



The Complete Guide to Landing a Career in Data

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When choosing a career, there are safe paths to pursue, and there are risky ones.

A career in data offers the best of both worlds. On the one hand, it is a secure choice—demand for data talent continues to increase, and shows no sign of abating. With data skills in your toolkit, you're going to be in demand in virtually any industry. On the other hand, it's a brave new world out there. We're producing massive amounts of data, and that data is making amazing new things possible. But, the methods and strategies we're having to continually invent to harness all that data means the future is continually being redefined in real time. Those on the data front lines are at the forefront of technological progress.

The good news is, that no matter which route you take—the secure one, the risky one, or something in between—there are ample career opportunities out there for anyone interested in data.

But, how do you actually get started?

That's where this guide comes in. At Udacity, we're extremely fortunate to collaborate with some of the most forward-thinking companies in the world, and we work with some of the most innovative thinkers and creators in the data space. Our hiring partners represent some of the best career opportunities in the field, and are a critical source of information about what companies are seeing in their data hires.

We've marshalled all these resources together to create this guide for you, and all of our expert contributors offer unique perspectives and experiences. If you're interested in pursuing a career in data, this is your complete guide.



Career Options

Analysts, scientists, and engineers

Every time you send a text message, type a tweet, post a Facebook photo, click a link, or buy something online, you're generating data. And considering there are more than [3.5 billion Internet users](#) in the world and [2 billion cellphone users](#), that's a heck of a lot of data.

Fortunately, as data has multiplied, so has the ability to collect, organize, and analyze it. Data storage is cheaper than ever, processing power is more massive than ever, and tools are more accessible than ever to mine the zettabytes of available data for business intelligence. In recent years, data analysis has done everything from predict stock prices to prevent house fires.

All that data crunching requires an army of data masters. Translation: there's never been a better time to pursue a career in data. Back in 2011, the [McKinsey Global Institute](#) predicted in that by 2018 the U.S. could face a shortage of 1.5 million people who know how to leverage data analysis to make effective decisions—we're already on track to exceed that number. In a recent data science report from [CrowdFlower](#), a staggering "83% of data scientists polled feel that there is shortage of data scientists today."

Enter: You.

The first step on your path to professional data professional? Taking stock of your three main career options: Data Analyst, Data Scientist, and Data Engineer.

Data Analyst

A data analyst is essentially a junior data scientist. It's the perfect place to start if you're new to a career in data and eager to cut your teeth. Data analysts don't have the mathematical or research background to invent new algorithms, but they have a strong understanding of how to use existing tools to solve problems.

Skills and tools

Data analysts need to have a baseline understanding of five core competencies: programming, statistics, machine learning, data munging, and data visualization. Beyond technical skill, attention to detail and the ability to effectively present results are equally important to be successful as a data analyst.

How it translates

Data analysts are given direction from more experienced data professionals in their organization. Based on that guidance, they acquire, process, and summarize data. Data analysts are the ones managing the quality assurance of data scraping, regularly querying

databases for stakeholder requests, and triaging data issues to come to timely resolutions. They also then package the data to provide digestible insights in narrative or visual form.

An enduring curiosity about data and close examination of evolving best practices and tools serves all data professionals well, no matter the level of seniority.

Data Scientist

Some companies treat the titles of “Data Scientist” and “Data Analyst” as synonymous. But there’s really a distinction between the two in terms of skill set and experience. Though data scientists and data analysts have the same mission in an organization—to glean insights from the massive pool of data available—a data scientist’s work requires more sophisticated skills to tackle a higher volume and velocity of data.

As such, a data scientist is someone who can do undirected research and tackle open-ended problems and questions. Data scientists typically have advanced degrees in a quantitative field, like computer science, physics, statistics, or applied mathematics, and they have the knowledge to invent new algorithms to solve data problems.

Data scientists are extremely valuable to their companies, as their work can uncover new business opportunities or save the organization money by identifying hidden patterns in data (for example, highlighting surprising customer behavior or finding potential storage cluster failures).

Skills and tools

Whereas a data analyst might look at data from only a single source, a data scientist explores data from many different sources. Data scientists use tools like Hadoop (the most widely used framework for distributed file system processing), they use programming languages like Python and R, and they apply the practices of advanced math and statistics.

The exact set of skills differs by organization and project, but this example from Data Science London gives a sense of how complex the data scientist’s toolkit can be:

[Sort of a] Data Scientist Toolkit

- Java, R, Python... (bonus: Clojure, Haskell, Scala)
- Hadoop, HDFS & MapReduce... (bonus: Spark, Storm)
- HBase, Pig & Hive...(bonus: Shark, Impala, Cascalog)
- ETL, Web scrapers, Flume, Sqoop... (bonus: Hume)
- SQL, RDBMS, DW, OLAP...
- Knime, Weka, RapidMiner... (bonus: SciPy, NumPy, scikit-learn, pandas)
- D3.js, Gephi, ggplot2, Tableau, Flare, Shiny...
- SpSS, Matlab, SAS... (the enterprise man)
- NoSQL, Mondo DB, Couchbase, Cassandra...
- And Yes! ... MS-Excel: *the most used, most underrated DS tool*

Data Science London

Source: [Data Science London](#)

The most valuable nontechnical skill a data scientist brings to the table is an intense inquisitiveness. Data scientists have to be driven to pose questions and hunt down solutions, and in so doing to unearth information that could transform a business.

How it translates

Data scientists essentially leverage data to solve business problems. They interpret, extrapolate from, and prescribe from data to deliver actionable recommendations. A data analyst summarizes the past; a data scientist strategizes for the future.

Data scientists could identify precisely how to optimize websites for better customer retention, how to market products for stronger customer lifecycle value, or how to fine-tune a delivery process for speed and minimal waste.

Data Engineer

A data engineer builds a robust, fault-tolerant data pipeline that cleans, transforms, and aggregates unorganized and messy data into databases or data sources. Data engineers are typically software engineers by trade. Instead of data analysis, data engineers are responsible for compiling and installing database systems, writing complex queries, scaling to multiple machines, and putting disaster recovery systems into place.

Data engineers essentially lay the groundwork for a data analyst or data scientist to easily retrieve the needed data for their evaluations and experiments.

Skills and tools

Whereas data scientists extract value from data, data engineers are responsible for making sure that data flows smoothly from source to destination so that it can be processed.

As such, data engineers have deep knowledge of and expertise in:

- Hadoop-based technologies like MapReduce, Hive, and Pig
- SQL based technologies like PostgreSQL and MySQL
- NoSQL technologies like Cassandra and MongoDB
- Data warehousing solutions

How it translates

Data engineers do the behind-the-scenes work that enables data analysts and data scientists to do their jobs more effectively.

The Bottom Line

You have many options when it comes to a career working with data. If you're interested in exploring such a career, your three major options are data analyst, data scientist, and data engineer.

Sanjay Venkateswarulu, co-founder of big data analytics and visualization startup Datavore Labs, traces the history of these subdivisions:

"Data analysts have morphed into these three or more specialized disciplines. I believe it is the same specialization that doctors went through at the birth of modern medicine. First there was your village leader or elder who played the main role, but as tools of the trade have become more and more specialized, we now have GPs, surgeons, and neurosurgeons."

