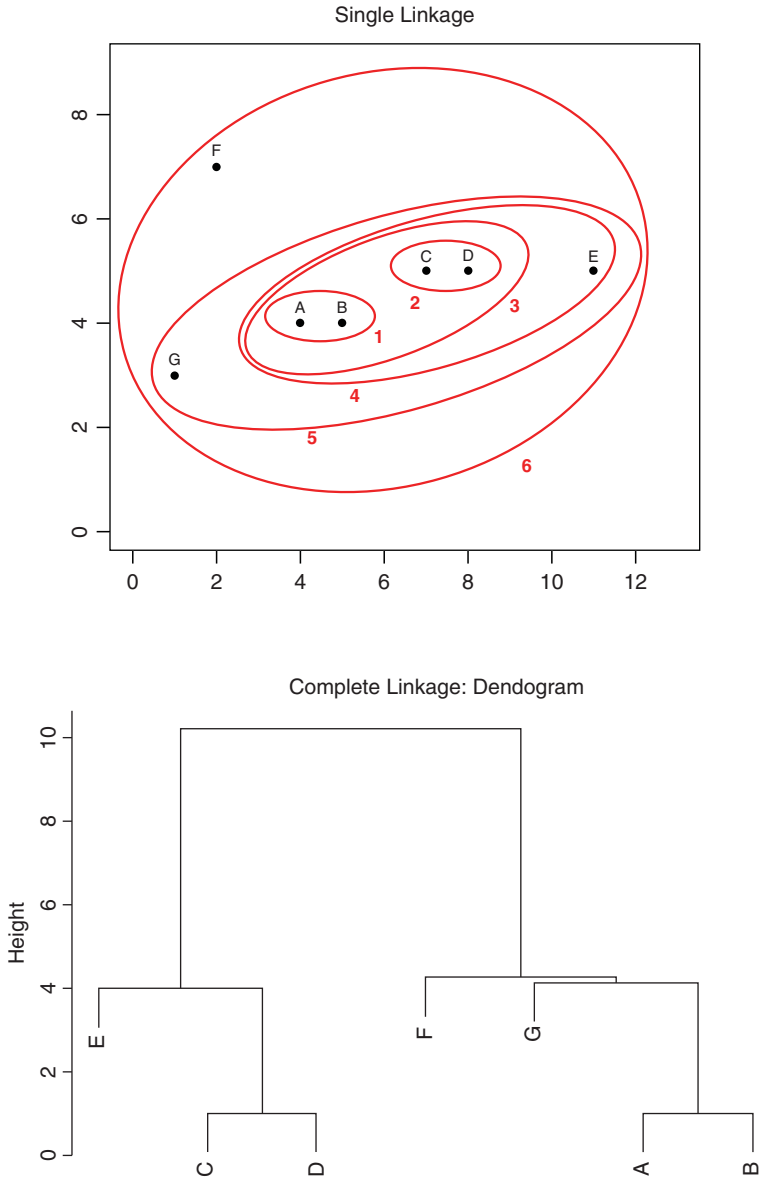


Figure 3.15 (*Continued*)

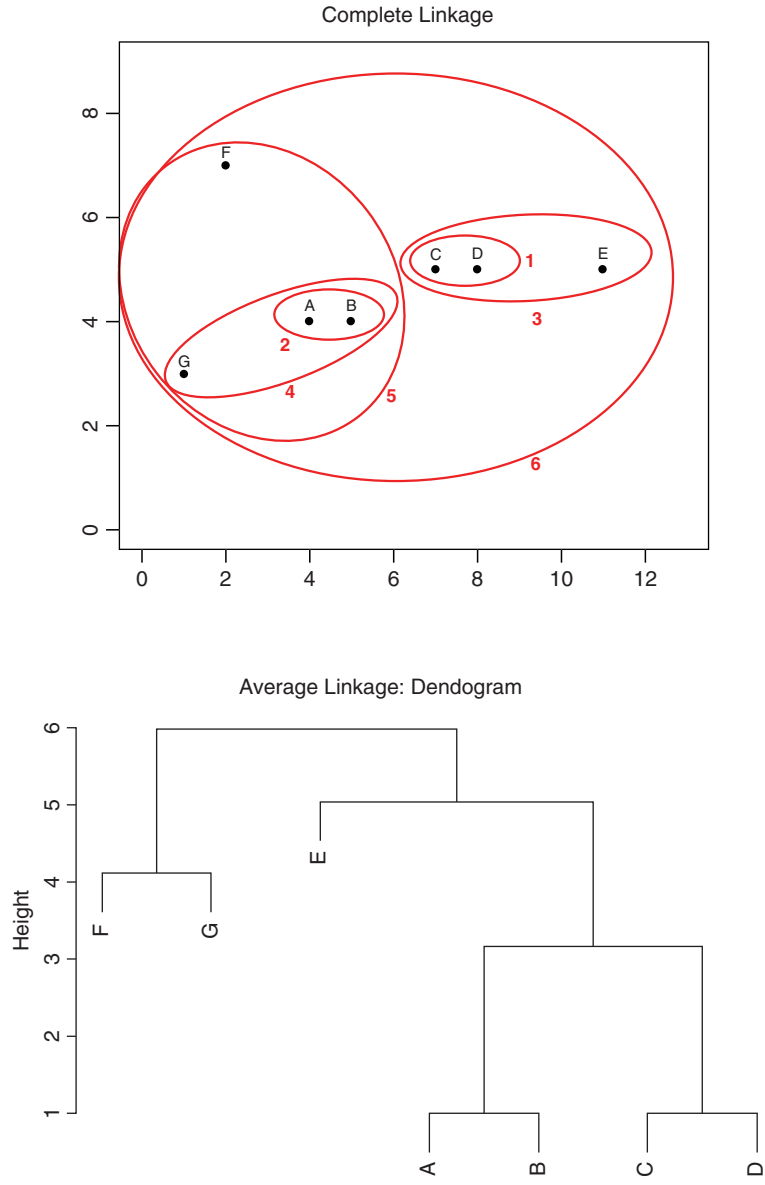


Figure 3.15 (*Continued*)

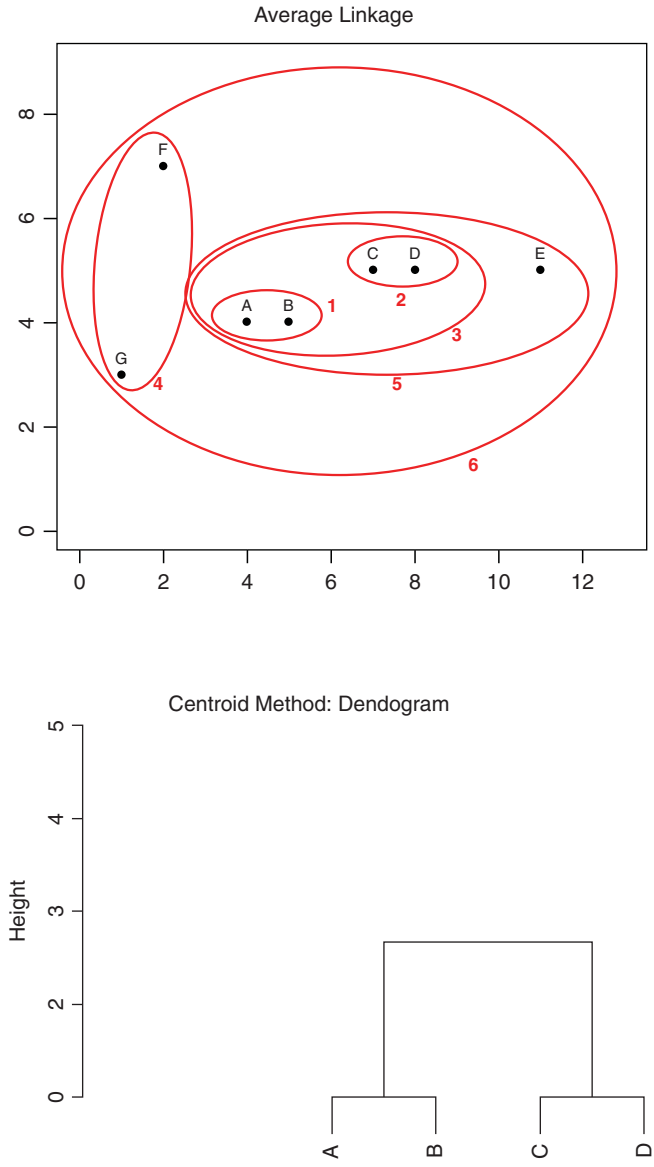


Figure 3.15 (*Continued*)

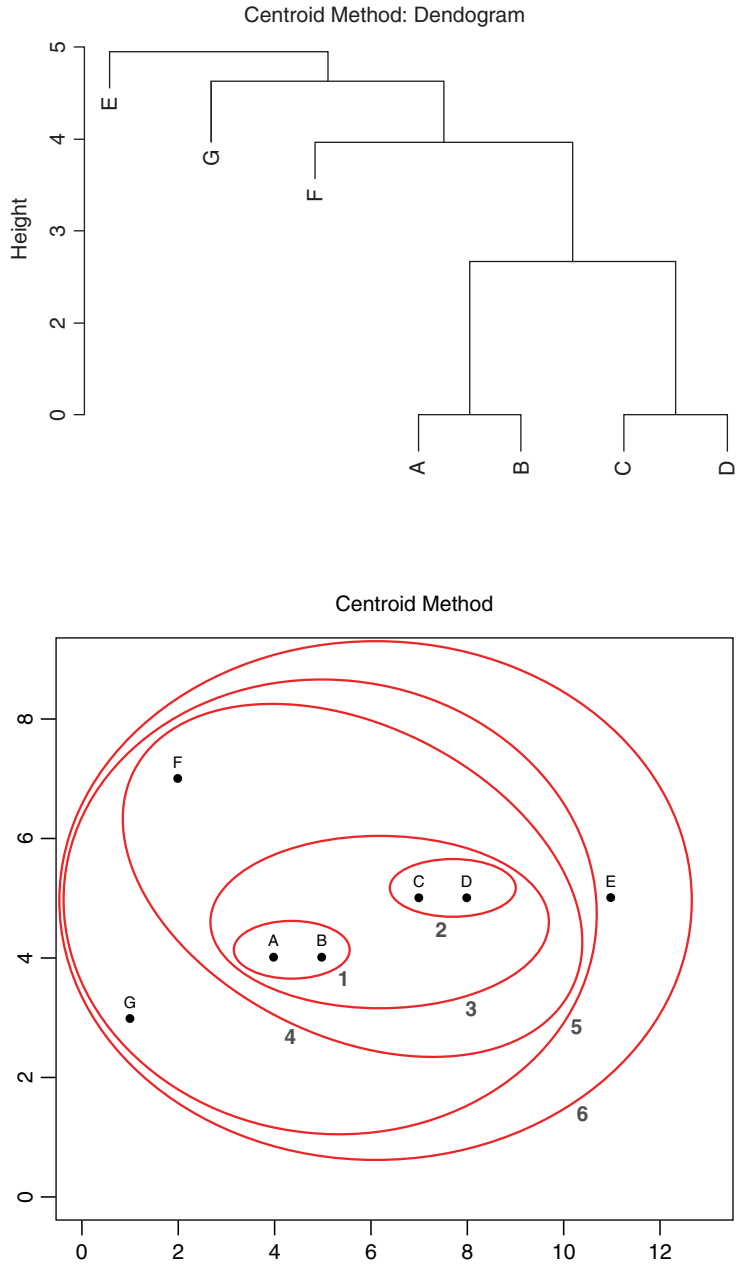


Figure 3.15 (*Continued*)

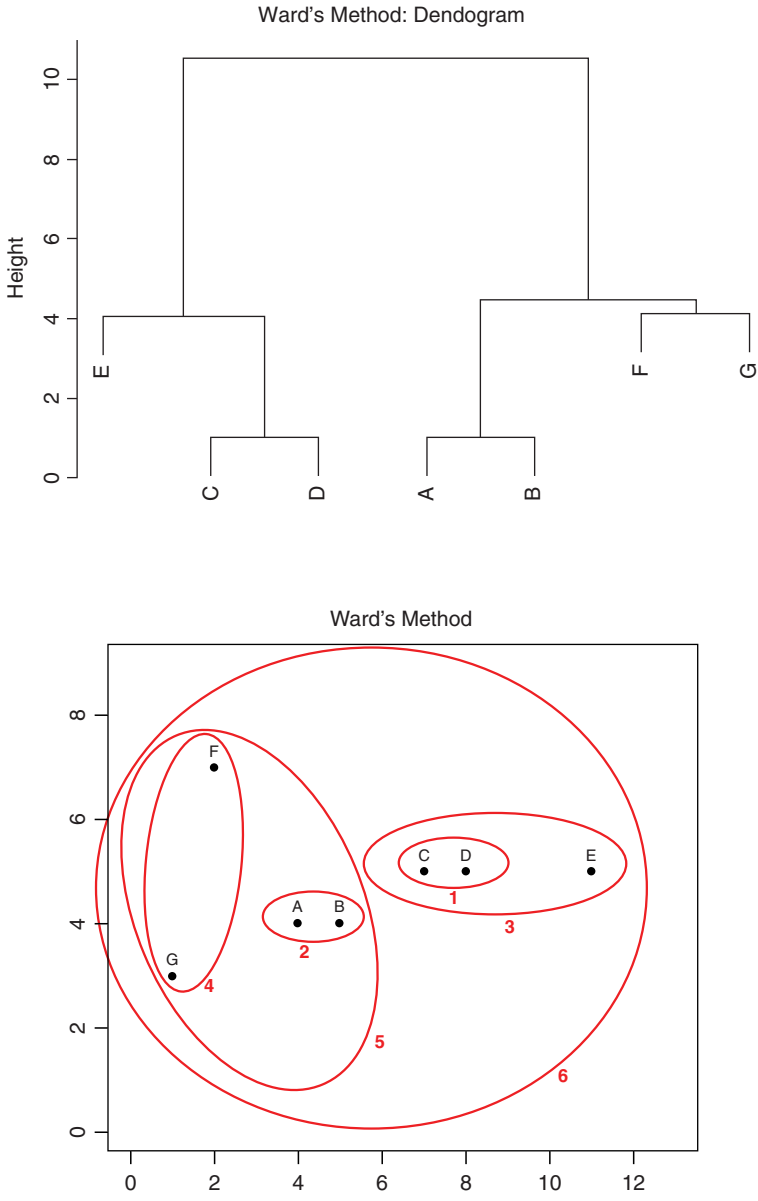


Figure 3.15 (*Continued*)

in thin, long, and elongated clusters since dissimilar objects are not accounted for. Complete linkage will make the cluster tighter, more balanced and spherical, which is often more desirable. Average linkage prefers to merge clusters with small variances, which often results in clusters with similar variance. Although the centroid method seems similar at first sight, the resulting clustering solution is different as depicted in the figure. Ward's method prefers to merge clusters with a small number of observations and often results into balanced clusters.

k-Means Clustering

k-means clustering is a nonhierarchical procedure that works along the following steps (see Jain 2010; MacQueen 1967):

1. Select *k* observations as initial cluster centroids (seeds).
2. Assign each observation to the cluster that has the closest centroid (for example, in Euclidean sense).
3. When all observations have been assigned, recalculate the positions of the *k* centroids.
4. Repeat until the cluster centroids no longer change or a fixed number of iterations is reached.

A key requirement here is that, as opposed to hierarchical clustering, the number of clusters, *k*, needs to be specified before the start of the analysis. This decision can be made using expert based input or based on the result of another (e.g., hierarchical) clustering procedure. Typically, multiple values of *k* are tried out and the resulting clusters evaluated in terms of their statistical characteristics and interpretation. It is also advised to try out different seeds to verify the stability of the clustering solution. Note that the mean is sensitive to outliers, which are especially relevant in a fraud detection setting. A more robust alternative is to use the median instead (*k*-medoid clustering). In case of categorical variables, the mode can be used (*k*-mode clustering). As mentioned, *k*-means is most often used in combination with a Euclidean distance metric, which typically results into spherical or ball-shaped clusters. See Figures 3.16 to 3.22.

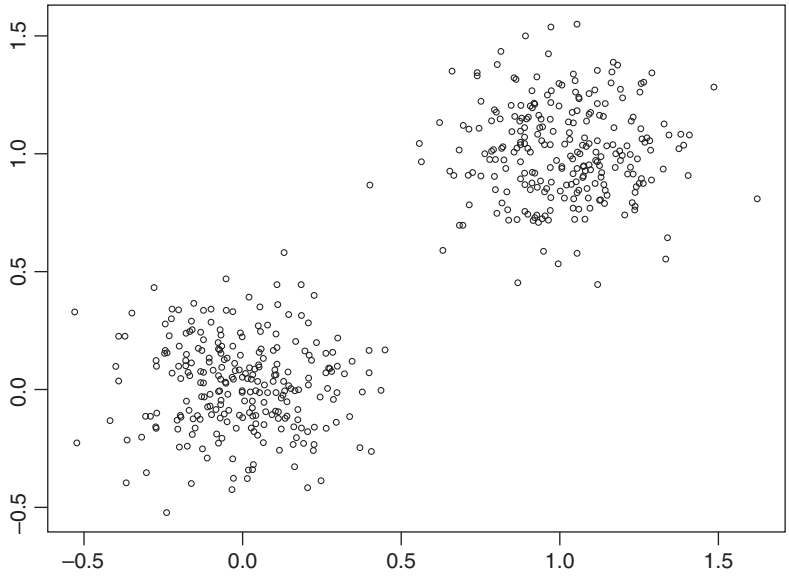


Figure 3.16 *k*-Means Clustering: Start from Original Data

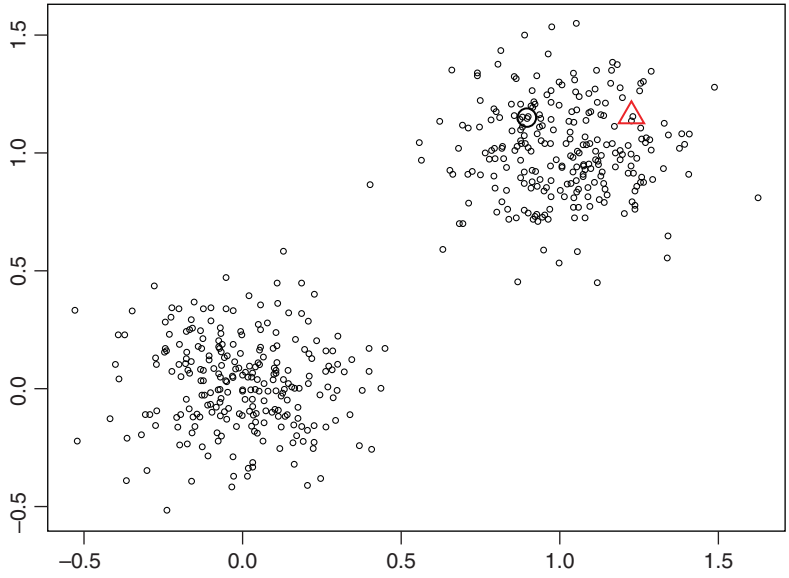


Figure 3.17 *k*-Means Clustering Iteration 1: Randomly Select Initial Cluster Centroids

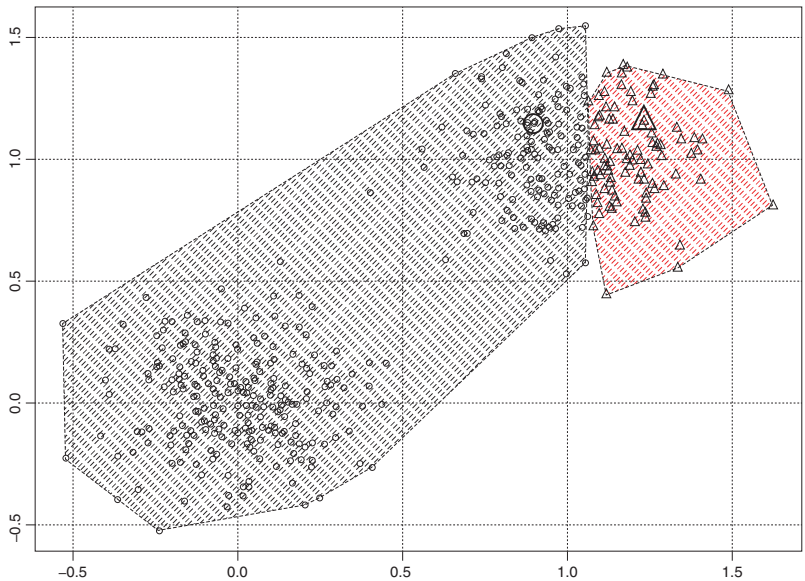


Figure 3.18 *k*-Means Clustering Iteration 1: Assign Remaining Observations

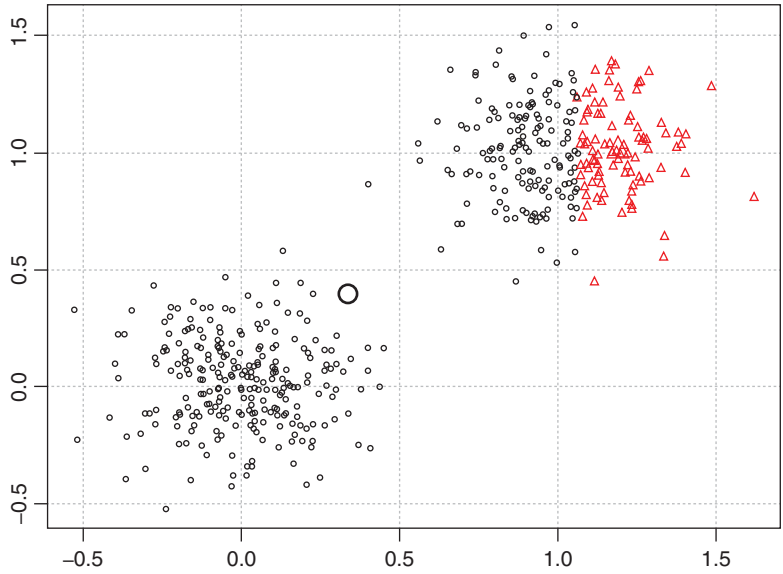


Figure 3.19 *k*-Means Iteration Step 2: Recalculate Cluster Centroids

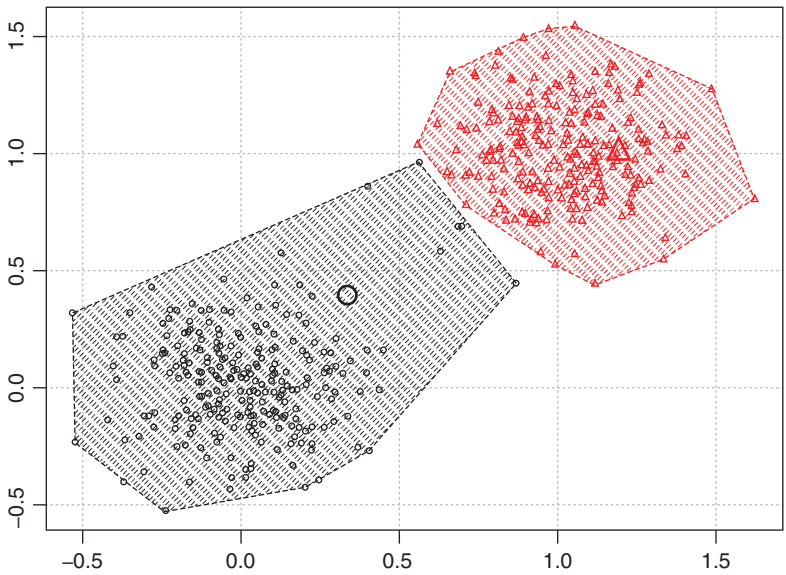


Figure 3.20 *k*-Means Clustering Iteration 2: Reassign Observations

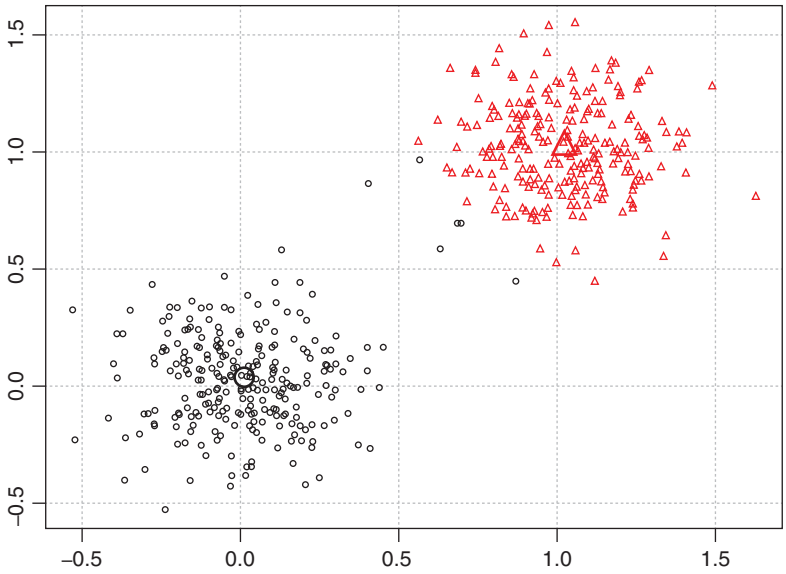


Figure 3.21 *k*-Means Clustering Iteration 3: Recalculate Cluster Centroids

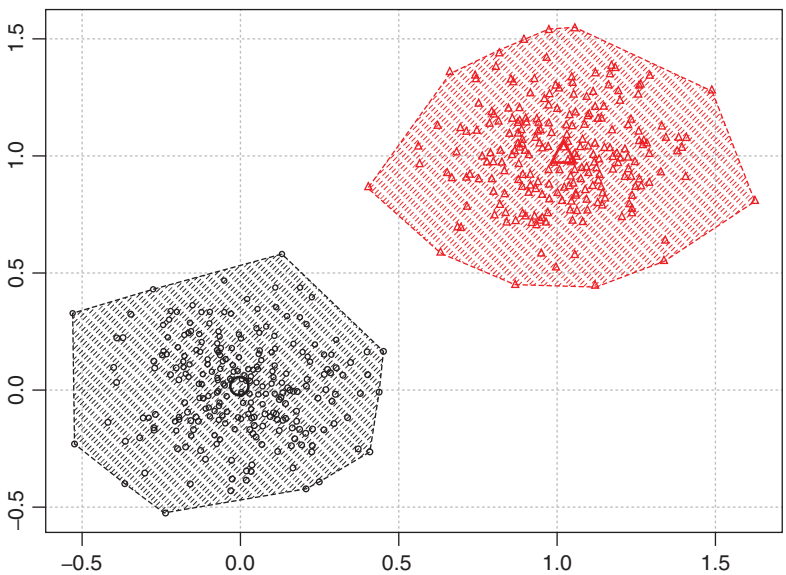


Figure 3.22 *k*-Means Clustering Iteration 3: Reassign Observations

Self-Organizing Maps

A self-organizing map (SOM) is an unsupervised learning algorithm that allows users to visualize and cluster high-dimensional data on a low-dimensional grid of neurons (Kohonen 2000; Huysmans et al. 2006; Seret et al. 2012). A SOM is a feedforward neural network with two layers: an input and an output layer. The neurons from the output layer are usually ordered in a two-dimensional rectangular or hexagonal grid (see Figure 3.23). For the former, every neuron has at most eight neighbors, whereas for the latter, every neuron has at most six neighbors.

Each input is connected to all neurons in the output layer with weights $\mathbf{w} = [w_1, \ldots, w_N]$, with N the number of variables. All weights are randomly initialized. When a training vector $\mathbf{x}$ is presented, the weight vector $\mathbf{w}_c$ of each neuron c is compared with $\boldsymbol{x}$, using for example, the Euclidean distance metric (beware to standardize the data first!):

$$d(\boldsymbol{x}, \boldsymbol{w}_c) = \sqrt{\sum_{i=1}^{N} (\boldsymbol{x}_i - \boldsymbol{w}_{ci})^2}.$$

The neuron that is most similar to $\mathbf{x}$ in Euclidean sense is called the best matching unit (BMU). The weight vector of the BMU and its neighbors in the grid are then adapted using the following learning rule:

$$\boldsymbol{w}_i(t+1) = \boldsymbol{w}_i(t) + h_{ci}(t)[\boldsymbol{x}(t) - \boldsymbol{w}_i(t)],$$

where t represents the time index during training and $h_{ci}(t)$ defines the neighborhood of the BMU c, specifying the region of influence.

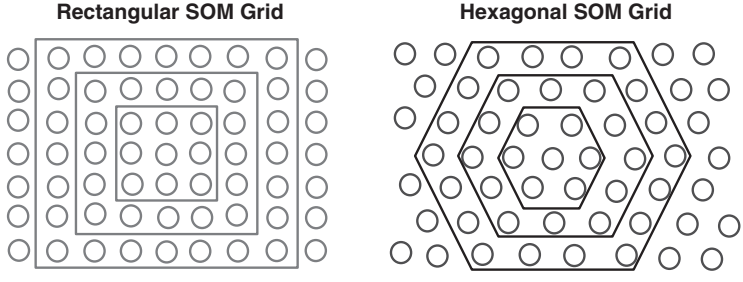


Figure 3.23 Rectangular Versus Hexagonal SOM Grid

The neighborhood function $h_{ci}(t)$ should be a nonincreasing function of time and the distance from the BMU. Some popular choices are:

$$h_{ci}(t) = \alpha(t)\exp\left(-\frac{||r_c - r_i||^2}{2\sigma^2(t)}\right),$$

$$h_{ci}(t) = \alpha(t) \text{ if } ||r_c - r_i||^2 \leq \textit{threshold},\ 0\ \textit{otherwise},$$

where r_c and r_i represent the location of the BMU and neuron i on the map, $\sigma^2(t)$ represents the decreasing radius, and $0 \leq \alpha(t) \leq 1$ the learning rate (e.g., $\alpha(t) = A/(t + B)$, $\alpha(t) = \exp(-At)$). The decreasing learning rate and radius will give a stable map after a certain amount of training. The neurons will then move more and more toward the input observations and interesting segments will emerge. Training is stopped when the BMUs remain stable, or after a fixed number of iterations (e.g., 500 times the number of SOM neurons).

SOMs can be visualized by means of a U-matrix or component plane:

- A **U (unified distance)-matrix** essentially superimposes a height Z dimension on top of each neuron visualizing the average distance between the neuron and its neighbors, whereby typically dark colors indicate a large distance and can be interpreted as cluster boundaries.
- A **component plane** visualizes the weights between each specific input variable and its output neurons, and as such provides a visual overview of the relative contribution of each input attribute to the output neurons.

Figure 3.24 provides a SOM example for clustering countries based on a Corruption Perception Index (CPI). This is a score between 0 (highly corrupt) and 10 (highly clean), assigned to each country in the world. The CPI is combined with demographic and macroeconomic information for the years 1996, 2000, and 2004. Uppercase countries (e.g., BEL) denote the situation in 2004, lowercase (e.g., bel) in 2000, and sentence case (e.g., Bel) in 1996. It can be seen that many of the European countries are situated in the upper-right corner of the map.

Figure 3.25 provides the component plane for literacy whereby darker regions score worse on literacy. Figure 3.26 provides the

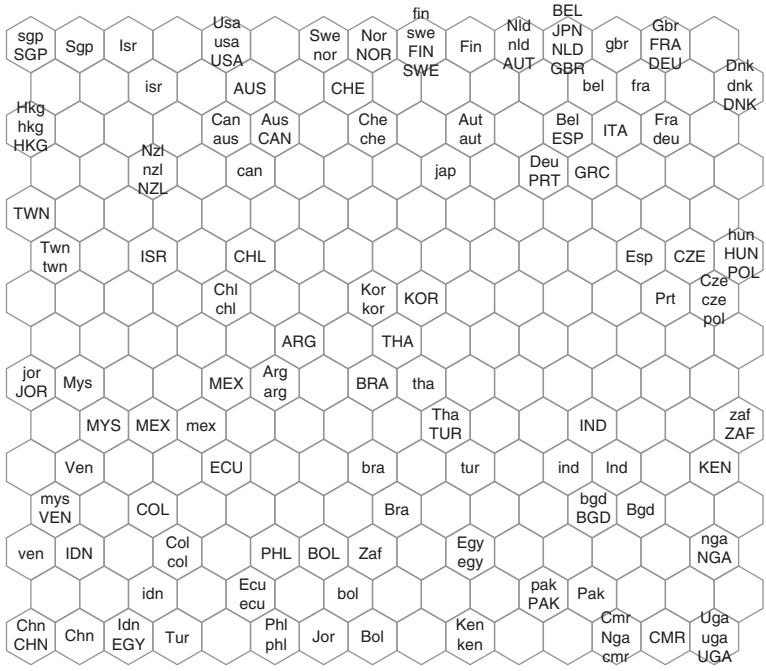


Figure 3.24 Clustering Countries Using SOMs

component plane for political rights whereby darker regions correspond to better political rights. It can be seen that many of the European countries score good on both literacy and political rights.

SOMs are a very handy tool for clustering high-dimensional data sets because of the visualization facilities. However, since there is no real objective function to minimize, it is harder to compare various SOM solutions against each other. Also, experimental evaluation and expert interpretation is needed to decide on the optimal size of the SOM. Unlike *k*-means clustering, a SOM does not force the number of clusters to be equal to the number of output neurons.

Clustering with Constraints

In many fraud application domains, the expert(s) will have prior knowledge about existing fraud patterns and/or anomalous behavior. This knowledge can originate from both experience as well as existing

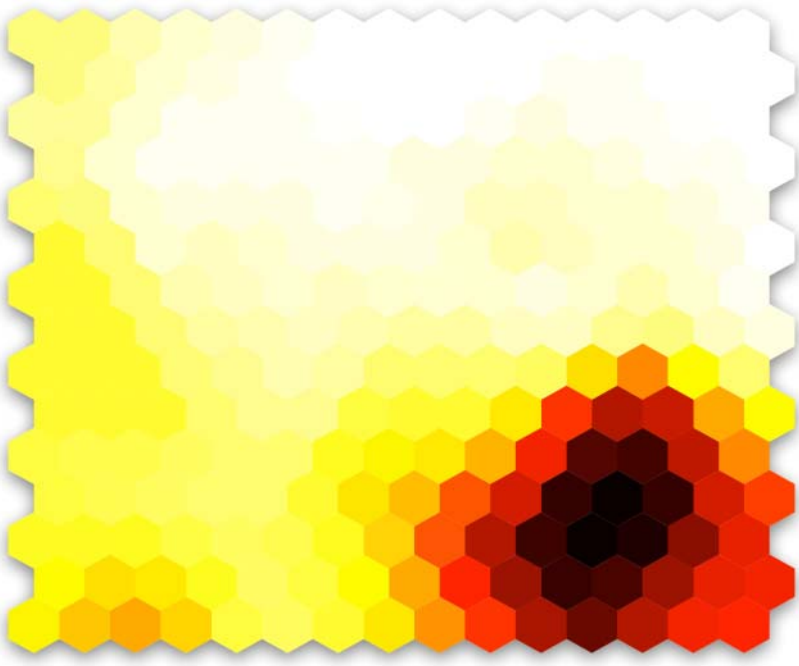


Figure 3.25 Component Plane for Literacy

literature. It will be handy if this background knowledge can be incorporated to guide the clustering. This is the idea of semi-supervised clustering or clustering with constraints (Basu, Davidson et al. 2012). The idea here is to bias the clustering with expert knowledge such that the clusters can be found quicker and with the desired properties.

Various types of constraints can be thought of. A first set of constraints is observation-level constraints. As the name suggests, these constraints are set for individual observations. A *must*-link constraint enforces that two observations should be assigned to the same cluster, whereas a *cannot*-link constraint will put them into different clusters (see Figure 3.27). This could be handy in a fraud-detection setting if the fraud behavior of only a few observations is known as these can then be forced into the same cluster. Cluster-level constraints are defined at the level of the cluster. A *minimum separation* or δ constraint specifies that the distance between any pair of observations

Figure 3.26 Component Plane for Political Rights

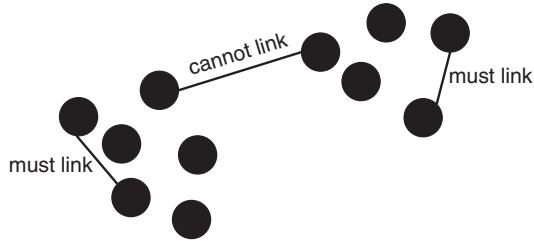


Figure 3.27 Must-Link and Cannot-Link Constraints in Semi-Supervised Clustering

in two different clusters must be at least δ (see Figure 3.28). This will allow data scientists to create well-separated clusters. An ε-constraint specifies that each observation in a cluster with more than one observation must have another observation within a distance of at most ε (see Figure 3.29). Another example of a constraint includes the requirement to have balanced clusters, whereby each cluster contains

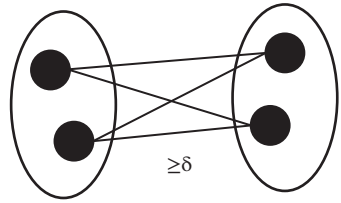


Figure 3.28 δ-Constraints in Semi-Supervised Clustering

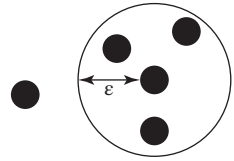


Figure 3.29 ε-Constraints in Semi-Supervised Clustering

the same amount of observations. Negative background information can also be provided whereby the aim is to find a clustering which is different from a given clustering.

The constraints can be enforced during the clustering process. For example, in a *k*-means clustering setup, the cluster seeds will be chosen such that the constraints are respected. Each time an observation is (re-)assigned, the constraints will be verified and the (re-)assignment halted in case violations occur. In a hierarchical clustering procedure, a must-link constraint can be enforced by setting the distance between two observations to 0, whereas a cannot-link constraint can be enforced by setting the distance to a very high value.

Evaluating and Interpreting Clustering Solutions

Evaluating a clustering solution is by no means a trivial exercise since there exists no universal criterion. From a statistical perspective, the sum of squared errors (SSE) can be computed as follows:

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} dist^2(x, m_i),$$

where K represents the number of clusters and m_i the centroid (e.g., mean) of cluster i. When comparing two clustering solutions, the one with the lowest SSE can then be chosen. Besides a statistical evaluation,

a clustering solution will also be evaluated in terms of its interpretation. To facilitate the interpretation of a clustering solution, various options are available. A first one is to compare cluster distributions with population distributions across all variables on a cluster-by-cluster basis. This is illustrated in Figure 3.30 whereby the distribution of a cluster C_1 is contrasted with the overall population distribution for the RFM

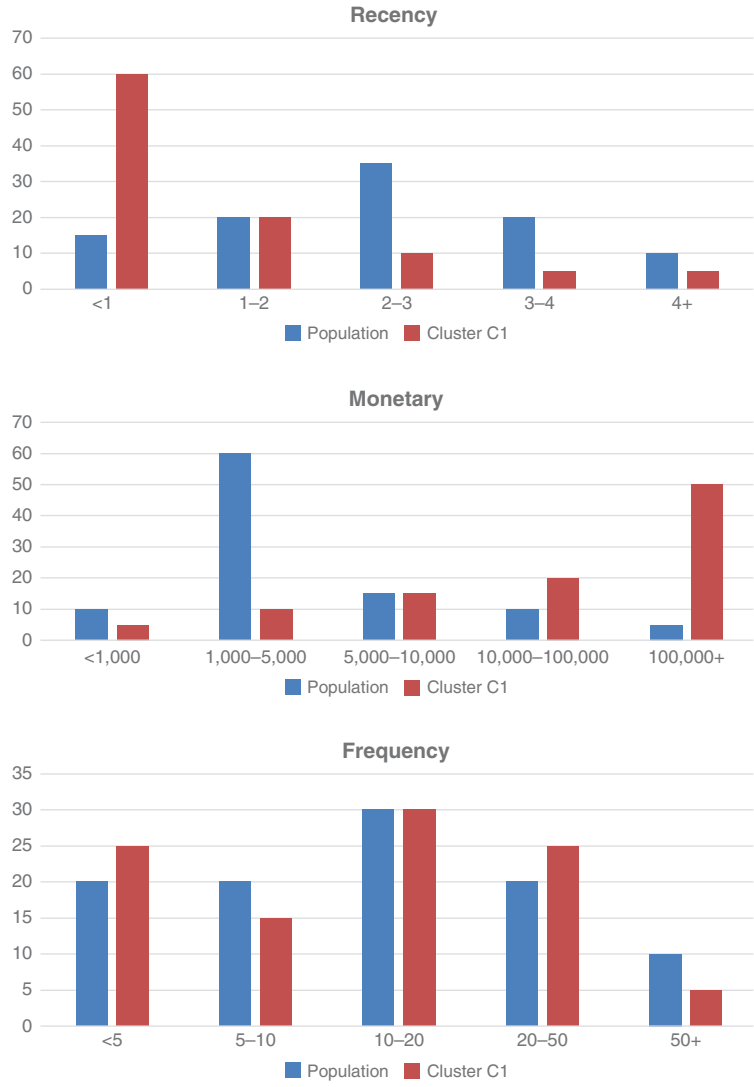


Figure 3.30 Cluster Profiling Using Histograms

Table 3.4 Output from a *k*-Means Clustering Exercise (*k*=4)

Claim	Recency	Frequency	Monetary	. . . .	ClusterID
Claim1					Cluster2
Claim2					Cluster4
Claim3					Cluster3
Claim4					Cluster2
Claim5					Cluster1
Claim6					Cluster4
…					

variables. It can be clearly seen that cluster C_1 has observations with low recency values and high monetary values, whereas the frequency is relatively similar to the original population.

Another way to explain a given clustering solution is by building a decision tree with the ClusterID as the target variable. We will discuss how to build decision trees in the next chapter, but for the moment it suffices to understand how they should be interpreted. Assume we have the following output from a *k*-means clustering exercise with *k* equal to 4. (See Table 3.4)

We can now build a decision tree with the ClusterID as the target variable as follows.

The decision tree in Figure 3.31 gives us a clear insight into the distinguishing characteristics of the various clusters. For example, cluster 2 is characterized by observations having recency < 1 day and monetary > 1,000. Hence, using decision trees, we can easily assign new observations to the existing clusters. This is an example of how supervised or predictive techniques can be used to explain the solution from a descriptive analytics exercise.

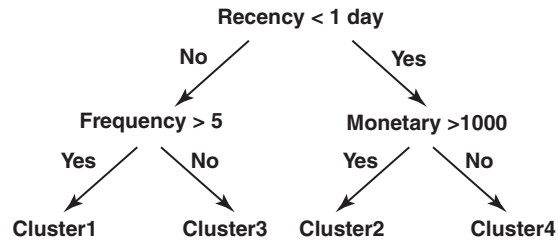


Figure 3.31 Using Decision Trees for Clustering Interpretation

ONE-CLASS SVMS

One-class SVMs try to maximize the distance between a hyperplane and the origin (Schölkopf et al. 2001). The idea is to separate the majority of the observations from the origin. The observations that lie on the other side of the hyperplane, closest to the origin, are then considered as outliers. This is illustrated in Figure 3.32.

Let's define the hyperplane as follows:

$$w^T \varphi(x) - \rho = 0.$$

Normal observations lie above the hyperplane and outliers below it, or in other words normal observations (outliers) will return a positive (negative) value for:

$$f(x) = sign(w^T \varphi(x) - \rho).$$

One-class SVMs then aim at solving the following optimization function:

$$Minimize\ \frac{1}{2}\sum_{i=1}^{N} w_i^2 - \rho + \frac{1}{\upsilon n}\sum_{i=1}^{n} e_i$$

$$\text{subject to } w^T \varphi(x_k) \geq \rho - e_k,\ k = 1 \ldots n$$

$$e_k \geq 0.$$

The error variables e_i are introduced to allow observations to lie on the side of the hyperplane closest to the origin. The parameter υ is a

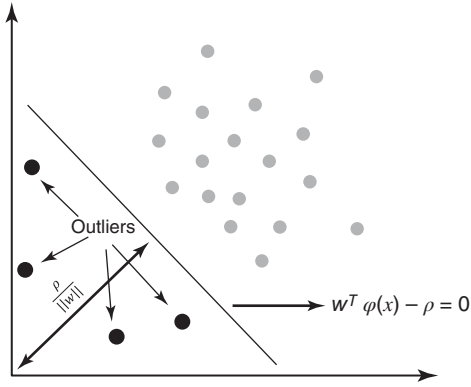


Figure 3.32 One-Class Support Vector Machines

regularization term. Mathematically, it can be shown that the distance between the hyperplane and the origin equals $\frac{\rho}{||w||}$ (see Figure 3.32). This distance is now maximized by minimizing $\frac{1}{2}\sum_{i=1}^{N} w_i^2 - \rho$, which is the first part in the objective function. The second part of the objective function then accounts for errors, or thus outliers. The constraints force the majority of observations to lie above the hyperplane. The parameter υ ranges between 0 and 1, and sets an upper bound on the fraction of outliers. A lower (higher) value of the regularization parameter υ will increase (decrease) the weight assigned to errors and thus decrease (increase) the number of outliers. Given the importance of this parameter, one-class SVMs are sometimes also referred to as υ-SVMs.

As with SVMs for supervised learning (see Chapter 4), the optimization problem can be solved by formulating its dual variant, which also here yields a quadratic programming (QP) problem, and applying the kernel trick. By again using Lagrangian optimization, the following decision function is obtained

$$f(x) = sign(w^T \varphi(x) - \rho) = sign\left(\sum_{i=1}^{n} \alpha_i K\left(x, x_i\right) - \rho\right),$$

where α_i represent the Lagrange multipliers, and $K(x, x_i)$ the kernel function. See Schölkopf et al. (2001) for more details.

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CHAPTER 4

Predictive Analytics for Fraud Detection

INTRODUCTION

In predictive analytics, the aim is to build an analytical model predicting a target measure of interest (Baesens 2014; Duda et al. 2001; Flach 2012; Han and Kamber 2001; Hastie et al. 2001; Tan et al. 2006). The target is then typically used to steer the learning process during an optimization procedure. Two types of predictive analytics can be distinguished depending on the measurement level of the target: *regression* and *classification*. In regression, the target variable is continuous and varies along a predefined interval. This interval can be limited (e.g., between 0 and 1) or unlimited (e.g., between 0 and infinity). A typical example in a fraud detection setting is predicting the amount of fraud. In classification, the target is categorical which means that it can only take on a limited set of predefined values. In binary classification, only two classes are considered (e.g., fraud versus no-fraud) whereas in multiclass classification, the target can belong to more than two classes (e.g., severe fraud, medium fraud, no fraud).

In fraud detection, both classification and regression models can be used simultaneously. Consider, for example, an insurance fraud setting. The expected loss due to fraud can be calculated as follows

$$\text{Expected fraud loss (EFL)} = PF \times LGF + (1 - PF) \times 0 = PF \times LGF$$

where PF represents the probability of fraud and LGF the loss given fraud. The latter can be expressed as an amount or as a percentage of a maximum amount (e.g., the maximum insured amount). *PF* can then be estimated using a classification technique whereas for *LGF*, a regression model will be estimated.

Different types of predictive analytics techniques have been developed in the literature originating from a variety of different disciplines such as statistics, machine learning, artificial intelligence, pattern recognition, and data mining. The distinction between those disciplines is getting more and more blurred and is actually not that relevant. In what follows, we will discuss a selection of techniques with a particular focus on the fraud practitioner's perspective.

TARGET DEFINITION

Since the target variable plays an important role in the learning process, it is of key importance that it is appropriately defined. In fraud detection, the target fraud indicator is usually hard to determine since one can never be fully sure that a certain transaction (e.g., credit card fraud), claim (e.g., insurance fraud), or company (e.g., tax evasion fraud) is fraudulent.

Let's take the example of insurance fraud (Viaene et al. 2002). If an applicant files a claim, the insurance company will perform various checks to flag the claim as suspicious or nonsuspicious. When the claim is considered as suspicious, the insurance firm will first decide whether it's worthwhile the effort to pursue the investigation. Obviously, this will also depend on the amount of the claim, such that small amount claims are most likely not further considered, even if they are fraudulent. When the claim is considered worthwhile to investigate, the firm might start a legal procedure resulting into a court judgment and/or legal settlement flagging the claim as fraudulent or not. It is clear that also this procedure is not 100 percent error-proof and thus nonfraudulent claims might end up being flagged as fraudulent, or vice versa.

Another example is tax evasion fraud. An often-used fraud mechanism in this setting is a spider construction, as depicted in Figure 4.1 (Van Vlasselaer et al. 2013 and 2015).

The key company in the middle represents the firm who is the key perpetrator of the fraud. It starts up a side company (Side Company 1), which makes revenue but deliberately does not pay its taxes and hence intentionally goes bankrupt. On bankruptcy, its resources (e.g., employees, machinery, equipment, buyers, suppliers, physical address, and other assets) are shifted toward a new side company (e.g., Side Company 2), which repeats the fraud behavior and thus again goes bankrupt. As such, a web of side companies evolves around the key company. It is clear that in this setting it becomes hard to distinguish a regular bankruptcy due to insolvency from a fraudulent bankruptcy due to malicious intent. In other words, all fraudulent companies go bankrupt, but not all bankrupt companies are fraudulent. This is depicted in Figure 4.2. Although suspension is seen as a normal way of

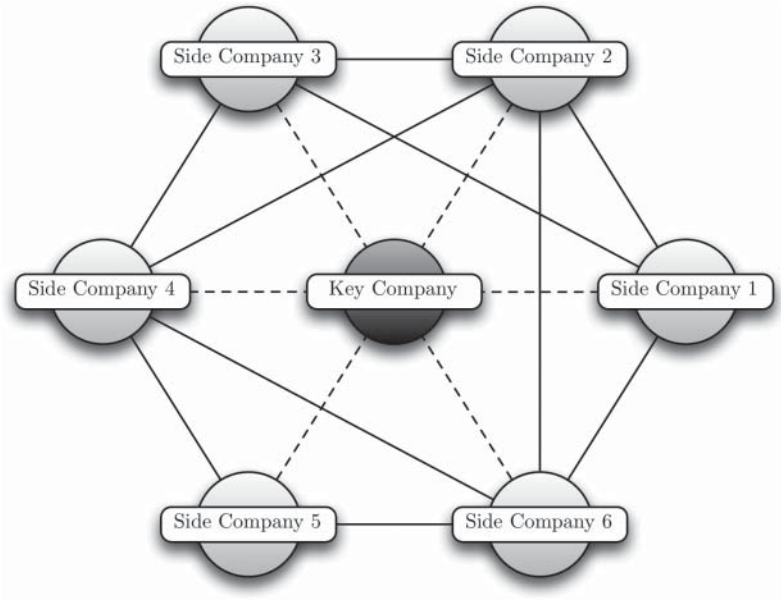


Figure 4.1 A Spider Construction in Tax Evasion Fraud

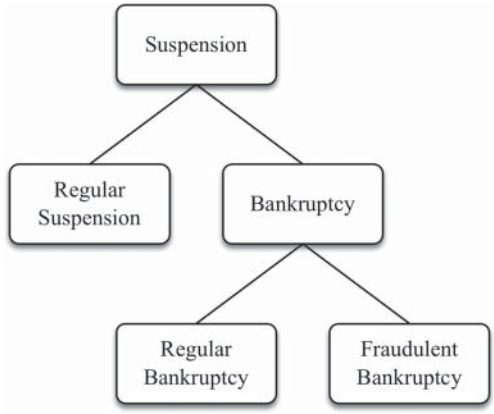


Figure 4.2 Regular Versus Fraudulent Bankruptcy

stopping a company's activities (i.e., all debts redeemed), bankruptcy indicates that the company did not succeed to pay back all its creditors. Distinguishing between regular and fraudulent bankruptcies is subtle and hard to establish. Hence, it can be expected that some regular bankruptcies are in fact undetected fraudulent bankruptcies.

Also, the intensity of the fraud when measured as an amount might be hard to determine since one has to take into account direct costs, indirect costs, reputation damage, and the time value of the money (e.g., by discounting).

To summarize, in supervised fraud detection the target labels are typically not noise-free hereby complicating the analytical modeling exercise. It is thus important for analytical techniques to be able to cope with this.

LINEAR REGRESSION

Linear regression is undoubtedly the most commonly used technique to model a continuous target variable. For example, in a car insurance fraud detection context, a linear regression model can be defined to model the amount of fraud in terms of the age of the claimant, claimed amount, severity of the accident, and so on.

$$Amount\ of\ fraud = \beta_0 + \beta_1 Age + \beta_2 ClaimedAmount + \beta_3 Severity + \ldots$$

The general formulation of the linear regression model then becomes:

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_N X_N,$$

where Y represents the target variable, and $X_1, \ldots, X_N$ the explanatory variables. The β parameters measure the impact on the target variable Y of each of the individual explanatory variables.

Let's now assume we start with a data set with n observations and N explanatory variables structured as depicted in Table 4.1.