If you're new to the field of data science, you'll want to start by aiming for the "General Practitioner" in Venkateswarulu's analogy—an analyst job. As you develop your skills and gain experience, you'll be able to progress to data scientist or data engineer.



In-Demand Skills

The sexiest job of the 21st century.

Few jobs have been surrounded by as much hyperbole as has Data Scientist. Most famously, the [Harvard Business Review](#) referred to it as “The Sexiest Job of the 21st Century.” With hype like that, a backlash is inevitable, and there certainly was one, with some of the more apocalyptic voices even stating that the role would be replaced completely by automation within a decade.

That’s not going to happen.

How Data Science Ranks

Regardless of where you stand on the matter of Data Science sexiness, it’s simply impossible to ignore the continuing importance of data, and our ability to analyze, organize, and contextualize it. When Glassdoor, drawing on their vast stores of employment data and employee feedback, released their [25 Best Jobs in America](#) list, guess what was number one? Data Scientist.

So the role is here to stay, but unquestionably, the specifics of what a Data Scientist does will evolve. With technologies like Machine Learning becoming ever-more commonplace, and emerging fields like Deep Learning gaining significant traction amongst researchers and engineers—and the companies that hire them—Data Scientists continue to ride the crest of an incredible wave of innovation and technological progress.

Businesses Are Drowning In Data, Starving For Insights

On top of all that, there is the simple matter of demand. A 2015 article in Forbes magazine entitled [The 10 Toughest Jobs To Fill In 2016](#) noted that “qualified candidates are in short supply.”

With the explosion of big data and the need to track it, employers keep on hiring data scientists. But qualified candidates are in short supply. The field is new enough that the Bureau of Labor Statistics doesn’t even track it as a profession. Yet thousands of companies—from startups that analyze credit card data in order to target marketing and advertising campaigns, to giant corporations like Ford Motor and Price Waterhouse Coopers—are bringing on scores of people who can take gigantic data sets and wrestle them into usable information. As an April 2016 report from technology market research firm Forrester put it, “Businesses are drowning in data but starving for insights.”

Work-Life Balance

The truth is, if you’re looking at launching a new career, or contemplating a career change, Data Scientist is an extremely alluring path to pursue. Not only is the demand there—and the salaries that accompany demand!—but the job itself offers great work-life balance.

According to another recent Glassdoor study (their [25 Best Jobs For Work-Life Balance](#) survey), Data Scientist is in fact #1 for work-life balance.

But that said, while you're now probably getting quite excited about a career in this very hot field (who wouldn't, after reading all the above???), be aware that despite the overwhelming demand, the rising salaries, and the great work-life balance, there are also real challenges to contend with if one is to succeed in the field. Perhaps the most critical one is the pace of technological change.

The Pace Of Change

The Forbes article quoted above pulls its information largely from a study released by the Society of Human Resource Management (SHRM), in collaboration with a California company called CareerCast. Writing about the study on [the SHRM website](#), author Tony Lee noted the following:

The fact that rapid technical innovation makes many skills obsolete quickly adds to the need to incorporate lots of on-the-job training, and reinforces the notion that a candidate's once-perfectly matched skills may be outdated by his or her first anniversary on the job.

There is a great deal of talk today about the modern educational paradigm shifting towards a lifelong learning model. Udacity president and co-founder Sebastian Thrun spoke on NPR about this, and noted that modern universities by definition cannot keep up with technology's pace, and are accordingly not equipped to adequately support either their students' career goals or the needs of the companies who are desperate to hire new talent.

"The Nanodegree program is really bleeding edge. Universities, by nature, lag behind. As a result, modern things like Data Science are rarely taught at universities today. I think the world is shifting from a one-time education to a lifelong education. More and more people have to go from one job to a new job, and that means that you have to move away from a one-time degree—and then done for the rest of your life—into a world where education is intermingled with your normal life, and your work life. I think we owe our students not just free education, but education that works."

The New Definition Of "Job"

Today's employment landscape is indeed changing, with new types of job being created every day, and job tenure shortening measurably. The very definition of "job" is being redefined in real-time to incorporate technology, mobility, flexibility, and global connectivity. In light of these transformation, it's critical that one have a clear understanding of the skills required to succeed.

In a recent [Wall Street Journal article](#), author Elizabeth Dwoskin—citing a report by RJ Analytics—wrote the following:

“The top five skills listed for data scientists were data analysis, data mining, machine learning and knowledge of the programming languages R and Python.”

What Do Data Scientists Do?

Let’s now go back to that possibly canonical, possibly apocryphal Harvard Business Review article about Data Scientist being the sexiest job of the 21st century. In that article, the authors describe what Data Scientists do in admittedly rather fanciful terms:

“What data scientists do is make discoveries while swimming in data. It’s their preferred method of navigating the world around them. At ease in the digital realm, they are able to bring structure to large quantities of formless data and make analysis possible. They identify rich data sources, join them with other, potentially incomplete data sources, and clean the resulting set. In a competitive landscape where challenges keep changing and data never stop flowing, data scientists help decision makers shift from ad hoc analysis to an ongoing conversation with data.”

And as to who does this kind of thing?

“Think of him or her as a hybrid of data hacker, analyst, communicator, and trusted adviser.”

If that sounds romantic, exciting, and, yes, sexy, then Data Scientist is right up your alley. But if that prose is a bit too purple for you, consider the following as an alternative summation:

Learn to:

- *Wrangle, extract, transform, and load data from various databases, formats, and data sources*
- *Use exploratory data analysis techniques to identify meaningful relationships, patterns, or trends from complex data sets*
- *Classify unlabeled data or predict into the future with applied statistics and machine learning algorithms*
- *Communicate data analysis and findings through effective data visualizations*

This language comes from the Udacity [Data Analyst Nanodegree program](#) summary, and offers a clear snapshot of just what a Data Scientist does on a daily basis—what tools they work with, what techniques they use, and how they apply their learnings.

In conclusion, I think we can safely say that just as data is here to stay, so too are those who make a science of understanding it. If you're seeking a career path that comes with opportunity, demand, a great salary, and unrivaled work-life balance, then it's a great time to look at becoming a Data Scientist!



Salaries

What do data analysts make,
and where do they make it?

Data is the new frontier of the 21st century, and companies across virtually all fields are literally buckling under a deluge of newly available information. Petabytes of data offer detailed intelligence on everything from when, how often, and where customers are using products, to precisely how a process is functioning along a near-infinite quantity of touchpoints.

But all that data is useless to a business without someone to organize it, evaluate it, glean actionable insights from it, and communicate those insights visually, verbally, or both.

That's where you come in.

High Demand for the Highly Skilled

Data analysts are in extremely high demand, and for good reason—the work itself is demanding. Data science sits at the intersection of statistics, business intelligence, sociology, computer science, and communication. You've got to be a numbers whiz, but also a strong communicator; you've got to be an analytical mastermind who can also think abstractly.

As Senior Web Technology Manager Erik Berger recently noted for us, there is more to it than just having the right skills:

"You obviously need the technical skills to be able to extract data and run statistical analyses, but there is the more intangible ability of finding patterns or irregularities to report on. To be good at it, you need to fully understand the nature of the business that you're analyzing—just looking at the numbers is only half the story."

This combination of technical skills and conceptual acumen is why good data scientists are in such consistent demand, and why they are both so highly-prized, and well-compensated.

What Data Analysts Make

According to our partners at PAYSА (who provide the dynamic salary data on our Nanodegree program pages) [Data Analyst](#) salaries can range from \$85k-125k!

As the need for data pros amplifies, so does the interconnecting web of data jobs. Data analysts often work closely with data scientists (note: some organizations conflate the two titles), database administrators, data engineers—and probably additional roles as the industry continues to develop.

Here is some financial context for your prospects as a data analyst, according to [DataJobs](#). National salary ranges for the following data jobs:

- Data analyst (entry level): \$50,000-\$75,000

- Data analyst (experienced): \$65,000-\$110,000
- Data scientist: \$85,000-\$170,000
- Database administrator (entry level): \$50,000-\$70,000
- Database administrator (experienced): \$70,000-\$120,000
- Data engineer (junior/generalist): \$70,000-\$115,000
- Data engineer (domain expert): \$100,000-\$165,000

Each of these roles contributes critically to obtaining, analyzing, and delivering data. Embarking on a career as a data analyst gives you plenty of options down the road as you hone your skills.

It's important to note that, given the talent crunch and the dynamic state of the data industry, compensation is far from standardized. Right now, salaries are essentially as much as a company is willing to spend to fill their immediate needs.

Where the Jobs Are

It's no surprise that data jobs are seriously skewed toward the main tech hubs of the country: San Francisco and New York.

While SF represents just 7% of the jobs posted on [Dice](#), it's home to 24% of the Big Data jobs posted. New York and the nearby Washington, D.C./Baltimore area have the second and third most Big Data job postings.

That said, prime data analyst jobs are available in plenty of other metropolitan areas around the country. Boston and Seattle each claim just 3% of the jobs posted on Dice, but are home to 7% and 6%, respectively, of the data gigs posted, which means they markedly over-index on exactly the roles you'll be looking for. Same goes for Philadelphia and L.A.

The main takeaway here is, you've got plenty of options when it comes to job location. And, there's more good news: if your desired hometown isn't brimming with data analyst jobs, know that there are more opportunities for contract, freelance, and remote work than ever before. You've got the freedom to determine what works best for your goals, lifestyle, and experience.

The Bottom Line

Whether you're contemplating a career change or just setting off in the professional world, pursuing the path of the data analyst holds serious promise for both your bank account and your brain.



Roles and Skills

What you need to know to get hired.

Many resources stress that becoming a data scientist requires comprehensive mastery of a number of fields, including software development, data munging, databases, statistics, machine learning and data visualization.

The truth is, this isn't always the case. You don't necessarily need to learn a lifetime's worth of data-related information to launch a data career. In order to determine the best opportunity for you and the skills you bring to the table, it's important to learn how to read data science job descriptions closely. This will enable you to apply to jobs for which you already have necessary skills, or develop specific data skill sets to match the jobs you want.

Four Data Science Job Scenarios

"Data Scientist" is often used as a blanket title to describe jobs that are drastically different. To help you navigate through multiple opportunities, let's get an understanding of four different types of data science jobs by looking at four common scenarios:

1. You're the Scientist, and the Analyst: There are many companies where being a data scientist is synonymous with being a data analyst. Your job might consist of tasks like pulling data out of MySQL databases, becoming a master at Excel pivot tables, and producing basic data visualizations (e.g., line and bar charts). You may on occasion analyze the results of an A/B test or take the lead on your company's Google Analytics account. A situation like this is a great opportunity for an aspiring data scientist to learn the ropes. Once you have a handle on your day-to-day responsibilities, a company like this can be a great environment to try new things and expand your skillset.

2. You're the First Data Hire: It seems like a number of companies get to the point where they have a lot of traffic (and an increasingly large amount of data), and they're looking for someone to set up a lot of the data infrastructure that the company will need moving forward. They're also looking for someone to provide analysis. You'll see job postings listed under both "Data Scientist" and "Data Engineer" for this type of position. In a situation like this, you're liable to be one of the first data hires, so it's likely less important that you're a statistics or machine learning expert. A data scientist with a software engineering background might excel in a role like this, where it's more important that a data scientist make meaningful data-like contributions to the production code and provide basic insights and analyses. Mentorship opportunities for junior data scientists may be less plentiful, so as a result, you'll often have great opportunities to shine and grow via trial by fire. But, there will be less guidance, and you may face a greater risk of flopping or stagnating.

3. Data IS the Business: There are a number of companies for whom their data (or their data analysis platform) is their product. In this case, the data analysis or

machine learning going on can be pretty intense. This is probably the ideal situation for someone who has a formal mathematics, statistics, or physics background and is hoping to continue down a more academic path. Data Scientists in this setting likely focus more on producing great data-driven products than they do answering operational questions for the company. Companies that fall into this group could be consumer-facing companies with massive amounts of data or companies that are offering a data-based service.

4. The Company is Data-Driven: A lot of companies fall into this bucket. In this type of role, you're probably joining an established team of other data scientists. Generally, these companies are either looking for generalists or they're looking to fill a specific niche where they feel their team is lacking, such as data visualization or machine learning. Some of the more important skills when interviewing at these firms are familiarity with tools designed for 'big data' (e.g., Hive or Pig) and experience with messy, 'real-life' datasets.

Hopefully this gives you a sense of just how broad the title 'data scientist' is. Each of the four scenarios above are seeking different skillsets, expertise, and experience levels. Despite that, all of these job postings would likely say "Data Scientist," so look closely at the job description for a sense of what kind of team you'll join, what kinds of challenges you'll face, what kind of opportunities for growth you'll have, and what sorts of skills you'll need to develop.

8 Data Skills to Get You Hired

As you start to consider which career path in data is the right one for you, it's important to establish those data fundamentals that are going to apply no matter which route you take. Below you'll find a core set of eight data science competencies you should develop regardless of the role:

Basic Tools: No matter what type of company you're interviewing for, you're likely going to be expected to know how to use the tools of the trade. This means a statistical programming language, like R or Python, and a database querying language like SQL.

Basic Statistics: At least a basic understanding of statistics is vital as a data scientist. You should be familiar with statistical tests, distributions, maximum likelihood estimators, etc. Think back to your basic stats class! This will also be the case for machine learning, but one of the more important aspects of your statistics knowledge will be understanding when different techniques are (or aren't) a valid approach. Statistics is important at all company types, but especially data-driven companies where the product is not data-focused and product stakeholders will depend on your help to make decisions and design/evaluate experiments.

Machine Learning: If you're at a large company with huge amounts of data, or working at a company where the product itself is especially data-driven, it may be the case that you'll want to be familiar with machine learning methods. This can mean things like k-nearest neighbors, random forests, ensemble methods—all of the machine learning buzzwords. It's true that a lot of these techniques can be implemented using R or Python libraries—because of this, it's not necessarily a dealbreaker if you're not the world's leading expert on how the algorithms work. More important is to understand the broad strokes and really understand when it is appropriate to use different techniques.