Table 4.1 Data Set for Linear Regression

Observation	X_1	X_2	…	X_N	Y
1	X_{11}	X_{21}	…	X_{N1}	Y_1
2	X_{12}	X_{22}	…	X_{N2}	Y_2
…					
n	X_{1n}	X_{2n}	…	X_{Nn}	Y_n

The β parameters of the linear regression model can then be estimated by minimizing the following squared error function:

$$\frac{1}{2}\sum_{i=1}^{n} e_i^2 = \frac{1}{2}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 = \frac{1}{2}\sum_{i=1}^{n}(Y_i - (\beta_0 + \beta_1 X_{1i} + \ldots + \beta_N X_{Ni}))^2,$$

where Y_i represents the target value for observation i and $\hat{Y}_i$ the prediction made by the linear regression model for observation i. Graphically, this idea corresponds to minimizing the sum of all error squares as represented in Figure 4.3.

Straightforward mathematical calculus then yields the following closed-form formula for the weight parameter vector $\hat{\beta}$:

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \ldots \\ \hat{\beta}_N \end{bmatrix} = (X^T X)^{-1} X^T Y,$$

where X represents the matrix with the explanatory variable values augmented with an additional column of ones to account for the intercept term β_0, and Y represents the target value vector (see Table 4.1). This model and corresponding parameter optimization procedure are often referred to as ordinary least squares (OLS) regression.

A key advantage of OLS regression is that it is simple and thus easy to understand. Once the parameters have been estimated, the model can be evaluated in a straightforward way, hereby contributing to its operational efficiency.

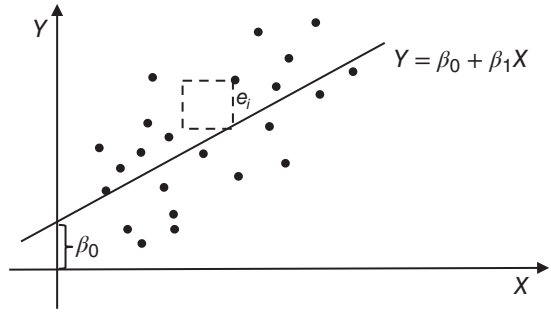


Figure 4.3 OLS Regression

Note that more sophisticated variants have been suggested in the literature, such as ridge regression, lasso regression, time series models (ARIMA, VAR, GARCH), multivariate adaptive regression splines (MARS), and so on. Most of these relax the linearity assumption by introducing additional transformations, however, at the cost of increased complexity.

LOGISTIC REGRESSION

Basic Concepts

Consider a classification data set in a tax-evasion setting as depicted in Table 4.2.

When modeling the binary fraud target using linear regression, one gets:

$$Y = \beta_0 + \beta_1 \text{Revenue} + \beta_2 \text{Employees} + \beta_3 \text{VATCompliant}$$

When estimating this using OLS, two key problems arise:

1. The errors/target are not normally distributed but follow a Bernoulli distribution with only two values;
2. There is no guarantee that the target is between 0 and 1, which would be handy since it can then be interpreted as a probability.

Consider now the following bounding function:

$$f(z) = \frac{1}{1 + e^{-z}}$$

which is shown in Figure 4.4.

Table 4.2 Example Classification Data Set

Company	Revenue	Employees	VATCompliant	…	Fraud	Y
ABC	3,000k	400	Y		No	0
BCD	200k	800	N		No	0
CDE	4,2000k	2,200	N		Yes	1
…						
XYZ	34k	50	N		Yes	1

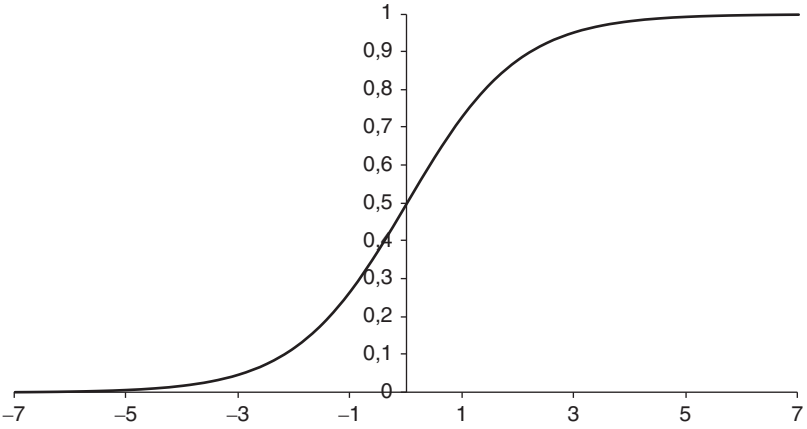


Figure 4.4 Bounding Function for Logistic Regression

For every possible value of z, the outcome is always between 0 and 1. Hence, by combining the linear regression with the bounding function, we get the following logistic regression model:

$$P(fraud = yes|Revenue,\ Employees,\ VATCompliant) = \frac{1}{1 + e^{-(\beta_0+\beta_1 \text{Revenue}+\beta_2 \text{Employees}+\beta_3 \text{VATcompliant})}}$$

The outcome of the above model is always bounded between 0 and 1, no matter which values of revenue, employees, and VAT compliant are being used, and can as such be interpreted as a probability.

The general formulation of the logistic regression model then becomes (Allison 2001):

$$P(Y = 1|X_1,\ \ldots\ ,\ X_n) = \frac{1}{1 + e^{-(\beta_0+\beta_1 X_1+\ldots+\beta_N X_N)}},$$

or alternatively,

$$P(Y = 0|X_1,\ \ldots\ ,\ X_N) = 1 - P(Y = 1|X_1,\ \ldots\ ,\ X_N) = 1 - \frac{1}{1 + e^{-(\beta_0+\beta_1 X_1+\ldots+\beta_N X_N)}} = \frac{1}{1 + e^{(\beta_0+\beta_1 X_1+\ldots+\beta_N X_N)}}$$

Hence, both $P(Y = 1|X_1, \ldots, X_N)$ and $P(Y = 0|X_1, \ldots, X_N)$ are bounded between 0 and 1.

Reformulating in terms of the odds, the model becomes:

$$\frac{P(Y = 1|X_1, \ldots, X_N)}{P(Y = 0|X_1, \ldots, X_N)} = e^{(\beta_0 + \beta_1 X_1 + \ldots + \beta_N X_N)}$$

or in terms of the log odds (logit),

$$\ln\left(\frac{P\left(Y = 1|X_1, \ldots, X_N\right)}{P(Y = 0|X_1, \ldots, X_N)}\right) = \beta_0 + \beta_1 X_1 + \ldots + \beta_N X_N$$

The β_i parameters of a logistic regression model are then estimated using the idea of maximum likelihood. Maximum likelihood optimization choses the parameters in such a way as to maximize the probability of getting the sample at hand. First, the likelihood function is constructed. For observation i, the probability of observing either class equals:

$$P(Y = 1|X_{1i}, \ldots, X_{Ni})^{Y_i}(1 - P(Y = 1|X_{1i}, \ldots, X_{Ni})^{1-Y_i},$$

where Y_i represents the target value (either 0 or 1) for observation i. The likelihood function across all n observations then becomes:

$$\prod_{i=1}^{n} P(Y = 1|X_{1i}, \ldots, X_{Ni})^{Y_i}(1 - P(Y = 1|X_{1i}, \ldots, X_{Ni})^{1-Y_i}.$$

To simplify the optimization, the logarithmic transformation of the likelihood function is taken and the corresponding log-likelihood can then be optimized using for instance the Newton-Raphson method.

Logistic Regression Properties

Since logistic regression is linear in the log odds (logit), it basically estimates a linear decision boundary to separate both classes. This is illustrated in Figure 4.5 whereby F represents fraudulent firms and L indicates legitimate or thus nonfraudulent firms.

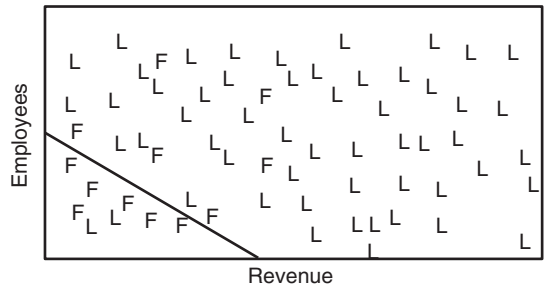


Figure 4.5 Linear Decision Boundary of Logistic Regression

To interpret a logistic regression model, one can calculate the odds ratio. Suppose variable X_i increases with one unit with all other variables being kept constant (ceteris paribus), then the new logit becomes the old logit with β_i added. Likewise, the new odds become the old odds multiplied by $e^{\beta i}$. The latter represents the odds ratio, that is, the multiplicative increase in the odds when X_i increases by 1 (ceteris paribus). Hence,

- $\beta_i > 0$ implies $e^{\beta i} > 1$ and the odds and probability increase with X_i
- $\beta_i < 0$ implies $e^{\beta i} < 1$ and the odds and probability decrease with X_i

Another way of interpreting a logistic regression model is by calculating the doubling amount. This represents the amount of change required for doubling the primary outcome odds. It can be easily seen that for a particular variable X_i, the doubling amount equals $\log(2)/\beta_i$.

Note that next to the $f(z)$ transformation, other transformations have been suggested in the literature. Popular examples are the probit and cloglog transformation as follows:

$$f(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{\frac{-t^2}{2}} dt,$$

$$f(z) = 1 - e^{-e^z}.$$

These transformations are visualized in Figure 4.6.

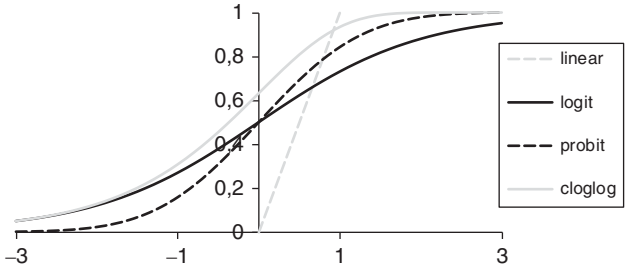


Figure 4.6 Other Transformations

Note, however, that empirical evidence suggests that all three transformations typically perform equally well.

Building a Logistic Regression Scorecard

Logistic regression is a very popular supervised fraud-detection technique due to its simplicity and good performance. Just as with linear regression, once the parameters have been estimated, it can be evaluated in a straightforward way, hereby contributing to its operational efficiency. From an interpretability viewpoint, it can be easily transformed into an interpretable, user friendly points based fraud scorecard. Let's assume we start from the following logistic regression model whereby the explanatory variables have been coded using weight of evidence coding:

$$P(fraud = yes|Revenue,\ Employees,\ VATCompliant,\ \dots) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 WOE_{Revenue} + \beta_2 WOE_{Employees} + \beta_3 WOE_{VATCompliant} + \dots)}}.$$

As discussed earlier, this model can be easily reexpressed in a linear way, in terms of the log odds as follows:

$$\log\left(\frac{P(fraud = yes|Revenue,\ Employees,\ VATCompliant,\ \dots)}{P(fraud = no|Revenue,\ Employees,\ VATCompliant,\ \dots)}\right) = \beta_0 + \beta_1 WOE_{Revenue} + \beta_2 WOE_{Employees} + \beta_3 WOE_{VATCompliant} + \dots\ .$$

A scaling can then be introduced by calculating a fraud score, which is linearly related to the log odds as follows:

$$\text{Fraud score} = \text{Offset} + \text{Factor} \times \log(\text{odds}).$$

Assume that we want a fraud score of 100 for odds of 50:1, and a fraud score of 120 for odds of 100:1. This gives the following:

$$100 = \text{Offset} + \text{Factor} \times \log(50)$$

$$120 = \text{Offset} + \text{Factor} \times \log(100)$$

The offset and factor then become:

$$\text{Factor} = 20/\ln(2) = 28.85$$

$$\text{Offset} = 100 - \text{Factor} \times \ln(50) = -12.87$$

Once these values are known, the fraud score becomes:

$$\text{Fraud score} = \left(\sum_{i=1}^{N} \left(WOE_i \times \beta_i\right) + \beta_0\right) \times \text{Factor} + \text{Offset}$$

$$\text{Fraud score} = \left(\sum_{i=1}^{N} \left(WOE_i \times \beta_i + \frac{\beta_0}{N}\right)\right) \times \text{Factor} + \text{Offset}$$

$$\text{Fraud score} = \left(\sum_{i=1}^{N} \left(WOE_i \times \beta_i + \frac{\beta_0}{N}\right) \times \text{Factor} + \frac{\text{Offset}}{N}\right)$$

Hence, the points for each attribute are calculated by multiplying the weight of evidence of the attribute with the regression coefficient of the characteristic, then adding a fraction of the regression intercept, multiplying the result by the factor, and finally adding a fraction of the offset. The corresponding fraud scorecard can then be visualized as depicted in Figure 4.7.

The fraud scorecard is very easy to work with. Suppose a new firm with the following characteristics needs to be scored:

$$\text{Revenue} = 750.000,\ \text{Employees} = 420,\ \text{VAT Compliant} = \text{No},\ \ldots$$

Characteristic Name	Attribute	Points
Revenue 1	Up to 100.000	80
Revenue 2	100.000–500.000	120
Revenue 3	500.000–1.000000	160
Revenue 4	1.000.000+	240
Employees 1	Up to 50	5
Employees 2	50–500	20
Employees 3	500+	80
VAT Compliant	Yes	100
VATCompliant	No	140
…		

Figure 4.7 Fraud Detection Scorecard

The score for this firm can then be calculated as follows: 160 + 20 + 140 + … This score can then be compared against a critical cut-off to help decide whether the firm is fraudulent. A key advantage of the fraud scorecard is its interpretability. One can clearly see which are the most risky categories and how they contribute to the overall fraud score. Hence, this is a very useful technique in fraud detection settings where interpretability is a key concern.

VARIABLE SELECTION FOR LINEAR AND LOGISTIC REGRESSION

Variable selection aims at reducing the number of variables in a model. It will make the model more concise and faster to evaluate, which is especially relevant in a fraud detection setting. Both linear and logistic regressions have built-in procedures to perform variable selection. These are based on statistical hypotheses tests to verify whether the coefficient of a variable *i* is significantly different from zero:

$$H_0 : \beta_i = 0$$

$$H_A : \beta_i \neq 0$$

In linear regression, the test statistic becomes:

$$t = \frac{\hat{\beta}_i}{s.e.(\hat{\beta}_i)},$$

and follows a Student's t-distribution with $n - 2$ degrees of freedom, whereas in logistic regression, the test statistic is:

$$\chi^2 = \left(\frac{\hat{\beta}_i}{s.e.\left(\hat{\beta}_i\right)} \right)^2$$

and follows a Chi-squared distribution with 1 degree of freedom. Note that both test statistics are intuitive in the sense that they will reject the null hypothesis H_0 if the estimated coefficient $\hat{\beta}_i$ is high in absolute value compared to its standard error $s.e.(\hat{\beta}_i)$. The latter can be easily obtained as a byproduct of the optimization procedure. Based on the value of the test statistic, one calculates the p-value, which is the probability of a getting a more extreme value than the one observed. This is visualized in Figure 4.8 assuming a value of 3 for the test statistic. Note that since the hypothesis test is two-sided, the p-value adds the areas to the right of 3 and to the left of –3.

In other words, a low (high) p-value represents an (in)significant variable. From a practical viewpoint, the p-value can be compared against a significance level. Table 4.3 presents some commonly used values to decide on the degree of variable significance.

Various variable selection procedures can now be used based on the p-value. Suppose one has four variables V_1, V_2, V_3, and V_4 (e.g., amount of transaction, currency, transaction type, and merchant category). The number of optimal variable subsets equals $2^4 - 1$ or 15, as displayed in Figure 4.9.

When the number of variables is small, an exhaustive search amongst all variable subsets can be performed. However, as the number of variables increases, the search space grows exponentially and heuristic search procedures are needed. Using the p-values, the variable space can be navigated in three possible ways. Forward regression starts from the empty model and always adds variables based on low p-values. Backward regression starts from the full

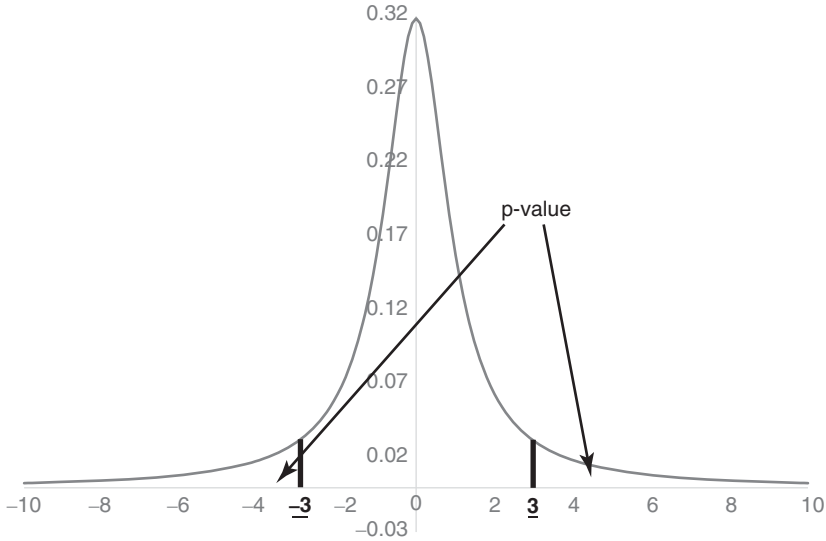


Figure 4.8 Calculating the *p*-Value with a Student's *t*-Distribution

Table 4.3 Reference Values for Variable Significance

p-value < 0.01	Highly significant
$0.01 < p$-value < 0.05	Significant
$0.05 < p$-value < 0.10	Weakly significant
p-value > 0.10	Not significant

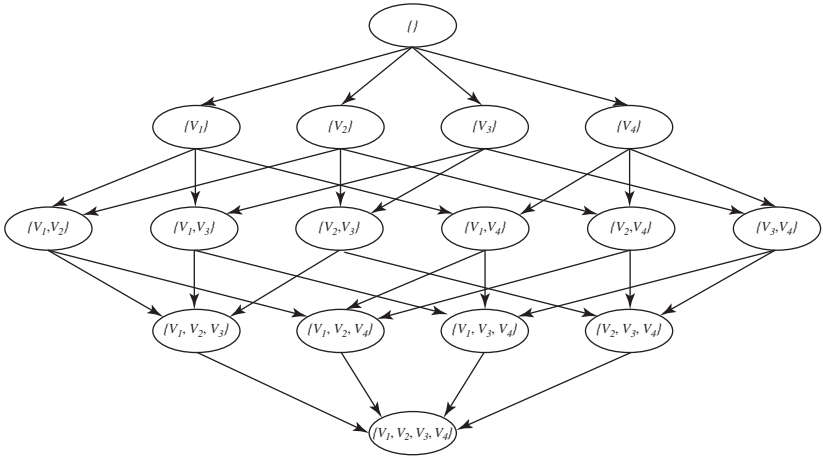


Figure 4.9 Variable Subsets for Four Variables V_1, V_2, V_3, and V_4

model and always removes variables based on high *p*-values. Stepwise regression is a mix between both. It starts off like forward regression, but once the second variable has been added, it will always check the other variables in the model and remove them if they turn out to be insignificant according to their *p*-value. Obviously, all three procedures assume preset significance levels, which should be set by the user before the variable selection procedure starts.

In fraud detection, it is very important to be aware that statistical significance is only one evaluation criterion to do variable selection. As mentioned before, *interpretability* is also an important criterion. In both linear and logistic regression, this can be easily evaluated by inspecting the sign of the regression coefficient. It is hereby highly preferable that a coefficient has the same sign as anticipated by the business expert, otherwise he/she will be reluctant to use the model.

Coefficients can have unexpected signs due to multicollinearity issues, noise or small sample effects. Sign restrictions can be easily enforced in a forward regression setup by preventing variables with the wrong sign from entering the model. Another criterion for variable selection is *operational efficiency*. This refers to the amount of resources that are needed for the collection and preprocessing of a variable. For example, although trend variables are typically very predictive, they require a lot of effort to be calculated and may thus not be suitable to be used in an online, real-time fraud scoring environment such as credit card fraud detection. The same applies to external data, where the latency might hamper a timely decision. In both cases, it might be worthwhile to look for a variable that is correlated and less predictive but easier to collect and calculate. Finally, also *legal issues* need to be properly taken into account. Some variables cannot be used in fraud-detection applications because of privacy or discrimination concerns.

DECISION TREES

Basic Concepts

Decision trees are recursive-partitioning algorithms (RPAs) that come up with a tree-like structure representing patterns in an underlying

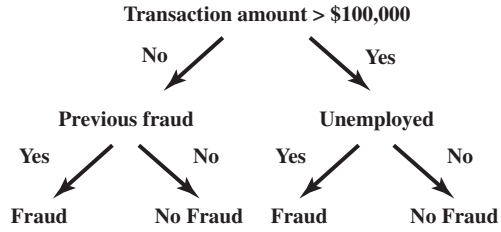


Figure 4.10 Example Decision Tree

data set (Duda et al. 2001). Figure 4.10 provides an example of a decision tree in a fraud-detection setting.

The top node is the root node specifying a testing condition, of which the outcome corresponds to a branch leading up to an internal node. The terminal nodes of the tree assign the classifications (in our case fraud labels) and are also referred to as the leave nodes. Many algorithms have been suggested in the literature to construct decision trees. Among the most popular are: C4.5 (See5) (Quinlan 1993), CART (Breiman et al. 1984), and CHAID (Hartigan 1975). These algorithms differ in their way of answering the key decisions to build a tree:

- **Splitting decision**: Which variable to split at what value (e.g., Transaction amount is > $100,000 or not, Previous fraud is yes or no, unemployed is yes or no)
- **Stopping decision:** When to stop adding nodes to the tree?
- **Assignment decision:** What class (e.g., fraud or no fraud) to assign to a leave node?

Usually, the assignment decision is the most straightforward to make since one typically looks at the majority class within the leave node to make the decision. This idea is also referred to as winner-take-all learning. The other two decisions are less straightforward to be made and are elaborated on in what follows.

Splitting Decision

In order to answer the splitting decision, one must define the concept of impurity or chaos. Consider, for example, the three data sets of Figure 4.11 each containing good (unfilled circles) and bad

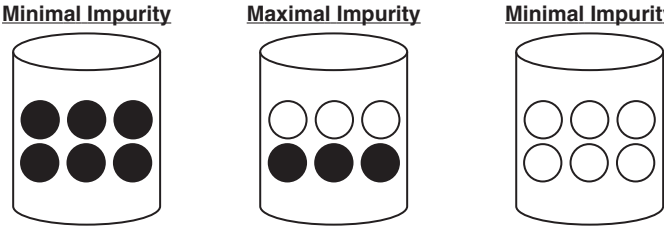


Figure 4.11 Example Data Sets for Calculating Impurity

(filled circles) customers. Quite obviously, the good customers are nonfraudulent, whereas the bad customers are fraudulent. Minimal impurity occurs when all customers are either good or bad. Maximal impurity occurs when one has the same number of good and bad customers (i.e., the data set in the middle).

Decision trees will now aim at minimizing the impurity in the data. In order to do so appropriately, one needs a measure to quantify impurity. Various measures have been introduced in the literature and the most popular are:

- Entropy: $E(S) = -p_G \log_2(p_G) - p_B \log_2(p_B)$ (C4.5/See5)
- Gini: $\text{Gini}(S) = 2p_G p_B$ (CART)
- Chi-squared analysis (CHAID)

with p_G and p_B being the proportions of good and bad, respectively. Both measures are depicted in Figure 4.12 where it can be clearly seen that the entropy (gini) is minimal when all customers are either good or bad, and maximal in case of the same number of good and bad customers.

In order to answer the splitting decision, various candidate splits will now be evaluated in terms of their decrease in impurity. Consider a split on age, as depicted in Figure 4.13.

The original data set had maximum entropy since the amount of goods and bads were the same. The entropy calculations now become:

- Entropy top node $= -1/2 \times \log_2(1/2) - 1/2 \times \log_2(1/2) = 1$
- Entropy left node $= -1/3 \times \log_2(1/3) - 2/3 \times \log_2(2/3) = 0.91$
- Entropy right node $= -1 \times \log_2(1) - 0 \times \log_2(0) = 0$

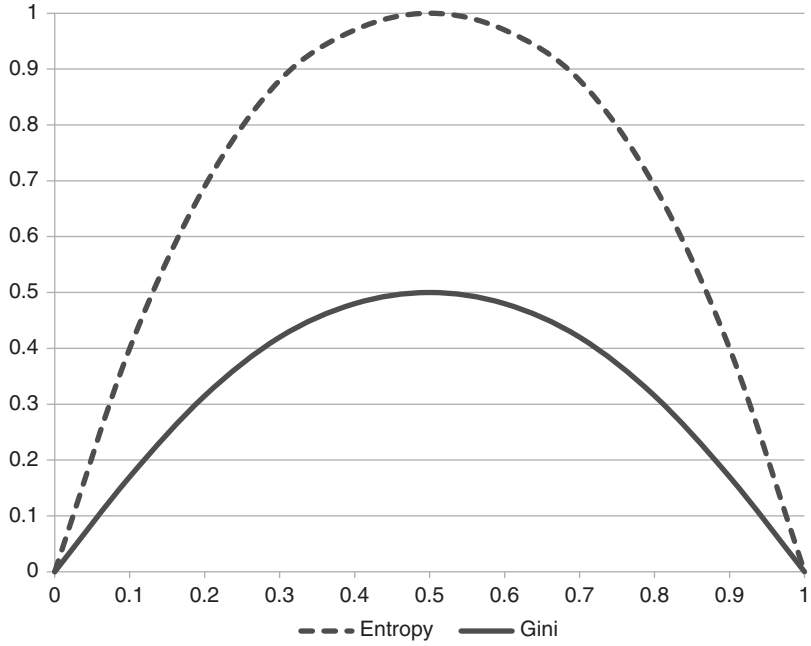


Figure 4.12 Entropy Versus Gini

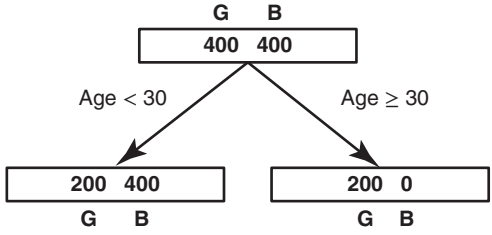


Figure 4.13 Calculating the Entropy for Age Split

The weighted decrease in entropy, also known as the *gain,* can then be calculated as follows:

$$\text{Gain} = 1 - (600/800) \times 0.91 - (200/800) \times 0 = 0.32$$

The gain measures the weighted decrease in entropy thanks to the split. It speaks for itself that a higher gain is to be preferred. The decision

tree algorithm will now consider different candidate splits for its root node and adopt a greedy strategy by picking the one with the biggest gain. Once the root node has been decided on, the procedure continues in a recursive way, each time adding splits with the biggest gain. In fact, this can be perfectly parallelized and both sides of the tree can grow in parallel, hereby increasing the efficiency of the tree construction algorithm.

Stopping Decision

The third decision relates to the stopping criterion. Obviously, if the tree continues to split, it will become very detailed with leaf nodes containing only a few observations. In the most extreme case, the tree will have one leaf node per observation and as such perfectly fit the data. However, by doing so, the tree will start to fit the specificities or noise in the data, which is also referred to as *overfitting*. In other words, the tree has become too complex and fails to correctly model the noise free pattern or trend in the data. As such, it will generalize poorly to new unseen data. In order to avoid this from happening, the data will be split into a training sample and a validation sample. The training sample will be used to make the splitting decision. The validation sample is an independent sample, set aside to monitor the misclassification error (or any other performance metric such as a profit-based measure) as the tree is grown. A commonly used split up is a 70 percent training sample and 30 percent validation sample. One then typically observes a pattern as depicted in Figure 4.14.

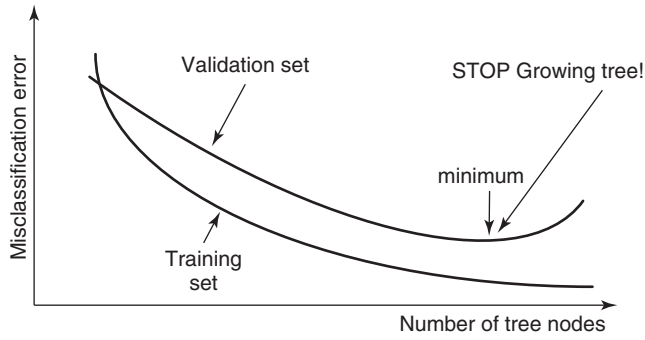


Figure 4.14 Using a Validation Set to Stop Growing a Decision Tree

The error on the training sample keeps on decreasing as the splits become more and more specific and tailored towards it. On the validation sample, the error will initially decrease, which indicates that the tree splits generalize well. However, at some point the error will increase since the splits become too specific for the training sample as the tree starts to memorize it. Where the validation set curve reaches its minimum, the procedure should be stopped, as otherwise overfitting will occur. Note that, as already mentioned, besides classification error, one might also use accuracy or profit based measures on the *Y*-axis to make the stopping decision. Also note that sometimes, simplicity is preferred above accuracy, and one can select a tree that does not necessarily have minimum validation set error, but a lower number of nodes.

Decision Tree Properties

In the example of Figure 4.10, every node had only two branches. The advantage of this is that the testing condition can be implemented as a simple yes/no question. Multiway splits allow for more than two branches and can provide trees that are wider but less deep. In a read-once decision tree, a particular attribute can be used only once in a certain tree path. Every tree can also be represented as a rule set since every path from a root note to a leave node makes up a simple if-then rule. For the tree depicted in Figure 4.10, the corresponding rules are:

If Transaction amount > $\$100,000$ **And** Unemployed = No **Then** no fraud

If Transaction amount > $\$100,000$ **And** Unemployed = Yes **Then** fraud

If Transaction amount ≤ $\$100,000$ **And** Previous fraud = Yes **Then** fraud

If Transaction amount ≤ $\$100,000$ **And** Previous fraud = No **Then** no fraud

These rules can then be easily implemented in all kinds of software packages (e.g., Microsoft Excel).

Decision trees essentially model decision boundaries orthogonal to the axes. This is illustrated in Figure 4.15 for an example decision tree.

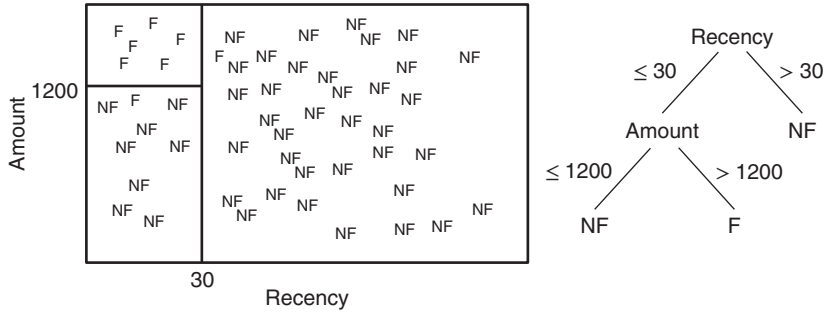


Figure 4.15 Decision Boundary of a Decision Tree

Regression Trees

Decision trees can also be used to predict continuous targets. Consider the example of Figure 4.16 where a regression tree is used to predict the fraud percentage (FP). The latter can be expressed as the percentage of a predefined limit based on, for example, the maximum transaction amount.

Other criteria need now be used to make the splitting decision since the impurity will need to be measured in another way. One way to measure impurity in a node is by calculating the mean squared error (MSE) as follows:

$$\frac{1}{n}\sum_{i=1}^{n}(Y_i - \overline{Y})^2,$$

where n represents the number of observations in a leave node, Y_i the value of observation i, and $\overline{Y}$, the average of all values in the leave node. Obviously, it is desirable to have a low MSE in a leave node since this indicates that the node is more homogeneous.

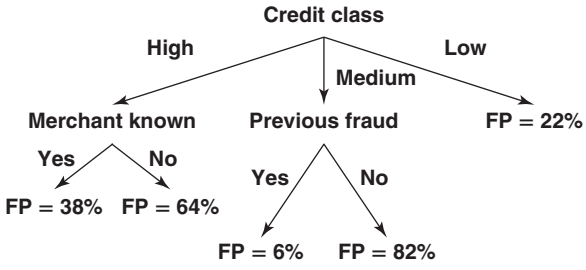


Figure 4.16 Example Regression Tree for Predicting the Fraud Percentage

Another way to make the splitting decision is by conducting a simple analysis of variance (ANOVA) test and calculating an F-statistic as follows:

$$F = \frac{SS_{between}/(B-1)}{SS_{within}/(n-B)} \sim F_{n-B,\ B-1},$$

whereby

$$SS_{between} = \sum_{b=1}^{B} n_b(\overline{Y}_b - \overline{Y})^2$$

$$SS_{within} = \sum_{b=1}^{B} \sum_{i=1}^{n_b} (Y_{bi} - \overline{Y}_b)^2$$

with B the number of branches of the split, n_b the number of observations in branch b, $\overline{Y}_b$ the average in branch b, Y_{bi} the value of observation i in branch b, and $\overline{Y}$ the overall average. Good splits favor homogeneity within a node (low SS_{within}) and heterogeneity between nodes (high $SS_{between}$). In other words, good splits should have a high F-value, or low corresponding p-value.

The stopping decision can be made in a similar way as for classification trees but using a regression based performance measure (e.g., mean squared error, mean absolute deviation, R-squared) on the Y-axis. The assignment decision can be made by assigning the mean (or median) to each leave node. Note that standard deviations and thus confidence intervals may also be computed for each of the leaf nodes.

Using Decision Trees in Fraud Analytics

Decision trees can be used for various purposes in fraud analytics. First, they can be used for variable selection as variables that occur at the top of the tree are more predictive of the target. One could also simply calculate the gain of a characteristic to gauge its predictive power. As an alternative, remember that we already discussed the information value in Chapter 2 to measure the predictive strength of a variable. Typically, both the gain and information value consider similar attributes to be predictive, so one can just choose the measure that is readily available in the analytics software. Decision trees can also be used for high-level segmentation. One then typically builds a tree two or three levels deep

as the segmentation scheme and then uses second-stage logistic regression models for further refinement. Finally, decision trees can also be used as the final analytical fraud model to be used directly into the business environment. A key advantage here is that the decision tree gives a white-box model with a clear explanation behind how it reaches its classifications.

Many software tools will also allow to grow trees interactively by providing at each level of the tree a top two (or more) of splits among which the fraud modeler can choose. This allows users to choose splits not only based on impurity reduction, but also on the interpretability and/or computational complexity of the split criterion. Hence, the modeler may favor a split on a less predictive variable, but which is easier to collect and/or interpret.

Decision trees are very powerful techniques and allow for more complex decision boundaries than a logistic regression. As discussed, they are also interpretable and operationally efficient. They are also nonparametric in the sense that no normality or independence assumptions were needed to build a decision tree. Their most important disadvantage is that they are highly dependent on the sample that was used for tree construction. A small variation in the underlying sample might yield a totally different tree. In a later section, we will discuss how this shortcoming can be addressed using the idea of ensemble learning.

NEURAL NETWORKS

Basic Concepts

A first perspective on the origin of neural networks states that they are mathematical representations inspired by the functioning of the human brain. Although this may sound appealing, another more realistic perspective sees neural networks as generalizations of existing statistical models (Bishop 1995; Zurada 1992). Let's take logistic regression as an example:

$$P(Y = 1|X_1, \ldots, X_N) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \ldots + \beta_N X_N)}},$$

We could visualize this model as shown in Figure 4.17.

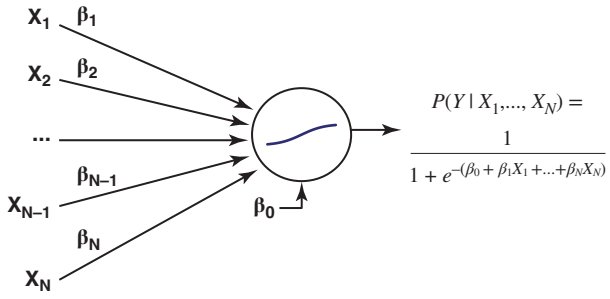


Figure 4.17 Neural Network Representation of Logistic Regression

The processing element or neuron in the middle basically performs two operations: it takes the inputs and multiplies them with the weights (including the intercept term β_0, which is called the bias term in neural networks) and then puts this into a nonlinear transformation function similar to the one we discussed in the section on logistic regression. So logistic regression is a neural network with one neuron. Similarly, we could visualize linear regression as a one neuron neural network with the identity transformation $f(z) = z$. We can now generalize the above picture to a multilayer perceptron (MLP) neural network by adding more layers and neurons, as shown in Figure 4.18 (Bishop 1995; Zurada 1992).

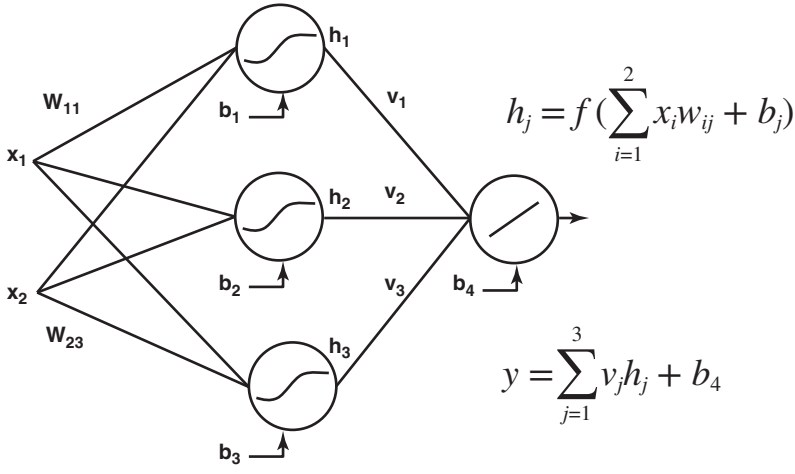


Figure 4.18 A Multilayer Perceptron (MLP) Neural Network

The example in Figure 4.18 is an MLP with one input layer, one hidden layer, and one output layer. The hidden layer essentially works like a feature extractor by combining the inputs into features that are then subsequently offered to the output layer to make the optimal prediction. The hidden layer has a nonlinear transformation function $f()$ and the output layer a linear transformation function. The most popular transformation functions (also called squashing, activation functions) are:

- Logistic, $f(z) = \frac{1}{1+e^{-z}}$, ranging between 0 and 1
- Hyperbolic tangent, $f(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$, ranging between –1 and +1
- Linear, $f(z) = z$, ranging between $-\infty$ and $+\infty$

Although theoretically the activation functions may differ per neuron, they are typically fixed for each layer. For classification (e.g., fraud detection), it is common practice to adopt a logistic transformation in the output layer, since the outputs can then be interpreted as probabilities (Baesens et al. 2002). For regression targets (e.g., amount of fraud), one could use any of the transformation functions listed above. Typically, one will use the hyperbolic tangent activation function in the hidden layer.

In terms of hidden layers, theoretical works have shown that neural networks with one hidden layer are universal approximators, capable of approximating any function to any desired degree of accuracy on a compact interval (Hornik et al. 1989). Only for discontinuous functions (e.g., a saw tooth pattern) or in a deep learning context, it could make sense to try out more hidden layers. Note, however, that these complex patterns rarely occur in practice. In a fraud setting, it is recommended to continue the analysis with one hidden layer.

In terms of data preprocessing, it is advised to standardize the continuous variables using, for example, the z-scores. For categorical variables, categorization can be used to reduce the number of categories, which can then be coded using, for example, dummy variables or weight of evidence coding. Note that it is important to only consider categorization for the categorical variables, and not for the continuous variables. The latter can be categorized to model nonlinear effects into linear models (e.g., linear or logistic regression), but since neural networks are capable of modeling nonlinear relationships, it is not needed here.

Weight Learning

As discussed earlier, for simple statistical models such as linear regression, there exists a closed-form mathematical formula for the optimal parameter values. However, for neural networks, the optimization is a lot more complex and the weights sitting on the various connections need to be estimated using an iterative algorithm. The algorithm then optimizes a cost-function. Similarly to linear regression, when the target variable is continuous, a mean squared error (MSE) cost function will be optimized as follows:

$$\frac{1}{2}\sum_{i=1}^{n} e_i^2 = \frac{1}{2}\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2,$$

where Y_i now represents the neural network prediction for observation i. In case of a binary target variable, a maximum likelihood cost function can be optimized as follows:

$$\prod_{i=1}^{n} P(Y = 1|X_{1i}, \ldots, X_{Ni})^{Y_i}(1 - P(Y = 1|X_{1i}, \ldots, X_{Ni})^{1-Y_i},$$

where $P(Y = 1|X_{1i}, \ldots, X_{Ni})$ represents the probability prediction from the neural network.

The optimization procedure typically starts from a set of random weights (e.g., drawn from a standard normal distribution), which are then iteratively adjusted to the patterns in the data using an optimization algorithm. Popular optimization algorithms here are back propagation learning, conjugate gradient, and Levenberg-Marquardt. See for more details (Bishop 1995). A key issue to note here is the curvature of the objective function, which is not convex and may be multimodal as illustrated in Figure 4.19. The error function can thus have multiple local minima but typically only one global minimum. Hence, if the starting weights are chosen in a suboptimal way, one may get stuck in a local minimum, which is clearly undesirable. One way to deal with this is to try out different starting weights, start the optimization procedure for a few steps, and then continue with the best intermediate solution. This approach is sometimes referred to as preliminary training. The optimization procedure then continues until the error function shows no further progress, the weights stop changing substantially, or after a fixed number of optimization steps (also called epochs).

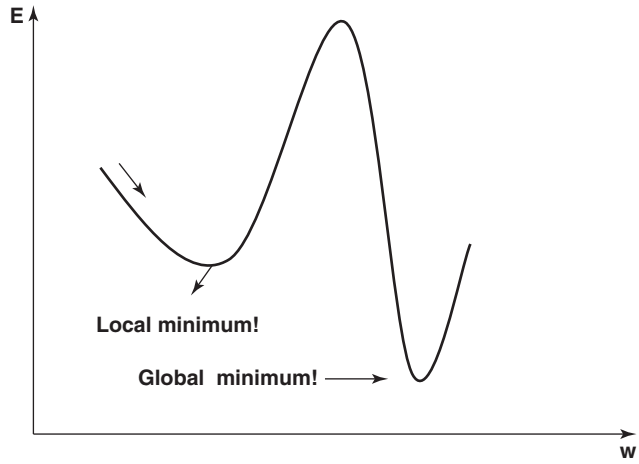


Figure 4.19 Local Versus Global Minima

Although multiple output neurons could be used (e.g., predicting fraud and fraud amount simultaneously), it is highly advised to use only one to make sure that the optimization task is well focused. The hidden neurons, however, should be carefully tuned and depend on the nonlinearity in the data. More complex, nonlinear patterns will require more hidden neurons. Although various procedures (e.g., cascade correlation, genetic algorithms, Bayesian methods) have been suggested in the scientific literature to do this, the most straightforward, yet efficient procedure is as follows (Moody and Utans 1994):

1. Split the data into a training, validation, and test set.
2. Vary the number of hidden neurons from 1 to 10 in steps of one or more.
3. Train a neural network on the training set and measure the performance on the validation set (may be train multiple neural networks to deal with the local minimum issue).
4. Choose the number of hidden neurons with optimal validation set performance.
5. Measure the performance on the independent test set.
   Note that for fraud detection, the number of hidden neurons typically varies between 6 and 12.

Neural networks can model very complex patterns and decision boundaries in the data and are as such very powerful. Just as with decision trees, they are so powerful that they can even model the noise in the training data, which is something that definitely should be avoided. One way to avoid this overfitting is by using a validation set in a similar way as with decision trees. This is illustrated in Figure 4.20. The training set is used here to estimate the weights and the validation set is again an independent data set used to decide when to stop training.

Another scheme to prevent a neural network from overfitting is weight regularization, whereby the idea is to keep the weights small in absolute sense since otherwise they may be fitting the noise in the data. This is then implemented by adding a weight size term (e.g., Euclidean norm) to the objective function of the neural network (Bartlett 1997). In case of a continuous output (and thus mean squared error), the objective function then becomes:

$$\frac{1}{2}\sum_{i=1}^{n} e_i^2 + \lambda \sum_{j=1}^{k} w_j^2,$$

where k represents the number of weights in the network and λ a weight decay (also referred to as weight regularization) parameter to weigh the importance of error versus weight minimization. Setting λ too low will cause overfitting, whereas setting it to high will cause underfitting. A practical approach to determining λ is to try out different values on an independent validation set and select the one with the best performance.

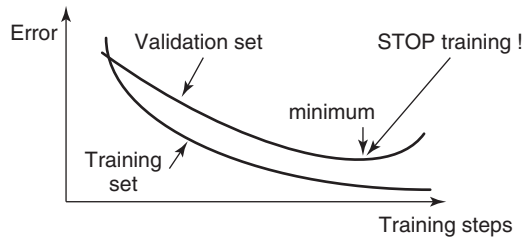


Figure 4.20 Using a Validation Set for Stopping Neural Network Training

Opening the Neural Network Black Box

Although neural networks have their merits in terms of modeling power, they are commonly described as black-box techniques since they relate the inputs to the outputs in a mathematically complex, nontransparent, and opaque way. They have been successfully applied as high-performance analytical tools in settings where interpretability is not a key concern (e.g., credit card fraud detection).

However, in application areas where insight into the fraud behavior is important, one needs to be careful with neural networks (Baesens, Martens et al. 2011). In what follows, we will discuss the following three ways of opening the neural network black box:

1. Variable selection
2. Rule extraction
3. Two-stage models

A first way to get more insight into the functioning of a neural network is by doing variable selection. As previously, the aim here is to select those variables that actively contribute to the neural network output. In linear and logistic regression, the variable importance was evaluated by inspecting the *p*-values. Unfortunately, in neural networks this is not that easy, as no *p*-values are readily available. One easy and attractive way to do it is by visualizing the weights in a Hinton diagram. A Hinton diagram visualizes the weights between the inputs and the hidden neurons as squares, whereby the size of the square is proportional to the size of the weight and the color of the square represents the sign of the weight (e.g., black colors represent a negative weight and white colors a positive weight). Clearly, when all weights connecting a variable to the hidden neurons are close to zero, it does not contribute very actively to the neural network's computations, and one may consider leaving it out. Figure 4.21 shows an example of a Hinton diagram for a neural network with four hidden neurons and five variables. It can be clearly seen that the income variable has a small negative and positive weight when compared to the other variables and can thus be considered for removal from the network. A very straightforward variable selection procedure is:

1. Inspect the Hinton diagram and remove the variable whose weights are closest to zero.

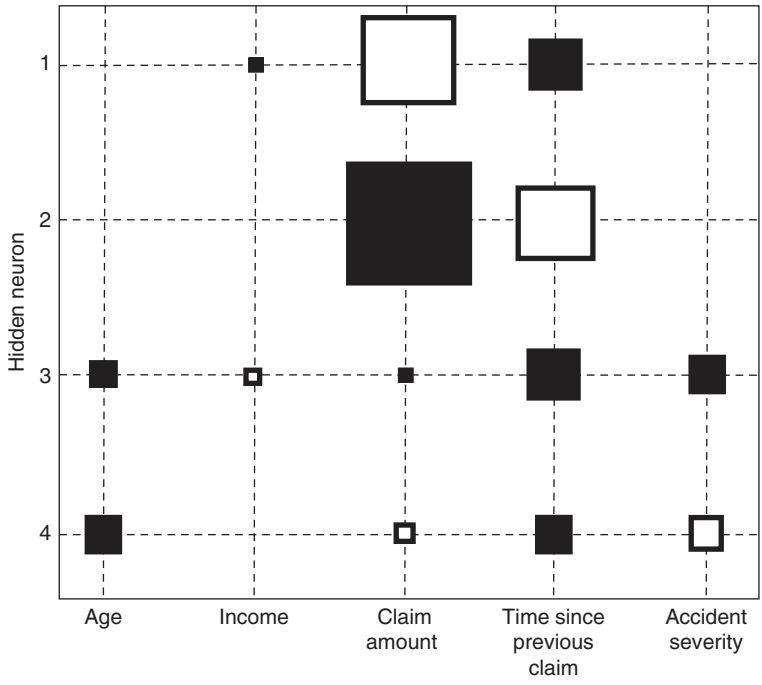


Figure 4.21 Example Hinton Diagram

2. Reestimate the neural network with the variable removed. To speed up the convergence, it could be beneficial to start from the previous weights.
3. Continue with step 1 until a stopping criterion is met. The stopping criterion could be a decrease of predictive performance or a fixed number of steps.

Another way to do variable selection is by using the following backward variable selection procedure:

1. Build a neural network with all N variables.
2. Remove each variable in turn and reestimate the network. This will give N networks each having $N - 1$ variables.
3. Remove the variable whose absence gives the best performing network (e.g., in terms of misclassification error, mean squared error).
4. Repeat this procedure until the performance decreases significantly.

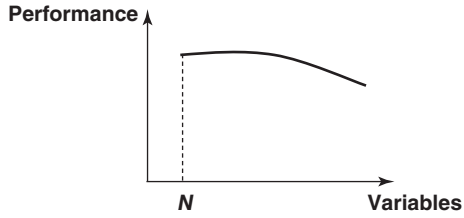


Figure 4.22 Backward Variable Selection

When plotting the performance against the number of variables, a pattern as depicted in Figure 4.22 will likely be obtained. Initially, the performance will stagnate, or may even increase somewhat. When important variables are being removed, the performance will start decreasing. The optimal number of variables can then be situated around the elbow region of the plot and can be decided in combination with a business expert. Sampling can be used to make the procedure less resource intensive and more efficient. Note that this performance-driven way of variable selection can easily be adopted with other analytical techniques such as linear or logistic regression or support vector machines (see next section).

Although variable selection allows users to see which variables are important to the neural network and which ones are not, it does not offer a clear insight into its internal workings. The relationship between the inputs and the output remains nonlinear and complex. A first way to get more transparency is by performing rule extraction, as will be discussed next.

The purpose of rule extraction is to extract if-then classification rules, mimicking the behavior of the neural network (Baesens 2003; Baesens et al. 2003; Setiono et al. 2009). Two important approaches here are decompositional and pedagogical techniques. Decompositional rule extraction approaches decompose the network's internal workings by inspecting weights and/or activation values. A typical approach here could be (Lu et al. 1995; Setiono et al. 2011):

1. Train a neural network and do variable selection to make it as concise as possible.
2. Categorize the hidden unit activation values by using clustering.

3. Extract rules that describe the network output in terms of the categorized hidden unit activation values.
4. Extract rules that describe the categorized hidden unit activation values in terms of the network inputs.
5. Merge the rules obtained in step 3 and 4 to directly relate the inputs to the outputs.

This is illustrated in Figure 4.23.

Pedagogical rule extraction techniques consider the neural network as a black box and use the neural network predictions as input to a white-box analytical technique such as decision trees (Craven and Shavlik 1996). This is illustrated in Figure 4.24.

In this approach, the learning data set can be further augmented with artificial data, which is then labeled (e.g., classified or predicted) by the neural network, so as to further increase the number of observations to make the splitting decisions when building the decision tree. Note that since the pedagogical approach does not make use of the parameters or internal model representation, it can essentially be used

Customer	Age	Income	Known Customer	…	Fraud
Emma	28	1000	Y		No
Will	44	1500	N		Yes
Dan	30	1200	N		No
Bob	58	2400	Y		Yes

Step 1: Start from original data

Customer	Age	Income	Known Customer	h1	h2	h3	h1	h2	h3	Fraud
Emma	28	1000	Y	–1.20	2,34	0,66	1	3	2	No
Will	44	1500	N	0,78	1,22	0,82	2	3	2	Yes
Dan	30	1200	N	2,1	–0,18	0,16	3	1	2	No
Bob	58	2400	Y	–0,1	0,8	–2,34	1	2	1	Yes

Step 2: Build a neural network (e.g., 3 hidden neurons)

Step 3: Categorize hidden unit activations

If h1 = 1 **and** h2 = 3 **Then** Fraud = No
If h2 = 2 **Then** Fraud = Yes

Step 4: Extract rules relating network outputs to categorized hidden units

If Age < 28 **and** Income < 1000 **Then** h1 = 1
If Known Customer = Y **Then** h2 = 3
If Age > 34 **and** Income > 1500 **Then** h2 = 2

Step 5: Extract rules relating categorized hidden units to inputs

If Age < 28 **and** Income < 1000 **and** Known Customer = Y **Then** Fraud = No
If Age > 34 **and** Income > 1500 **Then** Fraud = Yes

Step 6: Merge both rule sets

Figure 4.23 Decompositional Approach for Neural Network Rule Extraction

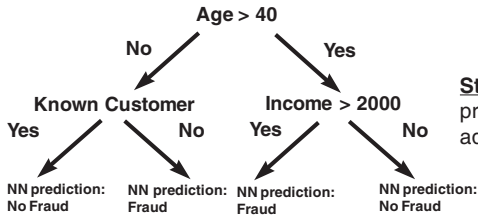
Customer	Age	Income	Known Customer	...	Fraud
Emma	28	1000	Y		No
Will	44	1500	N		Yes
Dan	30	1200	N		No
Bob	58	2400	Y		Yes

Step 1: Start from original data

Customer	Age	Income	Known Customer	Network Prediction	Fraud
Emma	28	1000	Y	No	No
Will	44	1500	N	Yes	Yes
Dan	30	1200	N	Yes	No
Bob	58	2400	Y	Yes	Yes

Step 2: Build a neural network

Step 3: Get the network predictions and add them to the data set



Step 4: Extract rules relating network predictions to original inputs. Generate additional data where necessary.

Figure 4.24 Pedagogical Approach for Rule Extraction

with any underlying algorithm, such as regression techniques, or SVMs (see later).

When using either decompositional or pedagogical rule extraction approaches, the rule sets should be evaluated in terms of their accuracy, conciseness (e.g., number of rules, number of conditions per rule), and fidelity. The latter measures to what extent the extracted rule set succeeds in mimicking the neural network and is calculated as follows:

Rule Set Classification		Neural Network Classification	
		No Fraud	Fraud
	No Fraud	*a*	*b*
	Fraud	*c*	*d*

$$\text{Fidelity} = (a + d)/(b + c).$$

It is also important to always benchmark the extracted rules/trees with a tree built directly on the original data to see the benefit of going through the neural network.

Another approach to make neural networks more interpretable is by using a two-stage model setup (Van Gestel et al. 2005, 2006). The

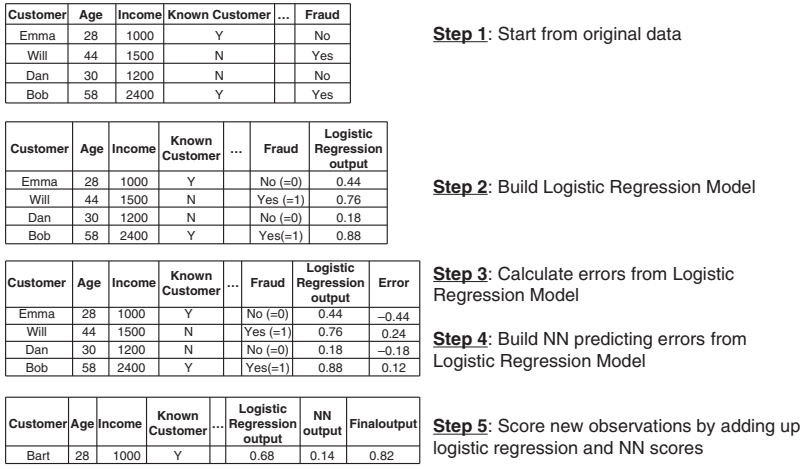


Figure 4.25 Two-Stage Models

idea here is to estimate an easy-to-understand model first (e.g., linear regression, logistic regression). This will give us the interpretability part. In a second stage, a neural network is used to predict the errors made by the simple model using the same set of predictors. This will give us the additional performance benefit of using a nonlinear model. Both models are then combined in an additive way, for example as follows:

- Target = Linear regression $(X_1, X_2, \ldots X_N)$ + Neural network $(X_1, X_2, \ldots X_N)$
- Score = Logistic regression $(X_1, X_2, \ldots X_N)$ + Neural network $(X_1, X_2, \ldots X_N)$

This setup provides an ideal balance between model interpretability (which comes from the first part) and model performance (which comes from the second part). This is illustrated in Figure 4.25.

SUPPORT VECTOR MACHINES

Linear Programming

Two key shortcomings of neural networks are the fact that the objective function is nonconvex (and hence may have multiple

local minima) and the effort that is needed to tune the number of hidden neurons. Support vector machines (SVMs) deal with both of these issues (Cristianini and Taylor 2000; Schölkopf and Smola 2001; Vapnik 1995).

The origins of classification SVMs date back to the early dates of linear programming (Mangasarian 1965). Consider, for example, the following linear program (LP) for classification in a fraud setting:

$$\min e_1 + e_2 + \ldots + e_{n_{nf}} + \ldots e_{n_{nf}+n_f}$$

subject to

$$w_1 x_{i1} + w_2 x_{i2} + \ldots + w_N x_{iN} \geq c - e_i,\ 1 \leq i \leq n_{nf},$$

$$w_1 x_{i1} + w_2 x_{i2} + \ldots + w_N x_{iN} \leq c + e_i, n_{nf} + 1 \leq i \leq n_{nf} + n_f,$$

$$e_i \geq 0,$$

with x_{ij} the value of variable j for observation i, and n_{nf} and n_f the number of no frauds and frauds, respectively. The LP assigns the no frauds a score above the cut-off value c, and the frauds a score below c. The error variables e_i are needed to be able to solve the program since perfect separation will typically not be possible. Linear programming has been very popular in the early days of credit scoring. One of its key benefits is that it is easy to include domain or business knowledge by adding extra constraints to the model. Suppose prior business experience indicates that age (variable 1) is more important than income (variable 2). This can be easily enforced by adding the constraint $w_1 \geq w_2$ to the linear program.

A key problem with linear programming is that it can estimate multiple optimal decision boundaries as illustrated in Figure 4.26 for a perfectly linearly separable case, where class 1 represents the fraudsters and class 2 the non-fraudsters.

The Linear Separable Case

SVMs add an extra objective to the analysis. Consider the situation depicted in Figure 4.27 with two variables x1 (e.g, age) and x2

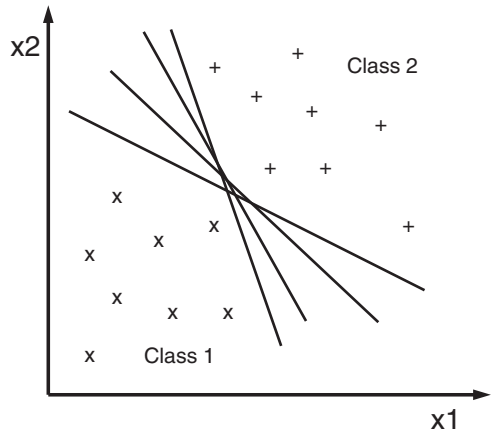


Figure 4.26 Multiple Separating Hyperplanes

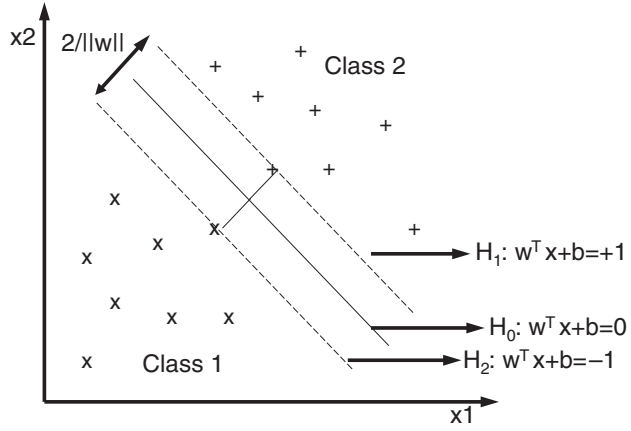


Figure 4.27 SVM Classifier for the Perfectly Linearly Separable Case

(e.g, income). It has two hyperplanes sitting at the edges of both classes, and a hyperplane in between which will serve as the classification boundary. The perpendicular distance from the first hyperplane H_1 to the origin equals $|b-1|/||w||$, whereby $||w||$ represents the Euclidean norm of w calculated as $||w|| = \sqrt{w_1^2 + w_2^2}$. Likewise, the perpendicular distance from H_2 to the origin equals $|b+1|/||w||$.

Hence, the margin between both hyperplanes equals 2/||w||. SVMs will now aim at maximizing this margin to pull both classes as far apart as possible. Maximizing the margin is similar to minimizing $||w||$, or minimizing $\frac{1}{2}\sum_{i=1}^{N} w_i^2$. In case of perfect linear separation, the SVM classifier then becomes as follows.

Consider a training set: $\{x_k, y_k\}_{k=1}^{n}$ with $x_k \in R^N$ and $y_k \in \{-1; +1\}$

The goods (e.g., class +1) should be above hyperplane H_1, and the bads (e.g., class –1) below hyperplane H_2, which gives:

$$w^T x_k + b \geq 1, \quad if \ y_k = +1$$
$$w^T x_k + b \leq -1, \quad if \ y_k = -1$$

Both can be combined as follows:

$$y_k(w^T x_k + b) \geq 1.$$

The optimization problem then becomes:

$$Minimize \ \frac{1}{2}\sum_{i=1}^{N} w_i^2$$
$$\text{subject to } y_k(w^T x_k + b) \geq 1, \ k = 1 \ \ldots \ n.$$

This quadratic programming (QP) problem can now be solved using Lagrangian optimization (Cristianini and Taylor 2000; Schölkopf and Smola 2001; and Vapnik 1995). Important to note is that the optimization problem has a quadratic cost function, giving a convex optimization problem with no local minima and only one global minimum. Training points that lie on one of the hyperplanes H_1 or H_2 are called support vectors and are essential to the classification. The classification hyperplane itself is H_0 and for new observations, it needs to be checked whether they are situated above H_0 in which case the prediction is +1 or below (prediction – 1). This can be easily accomplished using the sign operator as follows: $y(x) = \text{sign}(w^T x + b)$. Remember, sign($x$) is +1 if $x \geq 0$, and –1, otherwise.

The Linear Nonseparable Case

The SVM classifier discussed thus far assumed perfect separation is possible, which will, of course, be rarely the case for real-life data sets. In case of overlapping class distributions (as illustrated in Figure 4.28), the SVM classifier can be extended with error terms e_i as follows:

$$Minimize \frac{1}{2}\sum_{i=1}^{N} w_i^2 + C\sum_{i=1}^{n} e_i$$

$$\text{subject to } y_k(w^T x_k + b) \geq 1 - e_k,\ k = 1 \ \ldots \ n$$

$$e_k \geq 0.$$

The error variables e_k are needed to allow for misclassifications. The C hyperparameter in the objective function balances the importance of maximizing the margin versus minimizing the error on the data. A high (low) value of C implies a higher (lower) risk of overfitting. Note the similarity with the idea of weight regularization discussed in the section on neural networks. Also, there the objective function consisted out of an error term and the sum of the squared weights. We will discuss procedures to determine the optimal value of C later in this section. Just as before, the problem is a quadratic programming (QP) problem, which can be solved using Lagrangian optimization.

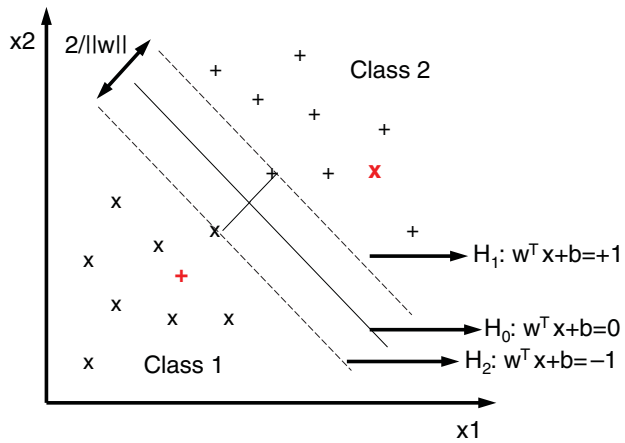


Figure 4.28 SVM Classifier in Case of Overlapping Distributions

The Nonlinear SVM Classifier

Finally, the nonlinear SVM classifier will first map the input data to a higher dimensional feature space using some mapping $\varphi(x)$. This is illustrated in Figure 4.29.

The SVM problem formulation now becomes:

$$\text{Minimize } \frac{1}{2}\sum_{i=1}^{N} w_i^2 + C\sum_{i=1}^{n} e_i$$

$$\text{subject to } y_k(w^T\varphi(x_k) + b) \geq 1 - e_k,\ k = 1 \ \ldots \ n$$

$$e_k \geq 0.$$

When working out the Lagrangian optimization (Cristianini and Taylor 2000; Schölkopf and Smola 2001; and Vapnik 1995), it turns out that the mapping $\varphi(x)$ is never explicitly needed, but only implicitly by means of the kernel function K defined as follows $K(x_k, x_l) = \varphi(x_k)^T\varphi(x_l)$. Hence, the feature space does not need to be explicitly specified. The nonlinear SVM classifier then becomes:

$$y(x) = sign\left[\sum_{k=1}^{n} \alpha_k y_k K\left(x, x_k\right) + b\right],$$

where α_k are the Lagrangian multipliers stemming from the optimization. Support vectors will have nonzero α_k since they are needed to

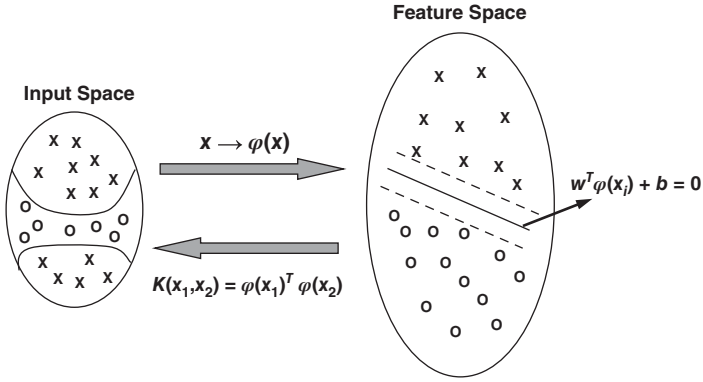


Figure 4.29 The Feature Space Mapping

construct the classification hyperplane. All other observations have zero α_k, which is often referred to as the sparseness property of SVMs. Different types of kernel functions can be used. The most popular are:

- Linear kernel: $K(x, x_k) = x_k^T x$
- Polynomial kernel: $K(x, x_k) = (1 + x_k^T x)^d$
- Radial basis function (RBF) kernel: $K(x, x_k) = \exp\{-||x - x_k||^2 / \sigma^2\}$

Empirical evidence has shown that the RBF kernel usually performs best, but note that it includes an extra parameter σ to be tuned (Van Gestel et al. 2004).

A key question to answer when building SVM classifiers is the tuning of the hyperparameters. For example, suppose one has an RBF SVM, which has two hyperparameters C and σ. Both can be tuned using the following procedure (Van Gestel et al. 2004):

1. Partition the data into 40%/30%/30% training, validation and test data.
2. Build an RBF SVM classifier for each (σ, C) combination from the sets $\sigma \in \{0.5, 5, 10, 15, 25, 50, 100, 250, 500\}$ and $C \in \{0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100, 500\}$.
3. Choose the (σ, C) combination with the best validation set performance.
4. Build an RBF SVM classifier with the optimal (σ, C) combination on Combined training + Validation data set.
5. Calculate the performance of the estimated RBF SVM classifier on the test set.

In case of linear or polynomial kernels, a similar procedure can be adopted.

SVMs for Regression

SVMs can also be used for regression applications with a continuous target. The idea here is to find a function $f(x)$ that has at most ε deviation from the actual targets y_i for all the training data, and is at the same time as flat as possible. Hence, the loss function will tolerate (penalize) errors less (higher) than ε. This is visualized in Figure 4.30.

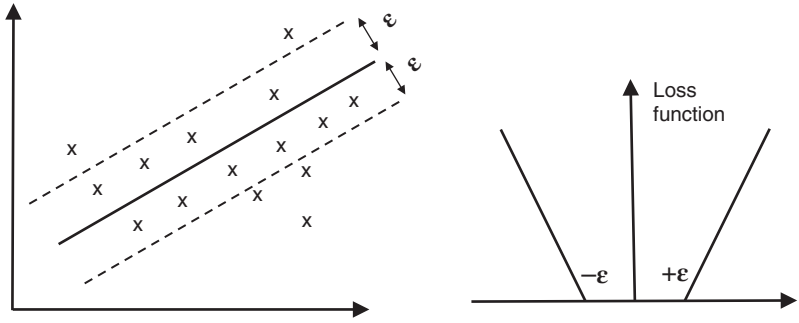


Figure 4.30 SVMs for Regression

Consider a training set: $\{x_k, y_k\}_{k=1}^{n}$ *with* $x_k \in R^N$ *and* $y_k \in R$
The SVM formulation then becomes:

$$Minimize\ \frac{1}{2}\sum_{i=1}^{N} w_i^2 + C\sum_{i=1}^{n}(\varepsilon_k + \varepsilon_k^*)$$

subject to

$$y_k - w^T\varphi(x_k) - b \leq \varepsilon + \varepsilon_k$$

$$w^T\varphi(x_k) + b - y_k \leq \varepsilon + \varepsilon_k^*$$

$$\varepsilon,\ \varepsilon_k,\ \varepsilon_k^* \geq 0.$$

The hyperparameter C determines the trade-off between the flatness of f and the amount to which deviations larger than ε are tolerated. Note the feature space mapping $\varphi(x)$, which is also used here. Using Lagrangian optimization, the resulting nonlinear regression function becomes:

$$f(x) = \sum_{i=1}^{n}(\alpha_k - \alpha_k^*)K(x_k, x) + b,$$

where α_k and α_k^* represent the Lagrangian multipliers. The hyperparameters C and ε can be tuned using a procedure similar to the one outlined for classification SVMs.

Opening the SVM Black Box

Similar to neural networks, SVMs have a universal approximation property. As an extra benefit, they do not require tuning of the number of hidden neurons and are characterized by convex optimization. However, they are also very complex to be used in settings where interpretability is important. Just as with neural networks, procedures can be used to provide more transparency by opening up the SVM black box.

Variable selection can be performed using the backward variable selection procedure discussed in the section on neural networks. This will essentially reduce the variables but not provide any additional insight into the workings of the SVM. Rule extraction approaches can then be used in a next step. In order to apply decompositional rule extraction approaches, the SVM can be represented as a neural network as depicted in Figure 4.31.

The hidden layer uses kernel activation functions, whereas the output layer uses a linear activation function. Note that the number of hidden neurons now corresponds to the number of support vectors and follows automatically from the optimization. This is in strong contrast to neural networks where the number of hidden neurons needs to be tuned manually. The decompositional approach can then proceed by first extracting If-Then rules relating the output to the hidden

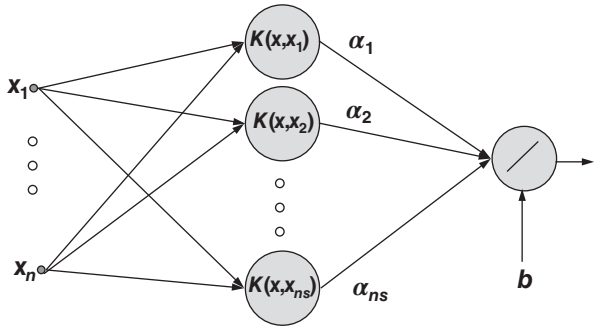


Figure 4.31 Representing an SVM Classifier as a Neural Network

unit activation values. In a next step, rules are extracted relating the hidden unit activation values to the inputs, followed by the merger of both rule sets.

Since a pedagogical approach considers the underlying model as a black box, it can be easily combined with SVMs. Just as in the neural network case, the SVM is first used to construct a data set with SVM predictions for each of the observations. This data set is then given to a decision tree algorithm to build a decision tree. Also here, additional training set observations can be generated to facilitate the tree construction process.

Finally, also two-stage models can be used to provide more comprehensibility. Remember, in this approach a simple model (e.g., linear or logistic regression) is estimated first, followed by an SVM to correct the errors of the latter.

ENSEMBLE METHODS

Ensemble methods aim at estimating multiple analytical models instead of using only one. The idea here is that multiple models can cover different parts of the data input space and as such complement each other's deficiencies. In order to successfully accomplish this, the analytical technique needs to be sensitive to changes in the underlying data. This is especially the case for decision trees and that's why they are commonly used in ensemble methods. In what follows, we will discuss bagging, boosting, and random forests.

Bagging

Bagging (Bootstrap aggregating) starts by taking B bootstraps from the underlying sample (Breiman 1996). Note that a bootstrap is a sample with replacement (see section on evaluating predictive models). The idea is then to build a classifier (e.g., decision tree) for every bootstrap. For classification, a new observation will be classified by letting all B classifiers vote, using, for example, a majority voting scheme whereby ties are resolved arbitrarily. For regression, the prediction is the average of the outcome of the B models (e.g., regression trees). Note that here also a standard error and thus confidence interval can be calculated.

The number of bootstraps B can either be fixed (e.g., 30) or tuned via an independent validation data set.

The key element for bagging to be successful is the instability of the analytical technique. If perturbing the data set by means of the bootstrapping procedure can alter the model constructed, then bagging will improve the accuracy (Breiman 1996). However, for models that are robust with respect to the underlying data set, it will not give much added value.

Boosting

Boosting works by estimating multiple models using a weighted sample of the data (Freund and Schapire 1997, 1999). Starting from uniform weights, boosting will iteratively reweight the data according to the classification error whereby misclassified cases get higher weights. The idea here is that difficult observations should get more attention. Either the analytical technique can directly work with weighted observations, or if not, we can just sample a new data set according to the weight distribution. The final ensemble model is then a weighted combination of all the individual models. A popular implementation of this is the Adaptive boosting/Adaboost procedure, which works as follows:

1. Given the following observations: $(x_1, y_1), \ldots, (x_n, y_n)$ where x_i is the attribute vector of observation i and $y_i \in \{1,-1\}$
2. Initialize the weights as follows: $W_1(i) = 1/n,\ i = 1, \ldots, n$
3. For $t = 1 \ldots T$
   a. Train a weak classifier (e.g., decision tree) using the weights W_t
   b. Get weak classifier C_t with classification error ε_t
   c. Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$
   d. Update the weights as follows:
      i. $W_{t+1}(i) = \frac{W_t(i)}{Z_t}\, e^{-\alpha_t}$ *if* $C_t(x) = y_i$
      ii. $W_{t+1}(i) = \frac{W_t(i)}{Z_t}\, e^{\alpha_t}$ *if* $C_t(x) \neq y_i$
4. Output the final ensemble model: $E(x) = sign\left(\sum_{t=1}^{T} \left(\alpha_t C_t(x)\right)\right)$

Note that in this procedure, T represents the number of boosting runs, α_t measures the importance that is assigned to classifier C_t and increases as ε_t gets smaller, Z_t is a normalization factor needed to make sure that the weights in step t make up a distribution and as such sum to 1, and $C_t(x)$ represents the classification of the classifier built in step t for observation x. Multiple loss functions may be used to calculate the error ε_t although the misclassification rate is undoubtedly the most popular. In substep i of step d, it can be seen that correctly classified observations get lower weights, whereas substep ii assigns higher weights to the incorrectly classified cases. Again, the number of boosting runs T can be fixed or tuned using an independent validation set. Note that various variants of this Adaboost procedure exist, such as Adaboost.M1, Adaboost.M2 (both for multiclass classification), and Adaboost.R1, Adaboost.R2 (both for regression). See Freund and Schapire (1997 and 1999) for more details. A key advantage of boosting is that it is really easy to implement. A potential drawback is that there may be a risk of overfitting to the hard (potentially noisy) examples in the data, which will get higher weights as the algorithm proceeds. This is especially relevant in a fraud detection setting because, as mentioned earlier, the target labels in a fraud setting are typically quite noisy.

Random Forests

The technique of random forests was first introduced by Breiman (2001). It creates a forest of decision trees as follows:

1. Given a data set with n observations and N inputs.
2. m = constant chosen on beforehand.
3. For $t = 1, \ldots, T$
   a. Take a bootstrap sample with n observations.
   b. Build a decision tree whereby for each node of the tree, randomly choose m variables on which to base the splitting decision.
   c. Split on the best of this subset.
   d. Fully grow each tree without pruning.

Common choices for m are 1, 2, or floor $(\log_2(N) + 1)$, which is recommended. Random forests can be used with both classification trees and regression trees. Key in this approach is the dissimilarity amongst the base classifiers (i.e., decision trees), which is obtained by adopting a bootstrapping procedure to select the training samples of the individual base classifiers, the selection of a random subset of attributes at each node, and the strength of the individual base models. As such the diversity of the base classifiers creates an ensemble that is superior in performance compared to the single models.

More recently, an alternative to random forests was proposed: rotation forests. This ensemble technique takes the idea of random forests one step further. It combines the idea of pooling a large number of decision trees built on a subset of the attributes and data, with the application of principal component analysis prior to decision tree building, explaining its name. Rotating the axes prior to model building was found to enhance base classifier accuracy at the expense of losing the ability of ranking individual attributes by their importance (Rodriguez et al. 2006).

Evaluating Ensemble Methods

Various benchmarking studies have shown that random forests can achieve excellent predictive performance. Actually, they generally rank amongst the best performing models across a wide variety of prediction tasks (Dejaeger et al. 2012). They are also perfectly capable of dealing with data sets having only a few observations, but with lots of variables. They are highly recommended when high performing analytical methods are needed for fraud detection. However, the price that is paid for this, is that they are essentially black-box models. Due to the multitude of decision trees that make up the ensemble, it is very hard to see how the final classification is made. One way to shed some light on the internal workings of an ensemble is by calculating the variable importance. A popular procedure to do so is as follows:

1. Permute the values of the variable under consideration (e.g., X_j) on the validation or test set.

2. For each tree, calculate the difference between the error on the original, unpermuted data and the error on the data with X_j permuted as follows:

$$VI(X_j) = \frac{1}{ntree}\sum_t (error_t(D) - error_t(\tilde{D}_j)),$$

whereby *ntree* represents the number of trees in the ensemble, D the original data, and $\tilde{D}_j$ the data with variable X_j permuted. In a regression setting, the error can be the mean squared error (MSE), whereas in a classification setting, the error can be the misclassification rate.

3. Order all variables according to their VI value. The variable with the highest VI value is the most important.

MULTICLASS CLASSIFICATION TECHNIQUES

In the introduction of this chapter, we already discussed the difficulty of appropriately determining the target label in a fraud detection setting. One way to deal with this is by creating more than two target values, e.g., as follows: clear fraud, doubt case, no fraud. These values are nominal, implying that there is no meaningful order between them. As an alternative, the target values can also be ordinal: severe fraud, medium fraud, light fraud, no fraud. All of the classification techniques discussed earlier in this chapter can be easily extended to a multiclass setting whereby more than two target values or classes are present.

Multiclass Logistic Regression

When estimating a multiclass logistic regression model, one first needs to know whether the target variable is nominal or ordinal. For nominal target variables, one of the target classes (say class K) will be chosen as the base class as follows (Allison 2001):

$$\frac{P(Y = 1|X_1, \ldots, X_N)}{P(Y = K|X_1, \ldots, X_N)} = e^{(\beta_0^1 + \beta_1^1 X_1 + \beta_2^1 X_2 + \ldots \beta_N^1 X_N)}$$

$$\frac{P(Y = 2|X_1, \ldots, X_N)}{P(Y = K|X_1, \ldots, X_N)} = e^{(\beta_0^2 + \beta_1^2 X_1 + \beta_2^2 X_2 + \ldots \beta_N^2 X_N)}$$

$$\ldots$$

$$\frac{P(Y = K - 1|X_1, \ldots, X_N)}{P(Y = K|X_1, \ldots, X_N)} = e^{(\beta_0^{K-1} + \beta_1^{K-1} X_1 + \beta_2^{K-1} X_2 + \ldots \beta_N^{K-1} X_N)}$$

Using the fact that all probabilities must sum to one, one can then obtain the following:

$$P(Y = 1|X_1, \ldots, X_N) = \frac{e^{(\beta_0^1 + \beta_1^1 X_1 + \beta_2^1 X_2 + \ldots \beta_N^1 X_N)}}{1 + \sum_{k=1}^{K-1} e^{(\beta_0^k + \beta_1^k X_1 + \beta_2^k X_2 + \ldots \beta_N^k X_N)}}$$

$$P(Y = 2|X_1, \ldots, X_N) = \frac{e^{(\beta_0^2 + \beta_1^2 X_1 + \beta_2^2 X_2 + \ldots \beta_N^2 X_N)}}{1 + \sum_{k=1}^{K-1} e^{(\beta_0^k + \beta_1^k X_1 + \beta_2^k X_2 + \ldots \beta_N^k X_N)}}$$

$$P(Y = K|X_1, \ldots, X_N) = \frac{1}{1 + \sum_{k=1}^{K-1} e^{(\beta_0^k + \beta_1^k X_1 + \beta_2^k X_2 + \ldots \beta_N^k X_N)}}$$

The β parameters are then usually estimated using maximum aposteriori estimation, which is an extension of maximum likelihood estimation. As with binary logistic regression, the procedure comes with standard errors, confidence intervals, and p-values.

In case of ordinal targets, one could estimate a cumulative logistic regression as follows (Allison 2001):

$$P(Y \leq 1) = \frac{1}{1 + e^{-\theta_1 + \beta_1 X_1 + \ldots + \beta_N X_N}}$$

$$P(Y \leq 2) = \frac{1}{1 + e^{-\theta_2 + \beta_1 X_1 + \ldots + \beta_N X_N}}$$

$$\ldots$$

$$P(Y \leq K - 1) = \frac{1}{1 + e^{-\theta_{K-1} + \beta_1 X_1 + \ldots + \beta_N X_N}}$$

or,

$$\frac{P(Y \leq 1)}{1 - P(Y \leq 1)} = e^{-\theta_1 + \beta_1 X_1 + \ldots + \beta_N X_N}$$

$$\frac{P(Y \leq 2)}{1 - P(Y \leq 2)} = e^{-\theta_2 + \beta_1 X_1 + \ldots + \beta_N X_N}$$

$$\ldots$$

$$\frac{P(Y \leq K-1)}{1-P(Y \leq K-1)} = e^{-\theta_{K-1}+\beta_1 X_1 + \ldots + \beta_N X_N}.$$

Note that since $P(Y \leq K) = 1$, $\theta_K = +\infty$.

The individual probabilities can then be obtained as follows:

$$\begin{aligned} P(Y = 1) &= P(Y \leq 1) \\ P(Y = 2) &= P(Y \leq 2) - P(Y \leq 1) \\ &\cdots \\ P(Y = K) &= 1 - P(Y \leq K-1). \end{aligned}$$

Also for this model, the β parameters can be estimated using a maximum likelihood procedure.

Multiclass Decision Trees

Decision trees can be easily extended to a multiclass setting. For the splitting decision, assuming K classes, the impurity criteria become:

$$Entropy(S) = -\sum_{k=1}^{K} p_k log_2(p_k)$$

$$Gini(S) = \sum_{k=1}^{K} p_k(1-p_k).$$

The stopping decision can be made in a similar way as for binary target decision trees by using a training set for making the splitting decision, and an independent validation data set on which the misclassification error rate is monitored. The assignment decision then looks for the most prevalent class in each of the leave nodes.

Multiclass Neural Networks

A straightforward option for training a multiclass neural network for K classes, is to create K output neurons, one for each class. An observation is then assigned to the output neuron with the highest activation value (winner-take-all learning). Another option is to use a softmax activation function (Bishop 1995).

Multiclass Support Vector Machines

A common practice to estimate a multiclass support vector machine is to map the multiclass classification problem to a set of binary classification problems. Two well-known schemes here are One-versus-One and One-versus-All coding (Van Gestel et al. 2015).

For K classes, One-versus-One coding estimates $K(K-1)/2$ binary SVM classifiers contrasting every possible pair of classes. Every classifier as such can cast a vote on the target class and the final classification is then the result of a (weighted) voting procedure. Ties are resolved arbitrarily. This is illustrated in Figure 4.32 whereby the aim is to classify the white triangle.

For K classes, One-versus-All coding estimates K binary SVM classifiers each time contrasting one particular class against all the other ones. A classification decision can then be made by assigning a particular observation to the class for which one of the binary classifiers assigns the highest posterior probability. Ties are less likely to occur with this scheme. This is illustrated in Figure 4.33, whereby the aim is to classify the white triangle. Note that for more than three classes, One-versus-All coding estimates less classifiers than One-versus-One coding. However, in One-versus-One coding the binary classifiers are estimated on a reduced subset of the data (i.e., each time contrasting only two classes), whereas in One-versus-All coding, all binary classifiers are estimated on the entire data set (i.e., each time contrasting a class against all the rest).

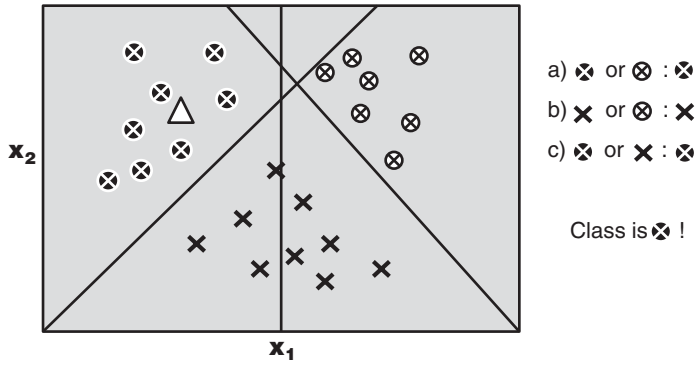


Figure 4.32 One-Versus-One Coding for Multiclass Problems

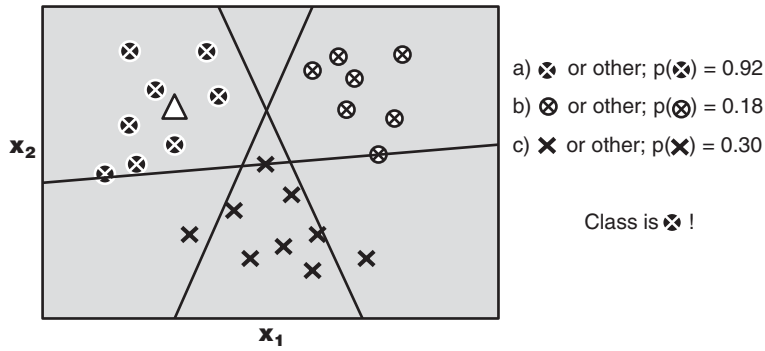


Figure 4.33 One-Versus-All Coding for Multiclass Problems

Both One-versus-One and One-versus-All coding are meta schemes that can be used with other base classifiers (e.g., neural networks) as well.

EVALUATING PREDICTIVE MODELS

Splitting Up the Data Set

When evaluating predictive models, two key decisions need to be made. A first decision concerns the data set split up, which specifies on what part of the data the performance will be measured. A second decision concerns the performance metric. In what follows, we will elaborate on both.

The decision how to split up the data set for performance measurement depends on its size. In case of large data sets (say, more than 1,000 observations), the data can be split up into a training and a test sample. The training sample (also called development or estimation sample) will be used to build the model whereas the test sample (also called the hold out sample) will be used to calculate its performance (see Figure 4.34). A commonly applied split up is a 70 percent training sample and a 30 percent test sample. There should be a strict separation between training and test sample. No observation that was used for model development, can be used for independent testing. Note that in case of decision trees or neural networks, the validation

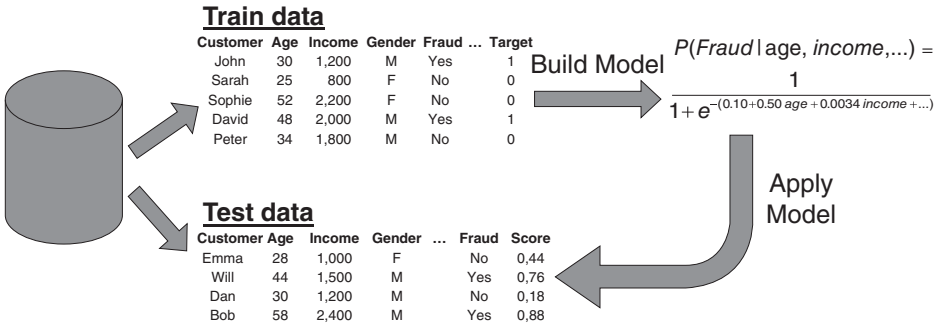


Figure 4.34 Training Versus Test Sample Set Up for Performance Estimation

sample is a separate sample since it is actively being used during model development (i.e., to make the stopping decision). A typical split-up in this case is a 40 percent training sample, 30 percent validation sample and 30 percent test sample. A stratified split-up ensures that the fraudsters/nonfraudsters are equally distributed amongst the various samples.

In case of small data sets (say, less than 1,000 observations), special schemes need to be adopted. A very popular scheme is cross-validation. In cross-validation, the data is split into K folds (e.g., 5 or 10). An analytical model is then trained on $K - 1$ training folds and tested on the remaining validation fold. This is repeated for all possible validation folds resulting in K performance estimates, which can then be averaged. Note that also a standard deviation and/or confidence interval can be calculated if desired. Common choices for K are 5 and 10. In its most extreme case, cross-validation becomes leave-one-out cross-validation whereby every observation is left out in turn and a model is estimated on the remaining $K - 1$ observations. This gives K analytical models in total. In stratified cross validation, special care is taken to make sure the no fraud/fraud odds are the same in each fold (see Figure 4.35).

A key question to answer when doing cross-validation is what should be the final model that is being outputted from the procedure. Since cross-validation gives multiple models, this is not an obvious question. Of course, one could let all models collaborate in an ensemble setup by using a (weighted) voting procedure. A more pragmatic

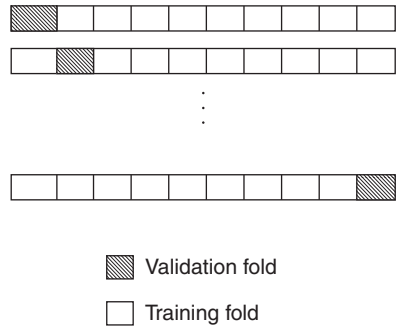


Figure 4.35 Cross-Validation for Performance Measurement

answer would be to do leave one out cross-validation and pick one of the models at random. Since the models differ up to one observation only, they will be quite similar anyway. Alternatively, one may also choose to build one final model on all observations but report the performance coming out of the cross-validation procedure as the best independent estimate.

For small samples, one may also adopt bootstrapping procedures (Efron 1979). In bootstrapping, one takes samples with replacement from a data set D (see Figure 4.36).

The probability that a customer is sampled equals $1/n$, with n the number of observations in the data set. Hence, the probability that a customer is not sampled equals $1 - 1/n$. Assuming a bootstrap with n samples, the fraction of customers that is not sampled equals:

$$\left(1 - \frac{1}{n}\right)^n.$$

We then have:

$$\lim_{n \to \infty} \left(1 - \frac{1}{n}\right)^n = e^{-1} = 0.368$$

where the approximation already works well for small values of n. So, 0.368 is the probability that a customer does not appear in the sample and 0.632 the probability that a customer does appear. If we then take the bootstrap sample as the training set, and the test set as all samples in D but not in the bootstrap, we can calculate the performance as follows:

$$\text{Error estimate} = 0.368\ \text{Error (Training)} + 0.632\ \text{Error (Test)},$$

whereby obviously a higher weight is being put on the test set performance.

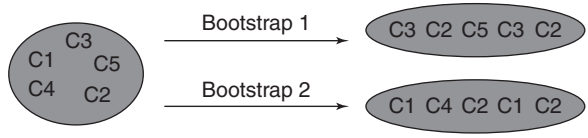


Figure 4.36 Bootstrapping

Performance Measures for Classification Models

Consider the following fraud detection example for a five-customer data set. The first column in Table 4.4 depicts the fraud status, whereas the second column the fraud score as it comes from a logistic regression, decision tree, neural network, and so on.

One can now map the scores to a predicted classification label by assuming a default cut-off of 0.5 as shown in Figure 4.37.

A confusion matrix can now be calculated as shown in Table 4.5.

Based on this matrix, one can now calculate the following performance measures:

- Classification accuracy = (TP + TN)/(TP + FP + FN + TN) = 3/5
- Classification error = (FP + FN)/(TP + FP + FN + TN) = 2/5

Table 4.4 Example Data Set for Performance Calculation

	Fraud	Fraud Score
John	Yes	0.72
Sophie	No	0.56
David	Yes	0.44
Emma	No	0.18
Bob	No	0.36

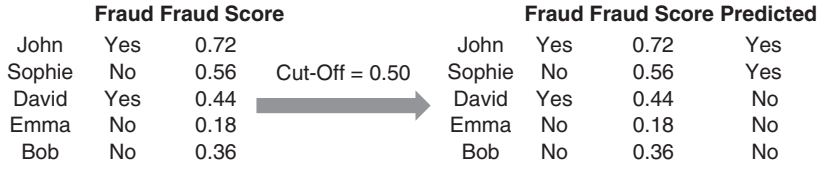


Figure 4.37 Calculating Predictions Using a Cut-Off

Table 4.5 Confusion Matrix

		Actual Status	
		Positive (Fraud)	Negative (No Fraud)
Predicted status	Positive (Fraud)	True Positive (John)	False Positive (Sophie)
	Negative (No Fraud)	False Negative (David)	True Negative (Emma, Bob)

- Sensitivity = Recall = Hit rate = TP/(TP + FN) = 1/2
- Specificity = TN/(FP + TN) = 2/3
- Precision = TP/(TP + FP) = 1/2
- F-measure = 2 × (Precision × Recall)/(Precision + Recall) = 1/2

The classification accuracy is the percentage of correctly classified observations. The classification error is the complement thereof and also referred to as the misclassification rate. The sensitivity, recall or hit rate measures how many of the fraudsters are correctly labeled by the model as a fraudster. The specificity looks at how many of the nonfraudsters are correctly labeled by the model as nonfraudster. The precision indicates how many of the predicted fraudsters are actually fraudsters.

Note that all these classification measures depend on the cut-off. For example, for a cut-off of 0 (1), the classification accuracy becomes 40 percent (60 percent), the error 60 percent (40 percent), the sensitivity 100 percent (0), the specificity 0 (100 percent), the precision 40 percent (0) and the *F*-measure 0.57 (0). Given this dependence, it would be nice to have a performance measure that is independent from the cut-off. One could construct a table with the sensitivity, specificity, and 1-specificity for various cut-offs as shown in Table 4.6.

The receiver operating characteristic (ROC) curve then plots the sensitivity versus 1-specificity as illustrated in Figure 4.38 (Fawcett 2003).

Table 4.6 Table for ROC Analysis

Cut-off	Sensitivity	Specificity	1-Specificity
0	1	0	1
0.01			
0.02			
....			
0.99			
1	0	1	0

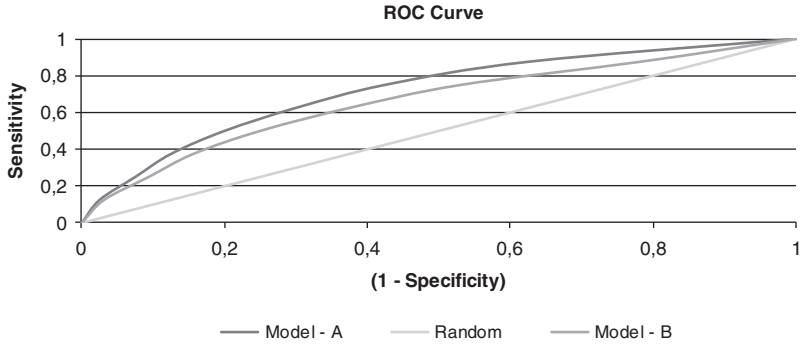


Figure 4.38 The Receiver Operating Characteristic Curve

Note that a perfect model detects all the fraudsters and nonfraudsters at the same time, which results into a sensitivity of 1, and a specificity of 1 and is thus represented by the upper-left corner. The closer the curve approaches this point, the better the performance. In Figure 4.38, model A has a better performance than model B. A problem, however, arises if the curves intersect. In this case, one can calculate the area under the ROC curve (AUC) as a performance metric. The AUC provides a simple figure-of-merit for the performance of the constructed classifier. The higher the AUC, the better the performance. The AUC is always bounded between 0 and 1 and can be interpreted as a probability. In fact, it represents the probability that a randomly chosen fraudster gets a higher score than a randomly chosen nonfraudster (DeLong et al. 1988; Hanley and McNeil 1982). Note that the diagonal represents a random scorecard whereby sensitivity equals 1-specificity for all cut-off points. Hence, a good classifier should have an ROC above the diagonal and AUC bigger than 50 percent.

A lift curve is another important performance metric. It starts by sorting the population from high score to low score. Suppose now that in the top 10 percent highest scores, there are 60 percent fraudsters whereas the total population has 10 percent fraudsters. The lift value in the top decile then becomes 60 percent/10 percent, or 6. In other words, the lift value represents the cumulative percentage of fraudsters per decile, divided by the overall population percentage of fraudsters. Using no model, or a random sorting, the fraudsters would be equally spread across the entire range and the lift value would always

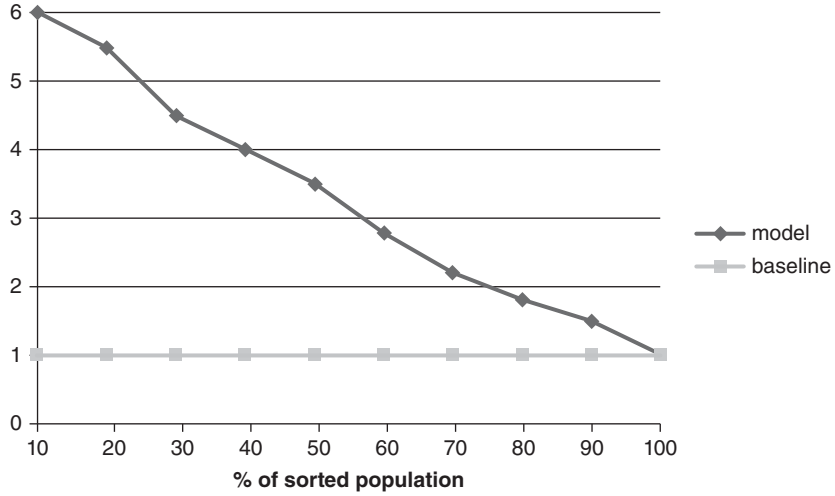


Figure 4.39 Lift Curve

equal 1. Obviously, the lift curve always decreases as one considers bigger deciles, until it will reach 1. This is illustrated in Figure 4.39. Note that a lift curve can also be expressed in a noncumulative way, and is also often summarized as the top decile lift.

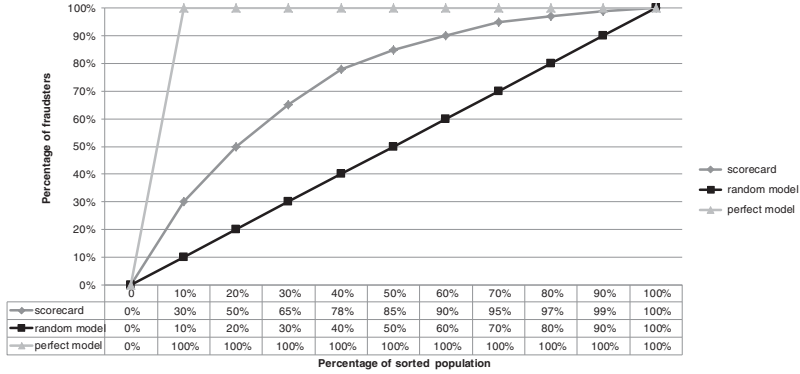
The cumulative accuracy profile (CAP), Lorenz or Power curve is very closely related to the lift curve (see Figure 4.40). It also starts by sorting the population from high score to low score and then measures the cumulative percentage of fraudsters for each decile on the *Y*-axis. The perfect models gives a linearly increasing curve up to the sample fraud rate and then flattens out. The diagonal again represents the random model.

The CAP curve can be summarized in an accuracy ratio (AR) as depicted in Figure 4.41.

The accuracy ratio is then defined as follows (see Figure 4.41):

(Area below power curve for current model – Area below power curve for random model) / (Area below power curve for perfect model – Area below power curve for random model)

A perfect model will thus have an AR of 1 and a random model an AR of 0. Note that the accuracy ratio is also often referred to as the



	0	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
scorecard	0%	30%	50%	65%	78%	85%	90%	95%	97%	99%	100%
random model	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
perfect model	0%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Percentage of sorted population

Figure 4.40 Cumulative Accuracy Profile

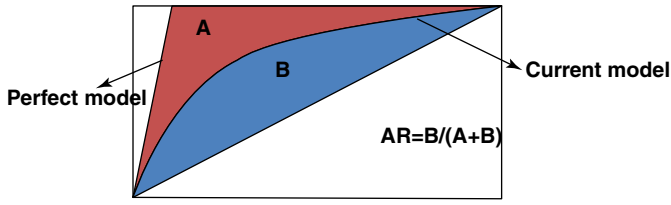


Figure 4.41 Calculating the Accuracy Ratio

Gini coefficient. There is also a linear relation between the AR and the AUC as follows: $AR = 2 \times AUC - 1$.

The Kolmogorov-Smirnov distance is a separation measure calculating the maximum distance between the cumulative score distributions of the nonfraudsters $P(s|NF)$ and fraudsters $P(s|F)$ defined as follows,

$$P(s|F) = \sum_{x \leq s} p(x|F)$$
$$P(s|NF) = \sum_{x \leq s} p(x|NF).$$

Note that by definition $P(s|F)$ equals 1 – Sensitivity, and $P(s|NF)$ equals the specificity. Hence, it can easily be verified that the KS distance can also be measured on an ROC graph. It fact, it is equal to the maximum vertical distance between the ROC curve and the

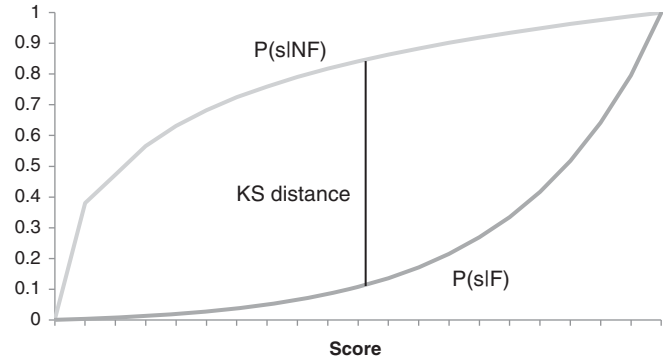


Figure 4.42 The Kolmogorov-Smirnov Statistic

diagonal. The KS statistic ranges between 0 and 1. If there exists a cut-off s such that all fraudsters have a score higher than s and all nonfraudsters a score lower than s, then perfect separation is achieved and the KS-statistic will equal 1.

Another performance measure is the Mahalanobis distance M between the score distributions defined as follows:

$$M = \frac{|\mu_F - \mu_{NF}|}{\sigma},$$

where μ_{NF} (μ_F) represents the mean score of the nonfraudsters (fraudsters) and σ the pooled standard deviation. Obviously, a high Mahalanobis distance is preferred since it means both score distributions are well separated. Closely related is the divergence metric D calculated as follows:

$$D = \frac{(\mu_{NF} - \mu_F)^2}{\frac{1}{2}(\sigma_{NF}^2 + \sigma_F^2)}.$$

For both M and D the minimum value is zero and there is no theoretical upper bound.

The Brier score (BS) measures the quality of the fraud probability estimates as follows:

$$BS = \sum_{i=1}^{n} (PF_i - \theta_i)^2,$$

where PF_i is the probability of fraud for observation i, and θ_i a binary indicator (θ_i equals 1 if fraud; 0 otherwise). The Brier score is always bounded between 0 and 1 and lower values indicate better discrimination ability.

In case of multiclass targets, other performance measures need to be adopted. Assume we have developed an analytical fraud detection model with four classes: A, B, C, and D. A first performance measure is the multiclass confusion matrix, which contrasts the predicted classes versus the actual classes as depicted in Table 4.7.

The on-diagonal elements correspond to the correct classifications. Off-diagonal elements represent errors. For Table 4.7, the classification accuracy becomes $(50 + 20 + 10 + 4)/100$, or 84 percent, and thus

Table 4.7 Multiclass Confusion Matrix

		Actual class			
		A	B	C	D
Predicted class	A	50	2	1	1
	B	3	20	2	1
	C	1	2	10	0
	D	1	0	2	4

the classification error equals 16 percent. Note that the sensitivity and specificity are no longer uniquely defined and need to be considered for each class separately. For example, for class A, 50 out of the 55 observations are correctly classified or 91 percent. Also the precision needs to be considered for each class individually. For example, for the 26 class B predictions, 20 are correct, or thus 77 percent.

Assume now that the ratings are ordinal, A = severe fraud, B = medium fraud, C = light fraud, D = no fraud. In this case, not all errors have equal impact. Given the ordinal nature of the target variable, the further away from the diagonal, the bigger the impact of the error. For example, when target class A is predicted as B, this is a less severe error than when target class A is predicted as D. One could summarize this in a notch difference graph, which is a bar chart depicting the cumulative accuracy for increasing notch differences. For our example, at the 0 notch difference level the cumulative accuracy equals 84 percent, at the one-notch difference level 95 percent, at the two-notch difference level 98 percent, and at the three-notch difference level 100 percent. Figure 4.43 gives the corresponding notch difference graph. Obviously, the cumulative accuracy always increases as the notch level increases and will become 100 percent eventually.