Multivariable Calculus and Linear Algebra: You may in fact be asked to derive some of the machine learning or statistics results you employ elsewhere in your interview. Even if you're not, your interviewer may ask you some basic multivariable calculus or linear algebra questions, since they form the basis of a lot of these techniques. You may wonder why a data scientist would need to understand this material if there are a bunch of out of the box implementations in sklearn or R. The answer is that at a certain point, it can become worth it for a data science team to build out their own implementations in-house. Understanding these concepts is most important at companies where the product is defined by the data and small improvements in predictive performance or algorithm optimization can lead to huge wins for the company.

Data Munging: Often times, the data you're analyzing is going to be messy and difficult to work with. Because of this, it's really important to know how to deal with imperfections in data. Some examples of data imperfections include missing values, inconsistent string formatting (e.g., 'New York' versus 'new york' versus 'ny'), and date formatting ('2014-01-01' vs. '01/01/2014', unix time vs. timestamps, etc.). This will be most important at small companies where you're an early data hire, or data-driven companies where the product is not data-related (particularly because the latter has often grown quickly with not much attention to data cleanliness), but this skill is important for everyone to have.

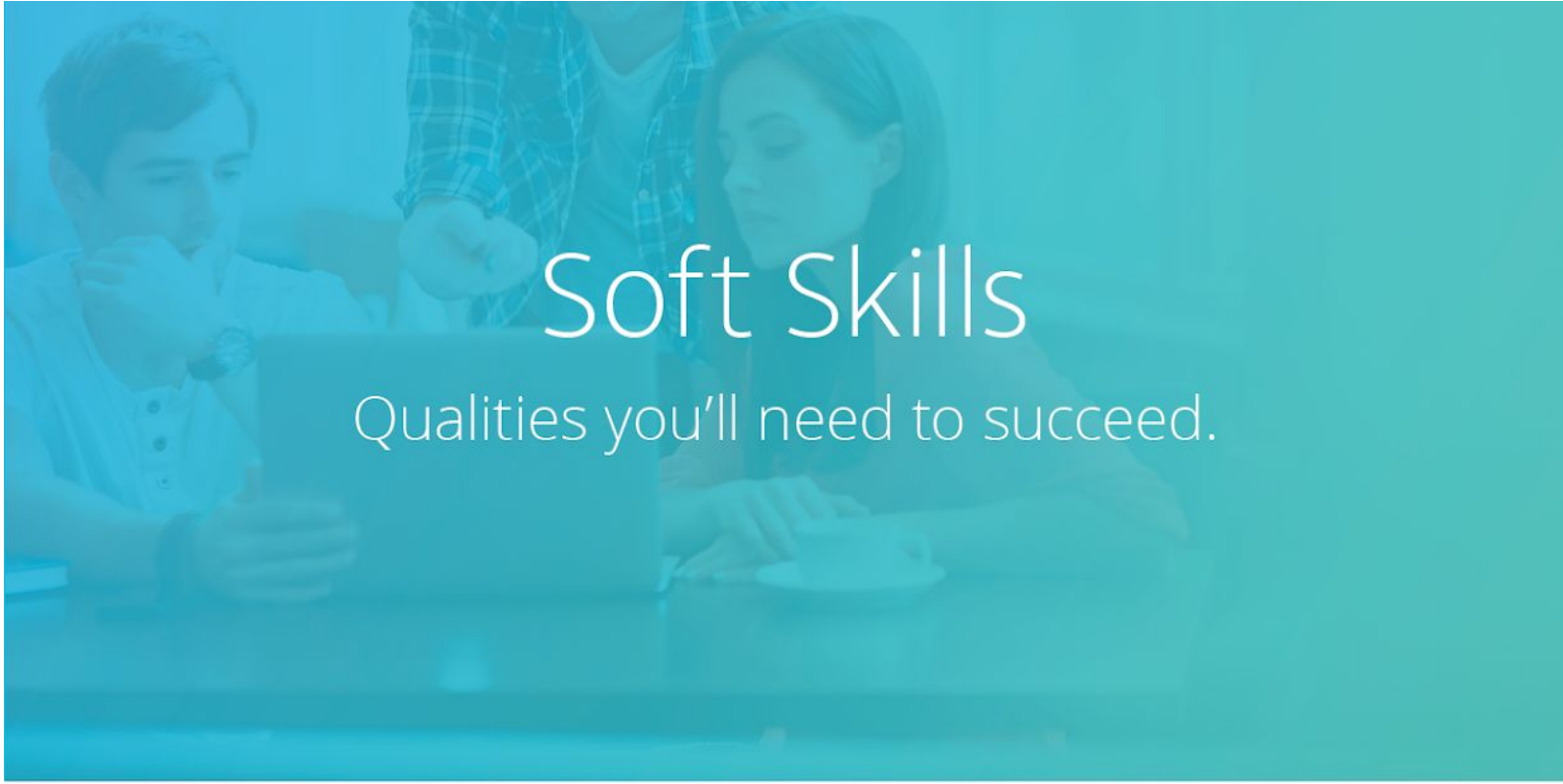
Data Visualization & Communication: Visualizing and communicating data is incredibly important, especially at young companies who are making data-driven decisions for the first time or companies where data scientists are viewed as people who help others make data-driven decisions. When it comes to communicating, this means describing your findings or the way techniques work to audiences, both technical and non-technical. Visualization-wise, it can be immensely helpful to be familiar with data visualization tools like ggplot and d3.js. It is important to not just be familiar with the tools necessary to visualize data, but also the principles behind visually encoding data and communicating information.

Software Engineering: If you're interviewing at a smaller company and are one of the first data science hires, it can be important to have a strong software engineering background.

You'll be responsible for handling a lot of data logging, and potentially the development of data-driven products.

Thinking Like A Data Scientist: Companies want to see that you're a data-driven problem solver. Which means, at some point during your interview process, you'll probably be asked about some high level problem—for example, about a test the company may want to run or a data-driven product it may want to develop. It's important to think about what things are important, and what things aren't. How should you, as the data scientist, interact with the engineers and product managers? What methods should you use? When do approximations make sense?

Data science is being defined as a field. Getting a job is as much about finding a company whose needs match your skills as it is developing those skills.



Soft Skills

Qualities you'll need to succeed.

People love to make pronouncements about a year. 2017 will be the Year of ... what?

Data? That certainly doesn't seem possible, given that we've been talking about data—both big and otherwise—for some time now. And yet, there was Glassdoor, rating Data Scientist as the [#1 Best Job](#) in America for 2016. They weren't the only ones either. [CareerCast.com](#) put Data Scientist at #1 as well. These two studies have been so extensively cited that it's essentially become a given that Data Scientist is one of THE hot jobs of today, and of the future as well. So how do you prepare for a data science career?

In-Demand Skills

According to the team at [Crowdfunder](#), based on an analysis of literally thousands of LinkedIn job postings, there are five in-demand skills you need: SQL, Hadoop, Python, Java, and R. For perspective on this study, we can read Seamus Breslin's article on [KDNuggets](#), in which he riffs on the Crowdfunder findings, and provides some excellent additional insight. To Hadoop, Python, and R, for example, he adds Data Visualization, Statistics, and ... Creativity! Which is excellent, and as you'll see later, also very important.