Although ROC analysis was originally introduced in the context of binary classification, several multiclass extensions have been developed in the literature, in line with the One-versus-All or One-versus-One setups of casting a multiclass problem to several binary ones, as discussed earlier (Hand 2001). A first approach is to generate an ROC curve using each class in turn as the positive class and merging all other classes into one negative class (similar to One-versus-All

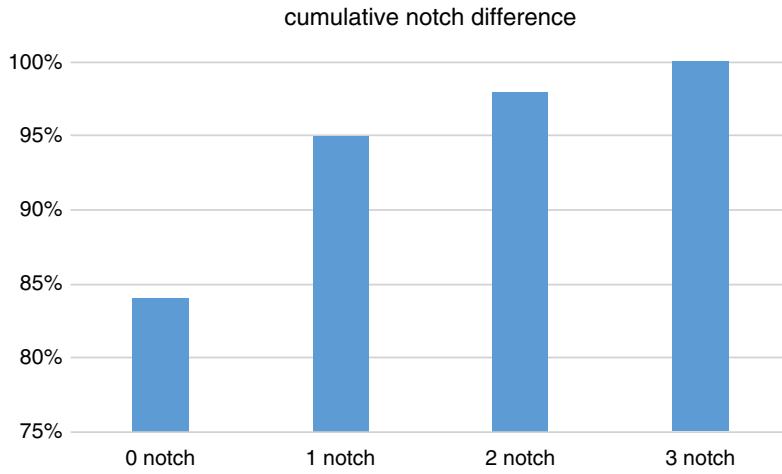


Figure 4.43 A Cumulative Notch Difference Graph

coding). The multiclass AUC, AUC_m, can then be computed as the sum of the binary AUCs weighted by the class distribution as follows:

$$AUC_m = \sum_{i=1}^{m} AUC(c_i)p(c_i),$$

where m is the number of classes, $AUC(c_i)$ the AUC obtained from considering class c_i as the reference class, and $p(c_i)$ the prior probability of class c_i. Another approach is based on the pairwise discriminability of classes and computes the multiclass AUC as follows (similar to One-versus-One coding):

$$AUC_m = \frac{2}{m(m-1)} \sum_{i<j} AUC(c_i, c_j),$$

where $AUC(c_i, c_j)$ is the area under the two-class ROC curve involving classes c_i and c_j. The summation is averaged over all $m(m-1)/2$ possible pairs of classes.

Note that in case of ordinal targets, also rank order statistics such as Spearman's rank order correlation, Kendall's tau, and Goodman-Kruskal's gamma can be computed, as we will discuss later.

Performance Measures for Regression Models

A first way to evaluate the predictive performance of a regression model is by visualizing the predicted target against the actual target using a scatter plot (see Figure 4.44). The more the plot approaches a straight line through the origin, the better the performance of the regression model. It can be summarized by calculating the Pearson correlation coefficient as follows:

$$corr(\hat{y}, y) = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}},$$

where $\hat{y}_i$ represents the predicted value for observation i, $\bar{\hat{y}}$ the average of the predicted values, y_i the actual value for observation i, and $\bar{y}$ the average of the actual values. The Pearson correlation always varies between −1 and +1. Values closer to +1 indicate better agreement and thus better fit between the predicted and actual values of the target variable.

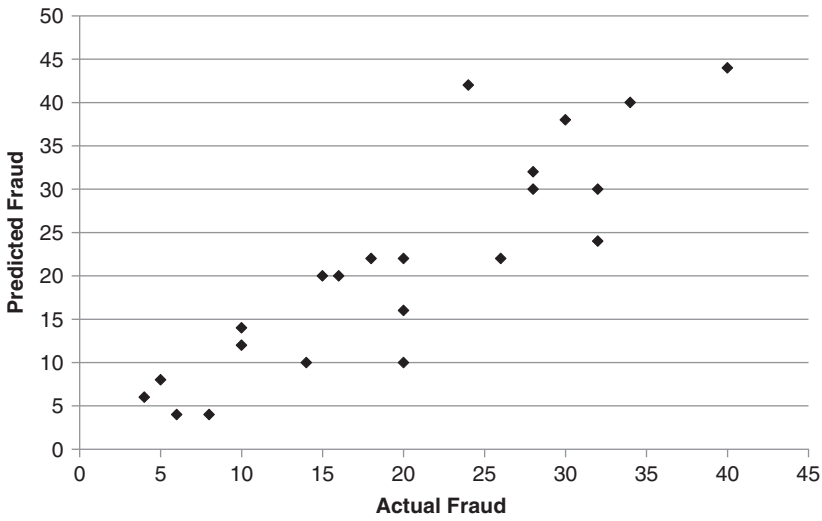


Figure 4.44 Scatter Plot: Predicted Fraud Versus Actual Fraud

Another key performance metric is the coefficient of determination or R^2 defined as follows:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \overline{y})^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2},$$

The R^2 always varies between 0 and 1, and higher values are to be preferred. Basically, this measure tells us how much better we can predict by using the analytical model to compute $\hat{y}_i$ than by using the mean $\overline{y}$ as predictor. To compensate for the variables in the model, an adjusted R^2, R^2_{adj}, has been suggested as follows:

$$R^2_{adj} = 1 - \frac{n-1}{n-p-1}(1 - R^2) = 1 - \frac{n-1}{n-p-1}\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2},$$

where p represents the number of variables in the model. Note that when the R^2 is measured on a test set, negative values are possible if the average value of the target on the training set differs from the average value of the target on the test set.

Two other popular measures are the mean squared error (MSE) and mean absolute deviation (MAD) defined as follows:

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n},$$
$$MAD = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n}.$$

A perfect model would have an MSE and MAD of 0. Higher values for both MSE and MAD indicate less good performance. Note that the MSE is sometimes also reported as the root mean squared error (RMSE) whereby $RMSE = \sqrt{MSE}$.

Also, CAP curves can be used to visualize and calculate the performance of regression models. Just as in classification, the X-axis represents the percentage of the sorted population, but now sorted based on the outcome of the regression model. For the Y-axis, a binary variable needs to be defined. One option is to create a binary

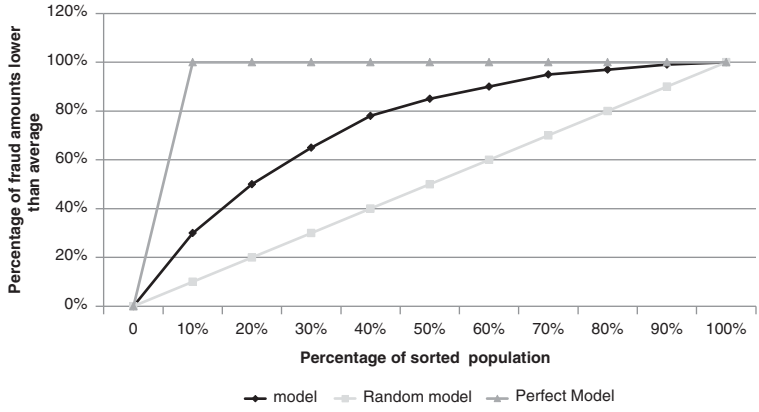


Figure 4.45 CAP Curve for Continuous Targets

outcome representing whether the observed fraud amount is lower than the average fraud amount. This is illustrated in Figure 4.45. The corresponding CAP plot and accuracy ratio will then indicate how much better the analytical model predicts than the average. Another option would be to create a binary variable indicating whether the observed fraud amount is smaller than the 25^{th} (75^{th}) percentile of the distribution, in which case the CAP curve and corresponding accuracy ratio will indicate how much better the analytical model allows to predict small (high) fraud amounts.

Another popular visual representation is the regression error characteristic (REC) curve (Bi and Bennett 2003). This is a regression variant of the ROC curve in classification and plots the error tolerance on the X-axis versus the percentage of points predicted within the tolerance on the Y-axis. The resulting curve estimates the cumulative distribution function of the error. The error on the X-axis can be defined as the squared error $(y_i - \hat{y}_i)^2$ or the absolute deviation $|y_i - \hat{y}_i|$. Just as with the ROC curve, the perfect model is situated in the upper-left corner. Hence, the quicker the curve approaches this point, the better the model. The area above the curve then represents an overall error measure, which should preferably be as small as possible. As an example, consider the data represented in Table 4.8.

The corresponding REC curve is depicted in Figure 4.46.

Table 4.8 Data for REC Curve

Tolerance (*X*)	Correct Predictions (Cumulative)	Cumulative Accuracy (*Y*)
0	1	10%
0,05	4	40%
0,1	7	70%
0,2	9	90%
0,5	10	100%

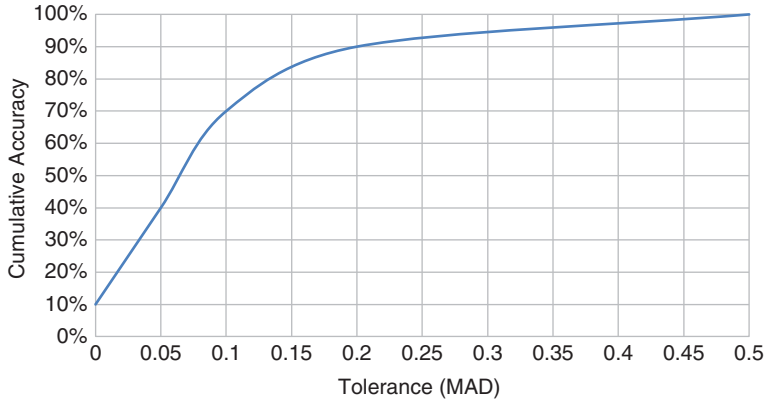


Figure 4.46 Regression Error Characteristic (REC) Curve

OTHER PERFORMANCE MEASURES FOR PREDICTIVE ANALYTICAL MODELS

As already mentioned in Chapter 1, statistical performance is just one aspect of model performance. Other important criteria are comprehensibility, justifiability, and operational efficiency.

Although comprehensibility is subjective and depends on the background and experience of the fraud analyst, linear and logistic regression, and decision trees are commonly referred to as white-box, comprehensible techniques. Neural networks, SVMs, and ensemble methods are essentially opaque models and thus much harder to understand. However, in fraud settings where statistical performance is superior to interpretability, they are the method of choice.

Remember, justifiability goes one step further and verifies to what extent the relationships modeled are in line with prior business knowledge and/or expectations. In a practical setting, this often boils down to verifying the univariate impact of a variable on the model's output. For example, for a linear/logistic regression model, the signs of the regression coefficients will be verified.

Finally, the operational efficiency can also be an important evaluation criterion to consider when selecting the optimal analytical model. Operational efficiency represents the ease with which one can implement, use, and monitor the final model. For example, in a (near) real-time fraud environment, it is important to be able to quickly evaluate the fraud model. With regards to implementation, rule-based models excel since implementing rules can be done very easily, even in spreadsheet software. Linear models are also quite easy to implement whereas nonlinear models are much more difficult to implement, due to the complex transformations that are being used by the model.

DEVELOPING PREDICTIVE MODELS FOR SKEWED DATA SETS

Fraud-detection data sets often have a very skew target class distribution whereby typically only about 1 percent or even less of the transactions are fraudulent. Obviously, this creates problems for the analytical techniques discussed earlier since they are being flooded by all nonfraudulent observations and will thus tend toward classifying every observation as nonfraudulent. Think about decision trees, for example. If they start from a data set with 99 percent/1 percent nonfraudulent/fraudulent observations, then the entropy is already very low and, hence, it is very likely that the decision tree does not find any useful split and classifies all observations as nonfraudulent, hereby achieving a classification accuracy of 99 percent, but essentially detecting none of the fraudsters. It is thus recommended to increase the number of fraudulent observations or their weight, such that the analytical techniques can pay better attention to them. Various procedures are possible to do this and will be outlined in what follows.

Varying the Sample Window

A first way to increase the number of fraudsters is by increasing the time horizon for prediction. For example, instead of predicting fraud with a six-month forward-looking time horizon, a 12-month time horizon can be adopted. This is likely to add more fraudsters to the sample and thus enable the analytical techniques to find a meaningful discrimination. Another approach works by sampling every fraudster twice (or more) as depicted in Figure 4.47. Let's assume we predict fraud with a one-year forward-looking time horizon using information from a one year backward looking time horizon. By shifting the observation point earlier or later, the same fraudulent observation can be sampled twice. Obviously, the variables collected will be similar but not perfectly the same, since they are measured on a different (although overlapping) time frame. This added variability can then come in handy for the analytical techniques to better discriminate between the fraudsters and nonfraudsters. Note that depending on the skewness of the target, multiple observation points can be considered such that the number of fraudsters is multiplied by 2, 3, 4,… Finding the optimal number is subject to a trial-and-error exercise.

Undersampling and Oversampling

Another way to increase the weight of the fraudsters is by either oversampling them or by undersampling the nonfraudsters. Oversampling is illustrated in Figure 4.48. Here, the idea is to replicate the fraudsters two or more times so as to make the distribution less skew. In our

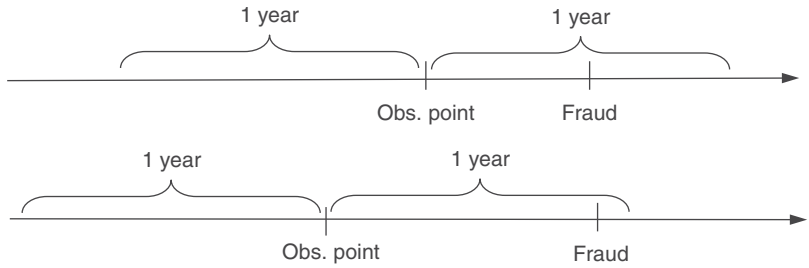


Figure 4.47 Varying the Time Window to Deal with Skewed Data Sets

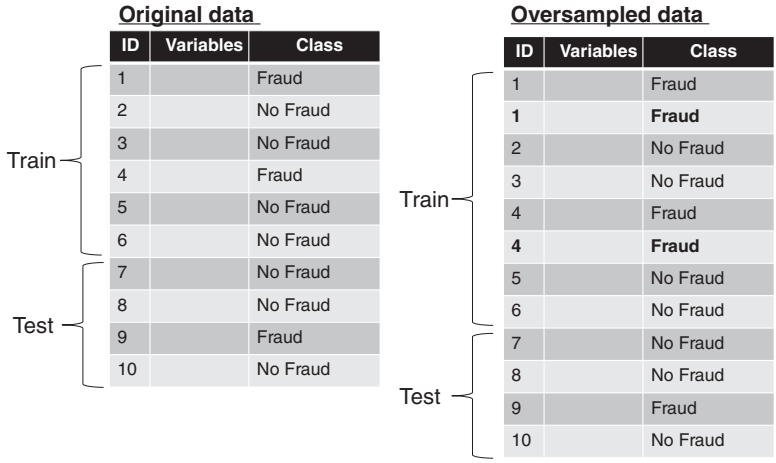


Figure 4.48 Oversampling the Fraudsters

example, observations 1 and 4, both fraudsters, have been replicated so as to create an equally balanced training sample having the same amount of fraudsters and nonfraudsters, respectively.

Undersampling is illustrated in Figure 4.49. Here, observations number 2 and 5, which are both nonfraudulent, have been left out so as to create an equally balanced training sample. The undersampling can be done based on business experience whereby obviously legitimate observations are removed. Also, low-value transactions or inactive accounts can be considered for removal.

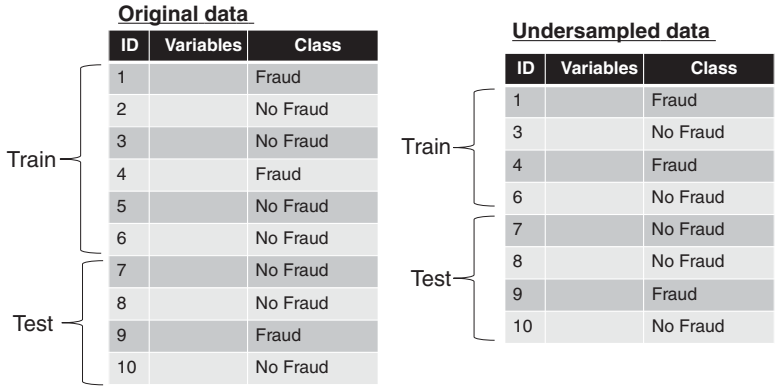


Figure 4.49 Undersampling the Nonfraudsters

Under- and oversampling can also be combined. In the literature, it has been shown that undersampling usually results in better classifiers than oversampling (Chawla et al. 2002).

It is very important to note that both oversampling and undersampling should be conducted on the training data and not on the test data. Remember, the latter should remain untouched during model development in order to give an unbiased view on model performance. A practical question concerns the optimal nonfraud/fraud odds, which should be aimed for by doing under- or oversampling. Although working toward a balanced sample with the same number of fraudsters and nonfraudsters seems attractive, it severely biases the probabilities, which will be output by the analytical technique. Hence, it is recommended to stay as close as possible to the original class distribution to avoid unnecessary bias. One practical approach to determine the optimal class distribution works as follows. In the first step, an analytical model is built on the original data set with the skew class distribution (e.g., 95%/5% nonfraudsters/fraudsters). The AUC of this model is recorded (possibly on an independent validation data set). In a next step, over- or undersampling is used to change the class distribution by 5 percent (e.g., 90%/10%). Again, the AUC of the model is recorded. Subsequent models are built on samples of 85%/15%, 80%/20%, 75%/25%, hereby each time recording their AUC. Once the AUC starts to stagnate (or drop), the procedure stops and the optimal odds ratio has been found. Although it does depend on the data characteristics and quality, practical experience has shown that the ratio 80%/20% is quite commonly used in the industry.

Synthetic Minority Oversampling Technique (SMOTE)

Rather than replicating the minority observations (e.g., fraudsters), Synthetic Minority Oversampling works by creating synthetic observations based on the existing minority observations (Chawla et al. 2001). This is illustrated in Figure 4.50 where the circles represent the majority class and the squares the minority class. For each minority class observation, SMOTE calculates the k nearest neighbors. Let's assume

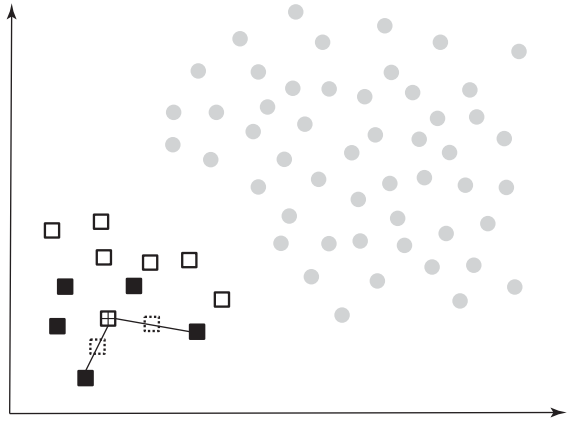


Figure 4.50 Synthetic Minority Oversampling Technique (SMOTE)

we consider the crossed square and pick the 5 nearest neighbors represented by the black squares. Depending on the amount of oversampling needed, one or more of the *k*-nearest neighbors are selected to create the synthetic examples.

Let's say our oversampling percentage is set at 200 percent. In this case, two of the five nearest neighbors are selected at random. The next step is then to randomly create two synthetic examples along the line connecting the observation under investigation (crossed square) with the two random nearest neighbors. These two synthetic examples are represented by dashed squares in the figure. As an example, consider an observation with characteristics (e.g., age and income) of 30 and 1,000, and its nearest neighbor with corresponding characteristics 62 and 3,200. We generate a random number between 0 and 1—let's say, 0.75. The synthetic example then has age $30 + 0.75 \times (62 - 30)$, or 54, and income $1000 + 0.75 \times (3200 - 1000) = 2,650$. SMOTE then combines the synthetic oversampling of the minority class with undersampling the majority class. Note that in their original paper, Chawla et al. (2001) developed an extension of SMOTE to work with categorical variables. Empirical evidence has shown that SMOTE usually works better than either under- or oversampling. Also, for fraud detection it has proven to be very valuable (Van Vlasselaer et al. 2013, 2015).

Likelihood Approach

Another interesting approach to work with a low number of fraudsters is the likelihood approach developed by Pluto and Tasche (2005). Although it was originally developed in a credit-risk modeling setting to tackle the issue of low-default portfolios, it can be easily transferred to a fraud-detection setting.

Let's start with the most extreme example of a skewed data set, which is a data set with no fraudsters at all. Obviously, none of the sampling approaches discussed so far will work for this. Assume now that we have an expert-based fraud detection system that can discriminate the observations into fraud risk classes A, B, and C using a set of predefined business rules. Although these three classes allow analysts to discriminate the observations in terms of their fraud risk, it would also be handy to accompany each of these classes with fraud probability estimates. These probabilities can be used to calculate the expected fraud loss. Remember, Expected fraud loss (EFL) = Probability of fraud (PF) × Loss given fraud (LGF). The EFL can then be used for provisioning purposes whereby a firm anticipates future losses by setting aside provisions.

In a first step, we will try to calculate the probability of fraud (*PF*) for class A, PF_A. A key assumption we will make is that fraud occurs independently. Although this assumption might seem naïve at first sight, it allows us to derive probability estimates in a fairly straightforward way given this complex setting with no data about fraudsters. More specifically, we will first assume that the ranking of the observations across the three fraud risk classes is correct, or in other words: $PF_A \leq PF_B \leq PF_C$. The most prudent estimate (sometimes also referred to as the most conservative estimate) is then obtained under the temporary assumption that $PF_A = PF_B = PF_C$. Hence, the probability of being fraudulent equals PF_A for every observation. Given that we have n_A observations in class A, n_B observations in class B, n_C observations in class C, and that fraud occurs independently, the likelihood of not observing any fraudster in the total data set equals:

$$(1 - PF_A)^{n_A + n_B + n_C}$$

Table 4.9 Values for PF_A for a Data Set with No Fraudsters

α	50%	75%	90%	95%	99%	99.9%
PF_A	0,20%	0,39%	0,65%	0,85%	1,31%	1,95%

Table 4.10 Values for PF_B for a Data Set with No Fraudsters

α	50%	75%	90%	95%	99%	99.9%
PF_B	0,28%	0,55%	0,92%	1,19%	1,82%	2,72%

We can now specify a confidence region for PF_A, which is the region of all values of PF_A such that the probability of not observing any fraudster is higher than $1 - \alpha$, or in other words:

$$1 - \alpha \leq (1 - PF_A)^{n_A + n_B + n_C},$$

or

$$PF_A \leq 1 - (1 - \alpha)^{1/(n_A + n_B + n_C)}.$$

Assume we have 100 observations in class A, 200 in class B, and 50 in class C. Table 4.9 illustrates the values obtained for PF_A by varying the confidence level from 50 percent to 99.9 percent. As can be observed, PF_A increases as the confidence level increases.

We can now continue this same procedure to compute PF_B. We have $n_B + n_C$ observations left. The most prudent estimate of PF_B is obtained by again assuming $PF_B = PF_C$. Hence, we have:

$$1 - \alpha \leq (1 - PF_B)^{n_B + n_C},$$

or

$$PF_B \leq 1 - (1 - \alpha)^{1/(n_B + n_C)}.$$

For our data set, this gives the values reported in Table 4.10.

Finally, we can calculate PF_C as follows:

$$1 - \alpha \leq (1 - PF_C)^{n_C},$$

Table 4.11 Values for PF_C for a Data Set with No Fraudsters

α	50%	75%	90%	95%	99%	99.9%
PF_C	1,38%	2,73%	4,50%	5,81%	8,80%	12,90%

or

$$PF_C \leq 1 - (1 - \alpha)^{1/n_C}.$$

This gives the values reported in Table 4.11.

Note that despite having no fraudsters in the data, PF_C at the 99.9 percent confidence level equals 12.90 percent, which is quite high. Also observe that for a given confidence level, $PF_A \leq PF_B \leq PF_C$ as required at the outset. An obvious question is what confidence level to adopt. Before answering this question, we will extend the procedure by assuming a few fraudsters occur in the data.

Let's now assume we have one fraudster in class A, 2 in class B, and 4 in class C. We first determine PF_A using again the most prudent estimate principle: $PF_A = PF_B = PF_C$. By using the binomial distribution to calculate the probability of observing less than seven fraudsters, PF_A can be found as follows:

$$1 - \alpha \leq \sum_{i=0}^{7} \binom{n_A + n_B + n_C}{i} PF_A^i (1 - PF_A)^{n_A + n_B + n_C - i}.$$

Likewise, PF_B and PF_C can be found as follows:

$$1 - \alpha \leq \sum_{i=0}^{6} \binom{n_B + n_C}{i} PF_B^i (1 - PF_B)^{n_B + n_C - i},$$

$$1 - \alpha \leq \sum_{i=0}^{4} \binom{n_C}{i} PF_C^i (1 - PF_C)^{n_C - i}.$$

Table 4.12 displays the values obtained depending on the confidence levels. Again, note that the probabilities increase for increasing confidence levels. Just as in the previous examples, also observe that $PF_A \leq PF_B \leq PF_C$ as required at the outset.

Table 4.12 Values for PF_A, PF_B, and PF_C for a Data Set with Fraudsters

α	50%	75%	90%	95%	99%	99.9%
PF_A	2,19%	2,76%	3,34%	3,72%	4,51%	5,51%
PF_B	2,66%	3,41%	4,17%	4,68%	5,73%	7,05%
PF_C	9,28%	12,26%	15,35%	17,38%	21,50%	26,56%

As already mentioned, a key question to answer when adopting this approach is the setting of the confidence level. Obviously, this depends on how conservative the estimates should be. As said, a higher confidence level results into a higher probability estimate. In their original paper, Pluto and Tasche suggest not exceeding 95 percent. In a credit-risk setting, Benjamin et al. (2006) suggested adopting confidence levels between 50 and 75 percent.

Adjusting Posterior Probabilities

The key idea of undersampling, oversampling and SMOTE is to adjust the class priors to enable the analytical technique to come up with a meaningful model discriminating the fraudsters from the nonfraudsters. By doing so, the class posteriors will also become biased. This is no problem in case the fraud analyst is only interested in ranking the observations in terms of their fraud risk. However, if well-calibrated fraud probabilities are needed (e.g., to accurately calculate expected fraud losses), then the posterior probabilities need to be adjusted. One straightforward way to do this is by using the following formula (Saerens et al. 2002):

$$p(C_i|x) = \frac{\frac{p(C_i)}{p_r(C_i)} p_r(C_i|x)}{\sum_{j=1}^{2} \frac{p(C_j)}{p_r(C_j)} p_r(C_j|x)},$$

whereby C_i represents class i (e.g., class 1 for the fraudsters and 2 for the nonfraudsters), $p(C_i)$ the prior probability (e.g., $p(C_1) = 1\%$ and $p(C_2) = 99\%$), $p_r(C_i)$ the resampled prior probability due to oversampling, undersampling or other resampling procedures (e.g., $p_r(C_1) = 20\%$ and $p_r(C_2) = 80\%$), and $p_r(C_i|x)$ represents the posterior probability

Table 4.13 Adjusting the Posterior Probability

	Posteriors Using Resampled Data		Posteriors Re-Calibrated to Original Data	
	P(Fraud)	P(No Fraud)	P(Fraud)	P(No Fraud)
Customer 1	0.1	0.9	0.004	0.996
Customer 2	0.3	0.7	0.017	0.983
Customer 3	0.5	0.5	0.039	0.961
Customer 4	0.6	0.4	0.057	0.943
Customer 5	0.85	0.15	0.186	0.814
Customer 6	0.9	0.1	0.267	0.733

for observation x as calculated by the analytical technique using the resampled data. Note that the formula can be easily extended to more than two classes.

Table 4.13 shows an example of adjusting the posterior probability, whereby $p(C_1) = 0,01$; $p(C_2) = 0,99$, $p_r(C_1) = 0,20$; and $p_r(C_2) = 0,80$. It can be easily verified that the rank ordering of the customers in terms of their fraud risk remains preserved after the adjustment.

Cost-sensitive Learning

Cost-sensitive learning is another alternative to deal with highly skewed data sets. The idea is to assign higher misclassification costs to the minority class, which is, in our case, the fraudsters. These costs are then taken into account during classifier estimation or evaluation. Table 4.14 gives the overview of the costs in a binary classification

Table 4.14 Misclassification Costs

		Predicted Class	
		Positive	Negative
Actual class	**Positive**	C(+,+)	C(–,+)
	Negative	C(+,–)	C(–,–)

setting whereby $C(i,j)$ represents the cost of misclassifying an example from class j into class i.

Note that usually $C(+,+) = C(-,-) = 0$, and $C(-,+) > C(+,-)$. The costs are typically also determined on an aggregated basis, rather than on an observation-by-observation basis.

A first straightforward way to make a classifier cost-sensitive is by adopting a cost-sensitive cut-off to map the posterior class probabilities to class labels. In other words, an observation x will be assigned to the class that minimizes the expected misclassification cost:

$$argmin_i \left(\sum_{j \in \{-,+\}} P(j|x).C(i,j) \right),$$

where P($j|x$) is the posterior probability of observation x to belong to class j. As an example, consider a fraud detection setting whereby class 1 are the fraudsters and class 2 the nonfraudsters. An observation x will be classified as a fraudster (class 1) if

$$P(1|x).C(1,1) + P(2|x).C(1,2) < P(1|x).C(2,1) + P(2|x).C(2,2)$$

$$P(1|x).C(2,1) > P(2|x).C(1,2)$$

$$P(1|x).C(2,1) > (1 - P(1|x)).C(1,2)$$

$$P(1|x) > \frac{C(1,2)}{C(1,2) + C(2,1)}$$

$$P(1|x) > \frac{1}{1 + \frac{C(2,1)}{C(1,2)}}$$

So, the cut-off only depends on the ratio of the misclassification costs, which may be easier to determine than the individual misclassification costs themselves.

Another approach to cost-sensitive learning works by directly minimizing the misclassification cost during classifier learning. Again assuming there is no cost for correct classifications, the total misclassification cost is then as follows:

$$\text{Total cost} = \text{C}(-,+) \times \text{FN} + \text{C}(+,-) \times \text{FP},$$

whereby *FN* and *FP* represent the number of false negatives and positives, respectively. Various cost-sensitive versions of existing classification techniques have been introduced in the literature. Ting (2002) introduced a cost-sensitive version of the C4.5 decision tree algorithm where the splitting and stopping decisions are based on the misclassification cost. Veropolous et al. (1999) developed a cost-sensitive version of SVMs whereby the misclassification costs are taken into account in the objective function of the SVM. Domingos (1999) introduced MetaCost, which is a meta-algorithm capable of turning any classifier into a cost-sensitive classifier by first relabeling observations with their estimated minimal-cost classes and then estimating a new classifier on the relabeled data set. Fan et al. (1999) developed AdaCost, a cost-sensitive variant of AdaBoost, which uses the misclassification costs to update the weights in successive boosting runs.

To summarize, cost-sensitive learning approaches are usually more complex to work with than the sampling approaches discussed earlier. López et al. (2012) conducted a comparison of sampling versus cost-sensitive learning approaches for imbalanced data sets and found both methods are good and equivalent. Hence, from a pragmatic viewpoint, it is recommended to use the sampling approaches in a fraud-detection setting.

FRAUD PERFORMANCE BENCHMARKS

To conclude this chapter, Table 4.15 provides some references of scientific papers discussing fraud detection across a diversity of settings. The type of fraud, size of data set used, class distribution, and performance are reported. To facilitate the comparison, only papers that report the area under the ROC curve (AUC) are included. The following conclusions can be drawn:

- Credit card, financial statement, and telecommunications fraud case studies report the highest AUC.
- Insurance and social security fraud report the lowest AUC.
- All case studies, except for financial statement fraud, start from highly skewed data sets.

Table 4.15 Performance Benchmarks for Fraud Detection

Reference	Type of Fraud	Size of Data Set Used	Class Distribution	Performance
Ortega, Figuerora et al. (2006)	Medical Insurance	8,819	5% fraud	AUC: 74%
Šubelj, Furlan et al. (2011)	Automobile Insurance fraud	3,451	1.3% fraud	AUC: 71%–92%
Bhattacharyya, Jha et al. (2011)	Credit card fraud	50 million transactions on about 1 million credit cards from a single country	0.005% fraud	AUC: 90,8%–95,3%
Whitrow, Hand et al. (2009)	Credit card fraud	33,000–36,000 activity records	0.1% fraud	Gini: 85% ($\sim$ AUC = 92.5%)
Van Vlasselaer, Bravo et al. (2015)	Credit card fraud	3,3 million transactions	<1% fraud	AUC: 98.6%
Dongshan and Girolami (2007)	Telecommunications fraud	809,395 calls from 1,087 accounts	0.024% fraud	AUC: 99.5%
Van Vlasselaer, Meskens et al. (2013)	Social security fraud	2000 observations	1% fraud	AUC: 80–85%
Ravisankar, Ravi et al. (2011)	Financial statement fraud	202 companies	50% fraud	AUC: 98.09%

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CHAPTER 5

Social Network Analysis for Fraud Detection

In the last decade, the use of social media websites in everybody's daily life is booming. People can continue their conversations on online social network sites like Facebook, Twitter, LinkedIn, Google+, Instagram, and so on and share their experiences with their acquaintances, friends, family, and others. It only takes one click to update your whereabouts to the rest of the world. Plenty of options exist to broadcast your current activities: by picture, video, geo-location, links, or just plain text. You are on the top of the world—and everybody's watching. And this is where it becomes interesting.

Users of online social network sites explicitly reveal their relationships with other people. As a consequence, social network sites are a (almost) perfect mapping of the relationships that exist in the real world. We know who you are, what your hobbies and interests are, to whom you are married, how many children you have, your buddies with whom you run every week, your friends at the wine club, etc. This whole interconnected network of people knowing each other, somehow, is an extremely interesting source of information and knowledge. Marketing managers no longer have to guess who might influence whom to create the appropriate campaign. It is all there—and that is exactly the problem. Social network sites acknowledge the richness of the data sources they have, and are not willing to share them as such and free of cost. Moreover, those data are often privatized and regulated, and well-hidden from commercial use. On the other hand, social network sites offer many good built-in facilities to managers and other interested parties to launch and manage their marketing campaigns by exploiting the social network, without publishing the exact network representation.

However, companies often forget that they can reconstruct (a part of) the social network using in-house data. Telecommunication providers, for example, have a massive transactional data base where they record call behavior of their customers. Under the assumption that good friends call each other more often, we can recreate the network and indicate the tie strength between people based on the frequency and/or duration of calls. Internet infrastructure providers might map the relationships between people using their customers' IP-addresses. IP-addresses that frequently communicate are represented by a stronger relationship. In the end, the IP-network will

envisage the relational structure between people from another point of view, but to a certain extent as observed in reality. Many more examples can be found in the banking, retail, and online gaming industry.

Also, the fraud detection domain might benefit from the analysis of social networks. In this chapter, we underline the social character of fraud. This means that we assume that the probability of someone committing fraud depends on the people (s)he is connected to. These are the so-called *guilt-by-associations* (Koutra et al. 2011). If we know that five friends of Bob are fraudsters, what would we say about Bob? Is he also likely to be a fraudster? If these friends are Bob's only friends, is it more likely that Bob will be influenced to commit fraud? What if Bob has 200 other friends, will the influence of these five fraudsters be the same?

In this chapter, we will briefly introduce the reader to networks and their applications in a fraud detection setting. One of the main questions answered in this chapter is how unstructured network information can be translated into useful and meaningful characteristics of a subject. We will analyze and extract features from the direct neighborhood (i.e., the direct associates of a certain person or subject) as well as the network as a whole (i.e., collective inferencing). Those network-based features can serve as an enrichment of traditional data analysis techniques.

NETWORKS: FORM, COMPONENTS, CHARACTERISTICS, AND THEIR APPLICATIONS

Networks are everywhere. Making a telephone call requires setting up a communication over a wired network of all possible respondents by sending voice packages between the caller and the callee. The supply of water, gas, and electricity for home usage is a complex distribution network that consists of many source, intermediary, and destination points where sources need to produce enough output such that they meet the demand of the destination points. Delivery services need to find the optimal route to make sure that all the packages are delivered at their final destination as efficiently as possible. Even a simple trip to

the store involves the processing of many networks. What is the best route to drive from home to the store given the current traffic? Given a shopping list, how can I efficiently visit the store such that I have every product on my list?

One of humans' talents is exactly the processing of these networks. Subliminally, people have a very good sense in finding an efficient way through a network. Consider your home-to-work connection. Depending on the time and the day, you might change your route to go from home to work without explicitly drawing the network and running some optimization algorithm. Reaching other people, even without the telecommunication media of nowadays like telephone and internet, is often an easy task for people. There is always a friend of a friend who knows the guy you are looking for.

The mathematical study of optimizing network-related problems has been introduced many years ago by Euler (1736). He formulated the problem of the *Köningsberg bridges*. Köningsberg (now Kaliningrad) was a city in Lithuania that was divided into four parts by the river Pregel. Seven bridges connected the four banks of the city (see Figure 5.1a and Figure 5.1b). The problem is as follows, "Does there exist a walking route that crosses all seven bridges exactly once?" A path that can traverse all edges (here: bridges) of a network exactly once, is a *Eulerian path*. Euler proved that such a path cannot exist for the Köningsberg bridge problem. More specifically, an Eulerian path only exists when all nodes (here: banks) are reached by an even number of edges, except for the source and sink node of the

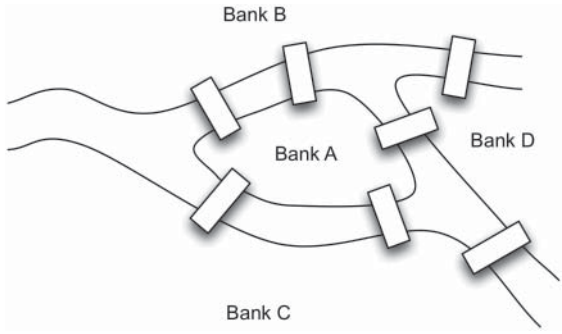


Figure 5.1a Köningsberg Bridges

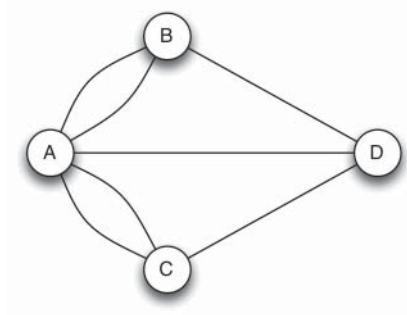


Figure 5.1b Schematic Representation of the Königsberg Bridges

path which should have an odd number of bridges pointing to it. Analogously, a *Hamiltonian path* in the network is a path that visits each node exactly once. For example, the *Traveling Salesman Problem (TSP)* tries to find a Hamiltonian path in the network. Given a set of cities, the idea is that a salesman has to visit each city (i.e., node) exactly once to deliver the packages. As this is an NP-hard problem, research mainly focuses on finding good heuristics to solve the TSP.

Social Networks

Although in the previous example networks are built and developed by humans, they are not social. A key question here is, "What makes a network social?" In general, we might say that a network is social whenever the actors are people or groups of people. A connection between actors is based on any form of social interaction between them, such as a friendship. As in the real world, social networks are also able to reflect the intensity of a relationship between people. How well do you know your contacts? The relationship between two best friends completely differs from the relationship between two distant acquaintances. Those relationships and their intensity are an important source of *information exchange*.

The psychologist Stanley Milgram measured in 1967 how social the whole world is. He conducted a *Small World experiment* whereby he distributed 100 letters to random people all over the world. The task at hand was to return the letter to a specified destination, which was

one of Milgram's friends. Rather than sending the letter back by mail, people could only pass the letter to someone they knew. This person, on their turn, had to forward the letter to one of his/her contacts, and so on … until the letter reached its final destination. Milgram showed that, on average, each letter reached its destination within six hops. That is, less than six people are necessary to connect two random people in the network. This is the *average path length* of the network. The result of the experiment is widely known as the *six degrees of separation* theorem. Milgram also found that many letters reached their target destination within three steps. This is the so-called *funneling effect*. Some people are known and know many other people, often from highly diverse contact groups (e.g., work, friends, hobby). Those people are sociometric superstars, connecting different parts of the network to each other. Many paths in the network pass through these people, giving them a high betweenness score (see section on Centrality metrics).

While the six degrees of separation theorem is based on results in real-life, many studies already proved that an average path length of six is an overestimation in online social networks. Those studies reported an average path length of approximately four hops between any two random people in an online social network (Kwak et al. 2010). Online social networks are thus denser than real-life networks. However, the intensity between the relationships might strongly differ.

Social networks are an important element in the analysis of fraud. Fraud is often committed through illegal set-ups with many accomplices. When traditional analytical techniques fail to detect fraud due to a lack of evidence, social network analysis might give new insights by investigating how people influence each other. These are the so-called *guilt-by-associations*, where we assume that fraudulent influences run through the network. For example, insurance companies often have to deal with groups of fraudsters, trying to swindle by resubmitting the same claim using different people. Suspicious claims often involve the same claimers, claimees, vehicles, witnesses, and so on. By creating and analyzing an appropriate network, inspectors might gain new insights in the suspiciousness of the claim and can prevent pursuit of the claim.

In social security fraud, employers try to avoid paying their tax contributions to the government by intentionally going bankrupt. Bankrupt employers are not capable of redeeming their tax debts to

the government, and are discharged from their obligations. However, social network analysis can reveal that the employer is refounded using almost the same structure a couple of weeks later. As such, experts can declare the foundation of the new employer unlawful and still recover the outstanding debts. Opinion fraud occurs when people untruthfully praise or criticize a product in a review. Especially online reviews lack control to establish the genuineness of the review. Matching people to their reviews and comparing the reviews with others using a network representation, enables review websites to detect the illicit reviews.

Identity theft is a special form of social fraud, as introduced in Chapter 1, where an illicit person adopts another person's profile. Examples of identity theft can be found in telecommunications fraud where fraudsters "share" an account with a legitimate customer. This is depicted in Figure 5.2. As fraudsters cannot withstand to call their family, friends, acquaintances, and so on, the network clearly links the account with the fraudster's previous (or current) account. Once the fraudster takes over a new customers' account, the contact list of the customer is extended by other contacts who were never called before. The frequent contact list of the fraudster is a strong indicator for fraud.

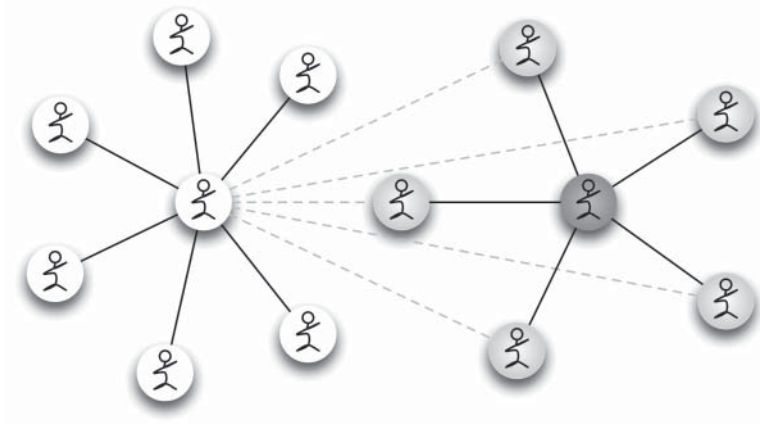


Figure 5.2 Identity Theft. The Frequent Contact List of a Person is Suddenly Extended with Other Contacts (Light Gray Nodes). This Might Indicate that a Fraudster (Dark Gray Node) Took Over that Customer's Account and "shares" his/her Contacts

While networks are a powerful visualization tool, they mainly serve to support the findings by automated detection techniques. We will focus on how to extend the detection process by extracting useful and meaningful features from the network. The network representation can be used afterward to verify the obtained results.

Network Components

This section will introduce the reader to graph theory, the mathematical foundation for the analysis and representation of networks.

Complex network analysis (CNA) studies the structure, characteristics, and dynamics of networks that are irregular, complex, and dynamically evolving in time (Boccaletti et al. 2006). Those networks often consist of millions of closely interconnected units. Most real-life networks are complex. CNA uses graph theory to extract useful statistics from the network. Boccaletti et al. (2006) define graph theory as the natural framework for the exact mathematical treatment of complex networks, and, they state that formally, a complex network is represented as a graph.

A graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ consists of a set $\mathcal{V}$ of vertices or nodes (the points) and a set $\mathcal{E}$ of edges or links (the lines connecting the points). This is illustrated in Figure 5.3. A node $v \in \mathcal{V}$ represents real-world objects such as people, computers or activities. An edge $v \in \mathcal{E}$ connects

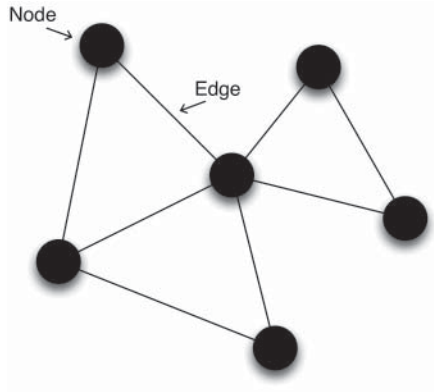


Figure 5.3 Network Representation

two nodes in the network, and

$$e(v_1, v_2) \mid e \in \mathscr{E} \ \& \ v_i \in \mathscr{V}.$$

An edge represents a *relationship* between the nodes it connects, such as a friendship (between people), a physical connection (between computers), or attendance (of a person to an event).

A graph where the edges impose an order or direction between the nodes in the network is a directed graph. If there is no order in the network, we say that the graph is undirected. This is shown in Figure 5.4. The social network website Twitter can be represented as a directed graph. Users follow other users, without necessarily being refollowed. This is expressed by the follower–followee relationships, and is illustrated in Figure 5.5. User 1 follows User 2, 3, and 5 (follower

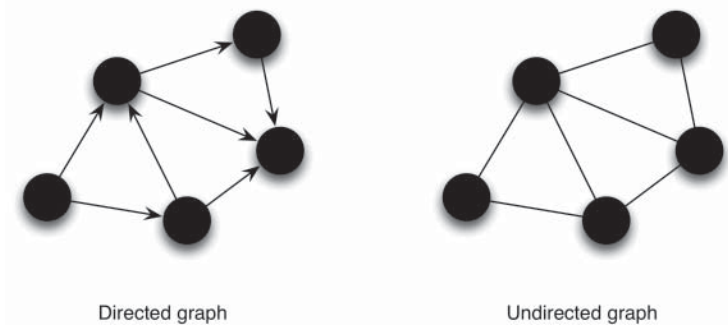


Figure 5.4 Example of a (Un)Directed Graph

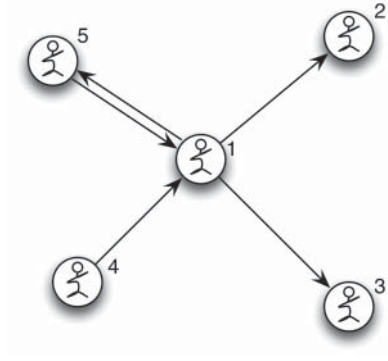


Figure 5.5 Follower–Followee Relationships in a Twitter Network

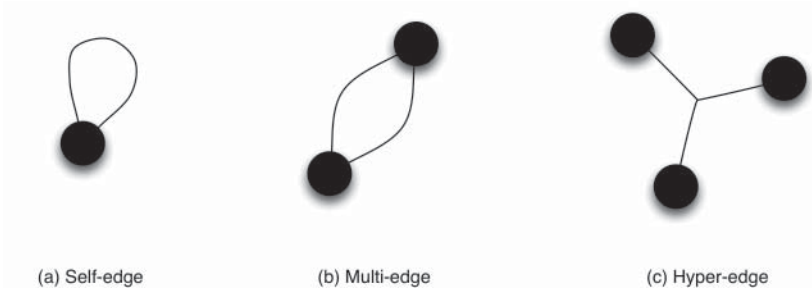


Figure 5.6 Edge Representation

relationships), and is followed by User 4 and 5 (followee relationship). There is a mutual relationship between User 1 and 5.

In general, edges connect two nodes to each other. However, some special variants are sometimes required to accurately map the reality (see Figure 5.6):

- **Self-edge**: A self-edge is a connection between the node and itself. For example, a person who transfers money from his/her account to another account s/he owns.
- **Multi-edge**: A multi-edge exists when two nodes are connected by more than one edge. For example, in credit card transaction fraud, a credit card holder is linked to a merchant by a multi-edge if multiple credit card transactions occurred between them.
- **Hyper-edge**: A hyper-edge is an edge that connects more than one node in the network. For example, three people who went to the same event.

A graph where the edges express the intensity of the relationships, is a weighted graph $\mathcal{G}^{W} = (\mathcal{V}, \mathcal{E})$.

- **Binary weight**: This is the standard network representation. Here, the edge weight is either 0 or 1, and reflects whether or not a link exists between two nodes. An extension of the binary weighted graphs are the signed graphs where the edge weight is negative (–1), neutral (0), or positive (1). Negative weights are used to represent animosity, and positive weights are used to represent friendships. Neutral weights represent an "I don't know you" relationship.

- **Numeric weight**: A numeric edge weight expresses the affinity of a person to other persons s/he is connected to. High values indicate a closer affiliation. As people do not assign a weight to each of their contacts by themselves, many approaches are proposed to define an edge weight between nodes. A popular way is the *Common Neighbor* approach. That is, the edge weight equals the total number of common activities or events both people attended. An activity/event should be interpreted in a broad sense: the total number of messages sent between them, common friends, likes on Facebook, and so on.
- **Normalized weight:** The normalized weight is a variant of the numeric weight where all the outgoing edges of a node sum up to 1. The normalized weight is often used in influence propagation over a network.
- **Jaccard weight**: The edge weight depends on how "social" both nodes are (Gupte and Eliassi-Rad 2012), and

$$w(v_1, v_2) = \frac{|\mathbf{\Gamma}(v_1) \cap \mathbf{\Gamma}(v_2)|}{|\mathbf{\Gamma}(v_1) \cup \mathbf{\Gamma}(v_2)|}$$

with $\mathbf{\Gamma}(v_i)$ the number of events node v_i attended. For example, assume that person A attended 10 events and person B attended 5 events. They both went to 3 common events. Then, according to the Jaccard Index, their edge weight equals 1/4.

Edge weights represent the connectivity within a network, and are in some way a measure of the sociality between the nodes in the network. Nodes, on the other hand, use labels to express the local characteristics. Those characteristics are mostly proper to the node and may include, for example, demographics, preferences, interests, beliefs, and so on. When analyzing fraud networks, we integrate the fraud label of the nodes into the network. A node can be fraudulent or legitimate, depending on the condition of the object it represents. For example, Figure 5.7 shows a fraud network where the legitimate and fraudulent people are represented by white- and black-colored nodes, respectively. Given this graph, we know that node A and B committed fraud beforehand. Node C is a friend of node A and is influenced by the actions of node A. On the other hand, node D is influenced by both node A and B. A simple conclusion would be that node D has the highest probability of perpetrating fraud, followed by node C.

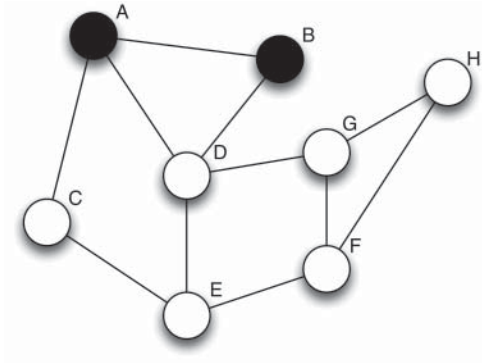


Figure 5.7 Example of a Fraudulent Network

While real-life networks often contain billions of nodes and millions of links, sometimes the direct neighborhood of nodes provides enough information to base decisions on. An *ego-centered network or egonet* represents the one-hop neighborhood of the node of interest. In other words, an egonet consists of a particular node and its immediate neighbors. The center of the egonet is the ego, and the surrounding nodes are the alters. An example of an egonet is illustrated in Figure 5.8. Such networks are also called the first-order neighborhood of a node. Analogously, the *n*-order neighborhood of a node encompasses all the nodes that can be reached within *n* hops from the node of interest.

Figure 5.8 An Egonet. The Ego is Surrounded by Six Alters, of Whom Two are Legitimate (White Nodes) and Four are Fraudulent (Gray Nodes)

Network Representation

Transactional data sources often contain information about how entities relate to each other (e.g., call record data, bank transfer data). An example transactional data source of credit card fraud is given in Table 5.1. Each line in the transactional data source represents a money transfer between two actors: a credit card holder and a merchant. Despite the structured representation of the data, the relationships between credit card holders and merchants are hard to capture. Real-life data sources contain billions of transactions, making it impossible to extract correlations and useful insights. Network visualization tools offer a powerful solution to make information hidden in networks easy to interpret and understand. Inspecting the visual representation of a network can be part of the preprocessing phase as it familiarizes the user with the data and can often quickly result in some first findings and insights. In the post-processing phase, the network is a useful representation to verify the obtained results and understand the rationale. In general, a network can be represented in two ways:

- Graphically
- Mathematically

Table 5.1 Example of Credit Card Transaction Data

Credit Card	Merchant	Merchant Category	Country	Amount	Date	Accept	Fraud
8202092217124626	207005	056	USA	112.99	2013-11-06 00:28:38	TRUE	FALSE
1887940000202544	105930	234	IRL	3.58	2013-11-06 00:28:40	TRUE	FALSE
2070050002009251	79768	612	BEL	149.50	2013-11-06 00:28:47	TRUE	FALSE
1809340000672044	11525	056	BEL	118.59	2013-11-06 00:28:49	FALSE	FALSE
4520563752703209	323158	056	USA	22.27	2013-11-06 00:28:50	TRUE	TRUE
5542610001561826	68080	735	FRA	50.00	2013-11-06 00:28:51	TRUE	FALSE
…							

The graphical representation of a network, or *sociogram*, is the most intuitive and straightforward visualization of a network. A toy example of a credit card fraud network is shown in Figure 5.9. Credit card holders are modeled by rectangles, the merchants by circles. The thin (thick) edges represent legitimate (fraudulent) transactions. Based on the figure, we expect that the credit card of user Y is stolen and that merchant 1 acts suspiciously. The sociogram can be used to present results at different levels in an organization: the operational, tactical, and strategic management all benefit from interpreting the network representation by evaluating how to detect and monitor suspicious business processes (operational), how to act on it (tactical) and how to deal with fraud in the future and take prevention measures (strategic).

While graphical network representations are mainly appropriate for visualization purposes, it is an unstructured form of data and cannot be used to compute useful statistics and extract meaningful

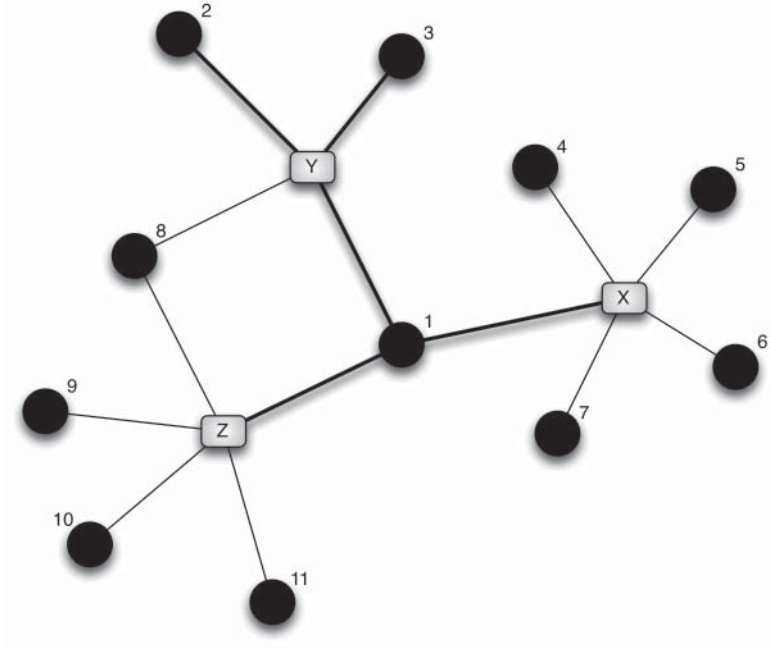


Figure 5.9 Toy Example of Credit Card Fraud

characteristics. As a consequence, there is an urge to represent the network in a mathematically interesting way. The adjacency matrix and the adjacency list are two network representations that fulfill these requirements. The *adjacency* or *connectivity matrix* $A_{n\times n}$ is a matrix of size $n \times n$ with n the number of nodes in the network; and $a_{i,j} = 1$ if a link exists between node i and j, and $a_{i,j} = 0$ otherwise. Figure 5.10a shows an example of a small network. The corresponding adjacency matrix is depicted in Figure 5.10b. Note that the adjacency matrix is a *sparse* matrix, containing many zero values. This is often the case in real-life situations. Social networks have millions of members, but people are only connected to a small number of friends—for example, Twitter has 500 million users, and each user follows approximately 200 other users.[1] The adjacency matrix of a network records which

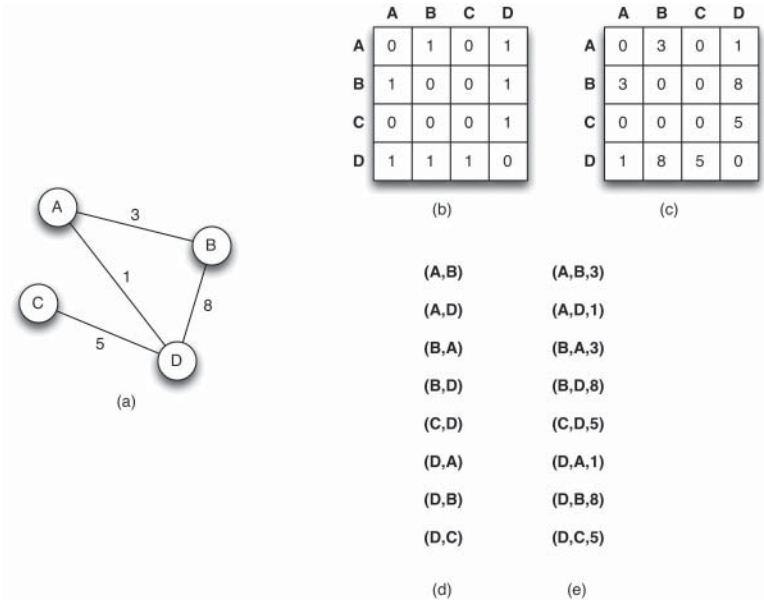


Figure 5.10 Mathematical Representation of (a) a Sample Network: (b) the Adjacency or Connectivity Matrix; (c) the Weight Matrix; (d) the Adjacency List; and (e) the Weight List

[1] http://news.yahoo.com/twitter-statistics-by-the-numbers-153151584.html, retrieved on December 2014.

nodes are connected to each other, irrespective of the edge weight. The *weight matrix* $W_{n \times n}$ expresses the edge weight between the nodes of a network, and $w_{i,j} \in \mathbb{R}$ if a link exists between node i and j, and $w_{i,j} = 0$ otherwise. The weight matrix of the sample network is given in Figure 5.10c. The *adjacency list* is an abstract representation of the adjacency matrix, and provides a list of all the connections present in the network. A relationship between node v_i and node v_j is denoted as (v_i, v_j). This is illustrated in Figure 5.10d. The *weight list* extends the adjacency matrix by specifying the weights of the relationships, and has the following format $(v_i, v_j, w_{i,j})$ with $w_{i,j}$ the weight between node v_i and node v_j (see Figure 5.10e).

IS FRAUD A SOCIAL PHENOMENON? AN INTRODUCTION TO HOMOPHILY

One of the essential questions before analyzing the network regarding fraud, is deciding whether the detection models might benefit from CNA (complex network analysis). In other words, do the relationships between people play an important role in fraud, and is fraud a contagious effect in the network? Are fraudsters randomly spread over the network, or are there observable effects indicating that fraud is a social phenomenon, that is, fraud tends to cluster together. We look for evidence that fraudsters are possibly exchanging knowledge about how to commit fraud using the social structure. Fraudsters can be linked together as they seem to attend the same events/activities, are involved in the same crimes, use the same set of resources, or even are sometimes one and the same person (see also identity theft).

Homophily is a concept borrowed from sociology and boils down to the expression: "Birds of a feather flock together." People have a strong tendency to associate with others whom they perceive as being similar to themselves *in some way* (Newman 2010). Friendships are mostly built because of similar interests, same origin, high school, neighborhood, hobbies, etc, or even the tendency to commit fraud. Relationships determine which people are influenced by whom and the extent to which information is exchanged.

A network is homophilic if nodes with label *x* (e.g., fraud) are to a larger extent connected to other nodes with label *x*. In marketing, the concept of homophily is frequently exploited to assess how individuals influence each other, and to determine which people are likely responders and should be targeted with a marketing incentive. For example, if all John's friends are connected to telecom provider *Beta*, John is likely to sign a same contract with provider *Beta*. A network that is not homophilic is heterophilic.

The same reasoning holds in fraud. We define a homophilic network as a network where fraudsters are more likely to be connected to other fraudsters, and legitimate people are more likely to be connected to other legitimate people. A homophilic network is shown in Figure 5.11. The gray (white) nodes represent fraudsters (legit people). Visually, gray nodes are grouped together, the so-called *web of frauds*. Legitimate nodes are also clustered together. Remark that the network is not perfectly homophilic: fraudulent nodes are not uniquely connected to other fraudulent nodes, but connect to legitimate nodes as well. Also, Figure 5.11 illustrates how small webs of frauds exist in the network, for example, subgraphs of less than one or two nodes.

Advanced network techniques take into account the time dimension. Few fraudulent nodes that are popping up together in the network might indicate a newly originating web of fraud, while subgraphs characterized with many fraudulent nodes are far-evolved structures. Preventing the growth of new webs and the expansion of existing webs are important challenges that both need to be addressed in the fraud detection models.

We already showed that a graphical representation of the fraud network can give a first indication of the homophilic character of the network, and thus whether network analysis might make sense in the fraud detection task at hand. Mathematically, a network is homophilic if fraudulent nodes are significantly more connected to other fraudulent nodes, and as a consequence, legitimate nodes connect significantly more to other legitimate nodes. More concretely, let l be the fraction of legitimate nodes in the network and f the fraction of fraudulent nodes in the network, then $2lf$ is the expected probability that an edge connects two dissimilar labeled nodes. These edges are called

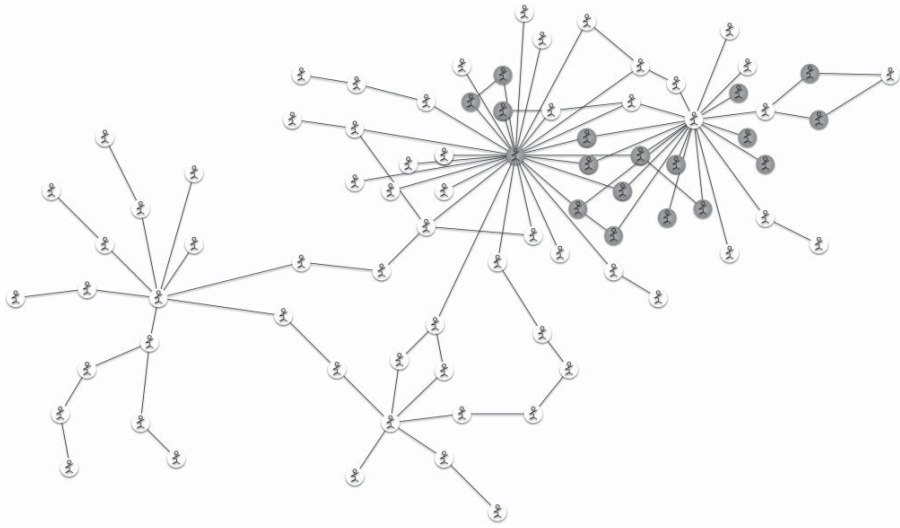


Figure 5.11 A Real-Life Example of a Homophilic Network

cross-labeled edges. A network is homophilic if the observed fraction of cross-labeled edges $\hat{r}$ is significantly less than the expected probability $2lf$, i.e. if the null hypothesis

$$H_0 : \hat{r} \geq 2lf$$

can be rejected. Consider Figure 5.12. The black (white) nodes are the fraudsters (legitimate people). The network consists in total of 12 nodes: 8 legitimate nodes and 4 fraudulent nodes. The fraction l and f equal $\frac{8}{12}$ and $\frac{4}{12}$, respectively. In a random network, we would expect that $2lf = 2 \cdot \frac{8}{12} \cdot \frac{4}{12} = \frac{8}{18}$ edges are cross-labeled. The network in Figure 5.12 has 5 cross-labeled edges, and 3 fraud and

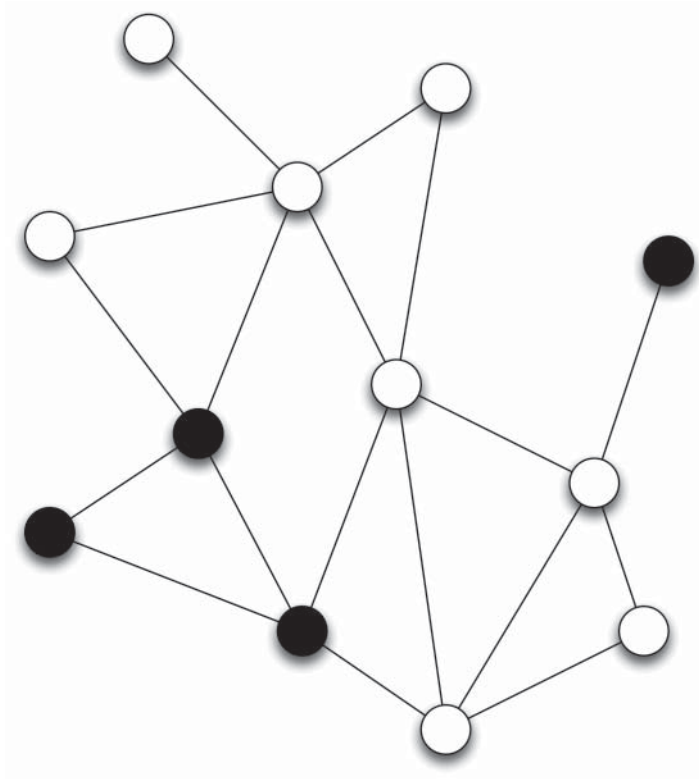


Figure 5.12 A Homophilic Network

10 legit same-labeled edges. The observed fraction of cross-labeled edges is thus $\hat{r} = \frac{5}{18}$. We expect to see 8 edges in the network that are cross-labeled, instead of the 5 edges we observe. The null hypothesis H_0 is rejected with a significance level of $\alpha = 0.05$ (p-value of 0.02967) using a one-tailed proportion test with a normal approximation. The network is homophilic.

Other measures to assess whether there are significant patterns of homophily present in the network include *dyadicity* and *heterophilicity* (Park and Barabási 2007). In many systems, the number of links between nodes sharing a common property is larger than if the characteristics were distributed randomly in the network. This is the dyadic effect. For a network where the labels can only take two values, **1** (Fraud) and **0** (Legitimate), let n_1 (n_0) be the number of fraudulent (legitimate) nodes and $N = n_0 + n_1$. Now, we can define three types of dyads: **(1 − 1)**, **(1 − 0)**, and **(0 − 0)**, indicating the label (*Fraud-Fraud*), (*Fraud-Legitimate*) and (*Legitimate-Legitimate*) of two end points connected by a link. The total number of dyads of each kind are represented as m_{11}, m_{10} and m_{00} respectively, and $M = m_{11} + m_{10} + m_{00}$. If nodes are randomly connected to other nodes regardless of their labels, then the expected values of m_{11} and m_{10} equal:

$$\overline{m}_{11} = \binom{n_1}{2} p = \frac{n_1(n_1 - 1)p}{2}$$

$$\overline{m}_{10} = \binom{n_1}{1}\binom{n_0}{1} p = n_1(N - n_1)p$$

with $p = 2M/(N(N-1))$ the *connectance*, representing the probability that two nodes are connected. If $p = 1$, all nodes in the network are connected to each other. Dyadicity and heterophilicity can then be defined as:

$$D = \frac{m_{11}}{\overline{m}_{11}}$$

$$H = \frac{m_{10}}{\overline{m}_{10}}$$

A network is dyadic if $D > 1$, indicating that fraudulent nodes tend to connect more densely among themselves than expected for

a random configuration. A network is heterophobic (opposite of heterophilic) if $H < 1$, meaning that fraud nodes have fewer connections to legitimate nodes than expected randomly (Park and Barabási 2007). The network represented in Figure 5.12 is dyadic and heterophobic. If a network is dyadic and heterophobic, it exhibits homophily; a network that is anti-dyadic and heterophilic, is inverse-homophilic.

A network that exhibits evidence of homophily, is worthwhile to investigate more thoroughly. For each instance of interest, we extract features that characterize the instance based on its relational structure.

IMPACT OF THE NEIGHBORHOOD: METRICS

In this section, we will discuss the main metrics to measure the impact of the social environment on the nodes of interest. In general, we distinguish between three types of analysis techniques:

- Neighborhood metrics
- Centrality metrics
- Collective Inference algorithms

Neighborhood metrics characterize the *target of interest* based on its direct associates. The *n*-order neighborhood around a node consists of the nodes that are *n* hops apart from that node. Due to scalability issues, many detection models integrate features derived from the egonet or first-order neighborhood (see the section on Network components). That is, the node and its immediate contacts. Neighborhood metrics include degree, triangles, density, relational neighbor, and probabilistic relational neighbor.

Centrality metrics quantify the importance of an individual in a social network (Boccaletti 2006). Centrality metrics are typically extracted based on the whole network structure, or a subgraph. We discuss geodesic paths, betweenness, closeness, and the graph theoretic center.

Given a network with known fraudulent nodes, how can we use this knowledge to infer a primary fraud probability for all the unlabeled nodes (i.e., the currently legitimate nodes)? As opposed to neighborhood and centrality metrics, *collective inference algorithms* compute the probability that a node is exposed to fraud and thus the probability

that fraud influences a certain node. Collective inference algorithms are designed such that the whole network is simultaneously updated. As a result, long-distance propagation is possible (Hill, Provost, and Volinsky 2007). We consider PageRank, and briefly explain Gibbs sampling, iterative classification, relaxation labeling, and loopy belief propagation.

Neighborhood Metrics

Neighborhood metrics are derived from a node's n-hop neighborhood. We discuss degree, triangles, density, relational neighbor, and probabilistic relational neighbor. For a graph of N nodes and M edges Table 5.2 summarizes each of the metrics. Figure 5.13 shows a toy example, which is used to illustrate how each metric is derived from the network. In this section, we will use the egonet to extract the features. This is the one-hop neighborhood of the target node.

Degree

The *degree* of a node summarizes how many neighbors the node has. In fraud, it is often useful to distinguish between the number of fraudulent and legitimate neighbors. This is the *fraudulent* and

Table 5.2 Overview of Neighborhood Metrics

Degree	Number of connections of a node (in- versus out-degree if the connections are directed)	
Triangles	Number of fully connected subgraphs consisting of three nodes.	
Density	The extent to which the nodes are connected to each other (reciprocal of farness).	$d = \frac{2M}{N(N-1)}$
Relational Neighbor	Relative number of neighbors that belong to class c (e.g., to class fraud)	$P(c\|n) = \frac{1}{Z}\Sigma_{\{n_j \in Neighborhood_n \| class(n_j)=c\}} w(n, n_j),$
Probabilistic Relational Neighbor	Probability to belong to class c given the posterior class probabilities of the neighbors	$P(c\|n) = \frac{1}{Z}\Sigma_{\{n_j \in Neighborhood_n\}} w(n, n_j)P(c\|n_j)$

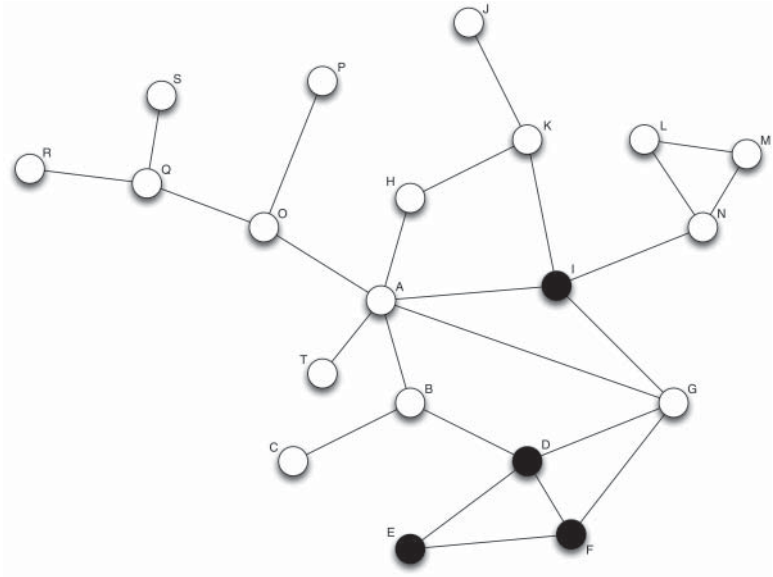


Figure 5.13 Sample Network

legitimate degree. In the toy example of Figure 5.13, node A has a degree of 6, which is the highest degree in the network. Recall that we derive the degree for the egonet of each node. Node G has a fraudulent degree of 3 and is thus highly influenced by fraud. The degree of each node is given in Table 5.3.

In case of a directed network, we can distinguish between the *in-degree* and the *out-degree*. The in-degree specifies how many nodes are pointing toward the target of interest. The out-degree describes the number of nodes that can be reached from the target of interest.

Table 5.3 Summary of the Total, Fraudulent, and Legitimate Degree

NODE	A	B	C	D	E	F	G	H	I	J
Total Degree	***6***	3	1	4	2	3	4	2	4	1
Fraud Degree	1	1	0	2	2	2	***3***	0	0	0
Legit Degree	5	2	1	2	0	1	1	2	4	1
NODE	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**
Total Degree	3	2	2	3	3	1	3	1	1	1
Fraud Degree	1	0	0	1	0	0	0	0	0	0
Legit Degree	2	2	2	2	3	1	3	1	1	1

The degree distribution of a network describes the probability distribution of the degree in the network. The degree distribution in real-life networks follows in general a *power law*. That is, many nodes are only connected with few other nodes while only few nodes in the network link to many other nodes. Figure 5.14a illustrates the degree distribution of the network in Figure 5.14b gives an example of the degree distribution (log-log scale) of a real-life fraud network of a social security institution (Van Vlasselaer et al. 2015a).

Networks with a constant degree distribution are k-regular graphs. Each node in the network has the same degree. An example of a 4-regular graph is given in Figure 5.15.

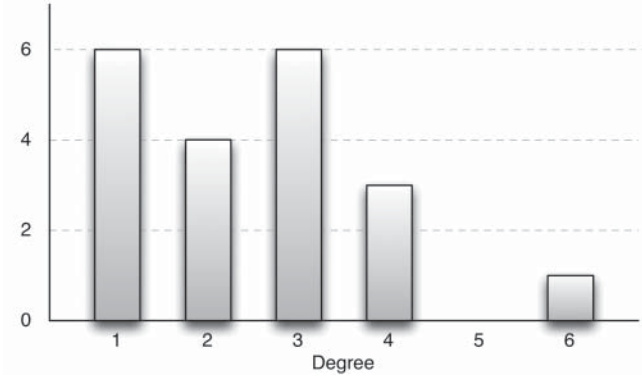


Figure 5.14a Degree Distribution

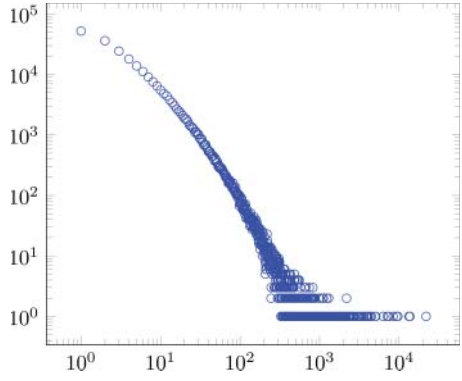


Figure 5.14b Illustration of the Degree Distribution for a Real-Life Network of Social Security Fraud. The Degree Distribution Follows a Power Law (log-log axes)

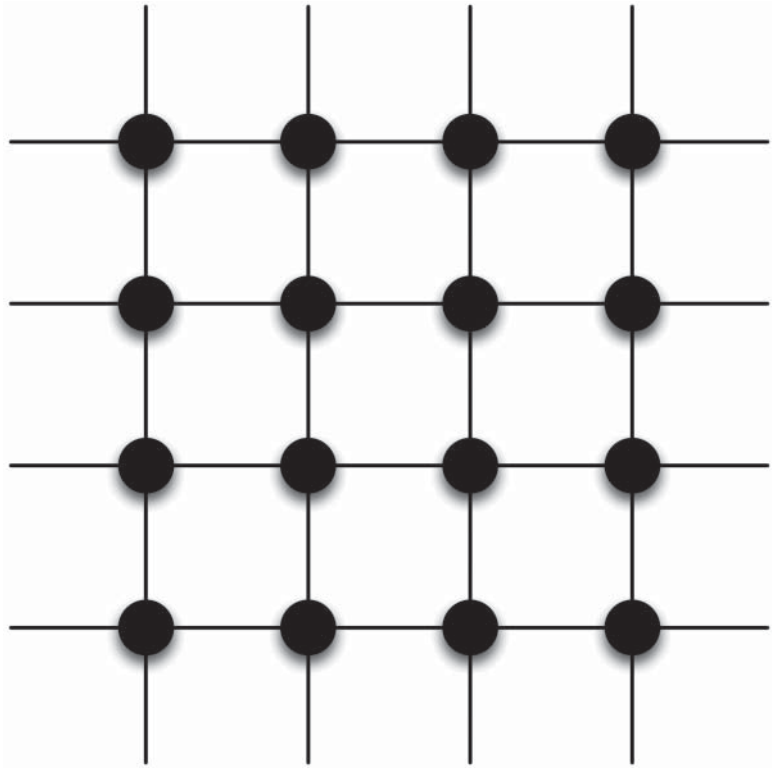


Figure 5.15 A *4*-regular Graph

Triangles

A triangle in a network is a subgraph that consists of three nodes that are all connected to each other. A triangle investigates the influential effect of closely connected groups of individuals. Nodes that are part of a group are to a larger extent affected by the beliefs, interests, opinions, and so on of that group. In an egonet a triangle includes the ego and two alters. If the two alters are both fraudulent (legitimate), we say that the triangle is fraudulent (legitimate). If only one of the two alters are fraudulent, the triangle is semi-fraudulent. In the network, there are four triangles: A-G-I, L-M-N, D-F-G, and D-E-F. The egonet analysis with regard to triangles is given in Table 5.4. The analysis of triangles can easily be extended to quadrangles, pentagons, hexagons, and so on.

Table 5.4 Summary of the Number of Legitimate, Fraudulent, and Semi-Fraudulent Triangles

NODE	A	B	C	D	E	F	G	H	I	J
Total	1	0	0	2	1	2	2	0	1	0
Fraud	0	0	0	1	1	1	1	0	0	0
Legit	0	0	0	0	0	0	0	0	1	0
Semi-Fraud	1	0	0	1	0	1	1	0	0	0
NODE	K	L	M	N	O	P	Q	R	S	T
Total	0	1	1	1	0	0	0	0	0	0
Fraud	0	0	0	0	0	0	0	0	0	0
Legit	0	1	1	1	0	0	0	0	0	0
Semi-Fraud	0	0	0	0	0	0	0	0	0	0

Density

Another neighborhood metric is the network's *density*. The density measures the extent to which nodes in a network are connected to each other. A *fully connected network* of N nodes has $\binom{N}{2} = \frac{N(N-1)}{2}$ edges. That is, each node is connected to every other node in the network. The density measures the number of observed edges to the maximum possible number of edges in the graph:

$$d = \frac{M}{\binom{N}{2}} = \frac{2M}{N(N-1)}$$

with M and N the number of edges and nodes in the network respectively. Remark that a triangle is a subgraph with density 1. An egonet with degree 1, has also a density of 1. The density derives how closely connected the group is. A high density might correspond to an intensive information flow between the instances, which might indicate that the nodes extensively influence each other. This may be important in the analysis of fraud. The combination of a high fraudulent degree and a high density can drastically increase a node's probability to commit fraud in the future. The density for each node in the toy example (see Figure 5.13) is given in Table 5.5.

Table 5.5 Summary of the Density

NODE	A	B	C	D	E	F	G	H	I	J
Density	*0.33*	*0.5*	*1*	*0.6*	*1*	*0.83*	*0.6*	*0.66*	*0.5*	*1*
NODE	K	L	M	N	O	P	Q	R	S	T
Density	*0.5*	*1*	*1*	*0.66*	*0.5*	*1*	*0.5*	*1*	*1*	*1*

Relational Neighbor Classifier

The relational neighbor classifier makes use of the *homophily* assumption which states that connected nodes have a propensity to belong to the same class. This idea is also referred to as guilt-by-association. If two nodes are associated, they tend to exhibit similar behavior. The posterior class probability for node n to belong to class c is then calculated as follows:

$$P(c|n) = \frac{1}{Z} \sum_{\{n_j \in Neighborhood_n | class(n_j)=c\}} w(n, n_j),$$

whereby $Neighborhood_n$ represents the neighborhood of node n, $w(n, n_j)$ the weight of the connection between n and n_j, and Z is a normalization factor to make sure all probabilities sum to one.

Consider, for example, the sample network depicted in Figure 5.16 whereby F and NF represent fraudulent and non-fraudulent nodes, respectively.

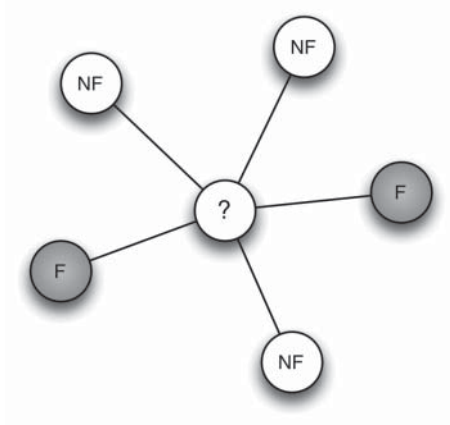


Figure 5.16 Example Social Network for a Relational Neighbor Classifier

The calculations then become:

$$P(F|?) = \frac{1}{Z}(1 + 1)$$
$$P(NF|?) = \frac{1}{Z}(1 + 1 + 1)$$

Since both probabilities have to sum to 1, Z equals 5, so the probabilities become:

$$P(F|?) = \frac{2}{5}$$
$$P(NF|?) = \frac{3}{5}$$

The relational neighbor probabilities for the network in Figure 5.13 are depicted in Table 5.6. Remark that these probabilities can be added as an additional feature to local models—that is, detection models that do not use network variables. Another possibility is to use the relational neighbor as a classifier. The final probabilities are then used to distinguish between fraud and nonfraud. A high value indicates a high likelihood that the node will be influenced to commit fraud as well. A cut-off value separates legitimate and fraudulent nodes.

Probabilistic Relational Neighbor Classifier

The probabilistic relational neighbor classifier is a straightforward extension of the relational neighbor classifier whereby the posterior class probability for node n to belong to class c is calculated as follows:

$$P(c|n) = \frac{1}{Z} \sum_{\{n_j \in Neighborhood_n\}} w(n, n_j) P(c|n_j).$$

Table 5.6 Summary of Relational Neighbor Probabilities

NODE	A	B	C	D	E	F	G	H	I	J
$P(NF\|?)$	0.80	0.66	1	0.50	0	0.33	0.25	1	1	1
$P(F\|?)$	0.20	0.33	0	0.50	**1**	0.66	**0.75**	0	0	0
NODE	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**
$P(NF\|?)$	0.66	1	1	0.66	1	1	1	1	1	1
$P(F\|?)$	0.33	0	0	0.33	0	0	0	0	0	0

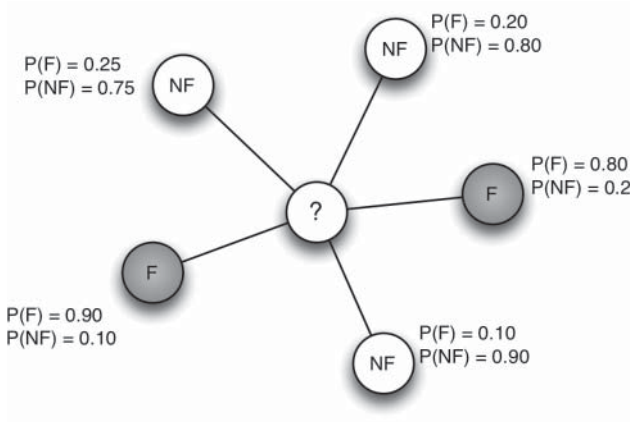


Figure 5.17 Example Social Network for a Probabilistic Relational Neighbor Classifier

Note that the summation now ranges over the entire neighborhood of nodes. The probabilities $P(c|n_j)$ can be the result of a local model, or of a previously applied network model. Consider the network of Figure 5.17.

The calculations then become:

$$P(F|?) = \frac{1}{Z}(0.25 + 0.20 + 0.80 + 0.10 + 0.90)$$
$$P(NF|?) = \frac{1}{Z}(0.75 + 0.80 + 0.20 + 0.90 + 0.10)$$

Since both probabilities have to sum to 1, Z equals 5, so the probabilities become:

$$P(F|?) = \frac{2.25}{5} = 0.45$$
$$P(NF|?) = \frac{2.75}{5} = 0.55$$

Analogously to the relational neighbor, the probabilities returned by the probabilistic relational neighbor can be used as an additional variable in local models, or as a classifier.

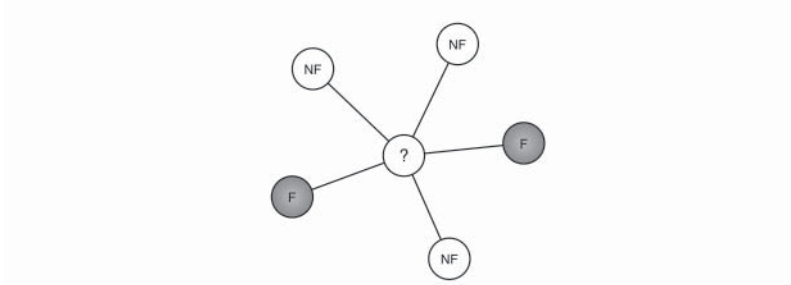
Relational Logistic Regression Classifier

Relational logistic regression was introduced by Lu and Getoor (2003). It basically starts off from a data set with local node-specific characteristics. These node-specific characteristics are the so-called *intrinsic variables*. Examples of intrinsic features in a social security fraud context include a company's age, sector, legal form, and so on. The data set is enriched with network characteristics, as follows:

- Most frequently occurring class of neighbor (mode-link)
- Frequency of the classes of the neighbors (count-link)
- Binary indicators indicating class presence (binary-link)

The network characteristics are illustrated in Figure 5.18. Remark that the count equals the degree.

A logistic regression model is then estimated using the data set which contains both intrinsic and network features. Note that there is some correlation between the network characteristics added, which should be filtered out during an input selection procedure (e.g., using stepwise logistic regression). This idea is also referred to as featurization, since the network characteristics are basically added as special features to the data set. These features can measure the behavior of the neighbors in terms of the target variables (e.g., fraud or not) or in terms of the intrinsic characteristics (e.g., age, sector, profit). Figure 5.19 provides an example of social security fraud, aiming to



ID	Age	Sector	...	Mode link	Count Fraud	Count Non-Fraud	Binary Fraud	Binary Non-Fraud
6357	2.4	transport	...	NF	2	3	1	1

Figure 5.18 Example of Social Network Features for a Relational Logistic Regression Classifier

Company ID	Intrinsic Variables								Network Variables				Fraud?
	Regional		Sectorial		Historical		Legal		Egonet		Second-order network		
	Province	...	Sector	...	Age	...	Form	...	Contacts with fraudsters (degree)	...	Contact with contacts of fraudsters	...	
3904	P4	...	catering	...	3	...	Corp.	...	0	...	0	...	***No***
6357	P7	...	transport	...	2.4	...	PLLC	...	2	...	0	...	***No***
3041	P5	...	cleaning	...	0.7	...	LLC	...	5	...	14	...	***Yes***
7932	P2	...	catering	...	8	...	Corp.	...	1	...	3	...	***No***
⋮													

Figure 5.19 Example of Featurization with Features Describing Intrinsic Behavior and Behavior of the Neighborhood

Table 5.7 Summary of Relational Features by Lu and Getoor (2003)

NODE	A	B	C	D	E	F	G	H	I	J
Mode link	NF	NF	NF	NF/F	F	F	F	NF	NF	NF
Count fraud	1	1	0	2	2	2	***3***	0	0	0
Count non-fraud	5	2	1	2	***0***	1	1	2	4	1
Binary fraud	1	1	0	1	1	1	1	0	0	0
Binary non-fraud	1	1	1	1	***0***	1	1	1	1	1
NODE	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**
Mode link	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF
Count fraud	1	0	0	1	0	0	0	0	0	0
Count non-fraud	2	2	2	2	3	1	3	1	1	1
Binary fraud	1	0	0	1	0	0	0	0	0	0
Binary non-fraud	1	1	1	1	1	1	1	1	1	1

detect fraudulent companies. Both intrinsic and network features are added to describe target behavior (i.e., fraud). Table 5.7 summarizes the features extracted from the network using the approach as suggested by Lu and Getoor (2003) for the toy example of Figure 5.13.

The set of network features as suggested by the relational logistic regression classifier can in a straightforward manner be extended with other metrics discussed in this and the next sections (Neighborhood Metrics, Centrality Metrics, and Collective Inference Algorithms).

Centrality Metrics

Centrality metrics are useful in fraud to prevent the expansion of future fraudulent activities. They tend to find the *central* node(s), that is, nodes that might impact many other nodes. These metrics include geodesic path, degree (see Section Neighborhood Metrics), closeness, betweenness and graph theoretic center. Assume a network with n nodes v_i, $i = 1, \ldots, n$. The geodesic represents the shortest path between two nodes. g_{jk} represents the number of geodesics from node j to node k, whereas $g_{jk}(v_i)$ represents the number of geodesics from node j to node k passing through node v_i. The centrality measures are summarized in Table 5.8. The formulas each time calculate the metric for node v_i. A toy example is given in Figure 5.13.

Table 5.8 Centrality Metrics

Geodesic path	Shortest path between two nodes in the network.	$d(v_i, v_j)$
Degree	Number of connections of a node (in- versus out-degree if the connections are directed). See previous section.	
Closeness	The average distance of a node to all other nodes in the network (reciprocal of farness).	$\left[\frac{\sum_{j=1(j\neq i)} d(v_i,v_j)}{n-1}\right]^{-1}$
Betweenness	Counts the number of times a node or connection lies on the shortest path between any two nodes in the network.	$\sum_{j<k} \frac{g_{jk}(v_i)}{g_{jk}}$
Graph theoretic center	The node with the smallest maximum distance to all other nodes in the network (see section Geodesic path).	

Geodesic Path

The *geodesic path* or *shortest path* computes the minimum distance needed to reach a node from a target node. A key question in fraud is: How far is any fraudulent node in the network removed from the target node? If a fraudulent node is in the close neighborhood, fraud might impact that node more intensively and contaminate the target of interest.

Geodesic path calculations are nevertheless computationally expensive. Dijkstra (1959) formulated a solution to compute the shortest path from one node to all other nodes.

-- ***Initialization*** --

1. Assign a label of zero to the source node (let's say node v_1), and initialize all other nodes in the network with a temporary label of ∞.
2. The set of permanent labeled nodes is $P = \{v_1\}$; the set of unlabeled nodes U contains all other nodes of the network.
3. $u := v_1$

-- ***Main loop*** --

while U is not empty **do**

1. ***Updating*** for each node adjacent to a permanent node u, replace the temporary label of node v_i with:

$$\min \begin{cases} \text{node } v_i\text{'s current temporary label} \\ \text{node } u\text{'s permanent label + edge weight } e\left(u, v_i\right) \end{cases}$$

2. ***Adding to permanent labeled set*** add the node with the smallest temporary label $v\_$ to the permanent labeled set P.
3. ***Reassign u*** u := $v\_$

end

Figure 5.20 illustrates Dijkstra's algorithm to calculate the shortest path from node A to the other nodes in a directed graph. The weights of the shortest paths between any two nodes in the network are:

$$\text{Shortest paths} = \begin{pmatrix} 0 & 2 & 4 & 4 & 8 & 13 & 7 \\ 4 & 0 & 2 & 3 & 6 & 11 & 5 \\ 2 & 4 & 0 & 1 & 4 & 9 & 3 \\ 1 & 3 & 5 & 0 & 9 & 11 & 4 \\ 5 & 7 & 3 & 4 & 0 & 5 & 1 \\ 6 & 8 & 4 & 5 & 1 & 0 & 2 \\ 4 & 6 & 2 & 3 & 6 & 7 & 0 \end{pmatrix}$$

Analogously, the shortest path between any two nodes in an undirected graph can be computed. Remark that Dijkstra's algorithm is only applicable to networks with non-negative edge weights.

Closely related to the geodesic path, is the *graph theoretic center*. The graph theoretic center is the node with the smallest, maximum distance to all other nodes. This node is the most central node in the network. In terms of information diffusion, the graph theoretic center is the node which influences other nodes the fastest. The example in Figure 5.20 has two graph theoretic centers: node E and G, each with a maximum distance of 7 hops to another node in the network.

The *average path length* of a network is the length one needs to traverse on average to reach one node from another. The average path

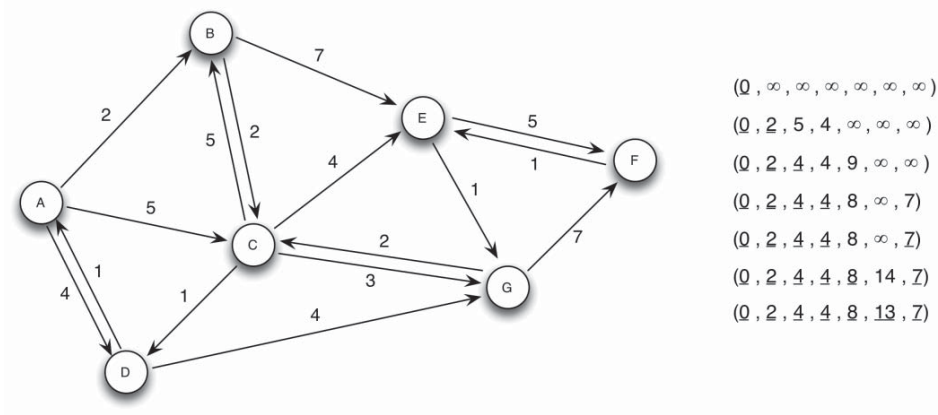


Figure 5.20 Illustration of Dijkstra's Algorithm

length of Figure 5.20 is 4.1. Note that the average path length corresponds to the "degrees of separation" in the section Social Networks.

In fraud, it is often interesting to know whether there are paths between fraudulent nodes and legitimate nodes. If more paths exist between two nodes, there is a higher chance that (fraudulent) influence will eventually reach the target node. Starting from the adjacency matrix of a network, the number of connecting paths between any two nodes is easily computed through matrix exponentiation.

Consider the small network as illustrated in Figure 5.21. The corresponding adjacency matrix is

$$A = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

The adjacency matrix represents how many one-hop paths exist between two nodes. For example, node A can reach node D by exactly one path of one hop. If we raise the matrix to the power of x, the resulting matrix contains how many x-hop paths exist between two nodes. This is Seidel's algorithm (Seidel 1995). For example,

$$A^2 = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} = \begin{pmatrix} 2 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 3 \end{pmatrix}$$

$$A^3 = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} 2 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 3 \end{pmatrix} = \begin{pmatrix} 2 & 3 & 1 & 4 \\ 3 & 2 & 1 & 4 \\ 1 & 1 & 0 & 3 \\ 4 & 4 & 3 & 2 \end{pmatrix}$$

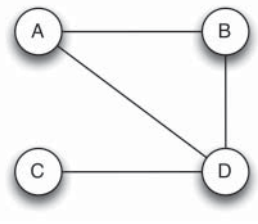


Figure 5.21 Illustration of the Number of Connecting Paths Between Two Nodes

In the toy example of Figure 5.21, there is exactly one two-hop path between node A and node D (through node B), one two-hop path between node B and node D (through node A) and three two-hop paths between node D and itself (D-A-D, D-B-D, and D-C-D). There is no two-hop path that connects node C and node D. This is exactly what A^2 represents. An overview of the three-hop paths between any two nodes is reported in A.[3]

For the sample network in Figure 5.13, Table 5.9 contains the geodesic path length of each node to fraudulent nodes, as well as the number of n-hop paths toward fraudulent nodes. The graph theoretic center of Figure 5.13 is node A, which is at most three hops removed from all other nodes in the network. This means that node A is the most influential node of the network and extra attention should be devoted in order to prevent this node to commit fraud. Whenever the graph theoretic center is contaminated with fraud, fraud might rapidly flow throughout the rest of the network.

Closeness

Closeness centrality measures the mean distance from a node to each other node in the network. The distance $d(v_i v_j)$ between a node and another node corresponds to the geodesic or shortest path (see below). Given a network with n nodes, the mean geodesic distance or farness $\not{g}(v_i)$ from a node i to the other nodes is computed as follows:

$$\not{g}(v_i) = \frac{\sum_{j=1(j\neq i)} d(v_i v_j)}{n-1}$$

Table 5.9 Summary of Geodesic Paths to Fraudulent Nodes

NODE	A	B	C	D	E	F	G	H	I	J
Geodesic path	1	1	2	0	0	0	1	2	0	2
# 1-hop paths	1	1	0	2	2	2	***3***	0	0	0
# 2-hop paths	4	3	1	8	4	7	***5***	2	6	1
# 3-hop paths	18	13	3	19	15	17	***25***	4	9	0
NODE	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**
Geodesic path	1	2	2	1	2	3	3	4	4	2
# 1-hop paths	1	0	0	1	0	0	0	0	0	0
# 2-hop paths	0	1	1	0	1	0	0	0	0	1
# 3-hop paths	9	1	1	8	4	1	1	0	0	4

A low value of farness indicates that the node easily reaches other nodes in the network, and thus has a stronger impact on other nodes. If a fraudulent node in a (sub)graph has a low value for $\mathcal{g}(v_i)$, fraud might easily spread through the (sub)network and contaminate other nodes. The distance to the node itself is excluded in the computation of farness.[2]

Closeness centrality is the inverse of farness. A node is more central in the network, if it has a higher value, and

$$\text{Closeness Centrality}(v_i) = \left(\frac{\sum_{j=1(j\neq i)} d(v_i v_j)}{n-1} \right)^{-1}$$

In general, two problems arise. First, the values of the closeness centralities for all the nodes in the network might lie closely together, and it is therefore often important to inspect the decimals. Second, if the geodesic distance between two nodes is infinite, the closeness centrality of both nodes is $\lim_{x\to\infty} \left(\frac{1}{x}\right) = 0$. To overcome this problem, closeness centrality often excludes the distances to nodes that cannot be reached.

The closeness centralities for the nodes in Figure 5.13 are summarized in Table 5.10. Node A is the closest connected to all other nodes in the network; node R and S are the farthest away from all other nodes.

Betweenness

Betweenness measures the extent to which a node lies on the geodesic paths connecting any two nodes in the network. This can be interpreted as the extent to which information passes through this node. A node with a high betweenness possibly connects communities (i.e., subgraphs in the network) with each other. This is depicted in Figure 5.22. In the figure, the shaded node connects the three communities with each other and has the highest betweenness. If this

[2]The closeness of a node is sometimes calculated by including the node itself.

Table 5.10 Summary of Closeness and Closeness Centrality for Each Node of the Network in Figure 5.13

NODE	A	B	C	D	E	F	G	H	I	J
Farness	2	2.57	3.53	2.89	3.79	3.00	2.32	2.74	2.21	3.89
Closeness Centrality	***0.50***	0.39	0.28	0.35	0.26	0.33	0.43	0.37	0.45	0.26
NODE	K	L	M	N	O	P	Q	R	S	T
Farness	2.95	3.84	3.84	2.95	2.53	3.47	3.26	***4.21***	***4.21***	2.95
Closeness Centrality	0.34	0.26	0.26	0.34	0.40	0.29	0.31	0.24	0.24	0.34

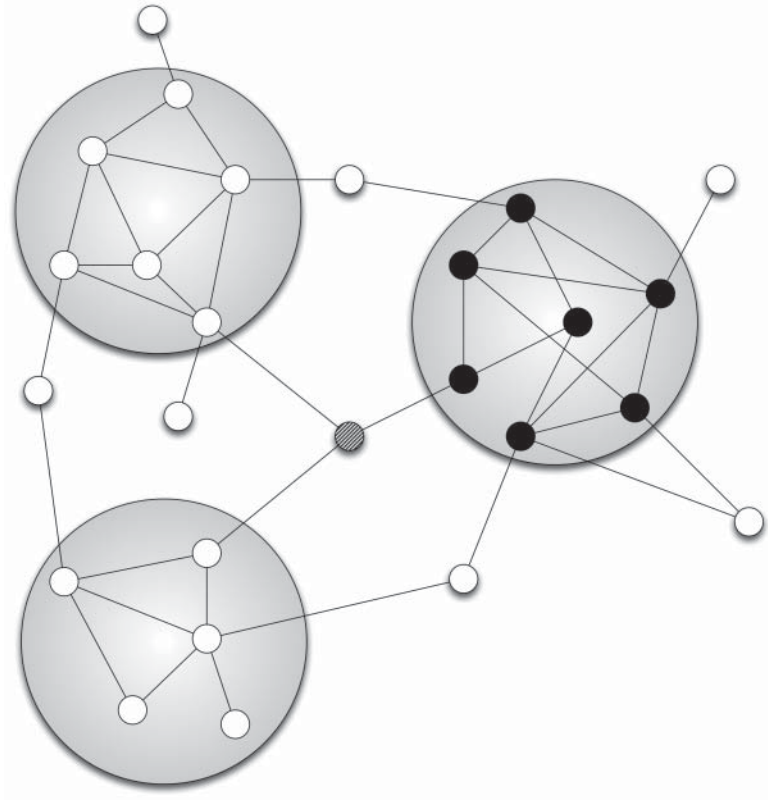


Figure 5.22 Illustration of Betweenness Between Communities of Nodes

Table 5.11 Summary of the Betweenness Centrality for Each Node of the Network in Figure 5.13

NODE	A	B	C	D	E	F	G	H	I	J
Betweenness	***104***	24.67	0	13.83	0	6.167	35.33	9	65	0
NODE	K	L	M	N	O	P	Q	R	S	T
Betweenness	20	0	0	34	63	0	35	0	0	0

node is infected by fraud from one community, fraud can easily pass on toward the other communities. One option is, for example, to remove this node from the network to prevent that fraud contaminates the other communities. Let g_{jk} be the number of shortest paths between node j and node k, and $g_{jk}(v_i)$ the number of shortest paths between node j and node k that pass through node v_i, then the betweenness becomes

$$\sum_{j<k} \frac{g_{jk}(v_i)}{g_{jk}}$$

Table 5.11 contains the betweenness centralities of the nodes in the network of Figure 5.13. Again, node A is the most central node.

Collective Inference Algorithms

Given a semi-labeled network with few labeled legitimate and fraudulent nodes and many unknown nodes, a collective inference procedure infers a set of class labels/probabilities for the unknown nodes by taking into account the fact that inferences about nodes can mutually affect one another. Some popular examples of collective inference procedures are:

- PageRank(Page and Brin 1999)
- Gibbs sampling (Geman and Geman 1984)
- Iterative classification algorithm (Lu and Getoor 2003)
- Relaxation labeling (Chakrabarti et al. 1998)
- Loopy belief propagation (Pearl 1986)

PageRank Algorithm

The PageRank algorithm was introduced by Page and Brin in 1999 and is the basis of Google's famous search engine algorithm for ranking web pages (Page and Brin 1999). The PageRank algorithm tries to simulate surfing behavior. Figure 5.23 represents a network of web pages linking to each other. Given the figure, what is the probability that a surfer will visit web page A? Assume for now that a surfer only browses to web pages by following the links on the web page s/he is currently visiting. The figure shows that web page A has three incoming links. A surfer that is currently visiting web page B, will visit web page A next with a probability of 20 percent (=1/5). This is because web page B has 5 links to web pages, among which is web page A. Analogously, if a surfer is currently on web page C or D, there is a probability of 33.33 percent and 50 percent, respectively, that web page A will be visited next. The probability of visiting a web page is called the *pagerank* of that web page. In order to know the pagerank of web page A, we need to know the pagerank of web page B, C, and D. This is collective inference: the ranking of one web page depends on the ranking of other web pages;

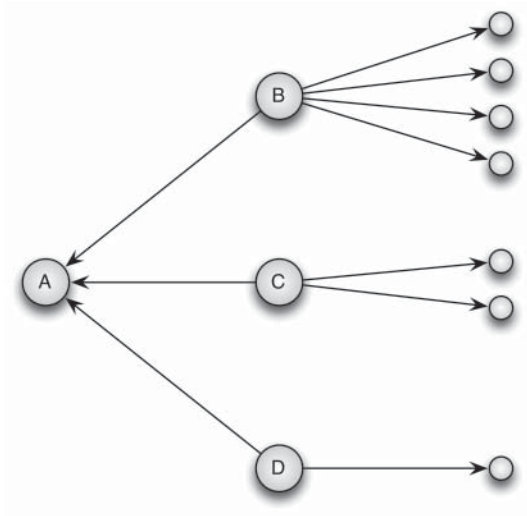


Figure 5.23 PageRank Algorithm

and a change in the ranking of one web page might impact the ranking of all other web pages.