The team at [Smart Data Collective](#) did an extensive LinkedIn study as well, and their findings largely mirror the Crowdfunder results, though they took the interesting step of also looking at variations by level of experience. As an example:

"We found that Senior and Chief Data Scientists are less likely to report technical skills. Instead, they list skills like business intelligence, leadership, strategy, and management. These are all skills that one has to develop if they're going to move into a role responsible for turning data-driven insights into strategic action."

For the full results of their study you can read [The State of Data Science](#) at [rjmetrics.com](#). You'll find a nice high-level summary there, which notes the following as top data science skills: Data Analysis, R, Python, Data Mining, and Machine Learning.

Universal Skills, Unique Skills

For an especially deep look at data science skills, consider reading "Top 10 Skills in Data Science" by Bob Hayes on the [Business 2 Community](#) site. Hayes' research is both rigorous and impressive, and most intriguingly perhaps, he breaks down shifts in skills needs by role. For example, among data professionals who self-identify as having a business manager role, 86% have project management skills. Whereas for data professionals self-identifying as holding developer roles, that number drops to 46%. In his summary, the author notes that some skills appear to be universal regardless of role—included on this list are skills like: managing structured data, math, data mining and visualizations tools, and product design and development. He also notes skills that are largely unique to specific roles—successful developers, for example, have programming skills, whereas researchers possess machine learning skills. The one item that tops virtually every list for every role?

Communication. A key reminder that data must be communicated effectively, in order to be effectively acted upon.

Softer Skills, and The Spirit of Data Science

It is in fact abundantly clear that comparatively “softer” skills like communication are critical for success in data science. Linda Burtch, an executive recruiter who specializes in the quantitative business sciences, and who heads up Burtch Works Executive Recruiting, notes some of these skills in a widely-shared article entitled [The Must-Have Skills You Need to Become a Data Scientist](#). She highlights three “non-technical” skills in particular: intellectual curiosity, business acumen, and communication skills. She also references a [guest post on her site from Frank Lo](#), who is the Director of Data Science at Wayfair, and who cites intellectual curiosity as the “#1 Intangible” skill data scientists should possess. Why does he believe this to be the case?

*“The spirit of data science is discovery.”
—Frank Lo, Director of Data Science, Wayfair*

Lo also offers the following cautionary recommendation:

“Don’t filter candidates based on degree.”

There is a notion out there that the best data scientists are the ones with Ph.D’s. From my experience interviewing and evaluating candidates, it is my opinion that academic degree is the last consideration that matters.”

Based on everything we’ve looked at above, and spurred on by Frank Lo’s quotes, we can make a clear case in favor of creating your own path to a successful career in data science, through mastering key technical skills, nurturing the development of non-technical skills, and taking advantage of rapidly increasing demand for qualified talent.



The Interview

Strategies to nail it.

You just spent the last year honing your skills. You dutifully spent your evenings—sometimes late into the night—on homework and projects, ignoring friends, family, and the ever-growing mountain of laundry in the corner. You coded hobby projects for your local municipality and wrote up an entire epic (at least, you thought it was epic) series of blog posts on your findings. And when a friend mentioned her department’s struggling marketing efforts, your mind spun away on ways you might capture meaningful data and process the results.

Now you want to get a job. Which, despite your best efforts as a data analyst, depends almost entirely on acing the interview.

It should come as no surprise that careful preparation, and understanding the expectations going into the process, is what it takes not only to survive an interview for a data analyst position, but to set yourself apart as the best and most qualified candidate.

And even if you’re not actively looking for a position—if you’re still learning your craft and working your way through your projects—you can get started right now practicing interview questions, so that in six or twelve months, you’ll have done all the legwork necessary to wow your potential employers and win that coveted dream job offer.

Know Your Field

Katie Malone, Physics PHD and former Udacity instructor, has interviewed with Groupon and others in the Bay Area and Chicago. Some deceptively basic questions she’s heard come up again and again:

- What do you think a data scientist is/does?
- What do you think are the most important skills for a data scientist to have?

Thoughtfully crafted answers demonstrate not only your interest and commitment to a career in data, but your communication skills as well. Keep in mind that you may be interviewed by a team lead or HR director without a technical background, in which case you want to be able to explain concepts in the most general terms.

Nick Gustafson, a former Udacity data scientist, notes that you need to be prepared to talk in depth about the skills and tools of data analysis. He suggests being prepared to discuss topics such as these:

- Which machine learning model (classification vs. regression, for example) to use given a particular problem.
- The tradeoffs between different types of classification models. Between different types of regression models.

- How to go about training, testing, and validating results. Different ways of controlling for model complexity.
- How to model a quantity that you can't directly observe (using Bayesian approaches, for example, and when doing so, how to choose prior distributions).
- The various numerical optimization techniques (maximum likelihood, maximum a posteriori).
- What types of data are important for a particular set of business needs, how you would go about collecting that data.
- Dealing with correlated features in your data set, how to reduce the dimensionality of data.

If you find yourself stumped on a question, don't panic. It's OK to ask for more context or a relevant example. But be prepared to talk theory as well. You need to know the field inside out to advance in it.

Brush Up Beforehand

Being able to talk fluently and confidently across the range of tools and methods of data analysis means a fair amount of study beforehand. You might find it useful to review your coursework and notes, and to go over the latest tech blogs and industry newsletters. Former Udacity data engineer Krasnoshtan Dmytro (now at Google) prepared for his interview by making sure he had a firm grasp on:

- Linear/polynomial regression
- Decision trees
- Dimensionality reduction
- Clustering

and keeping up with [Data Science Weekly](#) and [Machine Learning Mastery](#), as well as sharpening his skills through [Hacker Rank](#) and [Kaggle Competitions](#).

Reviewing your past work, and continuing to hone and use those skills, can only help ground you more thoroughly in the material.

Talk about Yourself

Undoubtedly, you'll be asked to go into some detail about a project you've worked on. As Katie Malone says, prospective employers always ask these questions.

This is your opportunity to demonstrate how you approach a data problem and how well you can report and share your results. Pick a project you really loved working on—your passion will underscore your presentation. Make sure you can explain:

- Why you chose the model you did, given the problem you were trying to solve.
- What the features of your data were.
- How you tested and validated the results.
- What you got out of the project.

And be able to extrapolate, talking about your skills in general, answering such questions as:

- When you get a new data set, what do you do with it to see if it will suit your needs for a given project?
- How do you handle big data sets — how would you start work on a project with an associated data set that was many tens of GB or larger?

Know the Company

In addition to knowledge and skill, employers are looking for individuals who will be a good fit with the company and its culture. It goes without saying that you need to do what you can to research the company you're interviewing with, looking not only at their products, but finding out what you can about their office culture as well. Think about a few reasons (other than a steady paycheck!) you'd like to work there.

Be able to answer:

- What's a project you would want to work on at our company?
- What data would you go after to start working on it?
- What unique skills do you think you'd bring to the team?

If you're able to provide a relevant sample or example, even better.

Beyond the Basics

Going through lists of questions typically heard during data science interviews by yourself won't be as effective as talking through a few of these problems with a friend or fellow student. Mock interviews give you practice not only in organizing and verbalising your thoughts, but in doing so under some degree of pressure (though prepare yourself for the possibility of an anxiety-ridden interview!).