Specifically, the main idea is that important web pages (i.e., web pages that appear at the top of the search results) have many incoming links from other (important) web pages. The ranking of a web page depends on (a) the ranking of web pages pointing towards that web page, and (b) the out-degree of the linking web pages. However, visiting web pages by following a random link on the current web page is not a realistic assumption. Surfers' behavior is more random: instead of following one of the links on a web page, they might randomly visit another web page. Therefore, the PageRank algorithm includes the *random surfer* model, which assumes that surfers often get bored, and randomly jump to another web page. With a probability of α the surfer will follow a link on the web page s/he is currently visiting. However, with a probability $1 - \alpha$, the surfer visits a random other web page.

The PageRank algorithm is expressed as follows:

$$PR(A) = \alpha \sum_{i \in N_A} \frac{PR(i)}{D_{out,i}} + (1 - \alpha) \cdot e_A$$

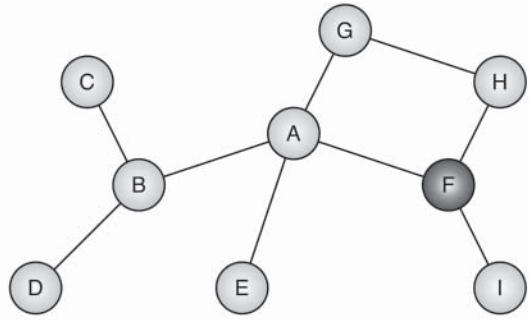
with *PR(i)* the ranking of web page i, $D_{out,i}$ the out-degree of web page i, $(1 - \alpha)$ the restart probability, and e_A the restart value for web page A, which is often uniformly distributed among all web pages. This equation requires the ranking of the neighboring web pages. One option is to start with a random pagerank value for every web page and iteratively update the pagerank scores until a predefined number of iterations is reached or a stopping criterion is met (e.g., when the change in the ranking is marginal).

The above equation can be rewritten such that ranking is computed for all web pages simultaneously, and

$$\vec{r} = \alpha \cdot \boldsymbol{A} \cdot \vec{r} + (1 - \alpha) \cdot \vec{e}$$

with $\vec{r}$ a vector of size n containing the pageranks of all n web pages, $\boldsymbol{A}$ the column-normalized adjacency matrix of size $n \times n$, $(1 - \alpha)$ the restart probability and $\vec{e}$ the restart vector. The restart vector is generally uniformly distributed among all web pages, and normalized afterward.

This equation can only be solved by matrix inversion, which is often unfeasible in practice. One of the most widely used ways to execute the algorithm is the power-iteration method, iterating the above equation until convergence (Tong et al. 2007). Convergence is reached when the change in the importance score is insignificant or after a maximum number of iteration steps. Figure 5.24 illustrates the iterative procedure



Starting vector is uniformly distributed among all nodes

iteration	A	B	C	D	E	F	G	H	I
0	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111
1	0.2213	0.2292	0.0481	0.0481	0.0403	0.1819	0.0875	0.0954	0.0481
2	0.2046	0.1455	0.0816	0.0816	0.0637	0.1452	0.1042	0.1054	0.0682
3	0.1975	0.0816	0.0579	0.0579	0.0601	0.1629	0.1049	0.1020	0.0578
4	0.2149	0.0579	0.0730	0.0730	0.0586	0.1511	0.1020	0.1074	0.0628
5	0.1972	0.0730	0.0612	0.0612	0.0623	0.1614	0.1080	0.1028	0.0595
⋮									
100	0.2063	0.1714	0.0652	0.0652	0.0605	0.1579	0.1057	0.1063	0.0614

Starting vector is personalized to fraud (node F)

iteration	A	B	C	D	E	F	G	H	I
0	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111
1	0.2046	0.2125	0.0315	0.0314	0.0236	0.3153	0.0708	0.0787	0.0315
2	0.1997	0.0970	0.0602	0.0602	0.0434	0.2537	0.0769	0.1194	0.0893
3	0.1690	0.1448	0.0275	0.0275	0.0424	0.3191	0.0932	0.1046	0.0719
4	0.2071	0.0826	0.0410	0.0410	0.0359	0.2915	0.0804	0.1300	0.0904
5	0.1707	0.1138	0.0234	0.0234	0.0440	0.3261	0.0993	0.1167	0.0826
⋮									
100	0.1897	0.0778	0.0220	0.0220	0.0403	0.3254	0.0970	0.1334	0.0922

Figure 5.24 Illustration of Iterative Process of the PageRank Algorithm

of PageRank. During the first iteration, the ranking of node A is calculated as follows:

$$r(A)_1 = 0.85\left(\frac{1}{3}\cdot\frac{1}{9} + 1\cdot\frac{1}{9} + \frac{1}{2}\cdot\frac{1}{9} + \frac{1}{3}\cdot\frac{1}{9}\right) + 0.15\cdot\frac{1}{9}$$

Page and Brin (1999) included an extension of the PageRank algorithm by personalizing the search to the user. This is done by changing the restart vector $\vec{e}$ from a uniform distribution to a vector that complies with a user's search interests. A higher score of the *i*th value of the restart vector corresponds to a higher interest that a user might have for the *i*th web page.

The PageRank algorithm can be seen as a propagation of page influence through the network. The same reasoning can be used to propagate *fraud* through the network. That is, we personalize the ranking algorithm by fraud. Instead of web pages, the adjacency matrix $\boldsymbol{A}$ represents a fraud network (e.g., a people-to-people network). As fraud detection infers a labeled graph (i.e., we know which nodes are fraudulent), we inject fraud in the network through the restart vector. That is, the *i*th entry of vector $\vec{e}$ is 1 if the *i*th node is fraudulent, and 0, otherwise. The vector $\vec{e}$ is normalized afterward. The vector $\vec{r}$ contains the fraud ranking of each node. The higher the ranking, the more the node is influenced by fraud compared to the other nodes. Recall that the equation is often solved through iteration. In that case, the vector $\vec{r}_k$ includes the fraud ranking after k iterations, with $\vec{r}_0$ a random vector with values between [0,1].

We note that the final ranking assigned to each node should be interpreted as a ranking and not as a score. The top-ranked nodes are the most influenced by fraud.

The PageRank scores for the toy example of Figure 5.13 are computed (a) without emphasizing the fraud labels ($\text{PageRank}_{\text{base}}$), and (b) with emphasis on fraud ($\text{PageRank}_{\text{fraud}}$). In the first case, the restart vector $\vec{e}$ is uniformly distributed among all nodes. For the $\text{PageRank}_{\text{fraud}}$ case, the restart vector $\vec{e}$ has a zero value for each legitimate node, and a non-zero value for the fraudulent nodes. The results are presented in Table 5.12. The highest ranking is assigned to node A when applying $\text{PageRank}_{\text{base}}$. This is not that remarkable, as node A has the highest degree in the network. Studies proved that

Table 5.12 PageRank Algorithm

NODE	A	B	C	D	E
$PageRank_{base}$	***0.1084***	0.0577	0.0238	0.0684	0.0367
$PageRank_{fraud}$	0.0877	0.0635	0.0180	***0.1685***	0.1144
NODE	F	G	H	I	J
$PageRank_{base}$	0.0519	0.0671	0.0400	0.0706	0.0246
$PageRank_{fraud}$	0.1452	0.1094	0.0236	0.0941	0.0112
NODE	K	L	M	N	O
$PageRank_{base}$	0.0604	0.0415	0.0415	0.0578	0.0667
$PageRank_{fraud}$	0.0396	0.0169	0.0169	0.0344	0.0206
NODE	P	Q	R	S	T
$PageRank_{base}$	0.0264	0.0755	0.0289	0.0289	0.0229
$PageRank_{fraud}$	0.0058	0.0112	0.0032	0.0032	0.0124

there is an interplay between the nodes' degree and the PageRank score (Fortunato et al. 2008). As can be seen from the results, the basic PageRank algorithm is not useful for fraud detection. There is no correlation between fraud (or fraud influence) and the ranking. However, when personalizing the restart vector to fraud using the adapted PageRank algorithm $PageRank_{fraud}$, the nodes with the highest ranking are nodes D, F, E. These results are not surprising, as those nodes were directly attributed to fraud. Node G receives a high fraud ranking as well, indicating that this node is affected by the influences of fraudulent nodes in its neighborhood. Notice that legitimate node G has a higher ranking than fraudulent node I.

Gibbs Sampling

Gibbs sampling (Geman and Geman, 1984) is a collective inference procedure that uses a local classifier to infer a posterior class probability in order to initialize the node labels in the network. More concretely, the original semi-labeled graph is transformed in a (fully) labeled graph by sampling the posterior probabilities of the local classifier. The predictive features of a local classifier consist of only intrinsic variables (see Relational Logistic Regression Classifier). Notice that the labels of

the unknown nodes in the graph express an expectation of the true class value. An iterative procedure continually updates the expected class labels of the unknown nodes. The first $iter_b$ steps of the procedure approach a stationary distribution. This is the so-called burn-in period, where no statistics are recorded. During the last $iter_c$ steps, the algorithm keeps track of which class labels are assigned to each node. The final class probability estimate is computed as the normalized count of the number of times each class is assigned to a particular node.

The algorithm is explained in more detail below.

-- **Input** --

Semi-labeled graph $\mathcal{G}$ with known and unknown nodes.

-- **Initialization** --

Assign posterior probabilities $P(c = k)$ with $k \in \{Fraud, Legitimate\}$ to each unknown node using a local classifier.

Given the posterior probabilities $P(c = k)$, sample the class value $L_j \in \{Fraud, Legitimate\}$ of each unknown node j. Each node in the graph is now labeled.

-- **Main loop** –

for $i = 0$ to $iter_b + iter_c$ **do**

1. **Learning phase**: Apply a relational learner (e.g., Relational Neighbor, Probabilistic Relational learner …) to each unknown node of the network to obtain new posterior probabilities $P\prime(c = k)$.
2. **Sampling phase**: Given the posterior probabilities $P\prime(c = k)$, sample the class value $L_j \in \{Fraud, Legitimate\}$ for each unknown node j.

end

For each unknown node, count the number of times each class label is assigned to that node during the iteration $iter_b + 1$ and $iter_c$. The normalized counts represent the final class probability estimates.

Iterative Classification Algorithm

Like Gibbs sampling, iterative classification initializes the semi-labeled graph by using a local classifier (Lu and Getoor 2003). Based on the local model's output, the most probable class label is assigned to each unknown node. This is the bootstrap phase. During the iteration phase, a relational learner updates the class labels of each unknown node based on the outcome of a relational logistic regression model (see Relational Logistic Regression Classifier). The input features are computed as link statistics of the current label assignments. Link statistics include, for example, *mode* (most occurring label of the neighboring nodes), *count* (number of neighboring fraud nodes), *binary* (at least one of the neighboring nodes are fraudulent). Nodes that are not yet classified are ignored. A new class label is assigned to each unknown node based on the largest posterior probability. This step is repeated until a stopping criterion is met. The final class label corresponds to the class label estimate generated during the last iteration.

Relaxation Labeling

Relaxation labeling starts from a local classifier to initialize a node's class label. Previous approaches assigned a hard label (i.e., either legitimate or fraud) to each node. Relaxation labeling starts with assigning to each node a probability that indicates the likelihood of a node to belong to a certain class. This is soft labeling. Next, the probability class labels are used to iteratively update the class probability using a relational model. The class estimates of the last iteration are the final class label estimates.

Loopy Belief Propagation

Loopy belief propagation is a collective inference procedure based on iterative message passing (Pearl 1988). The main idea is that the belief of each node to be in state x (let's say fraud) depends on the messages it receives from its neighbors. The belief of a node to be in state x is the normalized product of the received messages. The message as well as the belief is continuously updated during the algorithm.

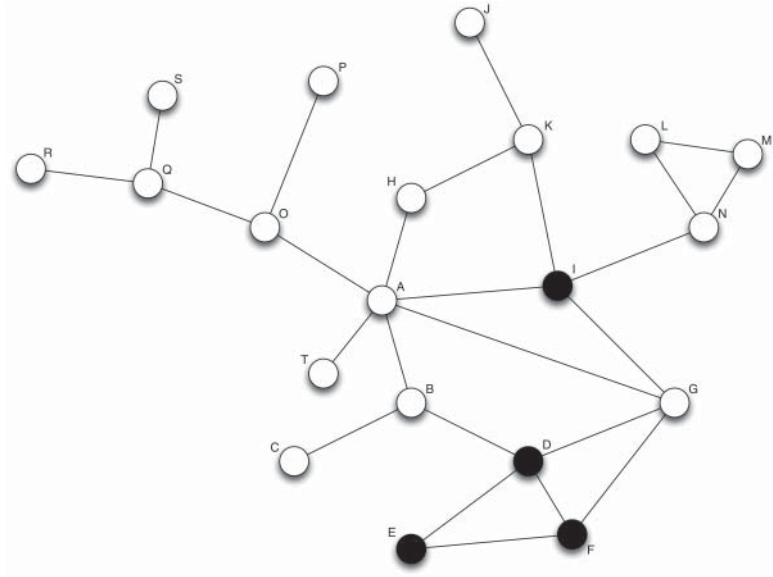


Figure 5.25 Sample Network

Featurization: Summary Overview

Given all aforementioned metrics, we are able to extract features from the network for every node of interest. The *featurization process* entails the mapping of an unstructured data source like a network into useful and meaningful characteristics of each node. For each node in the network of Figure 5.25, all the metrics are computed. Table 5.13 summarizes the different variables. Although most network-based features already give a good indication which nodes might be fraudulent in the future, these network-based characteristics can be combined with local (or intrinsic) features into a classification model, as defined in the previous chapters.

COMMUNITY MINING: FINDING GROUPS OF FRAUDSTERS

Social networks are a powerful visualization technique to reveal the individual relationships among people by means of the links in the network. In the previous sections, the neighboring nodes were treated as

Table 5.13 Featurization Process. The Unstructured Network Is Mapped into Structured Data Variables

NODE	A	B	C	D	E	F	G	H	I	J
Total Degree	***6***	3	1	4	2	3	4	2	4	1
Fraud Degree	1	1	0	2	2	2	***3***	0	0	0
Legit Degree	5	2	1	2	0	1	1	2	4	1
Total Triangles	1	0	0	2	1	2	2	0	1	0
Fraud Triangles	0	0	0	1	1	1	1	0	0	0
Legit Triangles	0	0	0	0	0	0	0	0	1	0
Semi-Fraud Triangles	1	0	0	1	0	1	1	0	0	0
Density	0.33	0.5	1	0.6	1	0.83	0.6	0.66	0.5	1
Rel. Neighbor P(NF|?)	0.80	0.66	1	0.50	0	0.33	0.25	1	1	1
Rel. Neighbor P(F|?)	0.20	0.33	0	0.50	***1***	0.66	***0.75***	0	0	0
Mode link	NF	NF	NF	**NF/F**	**F**	**F**	**F**	NF	NF	NF
Count fraud	1	1	0	2	2	2	***3***	0	0	0
Count non-fraud	5	2	1	2	***0***	1	1	2	4	1
Binary fraud	1	1	0	1	1	1	1	0	0	0
Binary non-fraud	1	1	1	1	0	1	1	1	1	1
Geodesic path	***1***	1	2	0	0	0	1	2	0	2
# 1-hop paths	1	1	0	2	2	2	***3***	0	0	0
# 2-hop paths	4	3	1	8	4	7	***5***	2	6	1

(*continued*)

Table 5.13 (*Continued*)

NODE	A	B	C	D	E	F	G	H	I	J
# 3-hop paths	18	13	3	19	15	17	***25***	4	9	0
Farness	2	2.57	3.53	2.89	3.79	3.00	2.32	2.74	2.21	3.89
Closeness Centrality	0.50	0.39	0.28	0.35	0.26	0.33	0.43	0.37	0.45	0.26
Betweenness	***104***	24.67	0	13.83	0	6.167	35.33	9	65	0
$PageRank_{base}$	***0.1084***	0.0577	0.0238	0.0684	0.0367	0.0519	0.0671	0.0400	0.0706	0.0246
$PageRank_{fraud}$	0.0877	0.0635	0.0180	***0.1685***	0.1144	0.1452	0.1094	0.0236	0.0941	0.0112
NODE	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**
Total Degree	3	2	2	3	3	1	3	1	1	1
Fraud Degree	1	0	0	1	0	0	0	0	0	0
Legit Degree	2	2	2	2	3	1	3	1	1	1
Total Triangles	0	1	1	1	0	0	0	0	0	0
Fraud Triangles	0	0	0	0	0	0	0	0	0	0
Legit Triangles	0	1	1	1	0	0	0	0	0	0
Semi-Fraud Triangles	0	0	0	0	0	0	0	0	0	0
Density	0.5	1	1	0.66	0.5	1	0.5	1	1	1
Rel. Neighbor P(NF|?)	0.66	1	1	0.66	1	1	1	1	1	1
Rel. Neighbor P(F|?)	0.33	0	0	0.33	0	0	0	0	0	0

(*continued*)

Table 5.13 (*Continued*)

NODE	K	L	M	N	O	P	Q	R	S	T
Mode link	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF
Count fraud	*1*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*
Count non-fraud	*2*	*2*	*2*	*2*	*3*	*1*	*3*	*1*	*1*	*1*
Binary fraud	*1*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*
Binary non-fraud	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
Geodesic path	*1*	*2*	*2*	*1*	*2*	*3*	*3*	*4*	*4*	*2*
# 1-hop paths	*1*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*
# 2-hop paths	*0*	*1*	*1*	*0*	*1*	*0*	*0*	*0*	*0*	*1*
# 3-hop paths	*9*	*1*	*1*	*8*	*4*	*1*	*1*	*0*	*0*	*4*
Farness	*2.95*	*3.84*	*3.84*	*2.95*	*2.53*	*3.47*	*3.26*	***4.21***	***4.21***	*2.95*
Closeness Centrality	*0.34*	*0.26*	*0.26*	*0.34*	*0.40*	*0.29*	*0.31*	*0.24*	*0.24*	*0.34*
Betweenness	*20*	*0*	*0*	*34*	*63*	*0*	*35*	*0*	*0*	*0*
$PageRank_{base}$	*0.0604*	*0.0415*	*0.0415*	*0.0578*	*0.0667*	*0.0264*	*0.0755*	*0.0289*	*0.0289*	*0.0229*
$PageRank_{fraud}$	*0.0396*	*0.0169*	*0.0169*	*0.0344*	*0.0206*	*0.0058*	*0.0112*	*0.0032*	*0.0032*	*0.0124*

separate entities, and the relationships among the neighborhoods were neglected. Whereas these individual relationships might uncover many interesting flows of influence through individuals, groups of nodes in the network might have a higher impact in terms of information exchange like fraudulent influence. A friend group, for example, is a community in a social network where the friends of your friends are each other's friends. A similar opinion created within a group of friends might be more convincing than the opinion of only one friend. A *community* is a subgraph in the network with a higher number and more intensive relationships among the members of the community than a random other subgraph in the network. Such communities can play an important role in influence dispersion. Groups often share, reinforce, and complement ideas and alternatives on how to perpetrate fraud. The analysis or mining of communities in a network captures the effect of *peer pressure*. In a fraudulent environment, peer pressure can strengthen the tendency to commit fraud. That is, community mining in a fraud context is the process of finding groups of fraudsters in the network in order to identify subgraphs in which fraud occurs with a higher probability than in the rest of the graph, and tries to answer the following questions: Are people more likely to commit fraud if they are influenced by a whole community than if they were influenced by only one fraudulent individual? The answer is mostly yes. In many applications, the discovery of such communities can result in the detection of hidden fraudulent structures or the curtailment of existing fraudulent groups.

Figure 5.26 illustrates the usefulness of the detection of fraudulent groups in credit card fraud. Stores are represented by circles. All transactions between stores and credit cards are fraudulent. Fraudsters tend to behave in the same way. Often, fraudsters use stolen credit cards in the same stores. As a result, some stores are more sensitive to fraud, regardless of the fraudulent involvement of the store itself. Rather than implementing fraud detection on individual store level, community mining will expose which stores are often related to the same stolen credit cards. A known fraud pattern in credit card fraud is that the stolen card is used in many stores for a small amount of money. Community detection allows to identify the set of stores that are commonly associated to fraud with the same credit card. The use of

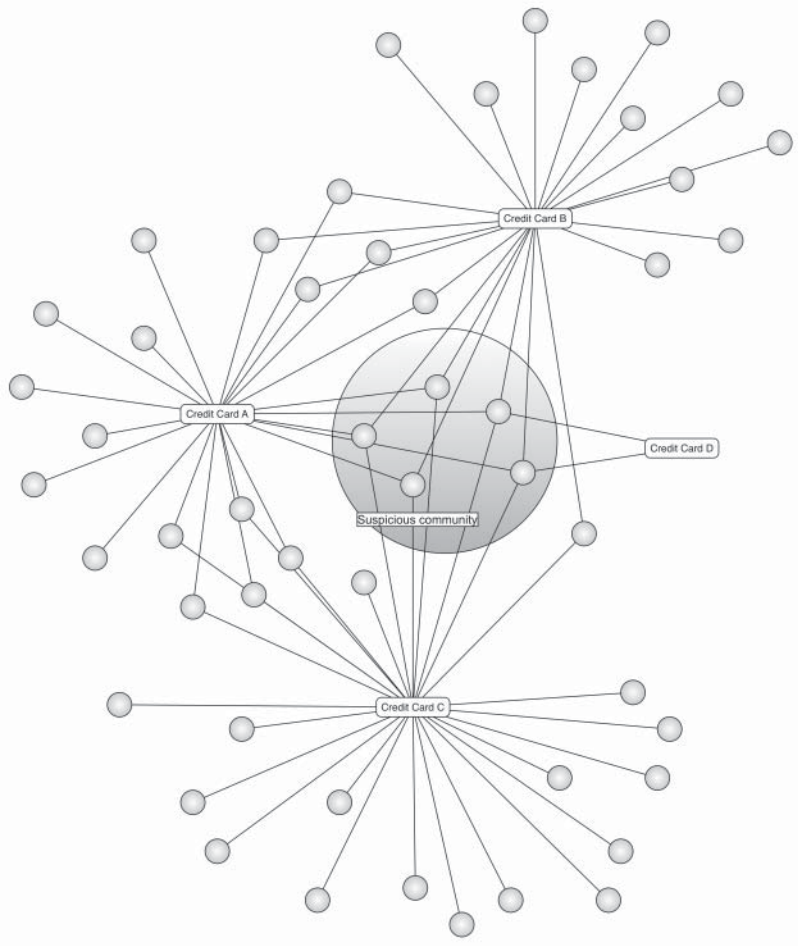


Figure 5.26 Community Detection for Credit Card Fraud

a card in more than one of these stores might drastically increase the risk of credit card theft.

One prevalent technique for community mining is *graph partitioning*. Graph partitioning approaches try to split the whole graph into a predetermined number of clusters by optimizing the ratio between the within-community and between-community edges. The within-community edges for a certain community are the edges that occur inside that community. The between-community edges designate

the edges that connect different communities with each other. There are different techniques to achieve the optimal cut within a graph. One of such techniques is *Iterative Bisection*. A bisection splits the given graph into two groups using the minimum cut size. The cut size quantifies the between-community edges. The two groups that are connected by the minimum number of between-community edges are maintained. Each group is thereafter subdivided in two groups, and so forth. The process is iteratively repeated until the required number of communities is found. Graph partitioning methods often derive clusters of equal size to avoid separating one node with the lowest degree from all the others. Another technique is *spectral clustering* where the Laplacian eigenvectors and eigenvalues of the connectivity matrix are used to find the optimal cut to split the network into clusters or communities. To gauge a single split, a set of evaluation metrics are proposed:

MinCut: Given all possible splits, the MinCut evaluation metric will split the graph $\mathcal{G}$ in communities $\mathcal{S}$ and $\mathcal{T}$ where the weight of between-community edges is minimal. The objective function is then,

$$\Gamma_{MinCut} = \min \text{ Cut}(\mathcal{S}, \mathcal{T})$$

whereby $\text{Cut}(\mathcal{S}, \mathcal{T})$ indicates the sum of the weight of between-community edges. Remark that this metric does not take into account the size of the clusters. In the most extreme case, the optimal cut might be one that separates one node from the others.

RatioCut: The RatioCut metric evaluates a cut by including the size of the clusters, and can be seen as an improvement of the MinCut evaluation metric. In the end, the obtained clusters are more balanced. The corresponding objective function is then,

$$\Gamma_{RatioCut} = \min \text{ Cut}(\mathcal{S}, \mathcal{T}) \left(\frac{1}{|\mathcal{S}|} + \frac{1}{|\mathcal{T}|} \right)$$

with $|\mathcal{S}|$ and $|\mathcal{T}|$ the size of each community, favoring communities that have similar sizes and thus are more balanced.

MinMaxCut: a shortcoming of the previous metrics is that the within-community edges are neglected. The MinMaxCut takes both the between- and within-community edges into consideration. A graph $\mathcal{G}$ is split into communities $\mathcal{S}$ and $\mathcal{T}$ if both communities have a low weight of between-community edges and a high weight of within-community edges. The objective function is then

$$\Gamma_{MinMaxCut} = \min \text{ Cut}(\mathcal{S}, \mathcal{T}) \left(\frac{1}{\text{Cut}(\mathcal{S}, \mathcal{S})} + \frac{1}{\text{Cut}(\mathcal{T}, \mathcal{T})} \right)$$

with Cut($\mathcal{S}$, $\mathcal{S}$) the sum of the weight of the within-community edges. The difference with the RatioCut metric is that the MinMaxCut metric uses the number of edges to determine the cluster size, while the RatioCut metric uses the number of nodes.

A toy example is given in Figure 5.27. For all aforementioned metrics, the optimal cut divides the network in communities $\mathcal{A}$ and $\mathcal{B}$ as indicated in the figure. The MinCut($\mathcal{A}$, $\mathcal{B}$), RatioCut($\mathcal{A}$, $\mathcal{B}$), and MinMaxCut($\mathcal{A}$, $\mathcal{B}$) equal 4, $^7/_3$ and $^1/_3$, respectively.

Another algorithm to find communities in a network is the ***Girvan-Newman algorithm***. The algorithm progressively removes edges from the original graph, and is therefore a divisive hierarchical clustering algorithm. The edges with the highest betweenness are removed first. Note that in the Section Centrality metrics, betweenness is measured on node level. The betweenness of an edge is computed

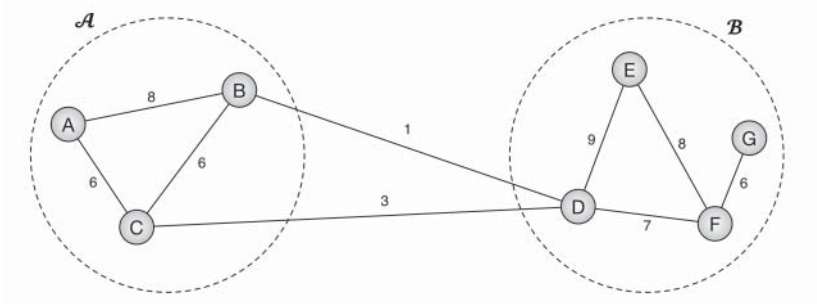


Figure 5.27 Iterative Bisection

as the number of shortest paths between pairs of nodes that contain the edge of interest. It starts from the idea that the communities of a network are connected by only a few edges. All shortest paths between nodes from different communities must go along these edges, which result in a high betweenness. The algorithm proceeds as follows:

1. Calculate the betweenness of all edges in the full network.
2. Remove the edge with the highest betweenness.
3. Recalculate the betweenness of the affected edges.
4. Repeat step 2 and 3 until no edges remain.

As with clustering, the result of the Girvan-Newman algorithm is a dendrogram. A dendrogram of the Girvan-Newman algorithm applied to Figure 5.27 is illustrated in Figure 5.28.

One major drawback of graph partitioning methods is that the number of clusters needs to be determined upfront which is often unfeasible for large networks. A metric that comes in very handy in assessing the optimal number of communities, is the *modularity Q*. The best community split is achieved when the modularity Q is maximized. The modularity Q evaluates a community split by identifying whether the nodes inside each community "communicate" to a higher extent to each other than to other communities. The modularity Q is computed as follows. Suppose we split the network into k communities. We now define a $k \times k$ symmetric matrix $\boldsymbol{E}$ where each entry $e_{i,j}$ specifies the fraction of all edges in the network linking nodes in community

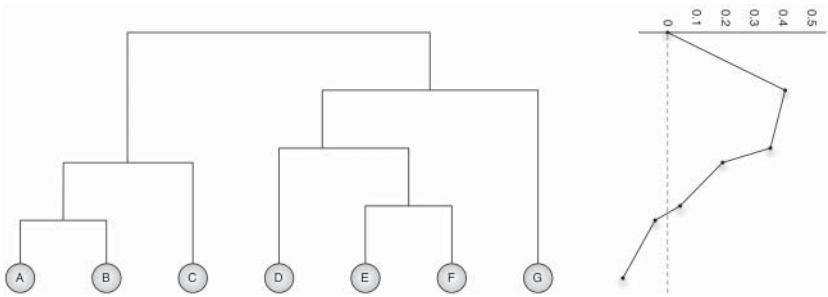


Figure 5.28 Dendrogram of the Clustering of Figure 5.27 by the Girvan-Newman Algorithm. The Modularity Q is Maximized When Splitting the Network into Two Communities ABC – DEFG

i to nodes in community j. The trace of this matrix is the sum of the diagonal elements

$$\text{Trace}(E) = \sum_{ii} e_{ii}$$

and represents the fraction of edges in the network that connect nodes in the same community. A good division into communities or modularity should have a high value for the trace. In case all nodes would be put in their own community, a maximal value of the trace equal to 1 would be obtained. Clearly, this is not desirable. Hence, let's define the row (or column) sum

$$a_i = \sum_j e_{i,j}$$

which represents the fraction of edges in the network connecting to nodes in community i. In case that the communities would be randomly connected, we would have $e_{i,j} = a_i \cdot a_j$. The modularity Q is then

$$Q = \sum_i (e_{ii} - a_i^2)$$

Hence, it measures the fraction of within-community edges in the network which is Trace(E) minus the fraction of within-community edges in a network that has the same communities, but with random connections between the nodes. For strong communities, Q will approach 1. The community split in Figure 5.27 has a modularity Q equal to 0.41, and is computed as follows

$$Q_{\mathcal{AB}} = \underbrace{\left(\frac{40}{108} - \left(\frac{44}{108}\right)^2\right)}_{\textbf{community } \mathcal{A}} + \underbrace{\left(\frac{60}{108} - \left(\frac{64}{108}\right)^2\right)}_{\textbf{community } \mathcal{B}}$$

The modularity Q is computed for each community split of the Girvan-Newman algorithm in Figure 5.28.

Upon applying community mining to a fraud context, we are interested in fraudulent communities instead of extracting all communities. That is, *bottom-up* approaches might be more suitable in contrast to top-down approaches as discussed above. In bottom-up clustering, one

starts with one node (e.g., a fraudulent node) and adds more nodes to the community based on the links of this node. The extracted communities can be either *complete* or *partial* communities. A complete community is a subgraph in the network where each node is connected to each other node in the subgraph. When constructing complete communities, a node is added to a community if it has a link to all the nodes in the community. An example of a complete community is given in Figure 5.29a. Partial communities are more loosely defined and do not require that each node in the subgraph is connected to each other node. A node is added to a partial community if it has connections to at least x% of all nodes in that community. A partial community is shown in Figure 5.29b.

Note that graph partitioning algorithms do not generate overlapping communities. These are communities where some nodes belong to more than one community. In graph partitioning, the graph is iteratively divided into small subgraphs that all have a set of unique nodes. These are the so-called *maximal* communities. Splitting a network in maximal or nonoverlapping communities is often not realistic. People are typically associated with different friend groups (e.g., from high school, the sport club, colleagues) with diverse backgrounds and beliefs. Overlapping communities reveal the various communities to which a certain person belongs. Bottom-up approaches are able to create overlapping communities. Figure 5.30 shows an example where node A belongs to different communities. While community $\mathscr{A}$ and $\mathscr{C}$ are "innocent" communities, community $\mathscr{B}$ is highly associated with

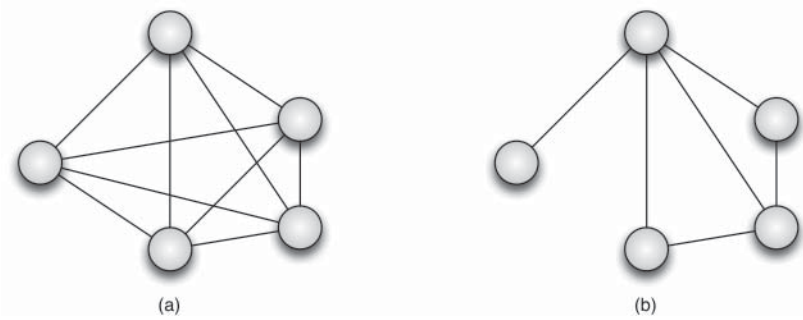


Figure 5.29 Complete (a) and Partial (b) Communities

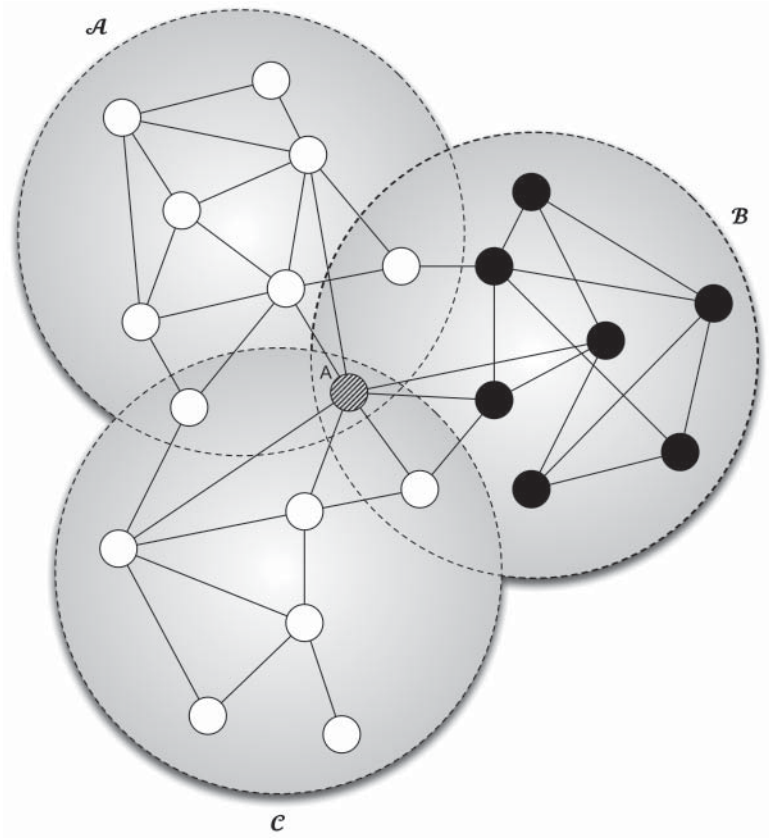


Figure 5.30 Overlapping Communities

fraud. A membership function describes the extent to which a node (here: a person) is influenced by fraud through its communities, and

$$M_A = \frac{1}{|\mathscr{C}_A|} \sum_{i \in \mathscr{C}_A} \xi_i$$

with M_A the exposure of node A to fraud, $\mathscr{C}_A$ the communities to which node A belongs and ξ_i the fraudulent influence of community i. The effect of one fraudulent community on a node is diminished if the node belongs to many legitimate communities. The membership exposure score can be used as a separate feature in the analytical modeling part.

EXTENDING THE GRAPH: TOWARD A BIPARTITE REPRESENTATION

All networks in the previous sections only consist of one node type representing for example, people connected to other people by means of a friendship relation. Such networks are *unipartite graphs*. The intensity of the relationship between the nodes in unipartite graphs often depends on the count of *shared events*. In call behavior data for example, two customers are more strongly connected to each other if they call each other more often. Co-authoring many papers with the same researchers defines a stronger relationship among them. Companies rely more on each other when they share more resources. In unipartite graphs, this information is aggregated in the link weight. The higher the weight, the more intense the relationship is. The link weight is often correlated with the influence that two objects have on each other. Two nodes are more influenced by each other if their relationship is more intense, and thus has a higher link weight. A unipartite graph of a people-to-people network is represented in Figure 5.31. The thickness of the links represents the edge weight. Specifically, the relationship between Paul and Lorian is stronger than the relationship between, say, Anna and Maria. Also, remark that there are two triangles in this network: Anna-Maria-Elsa and Lorian-Emilio-Gabby. Given the current representation, both triangles are equally sensitive to influence.

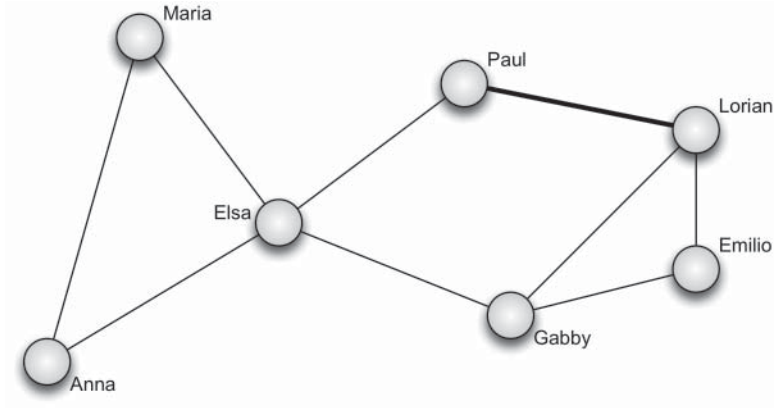


Figure 5.31 Unipartite Graph

In many applications, it might be useful to integrate a second node type in the network. *Affiliation or bipartite networks* represent the reason why people connect to each other, and include the events that network objects—like people or companies—attend or share. An event can for example refer to a paper (scientific fraud), a resource (social security fraud), an insurance claim (insurance fraud), a store (credit card fraud), and so on. Adding a new type of nodes to the network does not only enrich the imaginative power of graphs, but also creates new insights in the network structure and provides additional information neglected before. On the other hand, including a second type of node results in an increasing complexity of the analysis. The extended network representation of Figure 5.31 is depicted in Figure 5.32. Paul and Lorian are more closely connected to each other because they both attended two shared events. The triangle Maria-Anna-Elsa can quickly be influenced by fraud, as it is enough to disperse fraud through event 1. In order to affect the triangle Lorian-Emilio-Gaby, at least two events should be contaminated by fraud.

Mathematically, a bipartite graph is represented by an $n \times m$ connectivity matrix $\boldsymbol{M}$ with n and m the total number of people and events respectively. The rows specify type-one nodes, while the columns specify type-two nodes. The connectivity matrix corresponding to the bipartite network in Figure 5.32 is presented in Figure 5.33.

Recall that the edge weight in the unipartite graph of Figure 5.31 aggregates the frequency that both nodes were associated to the

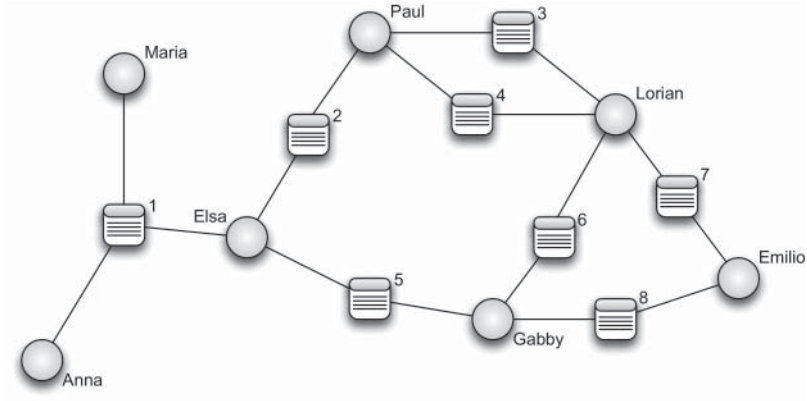


Figure 5.32 Bipartite Graph

	1	2	3	4	5	6	7	8
Elsa	1	1	0	0	1	0	0	0
Maria	1	0	0	0	0	0	0	0
Anna	1	0	0	0	0	0	0	0
Paul	0	1	1	1	0	0	0	0
Lorian	0	0	1	1	0	1	1	0
Emilio	0	0	0	0	0	0	1	1
Gabby	0	0	0	0	1	1	0	1

Figure 5.33 Connectivity Matrix of a Bipartite Graph

same event. In a bipartite graph, this is implicitly specified by the newly introduced node types. Instead of using a binary link between two node types in a bipartite graph (e.g., attended or not attended), the edge weights now allow to enrich the network with additional information, like the recency, the intensity, information exchange, and so on of the relationships between the people and the events. For example, the edge weight in Figure 5.32 might indicate the time person *x* spent at event *y*. Suppose that event 1 is a fraudulent event and that Maria attended event 1 longer than Anna. Maria is then more influenced by fraudulent event 1 than Anna. Another example is a credit card fraud network where credit card holders are connected to stores. A link between a credit card holder and a store exists if that credit card holder made a purchase in that store. The link weight might be proportional to the time passed since the transaction has been pursued and gradually decreases over time. The spread (or propagation) of influence, such as fraud, by collective inference algorithms as discussed in the section Collective Inference Algorithms is weighted over time. Nodes neighboring to a fraudulent node will be affected more intensively by fraud

if the relationship between the node and the fraudulent node is more recent.

Multipartite Graphs

Whenever a network integrates multiple node types, we say that the network is a multipartite graph or a multigraph. Those networks closely reflect the true reality, but simultaneously introduce a lot of complexity in the network. The network can quickly grow to immense sizes, and the need for scalable and efficient algorithms to process huge unstructured data sources is indisputable. Network sampling by splitting the network into small egonets, one for each node of interest, is one solution that can help to deal with scalability issues. Although the processing of such networks may be challenging, their visualization might shed light on new fraud patterns and result into valuable insights about which influentials play an important role in the spread of fraud through networks. An example of a multipartite graph is depicted in Figure 5.34.

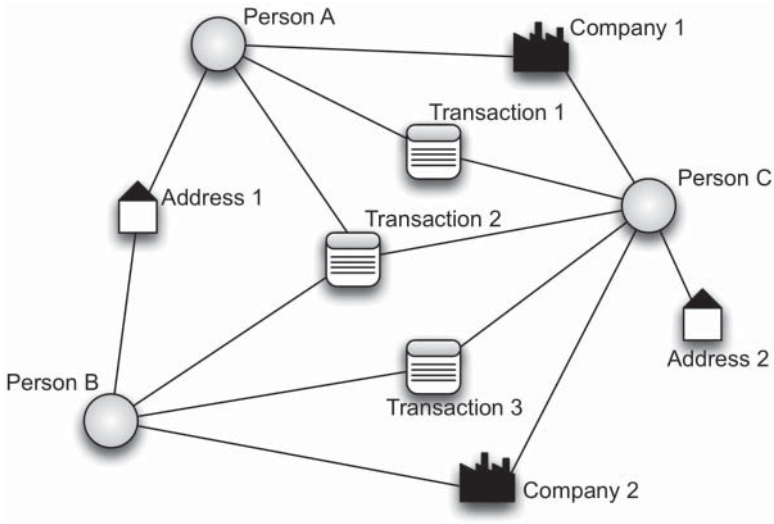


Figure 5.34 A Multipartite Graph

CASE STUDY

CASE STUDY: GOTCHA!

This section discusses a real-life application of network analysis for fraud detection (Van Vlasselaer et al. 2015a). The data under consideration are governmental tax data where companies try to avoid contributing their tax obligations. Companies use resources to perform their activities. Resources can be, for example, buyers, suppliers, customers, employees, machinery, accountants, etc. For reasons of interpretability, we do not distinguish between the different types of resources in the analysis.

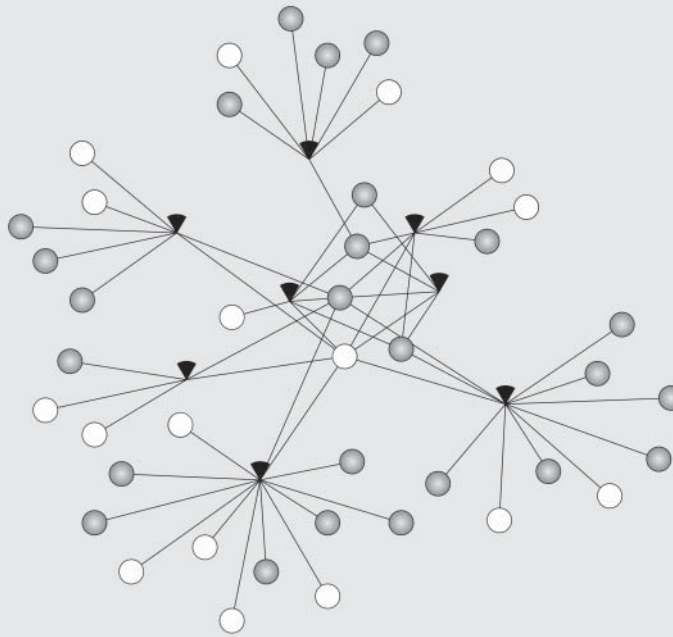


Figure 5.35 Sample Network of Gotcha!

A sample network is given in Figure 5.35. The companies and resources are represented by circles and wedges, respectively. Recall that this is a bipartite network. Rather than connecting the companies directly to each other by means of the resources they share, the resources are included in the network as separate entities. By doing so, the network reflects reality more

closely and provides more details about the intensity of the connections between companies and their resources. It will also be clear in the remainder of this section, that some resources are important instigators of fraud.

Given the experts' perceptions, companies set up illegal constructions to avoid tax contributions and closely work together to perpetrate fraud. In general, companies that are part of a fraudulent setup are organized in such a way that they do not gain enough profit to redeem their tax debts to the government. The real profit is pruned away by other companies in the setup. Once the company files for bankruptcy and is not capable of continuing its activities, the resources of the company are moved toward other existing companies, or to newly founded companies. The use of network analysis allows to follow the trail of resources from one bankrupt company to another, in order to uncover the fraudulent setups in the network. Those fraudulent setups are the so-called *spider constructions*. The companies in the spider construction form a web of fraud and are all closely connected to each other by means of the resources they share or transfer. The task at hand is then the following: Given a network of companies and resources, how can we use the label of a few confirmed fraudulent companies to infer a fraud probability for all the other (yet legitimate) companies in the network.

Gotcha! is a fraud detection technique designed to find individual company fraud by combining evidence from different sources: (1) the isolated environment of the company and (2) the relations among other companies. Gotcha! combines three types of data features:

1. **Intrinsic (or local) features**: these features comprise the characteristics of each observation (here: company) as if the observation was treated in isolation. Example features include the age of the company, the sector in which the company is operating, financial statements, address, and so on.
2. **Direct network features**: these features characterize the direct neighborhood or egonet of a company. Recall that the social security network is a bipartite graph of companies and resources. The direct neighborhood of a company is the company together with its current (and its past) resources. Remark, however, that fraud is only attributed to companies and that the resources and (yet) legitimate companies are initially unlabeled. Indirect network

features (see below) extract a primary indication of the fraudulence of each network object.

3. **Indirect network features**: a propagation algorithm is used to infer a fraud probability for each unlabeled resource and company. The propagation algorithm is based on Google's PageRank (see section PageRank Algorithm) and treats fraud as a virus moving throughout the network. A node in the network that is highly exposed to fraud receives a high *exposure score*.

Intrinsic features are extracted from the so-called *factual data sets* and *historical data sets*. A factual data set reflects the current situation of each observation. The factual data set in a social security context describes the as-is state of each company: In which sector is the company currently active? How long does the company already exist? Changes in the factual data set are kept in the *historical data sets*. Historical data sets log the previous states of the factual data set. For each company, the following past behavior is known: Did the company operate in another sector before? Did the company grow during the last x years, and if so, by how much? Those features characterize the company as if it was an isolated entity.

Transactional data sets comprise the interactions with other companies by means of their resources. Which resources were assigned to a specific company at what period in time? Remark that the transactional data set provides time-related data. Whereas a resource might be associated with a certain company in year t_2, it could be utilized by another company in year t_1. The transactional data set is used to create the network of companies and resources. As temporal information is available in the data set, the link weights between a company and a resource might express the recency of the relationship, varying between [0,1]. A link weight of 1 indicates a current association of the resource with the company. Rather than directly removing a past connection between a company and a resource, the link weight decreases over time using, for example, a linear or exponential decay. For example, a link weight of 0.8 might indicate that the resource was

associated to the company six months ago. This is *temporal weighing*. As such, the network dynamically adjusts over time.

Given the temporally weighted network of companies and resources, and knowing that a limited set of companies are labeled as fraud, a propagation algorithm infers an *exposure* score for each unlabeled network object. It implements an iterative approach where each resource and company simultaneously spread and absorb fraud. Recall that the network is bipartite. Each fraudulent company spreads fraud toward its neighboring resources. Each resource absorbs fraud from its neighboring companies. In a next phase, each resource spreads fraud toward its neighboring companies and each company absorbs fraud from its neighboring resources. This process is iterated until convergence or until a stopping criterion is met (see section Collective Inference Algorithms). As a result, each unlabeled node in the network receives an exposure score. The exposure scores of the resources are depicted in Figure 5.36. This figure represents the exposure score of the resources in terms of the number of fraudulent

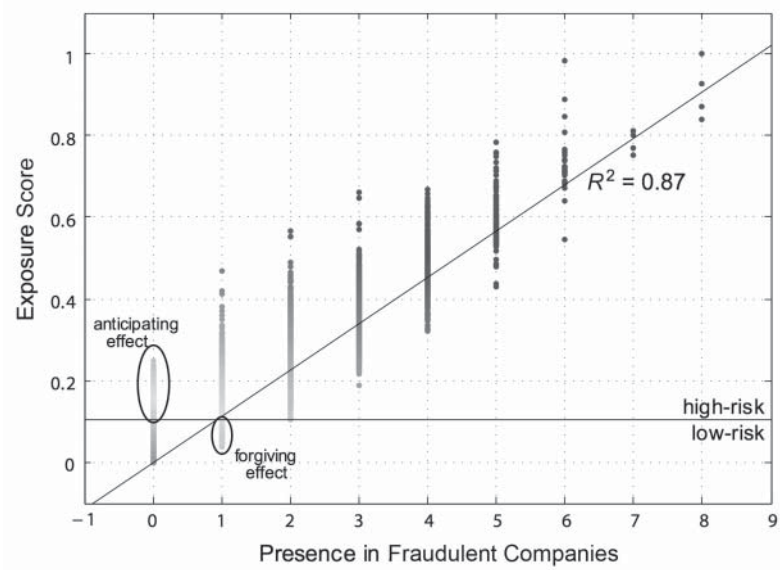


Figure 5.36 Exposure Score of the Resources Derived by a Propagation Algorithm. The Results are Based on a Real-life Data Set in Social Security Fraud

companies they were associated with. There is a positive correlation between the derived exposure score and the association to fraudulent companies. However, some resources receive a rather high exposure score although they were never connected to fraudulent companies. This is the *anticipating effect* and takes into account that fraud is approaching the resource node. On the other hand, some resources that were associated to fraud receive a low exposure score. This is the *forgiving effect* and is due to the incorporation of time into the network. The exposure scores of the companies can be used as an indirect network feature. The exposure scores of the resources are used to characterize the direct neighborhood of each company to infer the direct network features.

The direct network features characterize a company based on its direct neighborhood or egonet. In a bipartite network, these are the resources associated with the company. An example of a company's egonet is given in Figure 5.37. Features derived from the egonet include among others the count or proportion of suspicious resources connected to the company. In Figure 5.37, suspicious resources are shaded. The company has two suspicious resources and a suspiciousness ratio of 1:3.