Reach out to your connections in the field and ask them how their own interview processes went and what they would ask if they were looking for a right-fit data analyst with your particular skill set.

Lewis Kaneshiro is a former Udacity instructor and the co-founder of [Streamlio](#). Not only has he endured grueling interviews, he has also interviewed KPCB Fellows for summer internships.

When looking for stand-out candidates, Lewis asks, **What are the assumptions required for linear regression?**

“Surprisingly this question has come up in multiple interviews throughout the years, and it tends to separate those who know linear models as ‘a function in R/Python’ or worse ‘a function in Excel,’ and those who can apply the models to actual data.”

Being able to confidently and capably verbalize and demonstrate (via a whiteboard) those assumptions has been a large chunk of Lewis’s interview experiences. He also hints at the importance of including graphical demonstrations of data that will violate each assumption.

“It is simple, but students who ignore these conditions will tend to blindly apply models without understanding the underlying use cases, and fail to recognize the need for normalization, skew adjustment, outlier detection, or other real-world issues. They also tend to need far too much oversight to be useful in an actual job. Students sometimes think they are being hired to apply a bunch of cool models to data, when in reality 90%+ of work is done with linear models and data normalization/validation.”

Data Science Interviews

Questions and topics you should be ready to discuss during an interview for a data-related job.

- What are the most important skills for a data scientist to have?
- What types of data are important for business needs?
- What data [at the company] would you go after and start working on?
- Discuss various numerical optimization techniques.
- Show understanding of training, testing, and validation of results.
- Explain tradeoffs between different types of regression models and different types of classification models.
- What are the assumptions required for linear regression?

- When you get a new data set, what do you do with it to see if it will suit your needs for a given project?
- How do you handle big data sets?
- How do you detect outliers?
- How do you control model complexity?
- How do you model a quantity you can't observe?

Lewis emphasizes that a keen interest in data, curiosity, drive, and tenacity are critical to convey during an interview.

"I've found that interest and passion coupled with underlying curiosity and intellectual grit trump simple 'brilliance' or 'intelligence' every time. We've passed on PhD candidates that are pure intellectuals in favor of passionate masters or undergrads willing to dive into data and get dirty. For example, we are considering a summer intern who may not appear to be the strongest candidate, but his Kaggle approaches and his personal project (scraping bus arrival times to predict actual arrivals) demonstrate that he is willing to jump into messy situations and power through. This is far more useful than a brilliant candidate who wants to invent a new algorithm. He or she is probably better off in a PhD program, in that case, and they tend to be poor employees."

And finally, Lewis wants to know of those he interviews, how do you detect outliers?

"Some of the best interviews I've had begin and continue with this question. It separates academics who have only applied algorithms to cleaned data sets from those with real-world experience — or real-world curiosities. It is always better to spend the majority of one's time understanding the raw data and proceeding with the correct approach and model, than to frantically apply every R model known and check the accuracy. I think it is one of the questions asked by the most experienced interviewers."

To answer this one, Lewis recommends reviewing the practical method described in Sebastian Thrun and Katie Malone's [Intro to Machine Learning](#) "to use LR to fit [a predictive model to a data set], rank errors, and throw out the top 10% and refit iteratively as a test for stability."

The Bottom Line

If you were to ask a hundred different data professionals what they were asked during their interviews, you'd likely get a hundred different answers. Luckily, you don't have to collate that information yourself. There are tons of [lists](#) and [resources](#) full of sample questions that you can use to practice and [prepare](#) yourself for the big day.

Knowing your field inside and out, reviewing your projects, and rekindling your passion for data will go a long way toward a successful interview. Stretch and exercise now, by quizzing yourself, challenging yourself, and talking through the problems you've tackled — and hopefully you'll come out the other side of the interview process with the offer you've been waiting on.



Your Portfolio

Your secret weapon for getting hired.

At Udacity's inaugural [Intersect summit](#), a student attendee asked how to gain the data analysis experience needed to land a job. A suggestion made by Mat Leonard, a Senior Course Developer at Udacity, was to work on small data analysis projects then put them online, as he had done with [his own blog](#). As he noted, small projects let you deepen your understanding of analysis methods or learn new techniques. Publishing them online builds a portfolio of your work, showing potential employers that you can successfully answer questions with data.

Below, Mat lays out some strategies for how to successfully build a data analysis portfolio that can help get you hired.

There are a few bits of technology that make getting your projects online a simple process. Firstly, Jupyter notebooks are an excellent tool for combining text, code, and images. Notebooks can be converted to Markdown files for use with web frameworks, such as Pelican. Finally, you can host your blog for free on GitHub. For the information to follow, you'll need to know basic usage of git and GitHub: how to stage, commit, and push changes. You can learn about git and GitHub in Udacity's [course on version control](#). You'll also need to be comfortable working from the command line, which you can learn about [here](#).

Building Your Blog

To build the blog itself, you can use [Pelican](#), a static site generator written in Python. Pelican uses the Markdown files as blog posts and automatically creates an archive, categories, and tags. There are multiple themes to use with Pelican or you can make your own for a unique and personal touch.



Also, since Pelican creates a static site, you can host it on GitHub for free.

For detailed instructions on how to set up your own blog, please click [here](#), and please note, you'll need to have experience with [Git and GitHub](#), as well as Python and shell commands.

Your Data Projects: Where To Start

To flesh out your new website with content, you'll want to do some small data projects. Kaggle hosts [data science competitions](#) that are a great place to start. The data is typically already cleaned and formatted, so you can focus on building the model. Kaggle also hosts a bunch of [data sets](#) not associated with competitions for you to explore, such as Hillary Clinton's emails. Other resources include the [datasets subreddit](#), [Data.gov](#), and many more that you can find in [this Quora thread](#). Many cities also have open data sets, such as [San Francisco](#) and [New York City](#). You can also go [web scraping](#) to collect data like I did with [Yelp](#).

The most important thing is to find data you are interested in that creates questions you want to answer. Take this time to learn new techniques and dive deeper into methods you already know. Working on small data projects and putting them online can really support your career objectives, especially since it shows employers that you love working with data and want to continue improving yourself. Hopefully, from my guidance above, you can create your own online portfolio and get your excellent work out there for the world to see!



Your First Data Job

What it will be, and how to get it.

No matter where you are on your path to a career in data, it probably seems daunting to consider all the skills you still need to be recruiter-ready. Typically, data workers come from three different backgrounds:

1. Starting from zero
2. Strong programming background
3. Strong mathematical background

Given your starting point, what is your best path to your first data science job? What skills can you use to build your foundations in the most efficient and effective way?

It's helpful to examine each of those three scenarios—zero experience, programming but no math, math but no programming—in terms of the building blocks you'll need to build your ultimate data skill set.

Starting From Zero

So you want to be a data analyst? Congrats! You've chosen a lucrative, geographically flexible, and super-secure career in a field that's only going to continue to blossom in the years to come.

Of course, you've got to do the upfront work of learning and sharpening the necessary skills before you can reap the benefits. Below please find some recommendations for how to acquire the tools to become an ultra-hireable data analyst.

Programming

Programming is an integral aspect of data analysis. It's the core skill that sets data analysts apart from business analysts. You'll need to be able to program well in one or more programming languages—start with Python or [R](#)—and to have a good grasp of the landscape of the most commonly used data science libraries and packages (such as `ggplot2`, `reshape2`, `numpy`, `pandas`, and `scipy`).

Statistics

What good is all that programming prowess without the ability to interpret the data? An understanding of statistics, including statistical tests, distributions, and maximum likelihood estimators, is essential in data analysis.

Acquaint yourself with both [descriptive](#) and [inferential statistics](#). The former refers to quantitative measures that describe the properties of a sample; the latter, to predictive

measures that infer properties of the larger population by interpreting the sample. You'll need to know the basics, many of which will sound familiar from high school or college (mean, median, mode; standard deviation and variance; hypothesis testing), onto which you will layer more complex statistical skills as well (different types of data distribution: standard normal, exponential/poisson, binomial, chi-square; and tests for significance: Z-test, t-test, Mann-Whitney U, chi-squared, ANOVA).

Beyond descriptive and inferential stats, data analysts need to be adept at statistical experimental design. That's the systematic process of selecting parameters in order to make results both valid and significant. For example, you'll need to determine how many samples to collect, how different factors should be interwoven, how to choose good control and testing groups, and the like. To execute strong experimental design using tools like A/B testing and concepts like power law, best practice is to use as a barometer the idea of "SMART (Specific, Measurable, Actionable, Realistic, Timely) experiments."

Math

The language of data analysts is numbers, so it follows that a strong foundation in math is an essential building block on the path to becoming a data analyst.

At a basic level, you should be comfortable with college algebra. You'll have to translate what you once knew as "word problems" (real-world equivalent: business problems) into mathematical expressions; you'll need to be able to manipulate algebraic expressions and solve equations; and you'll need to be able to graph different types of functions, with a deep understanding of the relationship between a function's graph and its equation.

Beyond that, a solid grasp of multivariable calculus and linear algebra will serve you well as a data analyst. Think: matrix manipulations, dot product, eigenvalues and eigenvectors, and multivariable derivatives.

Machine learning

Multivariable calculus and linear algebra, along with statistics, make up the basic foundation of [machine learning](#), which enables data professionals to make predictions or calculated suggestions based on huge amounts of data. For a career as a data analyst, you won't need to invent new machine-learning algorithms (advanced skills like that qualify you to become a data scientist), but you should know the most common of them. A few examples include principal component analysis, neural networks, support vector machines, and k-means clustering. Note that you may not need to know the theory and implementation details behind these algorithms, but you should understand the pros and cons, as well as when to (and when not to) apply them to a dataset.

There are three main types of machine learning that data analysts need to know: [supervised learning](#), [unsupervised learning](#), and [reinforcement learning](#).

In supervised learning, the “learner” (computer program) is provided with two sets of data, a training set and a test set. The computer “learns” from a set of labeled examples in the training set so that it can identify unlabeled examples in the test set accurately. The goal is for the learner to develop a rule that can identify the elements in the test set. It is supervised learning that makes it possible for your phone to recognize your voice, and your email to filter spam. Specific tools you’ll use include:

- decision trees
- Naive Bayes classification
- Ordinary Least Squares regression
- logistic regression
- neural networks
- support vector machines
- and ensemble methods.

Unsupervised learning is what you’ll use when faced with the challenge of discovering implicit relationships, and thus hidden structure, in a given “unlabeled” dataset. Unsupervised learning makes it possible for Netflix to recommend movies you’d enjoy, and Amazon to predict products you’ll like. Specific tools you’ll use include:

- clustering algorithms
- Principal Component Analysis (PCA)
- Singular Value Decomposition (SVD)
- and Independent Component Analysis (ICA)

Lastly, reinforcement learning applies to situations that fall between the two extremes of supervised and unsupervised, i.e., when there is some form of feedback available for each predictive step or action, but no precise label or error measure. You can apply reinforcement learning when you want to figure out how to maximize rewards, for instance in arenas like robot control, chess, backgammon, checkers, and other activities that a software agent can learn. Specific tools you’ll use include:

- Q-Learning
- TD-Learning
- and genetic algorithms

Data wrangling

The last three abilities crucial to your development as a data analyst pertain to manipulating, displaying, and interpreting data. To transform raw material into a useful, organized datasets, data wrangling (also known as “data munging”) comes into play. This is the process of collecting and cleaning data so it can be easily explored and analyzed.

You’ll need to equip yourself with knowledge of database systems (both SQL-based and NoSQL-based) that act as a central hub to store information. It’ll be useful to be familiar with relational databases such as PostgreSQL, MySQL, Netezza, and Oracle, as well as Hadoop, Spark, and [MongoDB](#).

Other concepts and tools essential to data wrangling include regular expressions, mathematical transformations, and Python String library for string manipulations. You’ll also need to know how to parse common file formats such as csv and xml files and how to convert non-normal distribution to normal with log-10 transformation.

It may all sound overwhelming right now, especially if you’re brand new not only to the skills involved, but to some of the terms themselves. Remember that all of these skills are stackable: each one you master will help you build the next, and the next after that, until you’re a fully equipped data analyst ready to kick butt and take some names.

Data visualization

Once you’ve cleaned, organized, arranged, plied, and interpreted the data, you want to be able to illustrate your findings visually so that stakeholders, including the data-illiterate, can fully understand. You won’t get any credit for your data analysis chops if you don’t communicate your insights clearly and effectively.

It’ll be helpful to be familiar with [data visualization](#) tools like ggplot, matplotlib, sea born, and D3.js. Of course, it’s key to be familiar not just with the tools necessary to actually display the data visually, but also with the principles underlying the visual encoding of that data. To wit, you’ll need to intimately understand the context of the business situation in order to determine how to situate your data visualization to be maximally relevant.

Data intuition

Bolstered by the technical knowledge of the combined skills above, you’ve got to know how to think, how to ask the right questions. You could spend the rest of your life analyzing a single dataset and visualizing your interpretation in a multitude of formats with a plethora of findings. The reality is, you’ll only ever have a limited amount of time and space to

address your associates' questions in analyzing the data at hand. Therefore, it's important to nurture an intuition about what things are important, and what things aren't.

Work toward developing a deep understanding of the field in which you're working, whether it's the stock market or consumer packaged goods. Invest the time to work through as many datasets as you can, for example by participating in Kaggle competitions, to learn how to avoid dead ends. Learn to sense the "question behind the question" in assignments, digging down, in other words, to discover the exact business issues driving the need to analyze the data.

Building on a Programming Background

Here's what you'll need to learn next on the road to clicking "apply" on a data analyst job opening.

Foundational topics

- **Statistics:** You'll need to be able to rigorously interpret, make inferences, and compare different types of data by applying the right approach, technique, or statistical tests to different types of distributions. Check out the above breakdown for specific tools and skills.
- **Probability:** In order to draw accurate conclusions, data analysts need to be able to reason about the likelihood that an event could have happened or that it will happen. Check out the above breakdown for specific tools and skills.

Advanced topics

- **Multivariable calculus/linear algebra:** These advanced math skills are less important to know than statistics and probability, but will definitely be useful if you want to understand how machine learning actually works. In addition, if you envision wanting to leverage your data analyst chops into a career as a data scientist at some point, multivariable calc and linear algebra will provide the foundational knowledge to build your own algorithms.