The combination of all features (i.e., intrinsic and network features) is fed to the machine learning algorithms. This is the Gotcha! model. As the creation of network features drastically increases the number of features to learn from, ensemble methods like Random

Figure 5.37 Egonet in Social Security Fraud. A Company Is Associated with its Resources

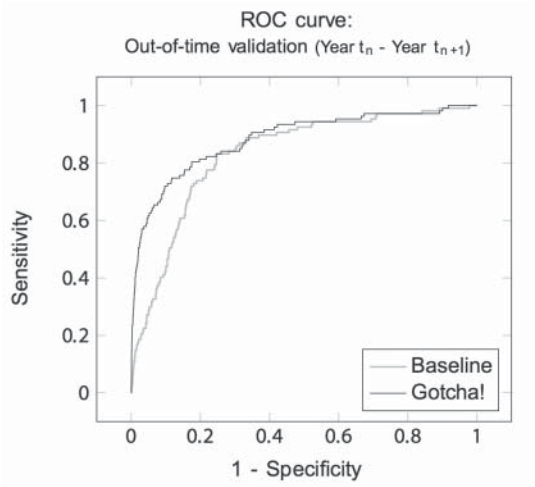


Figure 5.38 ROC Curve of the Gotcha! Model, which Combines both Intrinsic and Relational Features

Forest are used to train the models. Figure 5.38 shows the ROC curve for an out-of-time validation of the model. That is, the model is trained on timestamp t_n and evaluated on timestamp t_{n+1}. This is exactly how the model will be implemented in practice. The ROC curve shows that the model performs better when including network features (the Gotcha! model), then when solely relying on intrinsic features (Baseline). As fraud is often inspected manually afterward, only a limited number of fraudulent companies can be outputted by the models. Given that at each timestamp only 100 companies can be investigated by domain experts, how many fraudulent companies does the model actually detect? This corresponds to the model's precision (see Chapter 3). The results of an out-of-time validation are included in Table 5.14. Each model is evaluated according to the extent to which it is capable to detect fraud on short term (ST—fraud within six months), medium term (MT—fraud between six months and one year from now) and long term (LT—fraud after one year). The Gotcha! model outperforms the baseline for each time window of analysis. Furthermore, in the outputted list many bankruptcies are included. Recall how fraud is perpetrated through pruning away the profits of the company and filing for bankruptcy. Consequently, experts expect

Table 5.14 Overview of the 100 Companies with the Highest Score as Output by the Detection Model

		Total	ST Fraud	MT Fraud	LT Fraud	Total Fraud	Bankrupt	Nonactive	Active	% detected
Year t_1	Baseline	100	10	5	9	24%	24	16	36	48%
	Gotcha!	100	24	7	13	44%	27	5	24	71%
Year t_2	Baseline	100	6	2	11	19%	14	16	51	33%
	Gotcha!	100	18	5	14	37%	24	7	32	61%
Year t_3	Baseline	100	11	1	1	13%	4	4	79	17%
	Gotcha!	100	29	9	6	44%	15	4	37	59%

that the identified companies were undetected fraudulent companies. The remaining companies are investigated whether they are still active or not. Note that nonactive means that the company is regularly suspended and that all debts are redeemed. No fraud can be attributed to these companies. Given all confirmed fraudulent companies and the expectation of the experts that the found bankruptcies might also be fraudulent, the table indicates that the enrichment of traditional models (baseline) with network features might detect up to 71 percent fraudulent companies.

Gotcha! can easily be mapped to other fraud detection applications, like credit card fraud detection. The requirements of a fraud detection model in credit card fraud are stricter. In order to achieve sufficient Quality of Service (QoS) levels, credit card issuers apply a "six second rule of decision." This means that the processing of a credit card transaction might take at most six seconds. Most credit card transactions are liable to two checks: an acceptance check and a sanity check. During the first phase, the transaction processing system checks for example whether the user entered the right PIN or whether the spending amount is still sufficient. The sanity check often consists of an offline and online component. The offline check is not liable to the "six-second rule of decision" and is done when the transaction is already pursued. The online component happens in real-time, and decides whether the transaction contains signs of suspicious behavior. Network effects might have a huge impact on the detection model performance.

The network in credit card transaction fraud is a bipartite graph connecting merchants with credit card holders by means of transactions. Given a set of few fraudulent transactions, how can we

propagate fraud through the network? Collective inference algorithms initialize the *nodes* of the network. In credit card fraud, the edges are labeled. In order to introduce fraud in the network, one possibility is to include a new node type: the transaction. Every edge (transaction) in the network is replaced by a transaction node and two edges, to retain the connections between the merchant and the credit card holder. As a consequence, the labeled transaction nodes start the fraud propagation. Remark that fraud propagation affects all nodes in the network, and results in an exposure score for all merchants, credit card holders and transactions.

The network features are enriched with intrinsic features. An interesting approach in credit card fraud is to derive features using the RFM framework (recency, frequency, and monetary value). Given past transactional behavior of a certain customer (let's say, during the last day), RFM assesses for each transaction the (a) *recency* or the time passed since the previous transaction, (b) *frequency* or the number of transactions pursued, and (c) *monetary value* or the average amount of past transactions. A good approach is to derive the RFM variables at different levels of aggregation: merchant level, merchant category level, global level, country level, and currency level. Applied on the frequency, this means that one counts the number of transactions made at the merchant, the merchant category (e.g., groceries), overall, the country (e.g., Belgium) and the currency (e.g., euro). The combination of both intrinsic and network variables infers the Gotcha! model. Results have shown that the combined model achieves the best performance (Van Vlasselaer et al. 2015b).

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CHAPTER 6

Fraud Analytics: Post-Processing

INTRODUCTION

The result of the analytics step is an analytical fraud model built using either a descriptive, predictive, social network or combined technique. Essentially, the analytical model reduces to a mathematical formula predicting the fraud occurrence or fraud amount. In a next step, this model or formula needs to be integrated into the existing business environment and ICT architecture. In order to successfully complete this exercise, it is of key importance to perfectly understand the business requirements, which are usually specified by the end users of the analytical model(s). Furthermore, after the models have been put to work, they need to be closely monitored such that any deviation in performance due to changing fraud behavior can be detected in a timely way and corresponding actions can be undertaken. In this chapter, we will discuss various issues that arise when deploying, using, and monitoring analytical fraud models within a specific business context.

THE ANALYTICAL FRAUD MODEL LIFE CYCLE

In previous chapters, we discussed how to develop analytical fraud models using descriptive, predictive, and social network analytics. Once the model development has been completed, the analytical model can proceed to the next step in the model life cycle (see Figure 6.1).

During model testing, it will first be verified whether the model can satisfy all requirements needed to solve the business problem. For example, in a credit card fraud-detection setting, it will be verified whether the model can come up with a fraud score in a sufficient amount of time (e.g., less than 5 seconds). It can also be checked how the model behaves in case of missing or extreme inputs. Some dummy fraud cases can be used to verify the model's outcome.

Figure 6.1 The Analytical Model Life Cycle

Upon successful completion of the model testing, it can proceed to a staging step. Here, the model can run in parallel with the old model for a specific period of time (e.g., 1 month). A champion-challenger strategy can be adopted whereby the old model is the current champion and the new model the challenger.

In case the challenger beats the champion in performance, the model can proceed to the production step and the old model can be replaced. Various replacement strategies can be adopted. In a direct changeover strategy, the old model is immediately replaced by the new model. Obviously, this should be carefully planned by making sure all stakeholders have been appropriately informed and trained, and back-up facilities are available. Another alternative could be a phased-implementation strategy. The idea here is to gradually introduce the new model. For example, in a car insurance fraud setting, the new analytical model can be used to score all claims with claim amount below 5.000 euro, whereas the ones with claim amount above 5.000 euro are scored with the old model. If the new model works well on the low amount claims, it can then step-by-step be further migrated to handling all claim amounts.

Finally, a parallel strategy can also be adopted whereby the new and old model run in parallel in production during a transition period (e.g., 3 months). The overall fraud score is then a weighted combination of the scores of the new and old model, whereby gradually more weight is put on the new score such that at the end of the transition period the old score has been fully replaced by the new score.

The final step in a model's lifecycle is its retirement. The idea here is to bring the model out of the production environment and store it in a model repository, where it can be consulted later. Retired models can be useful for benchmarking or tracking purposes.

MODEL REPRESENTATION

When deploying a fraud analytics model, it is of crucial importance that the representation used is easily understandable and readable. Depending on how the analytical models were built, various representations

may be adopted. In what follows, we will discuss the traffic light indicator approach and decision tables.

Traffic Light Indicator Approach

A first way to represent the output of a fraud analytics model could be based on traffic light indicator coding (Van Gestel, Baesens, and Martin 2015). In this approach, colors are assigned to the outcome of the analytical model. These colors directly correspond to the probability of a customer being a fraudster. When using logistic regression, the outcome probabilities can be categorized and colors can be assigned to each category. This is illustrated in Figure 6.2. Green light indicates that the customer is low risk, whereas the red light corresponds to high probability of fraud. The colors in between can then be interpreted accordingly. The arrow shifts from left to right and indicates the color assigned to the customer under study. The number of colors and their encoding can be decided by the fraud analyst and business expert.

In many settings, a crisp decision is needed to classify an observation as fraudulent or not. A first alternative is to use a hard cut-off method. For example, the observation is considered a fraudster when the probability of fraud exceeds 0.5 and a nonfraudster otherwise. Alternatively, the fraud-scoring model can be used in semi-automated mode. The idea here is that observations belonging to the dark green, light green, orange, and red zone are automatically classified as nonfraudsters and fraudsters, respectively. The yellow zone is used as a referral zone, whereby these observations will be evaluated

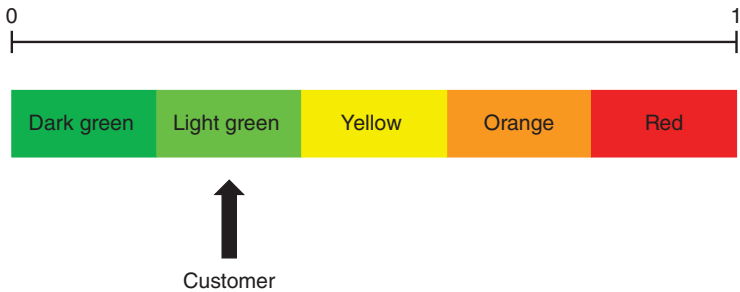

Figure 6.2 Traffic Light Indicator Approach

manually by one or more fraud analysts. These fraud analysts may then also decide to overrule the fraud scorecard.

Decision Tables

Decision tables provide an alternative way of representing rule-based patterns (Baesens et al. 2003; Mues 2002). These patterns can be obtained either from the business expert as If-Then business rules or from the data by using a decision tree or rule extraction algorithm for example.

Decision tables (DTs) are a tabular representation used to describe and analyze decision situations such as fraud detection, where the state of a number of conditions jointly determines the execution of a set of actions. The conditions correspond to the antecedents of the If-Then rules whereas the actions correspond to the outcome classes (e.g., customer = fraudster or not).

Essentially, a DT consists of four quadrants, separated by double-lines, both horizontally and vertically. The horizontal line divides the table into a condition part (above) and an action part (below). The vertical line separates subjects (left) from entries (right). The condition subjects are the criteria that are relevant to the decision making. Each condition entry describes a relevant subset of values (called a state) for a given condition subject (attribute), or contains a hyphen symbol (-) if its value is irrelevant within the context of that column. Every column in the entry part of the DT thus comprises a classification rule, indicating what actions apply to a certain combination of condition states. If each column contains only simple states (no contracted or irrelevant entries), the table is called an *expanded DT*. Otherwise, the table is called a *contracted DT*. Table contraction can be achieved by combining columns, which leads to the same action configuration. The number of columns in the contracted table can then be further minimized by changing the order of the conditions. It is obvious that a DT with a minimal number of columns is to be preferred because it provides a more compact and comprehensible representation of the extracted knowledge than an expanded DT. Let's illustrate this with an example in a fraud-detection setting.

Suppose we have the following set of eight If-Then rules to detect fraud in a credit card fraud detection setting.

If Suspicious merchant = yes **And** Transaction amount ≤ 1000 **And** Card present = yes **Then** Fraud = no

If Suspicious merchant = yes **And** Transaction amount ≤ 1000 **And** Card present = no **Then** Fraud = yes

If Suspicious merchant = yes **And** Transaction amount > 1000 **And** Card present = yes **Then** Fraud = yes

If Suspicious merchant = yes **And** Transaction amount > 1000 **And** Card present = no **Then** Fraud = yes

If Suspicious merchant = no **And** Transaction amount ≤ 1000 **And** Card present = yes **Then** Fraud = no

If Suspicious merchant = no **And** Transaction amount ≤ 1000 **And** Card present = no **Then** Fraud = yes

If Suspicious merchant = no **And** Transaction amount > 1000 **And** Card present = yes **Then** Fraud = no

If Suspicious merchant=No **And** Transaction amount > 1000 **And** Card present = no **Then** Fraud = yes

These rules can now be represented in an expanded decision table, as depicted in Table 6.1.

When inspecting the expanded decision table more closely, it can be seen that both columns 3 and 4, and columns 5, 6, 7, and 8 can be contracted, resulting into the contracted decision table as depicted in Table 6.2.

The size of the decision table can then be further minimized by rearranging the order of the conditions as represented in Table 6.3.

Table 6.1 Fully Expanded Decision Table

Suspicious merchant	Yes				No			
Transaction amount	≤1000		>1000		≤1000		>1000	
Card present	Yes	No	Yes	No	Yes	No	Yes	No
Fraud = yes		x	x	x		x		x
Fraud = no	x				x		x	
	1	2	3	4	5	6	7	8

Table 6.2 Contracted Decision Table

Suspicious merchant	Yes			No	
Transaction amount	≤ 1000		> 1000	-	
Card present	Yes	No	-	Yes	No
Fraud = yes		x	x		x
Fraud = no	x			x	
	1	2	3	4	5

Table 6.3 Minimized Decision Table

Card present	Yes			No
Suspicious merchant	Yes		No	-
Transaction amount	≤ 1000	> 1000	-	-
Fraud = yes		x		x
Fraud = no	x		x	
	1	2	3	4

Note that the minimized decision table only has four columns or classification rules, which is a substantial reduction when compared to the original table, which had eight columns or classification rules. The minimized decision table also gives some interesting additional insights, which were not that obvious from the original rule set. As an example, it is now clear that if Card Present is No then the transaction will always be classified as fraud. Similarly, if Card Present is Yes and Suspicious merchant is No then the transaction will not be considered fraudulent.

It is already clear now that decision tables come in handy for visualizing rule sets in an intuitive and user-friendly way. They can also be used to check rule sets for completeness and anomalies. As an example, consider the following rule set in an insurance fraud setting:

R1. **If** Age < 25 **And** Unemployed = Yes **And** Recent claims > 3, **Then** Fraud = yes

R2. **If** Age < 25 **And** Unemployed = No **Then** Fraud = yes

R3. **If** Age ≥ 25 **And** Unemployed = Yes, **Then** Fraud = no

R4. **If** Age < 25 **And** Recent Claims ≤ 3, **Then** Fraud = no

Table 6.4 Decision Table for Rule Verification

Age	<25				≥25			
Unemployed	Yes		No		Yes		No	
Recent claims	≤3	>3	≤3	>3	≤3	>3	≤3	>3
Fraud = yes		x	x	x				
Fraud = no	x		x		x	x		
	1	2	3	4	5	6	7	8
	R4	R1	R2; R4	R2	R3	R3		

These rules can now be represented in a decision table as depicted in Table 6.4.

From the decision table, various anomalies can be observed. In column 4, both rules R2 and R4 apply, resulting in the conflicting action entries Fraud = yes and Fraud = no simultaneously. The decision table also indicates missing entries in columns 7 and 8 where no action is specified in case Age ≥ 25 and Unemployed = No. These anomalies should be addressed before the decision table can be used in a production environment.

Although decision tables provide powerful rule visualization and verification facilities, not many commercial tools are available that provide support for them. Amongst the most popular is Prologa. See https://feb.kuleuven.be/prologa/ for more details.

SELECTING THE SAMPLE TO INVESTIGATE

In many organizations, a fraud-detection system is being used as a decision support system that helps in selecting the suspicious cases that require further investigation, for instance by using a traffic light indicator system as discussed above. In other words, the system helps in allocating the limited amount of resources that are available to further (manually) inspect cases and to confirm whether or not they actually concern fraud, as discussed in Chapter 1.

The available resources are typically limited and set by the management based on qualitative or semi-quantitative grounds. Therefore, only a fraction of all (suspicious) cases can be further inspected. The aim of adopting a data-driven fraud-detection system is to allocate the

limited resources more efficiently, or in other words, to improve the *hit rate*. In this context, the hit rate is the fraction of actual fraudulent cases among the cases that are further investigated by the inspectors. A hit rate of 100 percent means that all inspected cases concern fraud, and as such indicates that very efficient use is being made of the available resources, since they are not being spent on investigating nonfraudulent cases. However, a high hit rate may as well indicate that too few cases are being investigated and as such point toward an insufficient amount of resources to be available to facilitate the effective investigation of all suspicious cases.

Typically, a fraud-detection system is used to score all cases and rank them from low to high suspiciousness. Subsequently, inspectors are provided a draft list of cases that are to be further investigated based on this ranking. In a next step, a further manual screening and selection is performed by the inspectors, primarily based on experience and expertise as well as plain common sense.

The inspectors may be familiar with some of the cases in the list, as well as the reasons why they are being scored high by the system. For instance, when a firm has been inspected only recently and was found not to commit fraud, this firm might still be ranked high because no change occurred with respect to the fraud score drivers (i.e., with respect to the data values that are used by the fraud detection model to calculate a risk score).

The first screening may also be based on a preliminary, high-level investigation that looks into the drivers underlying the high fraud score that was assigned to a case by the system. This preliminary investigation may look into which exact pieces of information have led the detection system to rank a particular case to be highly suspicious—in other words, look into why the case scores are high and subsequently analyze whether the high score effectively raises cause for suspicion. Either the particular nature of a case or just pure coincidence may cause a case to be scored as highly suspicious. A preliminary investigation may detect this, and as such avoid unnecessary inquiries to be performed. This allows the inspectors to focus on truly suspicious cases and increase the hit rate, efficiency, and effectiveness of the inspections. Note that in order for the scores to be interpretable for the inspectors, the model needs to be represented or implemented in a manner that facilitates and supports such preliminary investigation and screening.

When many cases among the highly scored cases concern, in fact, nonsuspicious cases, the system may have to be recalibrated, updated, or fully retrained, since it appears to be no longer very precise with respect to the ranking it provides. In fact, the expertise and experience used by the inspectors during such a screening and preliminary investigation should be captured as much as possible by the system, or built in the underlying model. This can be done by including the information that is used during the screening in the data set for model building or analysis.

A dynamic interface or dashboard allowing inspectors to drill down on information related to particular cases as well as into the model scores may help them conduct a meaningful screening based on the scoring of the system, and to select cases that require further investigation. As such, the system becomes a decision support system in the true sense of the word.

With respect to deciding on the amount of resources an organization should allocate to further investigate suspicious cases and fight fraud, several elements have to be taken into account. A quantitative approach could be adopted to guide this decision. A first and important step in such a quantitative approach concerns the attribution of monetary value or utility to each possible outcome or event. Investigating a case comes at a certain cost (e.g., time of the inspector), which may vary from case to case, depending on the complexity of the case and the amount of resources required to investigate the case.

When the investigated case concerns a nonfraudulent case, clearly not as much value or utility has been generated by the inspection as when the case would concern fraud. Still, some utility may be generated, in creating a scare-off effect and making fraudsters aware of the fact that inspections do take place. Although possibly challenging, a monetary value could and should be attributed to such an outcome, as well as to the detection and investigation of an effectively fraudulent case. To such a positive outcome, a utility can be attributed equal to the sum of a number of components:

- The fraud amount
- All involved costs such as legal costs, cost of investigation, cost of the fraud detection infrastructure, etc.

- A penalty or fine
- A noneconomic value attributed to detecting fraud, representing the social benefits associated with a reduction of fraud

Which of these elements or possibly other factors to take into account in calculating a utility for a detected fraud case, as well as the exact value to assign, depends on the particular setting and application.

On the other hand, a utility must be assigned to not investigating a nonfraudulent case (positive utility) and to not investigating a fraudulent case (strongly negative utility). The amount of resources that is spent on investigating cases will determine how many cases and, as such, how many of each of these four types of outcomes will occur. Therefore, a total utility can be calculated for each possible amount of resources allocated by multiplying the number of outcomes with the associated utility of the outcome. The amount of resources that are required to maximize the total utility represents the optimal amount from the utility perspective, and as such may provide guidance in deciding about how much an organization should invest in inspection resources.

The values of the outcome utilities will clearly have a direct impact on the optimal amount or resources according to this approach. Therefore, it is important to stress that they may and should include noneconomic value or utilities when meaningful. These noneconomic utilities, however, do have to be expressed in monetary units—for instance, the utility of not detecting a fraudulent case may be assigned a very high value, since this is unacceptable from a societal point of view. This, however, is not always straightforward and should be determined by senior management.

Next to the utilities associated with the different outcomes also the power of the detection model will determine the optimal amount of resources to invest. The more accurate the ranking and the stronger the ability to rank fraudulent cases highly, the more return the investigations will generate since more true fraudulent cases will be addressed.

This approach to maximize the return of the fraud investigations is similar to an approach adopted in marketing, where the optimal fraction of customers to target in a marketing campaign is determined based on the estimated returns and the involved costs and benefits, as

Table 6.5 Using the Expected Fraud Amount to Decide on Further Investigation

		Fraud Probability				
		0–0.2	0.2–0.4	0.4–0.6	0.6–0.8	0.8+
Fraud Amount	0–100	Do Not Investigate				
	100–500					
	500–2,000					
	2,000–5,000				Investigate	
	5,000+					

well as on the predicted probability to respond to the campaign, the incentive that is offered and the effect it resorts, together with the predictive performance of the model (Verbeke, Dejaeger, Martens, Hur, & Baesens, 2012).

A complementary approach to deciding which cases to further investigate is to rank cases by combining the fraud probability with the intensity of the fraud or fraud amount, and computing as such the expected fraud amount. The idea here is that if the fraud probability is high (e.g., 90%) but the fraud amount is low (e.g., 10 euros), then the expected fraud amount (e.g., 90% × 10 euros or 9 euros) is small, making it not worthwhile to start an investigation. On the contrary, when the fraud probability is low (e.g., 25%) and the fraud amount is high (e.g., 10,000 euros), then the expected fraud amount is high (e.g., 2,500 euros), and a further investigation can be considered. This is illustrated in Table 6.5, where the claim amount and fraud probability have been categorized. The stepwise black line indicates the separation between further and no further investigation.

FRAUD ALERT AND CASE MANAGEMENT

In case the analytical model flags a transaction or observation as suspicious an alert with corresponding priority should be triggered. The priority is set based on the severity of the fraud as predicted by the analytical model. Alerts can be generated on a 24/7/365 basis. Depending on the setting, the prioritized alerts can then be further manually inspected and processed by business experts working in investigative units. The assignment and routing of alerts to investigators can be done in an automated way by using a set of predefined business rules.

It may be decided that further follow-up is not necessary because the intensity of the potential fraud (e.g., claim or transaction amount) is below a specific threshold, hereby not justifying the cost of additional investigation.

In case further follow-up is desirable, all necessary actions to further mitigate the fraud should be taken first, followed by notifying the parties involved. Examples of actions could be: Block credit card or money transfer, deny access to resources, and freeze account. Next, the fraud victim(s) must be informed via phone call, SMS, or email. A fully automated multichannel strategy can be adopted. For example, send email first, followed by SMS if no reaction after 5 minutes, followed by a phone call if no reaction after 10 minutes. Finally, the fraudsters should be dealt with. In case of strong evidence, the fraudsters can be prosecuted although some firms might not prefer to do this because of bad publicity or because legal action is simply not possible. As an alternative, the firm might consider a settlement with the fraudsters.

Every fraud alert should be appropriately tracked using a case management environment, which accurately records all investigation workflows, documentation, communication between the parties involved and actions undertaken. Ideally, this should be implemented using a browser-based digital dashboard hereby facilitating real-time fraud alert monitoring and management oversight. Every investigator can log on to the case management environment and get a personalized list of activities to be performed depending on his/her expertise. Summary and detail reports can be generated. Popular examples are a confirmed fraud report (e.g., daily and monthly), suspicious activity report, fraud alert year-to-date activity report, fraud recovery report, fraud trends report, investigator performance report, heat maps showing geographical fraud hotspots, and so on. Also, a complete audit trail of each alert and/or case can be requested including an overview of which investigator performed what action. To facilitate the creation of the various reports, the case management environment should offer advanced visualization and summarization facilities. It should offer online analytical processing (OLAP) functionality to allow for multidimensional analysis with roll-up, drill-down, slice and dice operations as we discussed earlier in the chapter on data preprocessing. Ideally, it should also implement link analysis to

visually map and analyze the links between various alerts, entities, transactions, and so on.

Figure 6.3 shows an example of the SAS Social Network Analysis dashboard in a car insurance fraud detection setting. It shows various characteristics such as ClaimID, Alert Type, and Claim score.

As depicted in Figure 6.4, every claim can then be further investigated in terms of linked documents, linked entities, relevant suspicion rules, and so on.

The investigation can then be further augmented with link analysis as depicted in Figure 6.5.

It shows the links between various types of nodes such as claims, claimant, house address, car, bank account, and phone. Facilities can be provided to show how the network grows in time, both cumulative whereby previous links are maintained as well as marginal whereby only new links are visualized. This allows to uncover more complex fraud patterns and fraud rings. As an example, assume claimant A shares the same address, car, bank account, and phone as claimant B. If claimant A has filed a fraudulent claim before, then all new claims filed by claimant B should be flagged as suspicious and an alert must be generated since most likely, claimant A and claimant B are the same person. These complex fraud patterns can be easily visualized using link analysis. Furthermore, the link analysis should be complemented with other applications such as Google Street View. By clicking an address node representing the home address of the claimant or location of the car accident, an inspector can immediately verify whether it's legitimate or not.

The case management environment should also provide preconfigured templates for sending out automated correspondence (e.g., emails, SMS, voice calls). When relevant (e.g., in anti-money laundering), it should also allow the generation of regulatory compliance reports, which can then be sent to the federal or law enforcement authorities involved. This is especially useful in case legal prosecutions are pursued.

Finally, once a particular fraud alert case can be closed, the result of the investigation should be fed back to the analytical models. This will allow the loop to close and to determine whether any adjustments to the analytical fraud models are necessary.

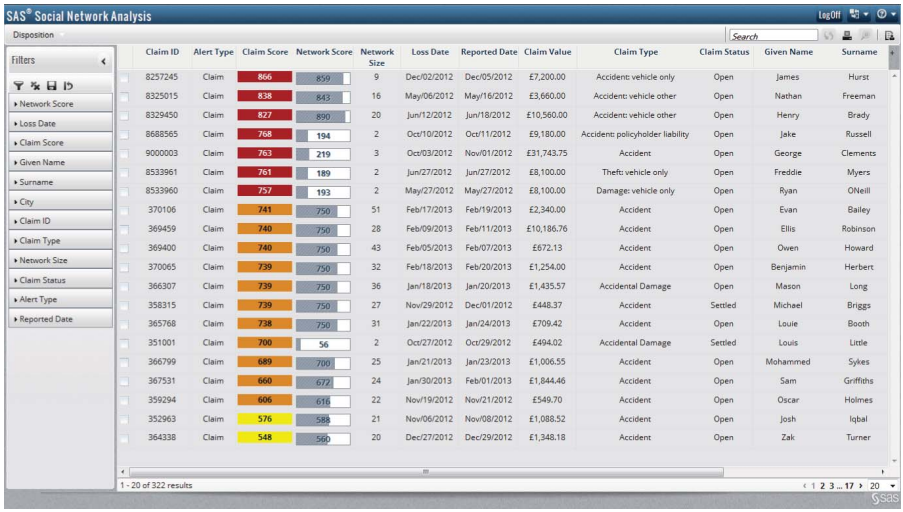

Figure 6.3 SAS Social Network Analysis Dashboard

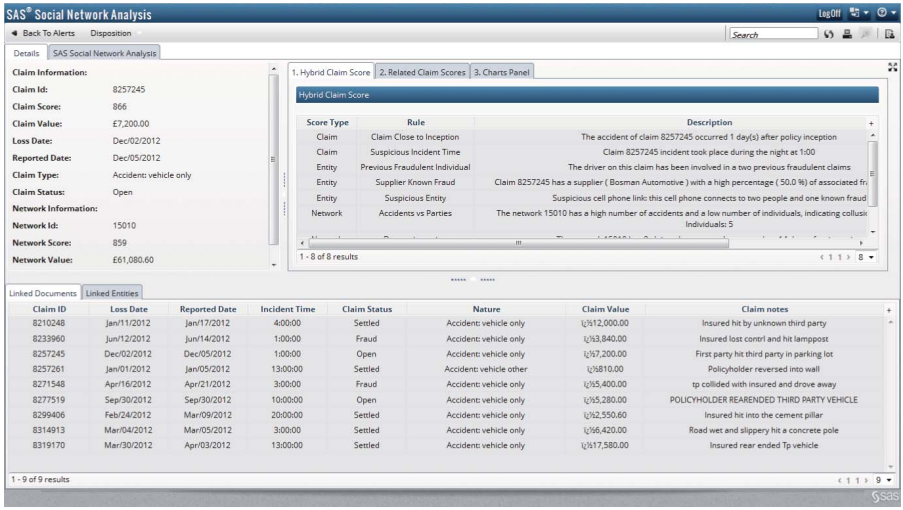

Figure 6.4 SAS Social Network Analysis Claim Detail Investigation

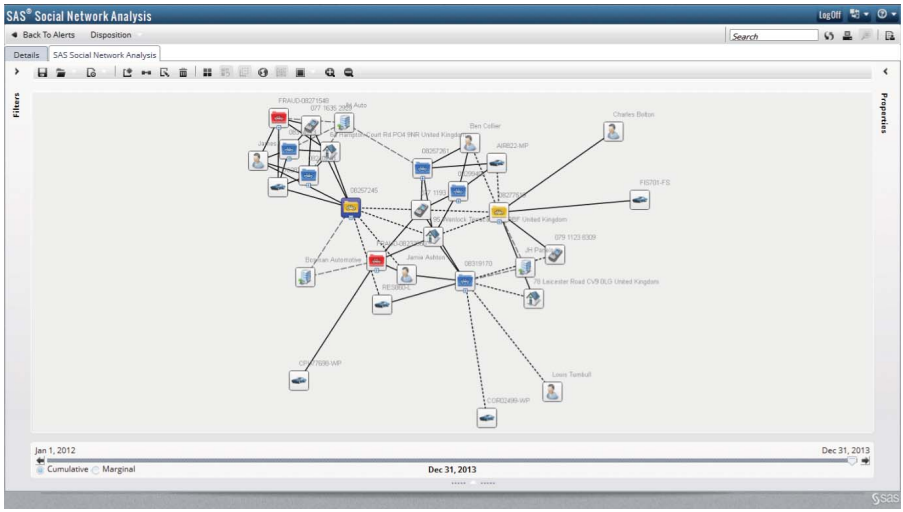

Figure 6.5 SAS Social Network Analysis Link Detection

VISUAL ANALYTICS

Visual analytics refers to the use of advanced visualization mechanisms supported by interactive interfaces to facilitate the various steps of the analytical model development, implementation, and monitoring process. It was originally introduced in the context of data preprocessing, such as to conduct exploratory data analysis, online analytical processing (OLAP) or multidimensional data analysis. It is nowadays also being actively used to support analytical model building and the post-processing activities. It has great potential for fraud detection, since it allows fraud analysts to disentangle complex fraud patterns hereby giving additional insights, which can then be appropriately translated to future fraud prevention strategies. Let's discuss an example of SAS Visual Analytics. Figure 6.6 shows an example of the distribution of claim counts and average claim value during October 2012 for a particular insurance company. You can immediately notice the peak in claims on day 20. When selecting this particular date, it can be seen in the pie chart left below in Figure 6.6 that most of the claims were filed due to a flood or storm event, whereas in the pie chart to the right, it can be seen that about half of the claims are still open and thus need to be processed further.

We can now further zoom into the flood-and-storm-related claims and look at the geographical distribution thereof. Figure 6.7 illustrates a map of France and its neighboring countries. The dots indicate geographical concentrations of flood and storm claims and are colored according to the average claim value.

It is then possible to drill down and look at specific regions and/or cities into more detail, as depicted in Figure 6.8.

We can also use visual analytics to evaluate the efficiency of the fraud detection process and identify performance bottlenecks. Figure 6.9 shows the distribution of the total number of investigated fraud claims and the corresponding hit rate for the year 2012, together with the fraud statistics by claim type and a pie chart of the fraud outcomes (fraud proven, fraud suspected, and investigated nonfraud).

Figure 6.10 shows a tree map displaying the efficiency of the fraud investigators. The size of the rectangles is proportional to the number

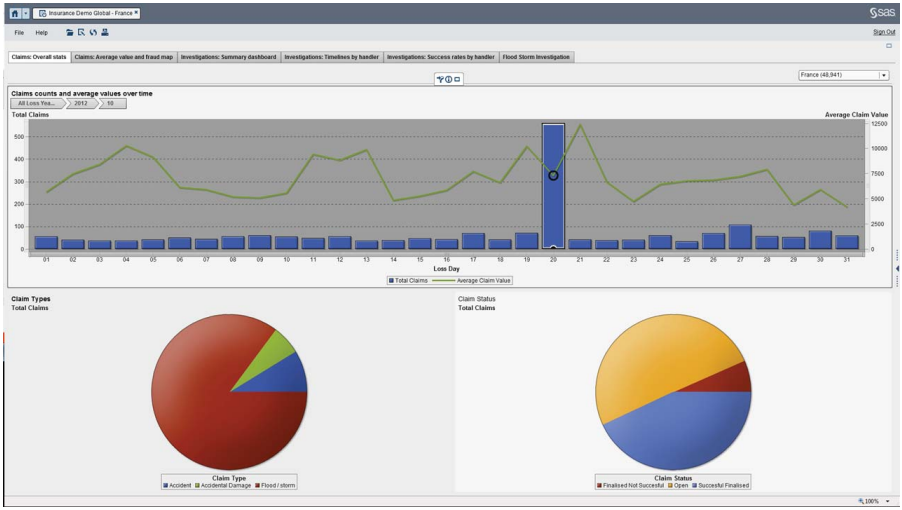

Figure 6.6 Distribution of Claim Amounts and Average Claim Value

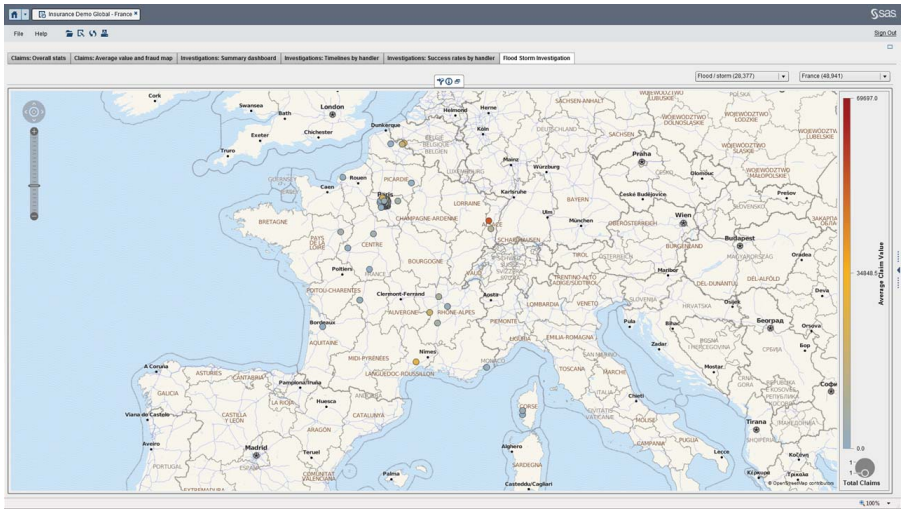

Figure 6.7 Geographical Distribution of Claims

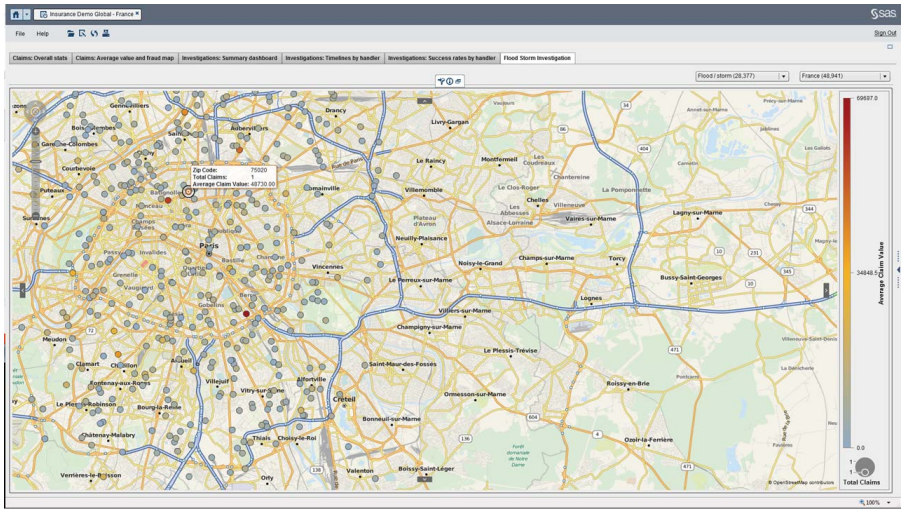

Figure 6.8 Zooming into the Geographical Distribution of Claims

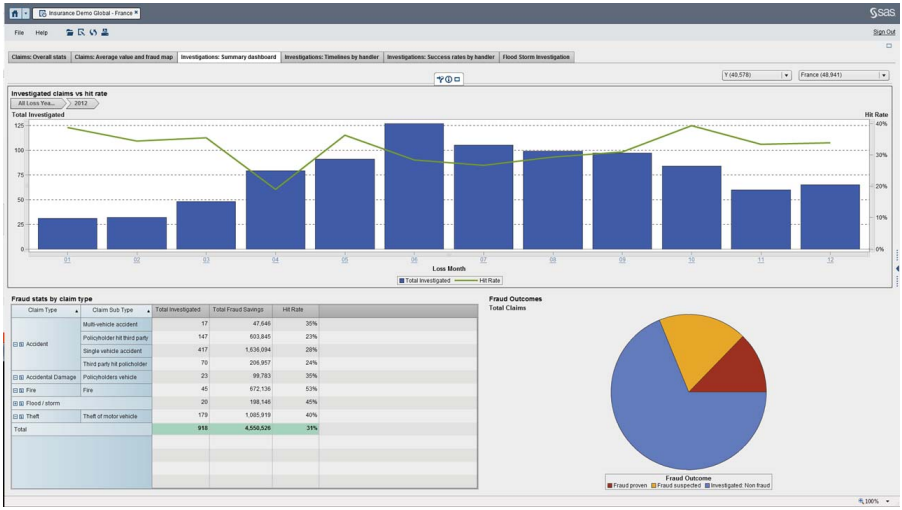

Figure 6.9 Measuring the Efficiency of the Fraud-Detection Process

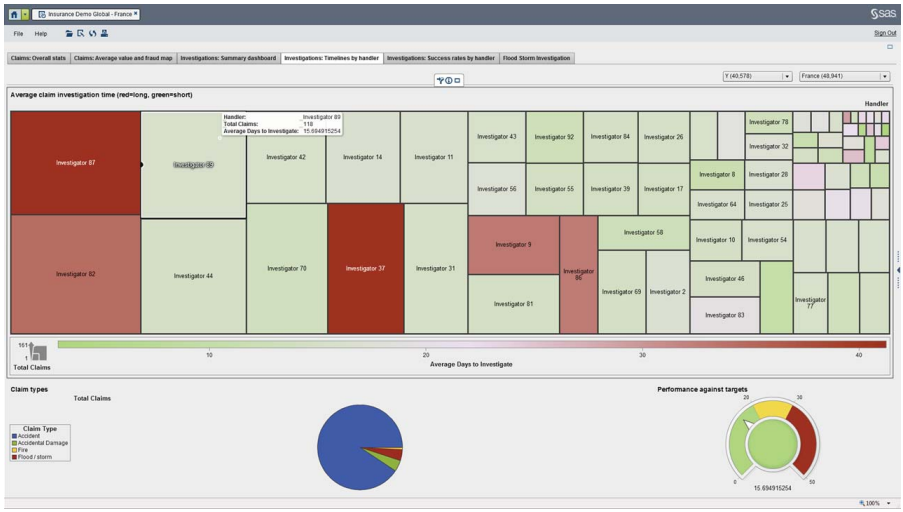

Figure 6.10 Evaluating the Efficiency of Fraud Investigators

of claims handled, whereas the color reflects the average days needed to investigate. For example, it can be easily seen that Investigators 87 and 37 take the most the time to investigate. The highlighted Investigator 89 handled 118 claims with an average of about 15 days. This corresponds to a good performance according to the gauge depicted in the lower-right corner.

BACKTESTING ANALYTICAL FRAUD MODELS

Introduction

Backtesting is an important model-monitoring activity that aims at contrasting ex-ante made predictions with ex-post realized outcomes (Baesens 2014). The key idea here is to verify whether the fraud model still performs satisfactory. Fraudsters will try to constantly outsmart fraud analytical models by continuously changing their strategies. This creates concept drift implying that the relationship between the target fraud indicator and the data available changes on an ongoing basis. Hence, it is important to closely follow-up the performance of the analytical model such that concept drift and any related performance deviation can be detected in a timely way.

Depending on the type of model and its purpose, various backtesting activities can be undertaken. In what follows, we will discuss backtesting data stability, model stability, and model calibration.

Backtesting Data Stability

When backtesting data stability, one should check whether internal or external environmental changes will impact the analytical model. Examples of external environmental changes are new developments in economic, political or legal environment, changes in commercial law, or new bankruptcy procedures. Examples of internal environmental changes are changes of business strategy, exploration of new market segments, or changes in internal organizational structure due to a merger or acquisition. Also, changing fraud patterns may give

instability problems. To backtest data stability, a two-step approach can be suggested, as follows:

- **Step 1:** Check whether the population on which the model is currently being used is similar to the population that was used to develop the model.
- **Step 2:** If differences occur in Step 1, verify the stability of the individual variables.

For step 1, a system stability index (SSI) can be calculated as follows.

$$SSI = \sum_{i=1}^{k} (observed_i - expected_i).\ln \frac{observed_i}{expected_i}.$$

This is illustrated in Table 6.6.

In case of a classification or regression exercise, the first column contains the categorized target value such as the predicted fraud score or predicted fraud amount. For a clustering exercise, the first column consists of the various clusters. The second column represents the distribution of the sample observed during training or model development. The third column gives the currently observed or actual

Table 6.6 Calculating the System Stability Index (SSI)

Score Range	Expected (Training)%	Observed (Actual)%	SSI
0–169	6%	7%	0.0015
170–179	10%	8%	0.0045
180–189	9%	7%	0.0050
190–199	12%	9%	0.0086
200–209	12%	11%	0.0009
210–219	8%	11%	0.0096
220–229	7%	10%	0.0107
230–239	8%	12%	0.0162
240–249	12%	11%	0.0009
250+	16%	14%	0.0027
	100%	100%	**0.0605**

population. The SSI then measures the difference between column 2 and 3. A higher SSI implies a population shift and instability. A practical rule of thumb is as follows:

- SSI < 0.10: no significant shift (green traffic light)
- 0.10 ≤ SSI < 0.25: moderate shift (yellow traffic light)
- SSI ≥ 0.25: significant shift (red traffic light)

Note that the system stability index is also referred to as the deviation index. It is identical to the information value measure discussed in Chapter 2 for variable screening.

It is also recommended to monitor the SSI through time as illustrated in Table 6.7. This will allow easy verification during which subsequent time periods instability issues started to arise.

When population instability has been diagnosed, one can then verify the stability of the individual variables. Again a system stability index can be calculated at the variable level as illustrated in Table 6.8. Note that also histograms and/or *t*-tests can be used for this purpose.

Table 6.7 Monitoring the SSI through Time

Score Range	Expected (Training) %	Observed (Actual) % at t	Observed (Actual) % at $t+1$
0–169	6%	7%	6%
170–179	10%	8%	7%
180–189	9%	7%	10%
190–199	12%	9%	11%
200–209	12%	11%	10%
210–219	8%	11%	9%
220–229	7%	10%	11%
230–239	8%	12%	11%
240–249	12%	11%	10%
250+	16%	14%	15%
SSI versus Expected		0.0605	0.0494
SSI versus $t-1$			0.0260

Table 6.8 Calculating the SSI for Individual Variables

	Range	Expected (Training)%	Observed (Actual)% at t	Observed (Actual) % at $t+1$
Fraud Amount	0–1,000	16%	18%	10%
	1,001–2,000	23%	25%	12%
	2,001–3,000	22%	20%	20%
	3,001–4,000	19%	17%	25%
	4,001–5,000	15%	12%	20%
	5,000+	5%	8%	13%
	SSI Reference		0.029	0.208
	SSI $t-1$			0.238
Years client	Unknown client	15%	10%	5%
	0–2 years	20%	25%	15%
	2–5 years	25%	30%	40%
	5–10 years	30%	30%	20%
	10+ years	10%	5%	20%
	SSI Reference		0,075	0.304
	SSI $t-1$			0.362

Backtesting Model Stability

Besides data stability, also the stability of the model needs to be evaluated and backtested. This refers to the volatility of the model performance. The idea here is to track the model performance using a report as depicted in Table 6.9. The first row contains the performance metric (PM), the number of observations on which it was calculated, the number of frauds and a corresponding traffic light as they were obtained during model development. Subsequent rows then represent how these numbers change during subsequent periods. Once a sufficient number of periods has been monitored, averages can be computed and contrasted (using, e.g., Student's t-tests) as indicated in the bottom two rows. The purpose of this report is to see when the model starts to degrade in performance and a new model needs to be built.

Table 6.9 Monitoring the Performance Metric of a Fraud Model

	Performance Metric (PM)	No. of Observations	No. of Frauds	Traffic Light
PM model				
PM year t				
PM year $t+1$				
PM year $t+2$				
…				
Average PM period 1				
Average PM period 2				

Obviously, the performance metric adopted depends on the goal of the model. In case of a classification model, the performance can be tracked by means of the area under the ROC curve, accuracy ratio, Kolmogorov-Smirnov statistic, top decile lift, and so on. For a regression model, the mean squared error (MSE), mean absolute deviation (MAD), correlation, area above the REC curve, and so on, can be used. In case of a clustering model, it can be monitored how the distance measures have changed on the new observations. This can be nicely summarized in an F-statistic comparing the intra-cluster similarity to the inter-cluster similarity. For association rules, the support and confidence of the rules on the new observations can be computed and tracked.

The traffic light coding procedure can be implemented in various ways. A first option is to look at absolute changes in the performance metric. As an example, the following procedure might be adopted:

- If the performance metric change is less than 5 percent, then assign green traffic light.
- If the performance metric change is between 5 percent and 10 percent then assign yellow traffic light.
- If the performance metric change is more than 10 percent then assign red traffic light.

Alternatively, also a bootstrapping procedure can be adopted. Since the theoretical distributions of most of the performance metrics (e.g., Area under the ROC curve, MSE, MAD, *R*-squared) are either unknown or hard to specify, it is not that straightforward to use them in a statistical way for backtesting. The idea of using bootstrapping is to statistically test the difference between a performance metric, PM, calculated on the training or model development data set, and the same PM measure calculated on an out-of-time test set. In other words, the null hypothesis H_0 becomes: $PM_{train} = PM_{out\text{-}of\text{-}time}$ and the two-sided alternative hypothesis then becomes $PM_{train} \neq PM_{out\text{-}of\text{-}time}$. The bootstrapping procedure then proceeds as follows (Loterman et al. 2014):

- Pool the training and out-of-time test observations with the predicted PM into one larger sample.
- Draw a training and a test set bootstrap sample with the same size as the original training and out-of-time test set. Remember, as discussed earlier, that a bootstrap sample is a sample with replacement. The same observations can thus occur multiple times in the bootstrap sample.
- Calculate the difference for PM between the bootstrap training and the bootstrap test sample.
- Repeat 1,000 or more times to get the distribution and statistically test whether the difference is zero.

This procedure will allow fraud analysts to obtain the distribution of the performance metric. A traffic light procure can then be adopted as follows:

- If no significant difference at the 95 percent level, then assign green traffic light.
- If significant difference at the 95 percent but not at the 99 percent level, then assign yellow traffic light.
- If significant difference at the 99 percent level, then assign red traffic light.

Depending on the application and/or business requirements, more or less traffic lights can be used.

Backtesting Model Calibration

In case of classification or regression models, the aim of the model might be to come up with well-calibrated estimates of fraud probabilities or fraud amounts. In this case, also the calibration itself needs to be monitored in time.

Let's assume that we have a classification model, which assigns fraud probabilities to various pools of customers. The pools can correspond to the leave nodes of a decision tree or can be the result of categorizing the outcome of a logistic regression or other predictive model. Each of the pools has a corresponding calibrated probability, as it was calculated during model development. The idea now is to see how these probabilities evolve in time and whether they remain stable. This is depicted in Table 6.10. The first row gives the calibrated fraud probabilities during model development for each of the pools. Subsequent rows then indicate the observed fraud rates for each of the pools during successive years. The bottom two rows depict averages for bigger time periods.

The binomial test is a popular statistical test to backtest the calibration of fraud probabilities. It assumes an experiment with only two outcomes (e.g., fraud or no fraud, in our case), whereby the experiment is repeated multiple times, and the individual outcomes are independent. Although the last assumption is not perfectly fulfilled in our fraud setting because of social network effects, as we discussed earlier,

Table 6.10 Monitoring the Calibration of a Classification Model

	Pool A	Pool B	Pool C	Pool D	Pool E	Pool F
Model fraud probability						
Observed fraud rate year *t*						
Observed fraud rate year *t*+1						
Observed fraud rate year *t*+2						
…						
Average observed fraud rate period 1						
Average observed fraud rate period 2						

the binomial test is often used as a heuristic for evaluating the quality of the calibration. It evaluates the following hypothesis:

H_0: The calibrated fraud probability $\hat{P}$ equals the true fraud probability P.

H_A: The calibrated fraud probability $\hat{P}$ is bigger/smaller/not equal to the true fraud probability.

Assuming a right-tailed test and given a significance level α, (e.g., $\alpha = 99\%$), H_0 is rejected if the number of frauds is greater than or equal to k^*, which is obtained as follows:

$$k^* = \min \left\{ k | \sum_{i=k}^{n} \binom{n}{k} \hat{P}^i (1-\hat{P})^i \leq 1-\alpha \right\}.$$

For large n, $n\hat{P} > 5$ and $n(1-\hat{P}) > 5$, the binomial distribution can be approximated by a normal distribution as $N(n\hat{P}, n\hat{P}(1-\hat{P}))$. Hence, we obtain:

$$P\left(z \leq \frac{k^* - n\hat{P}}{\sqrt{n\hat{P}\left(1-\hat{P}\right)}} \right) = \alpha,$$

with z a standard normally distributed variable. The critical value k^* can then be obtained as follows:

$$k^* = n\hat{P} + N^{-1}(\alpha)\sqrt{n\hat{P}(1-\hat{P})},$$

with $N^{-1}(\alpha)$ the inverse cumulative standard normal distribution. In terms of a critical fraud rate p^*, one then has:

$$p^* = \hat{P} + N^{-1}(\alpha)\sqrt{\frac{\hat{P}(1-\hat{P})}{n}}.$$

H_0 can then be rejected at significance level α, if the observed fraud rate is higher than p^*. Remember that the binomial test assumes that

all observations are independent. If the observations are correlated, then it can be shown that the binomial test has a higher probability to erroneously reject H_0 (type I error) so that's why it is often used as an early-warning system. It can be coded using traffic lights as follows:

- Green: no statistical difference at 90%.
- Yellow: statistical difference at 90% but not at 95%.
- Orange: statistical difference at 95% but not at 99%.
- Red: statistical difference at 99%.

The Hosmer-Lemeshow test is a closely related test that will test calibrated versus observed fraud rates across multiple pools simultaneously. It also assumes independence of the events and the test statistic is defined as follows:

$$\chi^2(k) = \sum_{i=1}^{k} \frac{(n_i \hat{P}_i - \theta_i)^2}{n_i \hat{P}_i (1 - \hat{P}_i)},$$

where n_i is the number of observations in pool i, $\hat{P}_i$ is the calibrated fraud probability for pool i, and θ_i is the number of observed frauds. The test statistic follows a Chi-squared distribution with k degrees of freedom. It can be coded using traffic lights in a similar way as for the binomial test.

To backtest the calibration of regression models, a parametric Student's t-test can be used. Table 6.11 gives an example report for monitoring a model predicting fraud amounts. Again, the output of the

Table 6.11 Monitoring the Calibration of a Regression Model

	Pool A	Pool B	Pool C	Pool D	Pool E	Pool F
Model fraud amount						
Observed fraud amount year t						
Observed fraud amount year $t+1$						
Observed fraud amount year $t+2$						
…						
Average observed fraud amount period 1						
Average observed fraud amount period 2						

regression model has been categorized into pools. As previously, these could be the leave nodes of a regression model or the result of categorizing the outcome of a linear regression or other analytical model.

A parametric Student's *t*-test can be used to evaluate the significance of the error defined as the difference between the amount predicted and observed. The *t*-test verifies whether the mean out-of-time error μ_E equals zero or not. The null hypothesis then becomes $H_0 : \mu_E = 0$ versus the alternative hypothesis $H_A : \mu_E \neq 0$. The test statistic is defined as follows:

$$T = \frac{\overline{e}}{\frac{s_e}{\sqrt{n}}}$$

and follows a Student's *t*-distribution with $n - 1$ degrees of freedom. Note that $\overline{e}$ represents the average of the error, and s_e the corresponding standard deviation. A *p*-value can then be computed and represented as a traffic light as discussed previously.

MODEL DESIGN AND DOCUMENTATION

All aspects related to the design of the fraud model should be well defined and documented. Some example questions that need to be answered from a model design perspective are:

- When was the model designed, and by who?
- What is the perimeter of the model (e.g., counterparty types, geographical region, industry sectors)?
- What are the key inputs and output(s) of the model?
- What are the strengths and weaknesses of the model?
- What data were used to build the model? How was the sample constructed? What is the time horizon of the sample?
- Is human judgment used, and if so, how?

It is important that all aspects of the model design, usage, and monitoring are appropriately documented. A model manual with accompanying FAQ section should also be available. All documentation should be transparent and comprehensive. It is advised to use document management systems with appropriate versioning facilities to keep track

of the different versions of the documents. An ambitious goal here is to aim for a documentation test, which verifies whether a newly hired analytical team could use the existing documentation to continue development or production of the existing analytical fraud model(s).

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CHAPTER 7

Fraud Analytics: A Broader Perspective

INTRODUCTION

In this chapter, we will zoom out on fraud analytics and discuss some issues from a much broader perspective. The availability of more and more data across a diversity of channels along which a customer interacts with a firm necessitates a thorough reflection about two key issues: data quality and privacy. This is especially relevant for a mission critical application like fraud detection. A key usage of analytical fraud-detection models is the calculation of both expected and unexpected fraud losses, which serve to determine a company's provisions and equity buffers. A thorough economical insight into the total cost of ownership and return on investment of analytical fraud models is also required from both a managerial and investment perspective. Both will be key inputs to decide whether a company should build the analytical skillset in house, or consider outsourcing as an alternative. We also briefly zoom into some modeling extensions such as text analytics and forecasting, and discuss the impact of the Internet of Things on fraud. The chapter is concluded with a discussion about corporate fraud governance.

DATA QUALITY

Data-Quality Issues

A broad perspective toward data quality covers both the fitness of data for its intended use as well as the correctness of the data with respect to representing, describing, or measuring real-world entities or events. The fitness of its use will not be discussed in depth in this section, since it was already covered in this book when discussing sampling methods as well as input selection procedures.

Also, the correctness of the data has been discussed before in the data preprocessing chapter, when discussing methods to prepare data for further analytical processing and dealing with issues such as missing values, outliers, etc. Indeed, issues such as missing values and outliers may be indicative for poor data quality.

Quality of data is key to the success of any analytical exercise, in the sense that the quality of the data has a direct and measurable impact

on the quality of the results—in our case, on the ability to detect fraud. The importance of what data quality is in essence about is captured by the well-known *GIGO,* or *garbage in, garbage out* principle.

Most organizations are becoming aware of this importance and are acting to improve data quality along with the increased awareness and use of the potential benefits of leveraging big data and analytics. However, improving and managing data quality often turn out to be harder than expected, more costly than planned, and definitely not a one-off project but, rather, a lasting challenge.

The causes of data-quality issues are often deeply rooted within the core organizational processes and culture, as well as the IT infrastructure and architecture. Whereas often only data analysts are directly confronted with the consequences of poor data quality, resolving these issues and importantly their causes typically involves and requires cooperation and commitment from almost every level and department within the organization. It most definitely requires support and sponsorship from senior executive management in order to increase awareness and setup data-quality governance structures to tackle data quality in a sustainable and effective manner, as well as to create incentives for everyone in the organization to commit and take their responsibilities.

Data-Quality Programs and Management

Data preprocessing activities such as handling missing values are *corrective* measures for dealing with data-quality issues. These are, however, short-term remedies against a lasting disease, and data analysts will have to keep applying such solutions until the root causes of the issues they are confronted with are resolved. In order to do so, data-quality programs may be developed that in the first instance aim to detect issues as if looking for possible symptoms of a disease. A logical next step, then, is investigating these issues and, more specifically, how exactly these have been caused or where they originate from, in order to find and resolve the problems at their very origin and, as such, to take *preventive* actions in complement of corrective measures.

A wide range of data-quality indicators can be designed and evaluated to detect possible issues with data, covering different aspects of the

broad concept *quality* as well as taking into account the proper nature of the data and the particular context at hand. A good set of indicators preferably has a high detection power and a low false alarm rate. A high detection power allows detecting almost any possible issue with the data, and a low false alarm rate ensures that the indicators do not falsely warn us about issues that in fact do not exist. As such, a good set of indicators allows us to direct our efforts and investigations into data-quality root causes in an efficient manner (in fact, almost as if these concerned fraud). However, designing such a good set of indicators is a challenging task, since the selection of the optimal set and the exact definition of the indicators should be customized to the data and the particular context.

A large body of literature exists providing extensive listings of data-quality indicators, covering different aspects of quality such as accuracy, completeness, timeliness, and so on. For further information, one may refer to a seminal book on data-quality assessment authored by Maydanchik (2007). A powerful detection system by itself is, in fact, powerless and will not resolve data-quality issues. Therefore, a data governance structure should be put in place assigning clear roles and responsibilities with respect to data quality. We will discuss briefly two roles that are essential in rolling out a data-quality program and structure—that is, *data stewards* and *data owners*.

Data stewards are data-quality experts who are in charge of assessing data quality by performing extensive and regular data-quality checks. These checks involve, among other evaluation steps, the application or calculation of the data-quality indicators. Clearly, they are also in charge of taking initiative and to further act on the results of these assessments. A first type of action to be taken is the application of corrective measures. However, data stewards are not in charge of correcting data themselves—this is the task of the data owner. Every data field in every database in the organization indeed should be *owned* by a data owner, who is able to fill in or update its value, which means that the data owner has knowledge about the meaning of the field and can look up the current correct value (e.g., by contacting a customer, by looking into a file). Data owners can be requested

by data stewards to check or complete the value of a field, as such correcting the issue.

A second type of action to be taken on the results of the data quality assessment by the data stewards concerns a deeper investigation into the root causes of the data-quality issues that were detected. Understanding these causes may allow designing preventive measures that aim at eradicating data-quality issues. Preventive measures may include for instance modifications to the operational information systems where the data originate from, for example, making fields mandatory, providing drop-down lists of possible values, and rationalizing the interface. Also, values entered in the system may immediately be checked for validity and the user requested to correct if not. For instance, a corporate tax portal may require employees to be identified based on their social security number, which can be checked in real-time by contacting the social security number database. Implementing such preventive measures will obviously require the close involvement of the IT department in charge of the application.

Although designing and implementing preventive measures will initially require more effort in terms of investment, commitment, and involvement than applying corrective measures, they are the only type of actions that will improve data quality in a sustainable manner, and as such the return on investment in analytics and big data.

PRIVACY

Privacy of data is an important concern when developing, implementing, using and maintaining fraud detection models. In general, there are two parties involved: the business and the data scientists. The ownership of the data is acquired by the business. This means that the business has a complete view of the data, how it is collected and how they have to interpret the data attribute values. Data scientist are not provided with the full data set, but only the data that might be useful for the detection models. It is the business that decides which data the data scientist may see and use, for how long, and on which level of detail.

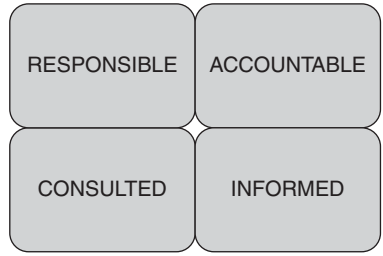

Figure 7.1 RACI Matrix

The RACI Matrix

The different roles in model development can be fit into the RACI matrix (see Figure 7.1). According to Drugescu and Etges (2006), the acronym RACI stands for:

- ***Responsible***: Whoever is responsible to develop the fraud detection model. These are the data scientists. The data scientists need to get the necessary input from other parties.
- ***Accountable***: This role refers to the people who delegate the work and decide what should be done. They approve the task at hand and provide the required data to the data scientists. This part is especially fulfilled by the business (e.g., the management, government).
- ***Consulted***: Often, a profound domain expertise is necessary to tune and polish detection models. Experts and (field) inspectors advise the business and data scientists with their valuable expertise and insights.
- ***Informed***: Certain people should be kept up-to-date of the output of the work, as the result might impact their working process. Customer service, for example, has to be informed about the changes in fraud detection and investigation.

Remark that the role of certain people can overlap (e.g., business people that also fulfill the consulting role) and change over time (e.g., certain inspectors are consultants in earlier phases of model development and should only be informed during later phases). As the RACI matrix is dynamic, the different roles should be reevaluated

on a regular basis. The RACI matrix can be extended to the RASCI or CAIRO matrix. The RASCI matrix includes the role of support (S) to indicate whoever helps to complete the fraud detection model. Out-of-the-loop (O) explicitly leaves specific people out of model development in the CAIRO matrix.

Accessing Internal Data

Before a data scientist starts an analysis for the development of fraud detection models, s/he has to file for a *data access request*. The data access request specifies what data are needed for which purpose and for which time period. A request to access internal data is approved by the internal privacy commission of the company. The privacy commission investigates whether the request can be granted or not, and answers the following questions:

- *Which variables are sensitive?*
  - Action: Anonymization
- *Which variables (columns) and instances (rows) should be shared?*
  - Action: Creating SQL views
- *Which user or user group should be authorized to access the data?*
  - Action: LBAC

Anonymization

Anonymization is the process of transforming sensitive data attributes such that the exact value cannot be recovered by other parties like the data scientist. Unique or key attributes are often converted into other (numeric) values. Key attributes are needed to link different databases to each other. For example, a company's VAT number uniquely identifies the company in various databases. The VAT number is a public given which is available in many other data sources, like on the company's website, in company registers, etc. Providing the VAT number enables to de-anonymize and identify the company. The conversion of a VAT number into another random number (ID) prevents the misuse of the data. The untransformed key is the *natural key* and reveals the true identity of the instance. The *technical key* is a conversion of the

natural key such that databases can be joined with each other, but protects the true identity of the instance. Remark that it is extremely important to preserve consistency among the different databases. The conversion of a natural key (e.g., VAT number) in database A should result in the same technical key as the conversion of the natural key (VAT number) in database B. Also, the conversion should be random and cannot follow the order in which the data appears in the database. New data instances are often inserted at the end of the database. In our company example, this means that the oldest companies appear at the top of the list, while the youngest companies end the list. Incrementally increasing the ID value is therefore strongly discouraged, as this can reveal the sequence in which companies were founded.

To anonymize other attributes, different techniques can be used:

- Aggregation
- Discretization
- Value distortion
- Generalization

If the privacy commission approves the request, they decide whether to provide raw or aggregated data. *Aggregated* data reports summary statistics of the data without compromising data about individuals. Summary statistics that are derived include a.o. minimum, mean, maximum, standard deviation, *p*th percentile, count, and so on. Raw data contains data of each individual/instance in the data set. In order to preserve privacy of raw data items, the data should be further anonymized.

Anonymization of numeric attributes can be achieved by *discretization*. Instead of specifying the exact value of each attribute, the attribute is partitioned into a set of disjoint, mutually exclusive classes (Agrawal and Srikant 2000). For example, rather than providing the exact income of a person, the income can be discretized by specifying the interval in which the value lies. Those intervals (mean, quantiles, quintiles, deciles, etc.) can be defined using an internal mapping schema or regional, national, or global summary statistics.[1] Alternatively, data

[1]Summary statistics for countries in the EU can be found at http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=ilc_di01&lang=en.

can be anonymized by adding noise to sensitive data attributes. *Value distortion* is achieved by returning a value $x_i + e$ instead of x_i (Agrawal and Srikant 2000). The value of e is randomly drawn from a predefined distribution (e.g., uniform, Gaussian …). Another approach is to *generalize* a specific value description into a less specific but semantically consistent description (Fung et al. 2007). The use of address records, for example, might positively impact the fraud detection models, but allows to identify a person/company. Therefore, the address is generalized into the corresponding city, region, country, etc. (In Van Vlasselaer et al. 2015) credit card fraud detection models are fed with three dummy attributes to express the locational information of the transactions on three levels: the transaction is pursued in (1) the issuing country, (2) the European Union, or (3) the rest of the world (ROW).

Figure 7.2 illustrates the anonymization process for social security fraud (i.e., tax evasion by companies). The business has two databases at their disposal. One contains the company's demographics, the other reports the company's personnel records. Both databases are linked to

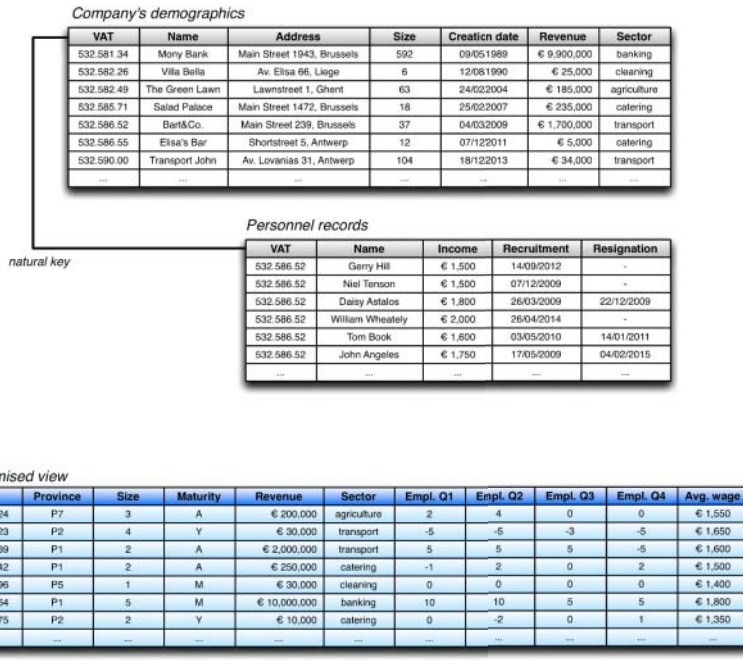

Figure 7.2 Anonymizing a Database

each other by means of the VAT number. Before they can be used safely by the data scientists, the databases need to be anonymized. The company's demographics are converted as follows: The VAT is converted into a new identifier (ID), randomly chosen. The name of the company is excluded from the data scientists' view. The company size is categorized in discrete intervals ranging from 1 to 5. The creation date is converted into three categories: young, adolescent, and mature. The mapping of both the size and the age is defined by the business, but is concealed for the data scientists. The value of the company's revenue is distorted by rounding the revenue using experts' domain knowledge. The address is generalized into the province. The sector is directly included in the view without any changes. The company's personnel records are aggregated on company level. It now specifies quarterly employee turnover, and their average wage. Remark that the rows in the anonymized table are sorted according to the randomly generated ID, and do not follow the sequence of the base tables.

SQL Views

SQL views enable users to extract part of the data tables and share the data authorized by the internal privacy commission. SQL views can be seen as virtual tables, without physical data (see Figure 7.3). A view definition consists of a formula that determines which attributes from the *base tables* are to be shown on invocation of the view. The view's content is generated on this invocation. The SQL view corresponding to Figure 7.2 is created as follows:

```
CREATE VIEW FRAUD_INPUT
AS SELECT C.ANON_VAT, C.PROVINCE, C.ANON_SIZE,
C.ANON_REVENUE, C.SECTOR, C.ANON_AGE, AVG(P.WAGE),
COUNT(*)
FROM COMPANIES C, PERSONNEL P
WHERE C.ANON_VAT = P.ANON_VAT
GROUP BY C.ANON_VAT;
```

Some views can be updated by the user (here: the data scientist). In that case, the view serves as a "window" through which updates are propagated to the underlying base table. *Updatable views* require that INSERT, UPDATE, and DELETE instructions on the view can be

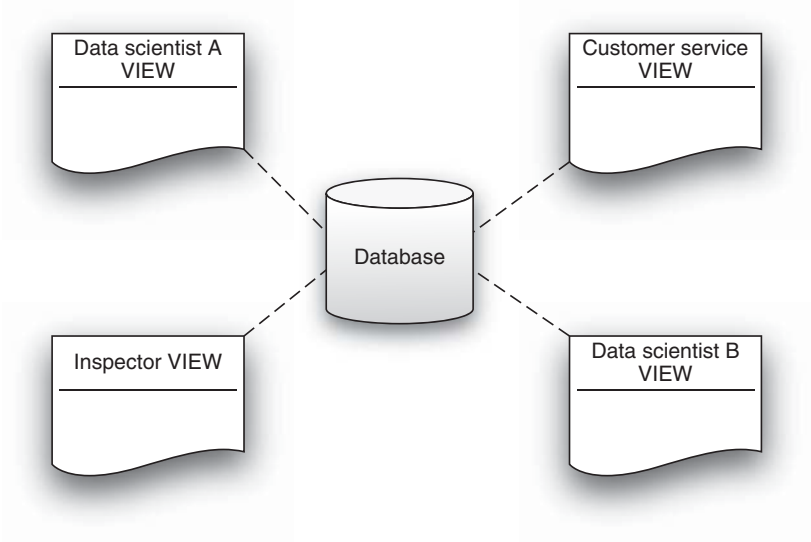

Figure 7.3 Different SQL Views Defined for a Database

mapped unambiguously to INSERTs, UPDATEs, and DELETEs on a base table. If this property of an unambiguous mapping does not hold, the view is *read only*. If rows are inserted or updated through an updatable view, there is the chance that such row does not satisfy the view definition after the update (i.e., the row cannot be retrieved through the view). The WITH CHECK option allows users to avoid such "unexpected" effects: UPDATE and INSERT statements are checked for conformity with the view definition. Assume, for example, that data scientists only have access to data from the transport sector. The corresponding view WITH CHECK option then becomes

```
CREATE VIEW FRAUD_INPUT
AS SELECT C.ANON_VAT, C.PROVINCE, C.ANON_SIZE,
C.ANON_REVENUE, C.SECTOR, C.ANON_AGE, AVG(P.WAGE),
COUNT(*)
FROM COMPANIES C, PERSONNEL P
WHERE C.ANON_VAT = P.ANON_VAT AND C.SECTOR =
'TRANSPORT'
GROUP BY C.ANON_VAT
WITH CHECK OPTION;
```

If the user changes the sector to, for example, "construction," the tuple will disappear from the view without a WITH CHECK option. The WITH CHECK option prevents this type of behavior.

Label-Based Access Control (LBAC)

LBAC is a control mechanism to protect your data against unauthorized access and is able to differentiate between the level of authorization that is granted to users. LBAC can be used to grant read and write access to specific tables, rows, and columns. For example, data items (e.g., individual rows) that are inserted by users with a higher security level cannot be seen by users with a lower security level. The use of LBAC comes in very handy when there are many views on a table, and when specific users can only access data with the same security level or lower. LBAC is implemented on databases by many governments and companies that use hierarchical classification labels such as CONFIDENTIAL, SECRET, and TOP SECRET, depending on the sensitivity of the data.[2]

In order to manage the internal access control of data, LBAC makes a distinction between *security label components, security policies*, and *security labels*. A security label is a collection of security label components. Each security label component defines a criterion that should be fulfilled when a user wants to access (a part of) the data. A security label component, for example, can distinguish between the sensitivity of individual rows. The following security label component indicates the hierarchical order between SECRET and CONFIDENTIAL.

CREATE SECURITY LABEL COMPONENT LEVEL
ARRAY [SECRET, CONFIDENTIAL];

Rows inserted by users who are granted the SECRET security label can only be seen by other users with a SECRET security label. Rows inserted by users who are granted the CONFIDENTIAL security label can be seen by all users labeled with a CONFIDENTIAL or SECRET security label.

[2]http://www.drdobbs.com/understanding-label-based-access-control/199201852.

A security policy is assigned to a table and dictates how the table is protected. A security policy consists of a set of security label components. Each table has exactly one security policy associated with it if it is LBAC protected. The same security policy can be used to protect multiple tables. The following security policy sec_policy consists of one security label component and states that users who have a SECRET role can access all the data. Users that have a CONFIDENTIAL role can only access data created by other users with a CONFIDENTIAL role.

CREATE SECURITY POLICY sec_policy
COMPONENTS LEVEL
WITH DB2LBACRULES;

The security policy is included in the create statement.

A security label is assigned to users and depicts which users are allowed to view or modify protected data. Assume the following statements.

CREATE SECURITY LABEL data_access.ds
COMPONENT LEVEL CONFIDENTIAL;
GRANT SECURITY LABEL data_access.ds **TO USER**
data_scientist1 **FOR ALL ACCESS**;
CREATE SECURITY LABEL data_access.bs
COMPONENT LEVEL SECRET;
GRANT SECURITY LABEL data_access.bs **TO USER** manager1
FOR READ ACCESS;

Given that a table is protected by sec_policy, data scientist 1 has read and write access to all data labeled as CONFIDENTIAL. The manager can read (not write) all data with a SECRET or CONFIDENTIAL label.

Accessing External Data

The use and sharing of external data must be approved by a national (and sometimes international) privacy commission. The privacy commission oversees which data companies can store and how they should protect it. It makes sure that individuals are able to claim, change, and retrieve their personal data.

One of the most important EU regulations enforced by the EU privacy commission is *the right to be forgotten*. The right to be forgotten originates from 1995 and specifies that a person can ask to remove his/her personal data. The 1995 privacy regulation is only applicable to EU companies. With the rise of e-sales, the 1995 regulation has become outdated, as EU citizens use more and more non-EU services. The Court of Justice of the European Union recently issued a new regulation that extends the privacy regulation to non-EU companies that offer services to European customers.

Although umbrella EU rules try to unify the privacy regulation within the European Union, there is still a lack of an international agreement on privacy. The regulation between countries strongly differs, making the European (global) privacy regulation extremely fragmented. There is a strong need for a unified organism that regulates cross-border privacy and data protection with a focus on integration and transparency.

CAPITAL CALCULATION FOR FRAUD LOSS

Fraud may cause an organization to incur significant financial losses, and as such concern a substantial threat to the very existence of an organization. In order to plan and cover for these losses, and in fact more generally for all kinds of risks an organization is exposed to, capital can be set aside to serve as a buffer and to absorb financial shocks. Setting aside capital to cover for risks may be a stringent requirement imposed by legislation. This is the case for financial organizations such as banks and insurance companies, who are subject to elaborate regulation (e.g., Basel and Solvency accords), as well as monitoring and control by national and supranational regulatory institutions, and requiring them to perform advanced analyses to assess and evaluate different kinds of risk they are exposed to. The objective of these regulations is amongst others for financial institutions to calculate and set aside a *sufficient* level of capital, primarily to make sure financial institutions individually, and as such, the entire financial system that is prone to systemic risk, are protected against financial shocks and can absorb the *unexpected losses* (UL) resulting from these shocks. Determining how much is *sufficient* is an extremely challenging and

complex task, for which several approaches exist, one of which will be elaborated in detail in the following paragraphs.

Expected and Unexpected Losses

Whereas *expected loss* (EL) is the average loss an organization experiences over a certain period of time, unexpected loss refers to the loss above the expected loss level. Expected loss can be calculated in a straightforward way, for instance, as the average observed value over a sufficiently long or suitable historical time window. Clearly, any organization confronted with regular losses due to its commercial activities should take these into account as a cost when pricing the services it delivers or the products it sells, as such covering a priori for these foreseen or expected losses.

However, due to random effects, but possibly as well due to non-random effects which a firm is not aware of or cannot take into account in calculating expected loss, losses may occur in a confined time window (e.g., a month or year) that exceed the expected loss level for that time window. Small, unexpected losses, such as losses exceeding the expected level only slightly, may occur rather frequently and can easily be covered for. However, also *loss peaks* may occur. It is exactly to cover for these rather exceptional but severe unexpected losses that a sufficient level of capital has to be calculated. Because these losses are exceptional, calculating unexpected loss and a sufficient protection level is challenging and requires a more complex approach than can be adopted for calculating expected loss.

Risk in a business setting can be simply defined as the chance or *probability* of financial loss. Causes of possible losses may differ in nature and are typically categorized to make a distinction with respect to the origin of the risk, as well as with respect to the approach followed to handle the risk. Losses due to fraud are typically categorized as an operational risk, meaning that the risk results from the daily operations or activities an organization undertakes in creating products or delivering services.

A first step in dealing with risk is describing the involved uncertainty (i.e., the probability that a loss occurs). This is certainly not self-evident and is typically done by gathering time series data—that is,

historical observations regarding the occurrence and characteristics of losses. Such data allow analysts to describe the chance of losses occurring by fitting a probability distribution to the observed data. The shape or functional form of the probability distribution may be chosen, or in other words an appropriate theoretical probability distribution may be selected, based on knowledge regarding the statistical nature of the uncertain phenomenon that is to be described or captured. The parameters of the selected distribution are then estimated to fit as good as possible the observed data. The analysis of a fraud data time series will be presented further on in this section to illustrate the process of fitting a distribution.

Alternatively, one could think of adopting an empirical probability distribution to describe the involved uncertainty, based on the observed historical frequency histogram. Such an empirical probability distribution, however, may significantly be underestimating the probability of extreme events or values with low probability to occur, certainly if the loss observations relate to a limited historical time window. Moreover, when adopting empirical distributions, one should not bother to separately describe frequency and severity, but, rather, immediately describe the overall loss distribution.

In order to calculate unexpected loss due to operational risk, typically the **frequency** and **severity** components of the overall loss distribution are assessed separately, meaning that a separate probability distribution is fitted to describe the frequency component and the severity component. The frequency component of the loss distribution is expressed in number of loss events per time unit and describes how often losses may occur. The severity of a loss event refers to the actual financial impact, measured in monetary units. These two components are considered to be independent, meaning that the number of loss events occurring during a particular time window is considered to be not related to the actual severity of these events. Therefore, separate probability distributions are fitted, which in a next step are combined to describe the *aggregate loss distribution*.

The frequency component can be described by a discrete probability distribution, since the number of events or loss occurrences due to fraud in a confined time window is a discrete stochastic variable. Usually a Poisson distribution is adopted for this purpose, which is a

theoretical probability distribution describing the probability of observing a number of events during the adopted unit of time, given the average number of events over time. The average number of events is the only parameter that determines the exact shape of the distribution. The severity component on the other hand is typically described by a continuous distribution, since the loss expressed in monetary units associated with the occurrence of fraud is considered a continuous stochastic variable.

Aggregate Loss Distribution

In order to calculate a sufficient capital level, we need in fact a probability distribution describing the probability of incurring a particular loss during a particular unit of time. This overall or aggregated loss distribution can be obtained by combining the probability distributions of the frequency and severity components of losses. This is however not straightforward to do since these two distributions are very different in nature. The frequency distribution is discrete whereas the severity is continuous.

Basically, there are two approaches that can be adopted in combining the two distributions to derive the overall loss distribution: a closed-form and open-form solution (Navarette 2006).

The **closed-form solutions** involve solving complex analytical formulas. The most direct closed form solution to the particular problem at hand is to combine distributions by means of a mathematical operation called *convolution*. However, to elaborate this operation complicated integrals need to be solved. An alternative approach to reach a closed-form solution (i.e., an exact formula describing the aggregated loss distribution) makes use of Fourier transformations, which allows to manipulate the frequency and severity distributions that we aim to combine more efficiently. The inverse Fourier transformation finally allows users to reach the closed form of the aggregate loss distribution after combining the distributions in the *frequency domain*. These closed-form solutions require statistical and mathematical expertise that is not always readily available.

An alternative, **open-form solution**, may be derived to obtain the aggregate loss distribution by making use of Monte Carlo simulation,

which is an approach that is, depending on one's knowledge and skills, more accessible and easier to implement than the closed form solutions as discussed. Monte Carlo simulation boils down to making use of brute computational force to simulate a system and observe how it behaves for a large number of randomly chosen values (according to the determined probability distributions) of the inputs, in order to observe the probability of a certain output. The inputs in our case are the frequency and the severity, whereas the output is the total loss resulting from the number of fraud events that occur in a time unit and the associated losses for each of these events.

Monte Carlo simulation generates a large amount of artificial loss observations. The probability distributions of the frequency and severity component can be used to generate *random* observations of loss, with a probability in line with these distributions. When a sufficient amount of observations are generated, straightforward derivation of the empirical distribution from these observations results in the aggregate loss distribution. Sufficient in this setting means that the resulting aggregate loss distribution remains stable with respect to the number of observations used to generate the distribution.

Once the aggregate loss distribution is obtained, a value for the unexpected loss can be determined as a function of the **confidence level** that is selected. The confidence level determines the level of protection by fixing the largest loss peak that can be covered for by the capital, and as such expresses the probability of observing an even higher loss peak for which capital will not be sufficient. The value of the total loss associated with the selected confidence level is called the operational value at risk (VaR). As shown in Figure 7.4, the difference between the VaR at the selected confidence level (99.9 percent in the figure) and the expected loss equals the unexpected loss.

Deciding on an appropriate confidence level and as such on the capital level is not self-evident. Intuitively, this confidence level corresponds to the probability that an organization will not go bankrupt because of extreme losses. From that perspective, a confidence level equal to or very close to 100 percent is preferred. However, since a confidence level of (very close to) 100 percent may be associated with a very high VaR and, consequently, a very high unexpected loss, setting aside the required capital to cover for such significant loss may be

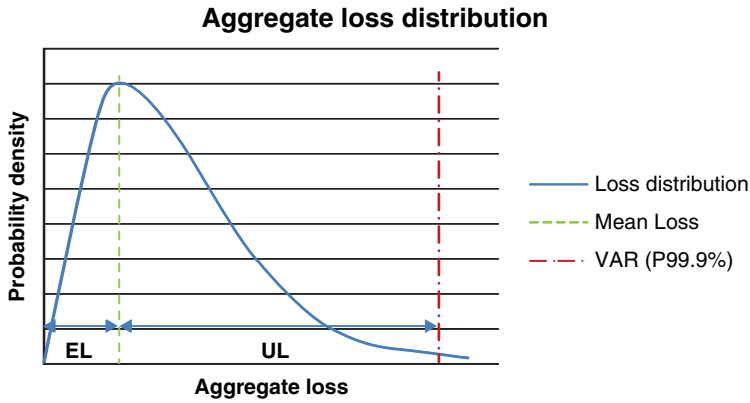

Figure 7.4 Aggregate Loss Distribution with Indication of Expected Loss, Value at Risk (VaR) at 99.9 Percent Confidence Level and Unexpected Loss

impossible or not desirable. Risk is inherent to any economic undertaking. Excluding and covering for all types of risk is not the goal of setting aside capital to cover for shocks. Therefore, setting the confidence level below 100 percent is definitely acceptable. The only question remaining, then, is at what exact level. But this is a question to which no general answer can be given, since it's dependent on many factors, many of which are specific to the organization, sector or industry, country, management, and so on. Usually, though, confidence levels in risk management lie in the range from 95 to 99 percent and higher.

Capital Calculation for Fraud Loss Using Monte Carlo Simulation

This section provides a practical illustration of capital calculation using Monte Carlo simulation as explained in the above sections. The example is based on a case study presented in Navarette (2006). Figure 7.5 provides a snapshot of a time series data set with two variables describing historical credit card fraud cases over a time horizon of one year—that is, the date of the fraud event and the involved fraud amount (€).

The date information allows analysts to fit a Poisson distribution to the frequency data. In order to do so the only parameter to be estimated

Date	Fraud amount
2/01/2014	€ 963,82
2/01/2014	€ 618,02
3/01/2014	€ 549,45
4/01/2014	€ 1.732,30
8/01/2014	€ 1.929,02
...	...
29/12/2014	€ 748,33
29/12/2014	€ 672,70
30/12/2014	€ 2.104,16
30/12/2014	€ 529,57
30/12/2014	€ 858,13

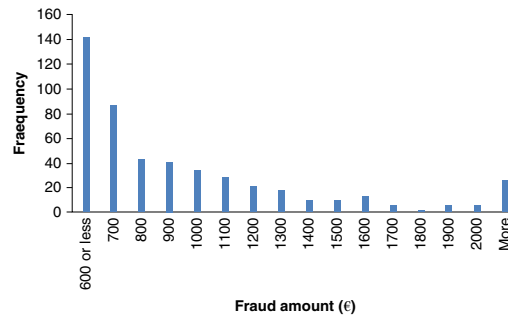

Figure 7.5 Snapshot of a Credit Card Fraud Time Series Data Set and Associated Histogram of the Fraud Amounts

or calculated is the average event rate λ, that is, the average number of fraud cases per month, which is equal to 41.67. In the Monte Carlo simulation, we will hence use a Poisson distribution with Poisson parameter equal to 41.67 to generate random yet realistic monthly event rates (i.e., the monthly number of fraud cases). Note that we adopted one month to be the base unit of time in our analysis. Hence, the aggregated loss distribution resulting from the Monte Carlo simulation will give us the distribution of potential monthly losses with associated probability density.

A second, continuous distribution needs to be estimated from the available data to describe the severity of the losses that occur. Several theoretical distributions such as the lognormal, exponential, and so on may be fitted. In this case, a Pareto distribution fits best (ranked according to the Chi-squared test statistic) to the observed historical loss distribution displayed in Figure 7.5. The estimated parameters for the Pareto severity distribution are $a = 500$ and $b = 2.75$.

The estimated Poisson frequency distribution and Pareto severity distribution allow analysts to generate a large number (in this case, 10,000 observations were generated) of *simulated monthly observations* with a randomly generated event rate and losses associated with the individual fraud events following the estimated distributions. As such, we get an extensive time series data set with artificial, pseudo-realistic observations of total monthly fraud losses. The frequency histogram of these monthly losses allows analysts to derive the aggregate loss distribution, as shown in Figure 7.6.

Figure 7.6 indicates both the expected loss—that is, the average monthly loss due to fraud (EL = 32,730€)—as well as the 99 percent value-at-risk figure—that is, the fraud loss for a confidence level equal to 99 percent (99 percent VaR = 49,449€). The difference between the 99 percent VaR and the EL is the unexpected loss (UL), which should be covered by capital that is to be set aside (UL = 16,718€). If we would raise the confidence level to 99.9 percent, the associate VaR figure rises to a value 99.9 percent VaR = 57,542€, and the UL increases to 24,812€.

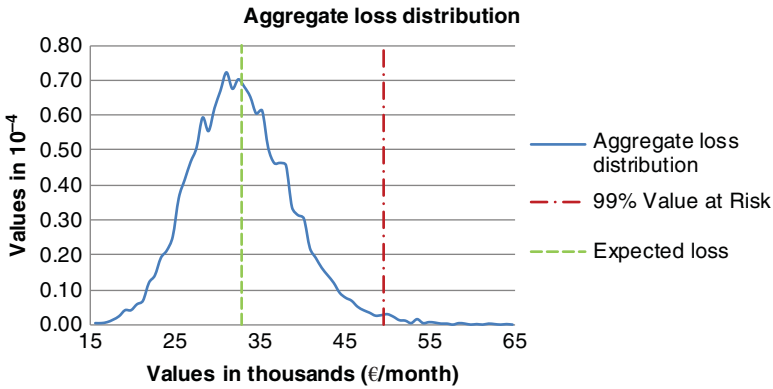

Figure 7.6 Aggregate Loss Distribution Resulting from a Monte Carlo Simulation with Poisson Distributed Monthly Fraud Frequency and Associated Pareto Distributed Fraud Loss

AN ECONOMIC PERSPECTIVE ON FRAUD ANALYTICS

In this section, we will zoom into the economic aspects of an analytical fraud model. We will first discuss the total cost of ownership and then elaborate on the return on investment.

Total Cost of Ownership

The total cost of ownership (TCO) of a fraud analytical model refers to the cost of owning and operating the analytical model over its expected lifetime, from inception to retirement. It should consider both quantitative and qualitative costs and is a key input to make strategic decisions about how to optimally invest in fraud analytics. The costs involved can be decomposed into: acquisition costs, ownership and operation costs, and post ownership costs, as illustrated with some examples in Table 7.1.

The goal of TCO analysis is to get a comprehensive view of all costs involved. From an economic perspective, this should also include the timing of the costs through proper discounting using, for example, the weighted average cost of capital (WACC) as the discount factor. Furthermore, it should help identifying any potential hidden and/or sunk costs. In many fraud analytical projects, the combined

Table 7.1 Example Costs for Calculating Total Cost of Ownership (TCO)

Acquisition Costs	Ownership and Operation Costs	Post Ownership Costs
■ Software costs, including initial purchase, upgrade, intellectual property, and licensing fees ■ Hardware costs including initial purchase price and maintenance ■ Network and security costs ■ Data costs including costs for purchasing external data ■ Model developer costs such as salaries and training	■ Model migration and change management costs ■ Model setup costs ■ Model execution costs ■ Model monitoring costs ■ Support costs (troubleshooting, helpdesk, etc.) ■ Insurance costs ■ Model staffing costs such as salaries and training ■ Model upgrade costs ■ Model downtime costs	■ Deinstallation and disposal costs ■ Replacement costs

cost of hardware and software is subordinate to the people cost that comes with the development and usage of the analytical models (e.g., training, employment, and management costs). Furthermore, TCO analysis allows pinpointing cost problems before they become material. For example, the change management costs to migrate from a legacy fraud model to a new analytical fraud model are often largely underestimated. TCO analysis is a key input for strategic decisions such as vendor selection, buy versus lease decisions, in- versus outsourcing, overall budgeting, and capital calculation. Note that when making these investment decisions, it is also very important to include the benefits in the analysis since TCO only considers the cost perspective.

Return on Investment

Return on investment (ROI) is defined as the ratio of a return (benefit or net profit) over the investment of resources that generated this return. Both the return and the investment are typically expressed in monetary units, whereas the ROI is calculated as a percentage. In this section, we discuss how to calculate the ROI of fraud detection,

which may be less straightforward to calculate than the ROI of a financial product, but nonetheless, can provide useful insights to an organization.

The returns of a fraud detection system have been discussed before in Chapter 6 in the section on selecting the sample to investigate. The optimal amount of resources to allocate to fraud investigation and as such the sample to investigate was defined as the amount of resources that maximized the total utility associated with inspecting a sample. This sample was selected either as a top-fraction of most suspicious cases with the highest scores assigned by the detection model, or as a top-fraction of the cases with the *highest expected fraud amount* (defined as the probability to be fraudulent times the estimated fraud amount).

The utility of different *outcomes* is expressed as a net monetary value, either positive or negative, representing the costs and benefits to an organization (of any nature, both economic and noneconomic, yet always expressed in monetary units) associated with the decision to inspect or not to inspect either a fraudulent or nonfraudulent case.

The investment required to generate the total returns or total utility can be assumed equal to the total cost of ownership as discussed in the previous section. The total cost of ownership includes costs of diverse nature, covering the full investment required to build, operate, and maintain a fraud-detection system. However, the total cost of ownership does not include costs related to resources that are required to further act on the outputs of the detection system (i.e., inspecting and handling suspicious cases). All these costs together will be denoted as the *Total Cost of Fraud Handling*, and include inspection costs, legal costs, and so on. Clearly, calculating the total cost of fraud handling may be a cumbersome task, yet indispensable to calculate the ROI.

Hence, we get to the final ROI formula:

$$\textit{Return on investment} = \frac{\textit{Total utility}}{\textit{Total cost of ownership} + \textit{Total cost of fraud handling}}$$

IN VERSUS OUTSOURCING

The growing interest and need for big data and analytics, combined with the shortage of skilled talent and data scientists in Western Europe and the United States, has triggered the question regarding outsourcing analytical activities. This need is further amplified by competitive pressure on reduced time to market and lower costs. Companies need to choose between insourcing or building the analytical skillset internally, either at the corporate or business line level, outsourcing all analytical activities, or going for an intermediate solution whereby only part of the analytical activities are outsourced. The dominant players in the outsourcing analytics market are India, China, and Eastern Europe, with some other countries (e.g., Philippines, Russia, South Africa) gaining ground as well.

Various analytical activities can be considered for outsourcing, ranging from the heavy lifting grunt work (e.g., data collection, cleaning, and preprocessing), set-up of analytical platforms (hardware and software), training and education, to the more complex analytical model construction, visualization, evaluation, monitoring, and maintenance. Companies may choose to grow conservatively and start by outsourcing the analytical activities step by step, or immediately go for the full package of analytical services. It speaks for itself that the latter strategy has more risk associated with it and should thus be more carefully and critically evaluated.

Despite the benefits of outsourcing analytics, it should be approached with a clear strategic vision and critical reflection with awareness of all risks involved. First of all, the difference between outsourcing analytics and traditional ICT services is that analytics concerns a company's front-end strategy, whereas many ICT services are part of a company's back-end operations. Another important risk is the exchange of confidential information. Intellectual property (IP) rights and data security issues should be clearly investigated, addressed and agreed on. Moreover, all companies have access to the same analytical techniques, so they are only differentiated by the data they provide. Hence, an outsourcer should provide clear guidelines and guarantees about how intellectual property and data will be managed and protected (using, e.g., encryption techniques

and firewalls), especially if the outsourcer collaborates with various companies operating in the same industry sector. Another important risk concerns the continuity of the partnership. Offshore outsourcing companies are often subject to mergers and acquisitions, not seldom with other outsourcing companies collaborating with the competition, hereby diluting any competitive advantage realized. Furthermore, many of these outsourcers face high employee turnover due to intensive work schedules, the boredom of performing low-level activities on a daily basis, and aggressive headhunters chasing these hard to find data science profiles. This attrition problem seriously inhibits a long-term thorough understanding of a customer's analytical business processes and needs. Another often-cited complexity concerns the cultural mismatch (e.g., time management, different languages, local versus global issues) between the buyer and outsourcer. Exit strategies should also be clearly agreed on. Many analytical outsourcing contracts have a maturity of three to four years. When these contracts expire, it should be clearly agreed on how the analytical models and knowledge can be transferred to the buyer thereof to ensure business continuity. Finally, the shortage of data scientists in the United States and Western Europe will also apply, and might even be worse, in the countries providing outsourcing services. These countries typically have universities with good statistical education and training programs, but their graduates lack the necessary business skills, insights, and experience to make a strategic contribution with analytics.

Given the above considerations, many firms currently adopt a partial outsourcing strategy, whereby baseline, operational analytical activities such as query and reporting, multidimensional data analysis, and OLAP are outsourced, whereas the advanced descriptive, predictive, and social network analytical skills are developed and managed in house.

MODELING EXTENSIONS

Forecasting

Chapter 4 introduced predictive learning techniques which allow estimating a target variable. Two types of predictive analytics have been

distinguished—that is, regression and classification, depending on the type of target variable. In case of regression a continuous target variable is estimated (either over a limited or unlimited interval), whereas in case of classification the target is categorical. A third type of predictive analytics, which is not covered in this book, is forecasting or time series regression, which concerns the prediction of a continuous target variable as a function of time. The value of the target variable in a forecasting problem *moves* or changes over time, as such adding a dimension to the prediction problem. Plenty of techniques are available to provide time-dependent estimates, which are different in nature compared to the techniques discussed and also come with different challenges. For further information on time series modeling, one may refer to seminal books and articles dedicated to the subject of forecasting (Armstrong 2001; Petropoulos, Makridakis, Assimakopoulos, & Nikolopoulos 2014). Although less common and straightforward, in a fraud-detection setting forecasting may be used for particular applications or purposes, either directly or indirectly related to fraud.

A first example of a possible use of forecasting techniques in a fraud-detection setting concerns the detection of deviations between forecasted (i.e., expected) values and observed values. Such deviations may be indicative of fraud. For instance, one particular type of fraud concerns avoidance of import taxes by shipping goods from the country of origin to the country of destination via a third country. The goods are relabeled in the third country, as if they were produced and expedited from that country to the destination country in order to avoid or reduce the import taxes that are to be paid in the destination country, and that are lower for goods originating from the third country than if originating from the true origin country. By forecasting the expected amount of import—typically per specific product category—a deviation will be observed between the expected and observed amount of import both from the true and the false origin countries, respectively, a negative deviation or lower amount of import than expected for the true origin country, and a positive deviation or higher amount of import than expected for the false origin country.

A second example use of forecasting methods in fraud concerns the estimation of the evolution of fraud losses as a function of time. Losses due to fraud, as discussed previously, may vary over time due to

random effects, but as well due to structural effects, meaning that other factors might partially explain the evolution or variation of observed fraud losses in time. For instance, the economic cycle might have a substantial impact, since it could be expected to observe more fraud during economic downturn times than during economic upturn times. Seasonal effects may be observed for particular types of fraud—for example, losses due to credit card fraud might be higher in the month of December since overall credit card spending is higher due to the holiday season and the associated shopping pattern. Also, the overall amount of insurance claims, and as such the amount of fraudulent claims may depend on the season or the weather, causing the total fraud loss to be seasonally dependent. These seasonal effects can be easily modeled using forecasting techniques.

Text Analytics

An additional and potentially very rich source of information that might be explored when building a fraud detection system concerns textual data. Text, such as reports, emails, text messages, tweets, documents on the Internet, blogs, reviews, financial statements, and so on, is an *unstructured* source of data. Unstructured data are not organized or fitted nicely into a table consisting of rows and columns, which can be explored by applying the techniques discussed in Chapters 3 and 4. Therefore, text is less evident to include in an analysis and to exploit in order to detect or predict fraud, although it potentially contains valuable information that may be of good use. Challenges encountered when analyzing text are plenty, and include the difficulty to recognize and interpret irony, synonyms, homonyms, and so on.

Other sources or types of unstructured data include images such as pictures, photographs and video, audio data, and (social) network data. Indeed, also network information can be considered to be unstructured in nature since the very essence of a network cannot be captured easily in a structured data table. As discussed in Chapter 5, with some effort and expertise networks may be turned into structured data tables, subsequently allowing analysis using the techniques discussed in this book. Chapter 5 also discussed techniques that have been specifically designed to deal with the particular nature and format of network data.

The same two approaches exist to handle textual data. The goal of both approaches is to identify patterns and associations between words and phrases. Specific techniques have been developed that allow deriving insights and patterns directly from text. Usually, however, these techniques are adopted to turn textual data into structured data, subsequently allowing application of techniques designed to analyze structured data. As such, text-mining insights are added to structured analysis in order to improve decision making.

Text can be mapped into numeric representations that summarize document collections and become inputs to a full range of predictive and data mining modeling techniques. For instance, text data may first be transformed into a set of numerical components called singular value decomposition (SVD) components, which collectively represent the text documents. These components are then used as additional inputs along with the structured input attributes to help improving the predictive power of the existing models.

An example application of text analytics in a fraud-detection setting concerns the analysis of car accident reports and claim notes in order to detect insurance claim fraud (e.g., staged collisions, see Chapter 1). In fact, unstructured data can represent up to 80 percent of claims data. This information can be used to help reduce investigation costs and optimize recovery operations. In fact, some firms reported the existence of a U-shaped relation between emotion and level of detail in the report, as measured by counting particular adjectives, either expressing strong feelings or describing in a very detailed manner the accident and the probability for the claim to be fraudulent. Both the absence and abundance of emotion and level of detail in the report appeared to be indicative for fraud. This may not be very surprising, since one can imagine that indeed it might prove hard not to include emotion and detail, but notice, that fraudsters must also mimic exactly *the right amount* of emotion and level of detail when falsifying a statement or report.

From this example, it might be clear that it is exactly the *ambiguity* and *complexity* that is present in textual data, and that makes text so hard to analyze using automated approaches. These factors make it such an interesting and rich source of information to explore. Since analyzing text is a rather challenging exercise, requiring advanced and

dedicated techniques and approaches, good software support is indispensable. Given the specificity of the topic, text analytics will not be covered further in this book. The reader may refer to the literature on text mining for more information (Chakraborty et al. 2013).

THE INTERNET OF THINGS

The Internet of Things (IoT) refers to the network of interconnected things such as electronics devices, sensors, software, IT infrastructure that creates and adds value by exchanging data with various stakeholders such as manufacturers, service providers, customers, other devices, and so on, hereby using the World Wide Web technology stack (e.g., Wi-Fi, IPv6). In terms of devices, you can think about heartbeat monitors; motion, noise, or temperature sensors; smart meters measuring utility (e.g., electricity, water) consumption, and so on. Some examples of applications follow:

- Smart parking: automatically monitoring free parking spaces in a city
- Smart lighting: automatically adjusting street lights to weather conditions
- Smart traffic: optimize driving and walking routes based on traffic and congestion
- Smart grid: automatically monitoring energy consumption
- Smart supply chains: automatically monitoring goods as they move through the supply chain

It speaks for itself that the amount of data generated is enormous and offers an unseen potential for analytical applications. As with all new technologies, the Internet of Things creates both new treats as well as emerging opportunities from a fraud perspective.

Some examples of new fraud treats are:

- Fraudsters might force access to web configurable devices (e.g., automated teller machines (ATMs)) and set up fraudulent transactions.

- Device hacking whereby fraudsters change operational parameters of connected devices (e.g., smart meters are manipulated to make them under register actual usage).
- Denial of service (DoS) attacks whereby fraudsters massively attack a connected device to stop it from functioning.
- Data breach whereby a user's log-in information is obtained in a malicious way, resulting in identity theft.
- Gadget fraud also referred to as gadget lust whereby fraudsters file fraudulent claims to either obtain a new gadget or free upgrade.
- Cyber espionage is where data are eavesdropped by an intelligence agency or used by a company for commercial purposes.

More than ever before, fraud will be dynamic and continuously changing in an IoT context. From an analytical perspective this implies that supervised techniques will continuously lag behind since they are based on a historical data set with known fraud patterns. Hence, as soon as the supervised model (e.g., classification or regression model) has been estimated, it will become outdated even before it has been put into production. Unsupervised methods such as anomaly detection, peer group and break-point analysis will gain in importance. These methods should be capable of analyzing evolving data streams and perform incremental learning to deal with concept drift. To facilitate (near) real-time fraud detection, the data and algorithms should be processed in-memory instead of relying on slow secondary storage. Furthermore, based on the results of these analytical models, it should be possible to take fully automated actions such as the shutdown of a smart meter or ATM.

Besides threats, the IoT will also bring new opportunities for improved fraud detection. Telematics is one example of an IoT application in an insurance setting. The idea here is to equip a car with a special device called black box, which continuously monitors the driving behavior by gathering data and streaming it to the insurance provider. Examples of telematics data that are collected in each trip are: the distance driven, the time of day, duration of the trip, the location, the speed, harsh or smooth breaking, aggressive acceleration or deceleration, and cornering and parking skills. This can then further

be augmented with road maps and weather and traffic information. By carefully analyzing all these data elements, the insurance provider can provide better risk assessment and work out personalized premiums based on individual driving data by reducing the cost for low-mileage clients and good drivers. It also enables hotspot analysis based on vehicle and accident location. However, telematics data can also be usefully adopted to improve fraud detection. When an insurance claim is filed, the facts provided can now be more carefully checked. For example, was the driver respecting the speed limit? Did the accident occur at the claimed location? Did the driver brake in a timely manner? Was the driving behavior different compared to recent driving behavior, possibly suggesting a different driver or alcohol intoxication? Furthermore, using telematics data, it becomes possible to re-enact car accidents. This is not only handy to define who is at fault, but also to identify fake accidents resulting into fraudulent claims.

CORPORATE FRAUD GOVERNANCE

Since fraud is a key treat to a firm's revenues and consequently its existence, it is important that senior management and the board of directors are actively involved in detecting, preventing, and managing fraud. In other words, they should demonstrate active involvement on an ongoing basis, assign clear responsibilities, and put into place organizational structures, procedures, and policies that will allow the proper and sound management of fraud. Example questions that need to be addressed are as follows:

- Do we adopt a reactive, proactive, or combined strategy toward fraud detection and prevention?
- What are the internal anti-fraud controls that allow us to mitigate fraud?
- Do we invest in continuous education and fraud awareness training?
- Do we provide adequate whistle blowing or hotline facilities, and how are they managed?
- Do we periodically conduct fraud vulnerability reviews?

- Do we adopt a closed-loop fraud-management strategy?
- How do we manage fraud from a regulatory compliance viewpoint?

To address all these questions, it is highly recommended that an anti-fraud steering group be set up, comprising employees from various business units and hierarchical levels in order to get a comprehensive, corporatewide view on fraud. The board of directors should then appoint one executive-level member to oversee the activities of this group, and regularly brief management regarding its activities.

It should be clear by now that analytics plays a pivotal role in managing fraud. Assuming a firm wants to build the analytical expertise in-house rather than outsourcing, a key question is how the analytical teams should be embedded in the organization structure. A first option would be to centralize all analytical teams and resources into a firm-wide analytical service center of excellence. The idea here is to create cross-fertilization opportunities across the firm and efficiently leverage the various resources available. However, given the close interaction that is needed between the data scientists and the business, this centralized structure may be suboptimal. A better alternative could be to organize analytics using the principle of subsidiarity. This principle states that the company should have a subsidiary function performing only those analytical tasks, which cannot be performed by the local business units. More specifically, each business unit where fraud is an issue can be complemented with small teams of data scientists (e.g., 2 to 5). This will facilitate the constant interaction needed to quickly and adequately respond to new fraud challenges. Companywide, transversal standards can then be developed to deal with issues such as software, privacy, model management, and documentation. For example, from a model management perspective, it may be enforced that every fraud model should be managed by a model board, which takes full responsibility for a model's development, usage, and monitoring.

Given that analytics continues to permeate every aspect of a firm's business, it is highly recommended that it be elevated to a corporate level and that executive leadership be assigned to it. Some companies

already added a chief analytics officer (CAO) to their C-suite. This person is responsible for overseeing all analytical model development and monitoring efforts across the entire enterprise.

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