Building on a Mathematical Background

OK, so maybe you're a math whiz, but have no knowledge of programming. Here's a step-by-step guide to building that programming knowledge that's so crucial to becoming a data analyst.

Foundational topics

- **Variables, control flow, loops, functions:** These are the basic building blocks of programming. Know them and love them.
- **Debugging:** Your code will probably not work correctly the first time around, or could break when unexpected situations occur. When that happens, you'll need to be able to figure out what the problem is and why it's happening. This is where debugging skills will come in handy.
- **Object-oriented programming:** Learn how to structure your code into object-oriented design patterns, so it can be easily reused, tested, and shared with other people.

Advanced topics

- **Data structures:** For extra credit, familiarize yourself with Stacks, Queues, Lists, Arrays, Hashmaps, Priority Queues, Tries, and Graphs. There are certain situations in which one data structure will be superior to others (in terms of memory usage and runtime efficiency), and if you understand these relationships, you can optimize your program to run faster and more efficiently. That'll impress your team, and set you apart among other data professionals.
- **Algorithms:** Knowing which algorithm to apply in which situation can reduce the running time of your program from a few days to a few hours, or the memory requirement from a few gigabytes to a few hundreds of megabytes. Work towards understanding divide and conquer (D&C) algorithms, greedy algorithms, dynamic programming, linear programming, and graph algorithms (depth vs. breadth vs. traversal, minimum spanning trees, and shortest path between two nodes).
- **Software design patterns:** Want to make your code robust, reusable, and testable? Many pioneering software engineers and computer scientists have developed software design patterns to help you do so. Become comfortable with them so you can excel at your data analysis.

The Bottom Line

Data analysis is a fast-growing field, and there are a lot of voices out there sharing what you need to learn, in what order. The variety of information can be confusing, overwhelming, and discouraging.

Know that you can rely on what we've printed here as a reliable guide to what you really do need to learn in order to land that first data analyst job, along with prescriptions for where to start, depending on your specific background.

The investment in a career as a data analyst is huge, no matter if you're just starting out or if you're expanding on existing abilities. But the payoff, we promise, is even bigger.



The Future of Data

A look at predictive analytics.

Historically, data analysis was a lot of looking backwards. What happened, and what does it mean? That way of doing things is literally history. With the amount of data now available to the modern business, analysis is all about looking forward. What can we expect, and how can we get ahead? Enter Predictive Analytics.

Predictive Analytics

There are a number of wonderful definitions out there for Predictive Analytics—some are more technical, some are comparatively plain-spoken. Here are good examples of each:

“Predictive analytics describes any approach to data mining with four attributes:

- 1. An emphasis on prediction (rather than description, classification or clustering)*
- 2. Rapid analysis measured in hours or days (rather than the stereotypical months of traditional data mining)*
- 3. An emphasis on the business relevance of the resulting insights (no ivory tower analyses)*
- 4. (increasingly) An emphasis on ease of use, thus making the tools accessible to business users.*

—Gartner IT Glossary

“Predictive Analytics is the art and science of using data to make better informed decisions. Predictive analytics helps you uncover hidden patterns and relationships in your data that can help you predict with greater confidence what may happen in the future, and provide you with valuable, actionable insights for your organization.”

—Predictive Analytics For Dummies

More and more companies are incorporating Predictive Analytics into their data strategies. Current research from [MarketsandMarkets](#) “predicts the global predictive analytics market to grow from USD 2.74 Billion in 2015 to USD 9.20 Billion by 2020, at a Compound Annual Growth Rate (CAGR) of 27.4%.” New research from [TDWI Research](#) identifies the top five reasons why companies are looking to use Predictive Analytics:

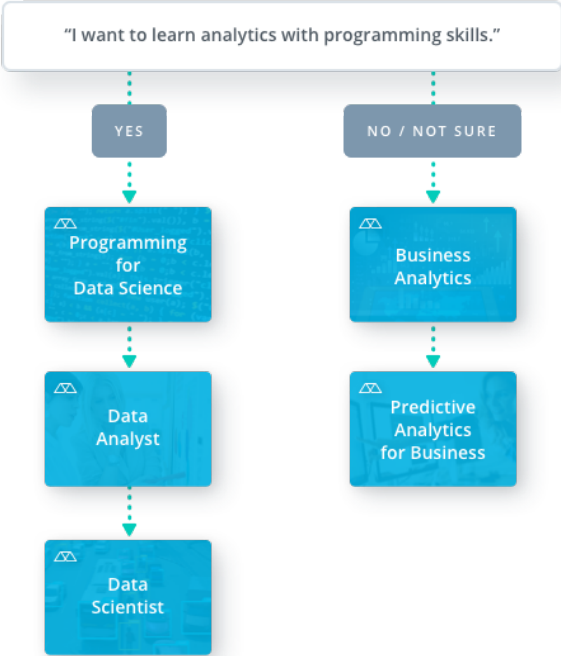
- predict trends
- understand customers
- improve business performance
- drive strategic decision-making
- predict behavior

The appeal of Predictive Analytics is very clear, and the ability to produce this kind of actionable, forward-looking analysis is rapidly becoming a key point of distinction for brands looking to stay ahead of their competitors. But, these new approaches bring up a

key reality—effective data analysis today requires two things: tools, and those who know how to use them. Enter the Udacity School of Data Science.

The Udacity School of Data Science

Udacity’s School of Data Science offers comprehensive learning experiences covering everything from programming in Python and SQL, to predictive analytics and applied machine learning. Every program is designed to support your career goals. You can choose programming or non-programming paths, and target roles like Business Analyst, Data Analyst, and Data Scientist. Our programs are designed to prepare you for these roles based on your career goals, and your current skills and experience levels. We have also differentiated our two paths by whether they focus on developing programming skills or not.



To learn more about these programs, visit Udacity’s [School of Data Science](#).



As we noted in the introduction to this guide, a career in data is both a secure and safe choice, and a cutting-edge one. Having read through all the insights we've offered here, we hope it's also become clear that data as an employment field offers an extraordinary range of entry points. While there are certain skills and tools you'll need regardless of the role, the field is also wide open to individuals with widely varying degrees of experience and areas of concentration.

Our [School of Data Science](#) is expressly designed to get you the skills you need to succeed in a career in analytics and data science. Whether you are just getting started in data, are looking to augment your existing skill set with in-demand data skills, or intend to pursue advanced studies and career roles, Udacity's School of Data Science has the right path for you to start building relevant skills right away.

Our project-based approach in these programs will help you not only learn the in-demand skills you'll need to succeed, but build the portfolio that will get you hired.

"I had a hard time finding a job due to lack of relevant experience. The projects I built in this program helped me build a strong resume, and launch my career." —Soumya Ranjan Mohanty, Data Analyst Nanodegree Program Alumnus, now a Data Specialist at Gramener

We hope you can take what you've read here, and apply it to your own chosen career path. If there's one thing that's certain, it's that individuals with data skills are going to be very in-demand for a very long time. If you want a career in data, then this is your complete

guide, and our School of Data Science Nanodegree programs will be your complete path to career advancement and career success.

Are you ready to take your place among the next generation of highly sought-after data experts? Start learning with Udacity's [School of Data Science](#) today.