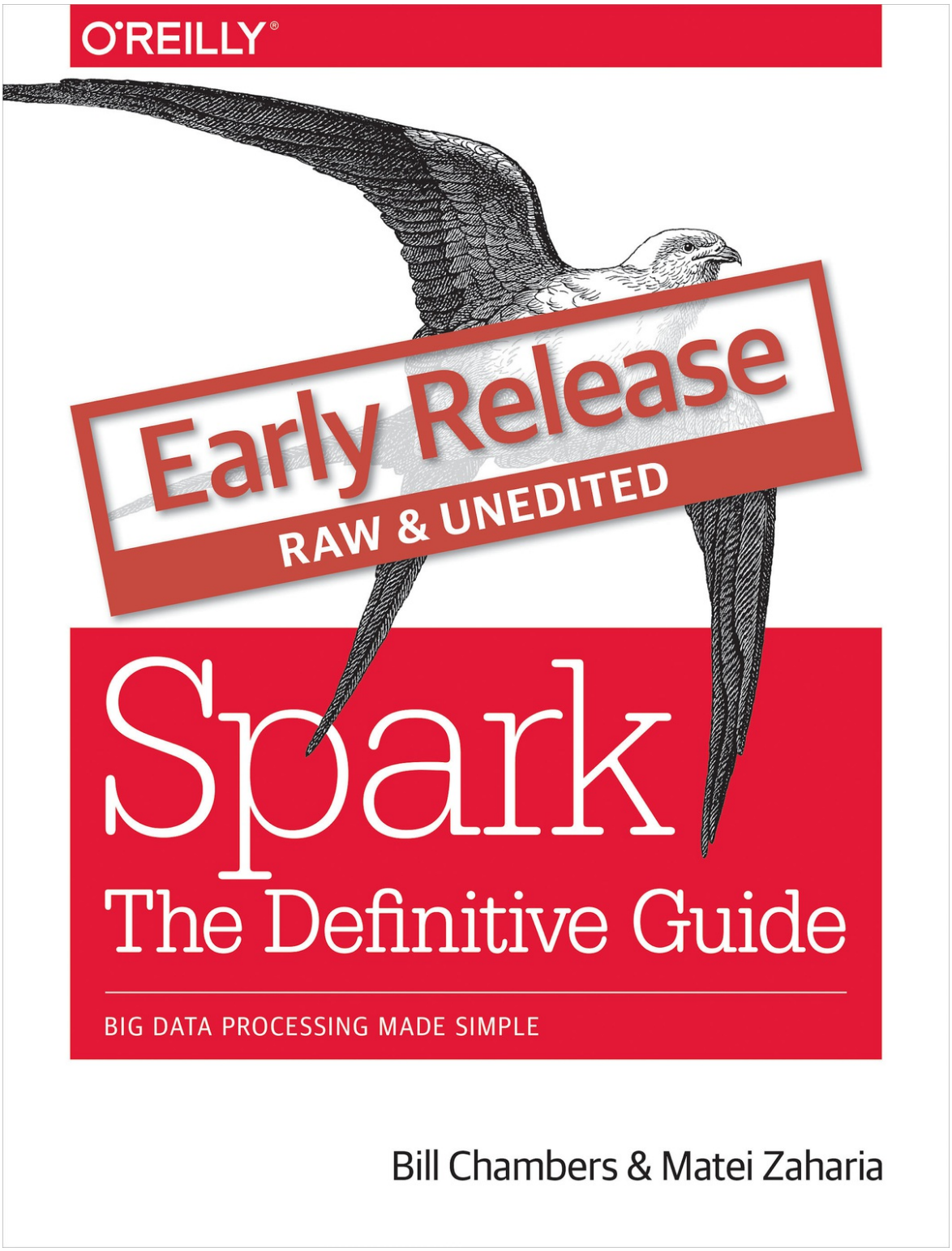

Spark: The Definitive Guide

by Matei Zaharia and Bill Chambers

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Spark: The Definitive Guide

Big data processing made simple

Bill Chambers, Matei Zaharia

Chapter 1. A Gentle Introduction to Spark

What is Apache Spark?

Apache Spark is a processing system that makes working with big data simple. It is a group of much more than a programming paradigm but an ecosystem of a variety of packages, libraries, and systems built on top of the Core of Spark.

Spark Core consists of two APIs. The Unstructured and Structured APIs. The Unstructured API is Spark's lower level set of APIs including Resilient Distributed Datasets (RDDs), Accumulators, and Broadcast variables. The Structured API consists of DataFrames, Datasets, Spark SQL and is the interface that most users should use. The difference between the two is that one is optimized to work with structured data in a spreadsheet-like interface while the other is meant for manipulation of raw java objects. Outside of Spark Core sit a variety of tools, libraries, and languages like MLlib for performing machine learning, the GraphX module for performing graph processing, and SparkR for working with Spark clusters from the R langauge.

We will cover all of these tools in due time however this chapter will cover the cornerstone concepts you need to write Spark programs and understand. We will frequently return to these cornerstone concepts throughout the book.

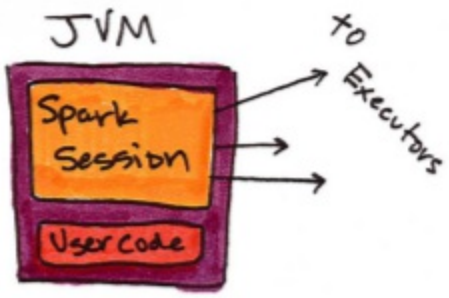
Spark's Basic Architecture

Typically when you think of a "computer" you think about one machine sitting on your desk at home or at work. This machine works perfectly well for watching movies, or working with spreadsheet software but as many users likely experienced at some point, there are somethings that your computer is not powerful enough to perform. One particularly challenging area is data processing. Single machines simply cannot have enough power and resources to perform computations on huge amounts of information (or the user may not have time to wait for the computation to finish). A *cluster*, or group of machines, pools the resources of many machines together. Now a group of machines alone is not powerful, you need a framework to coordinate work across them. Spark is a tool for just that, managing and coordinating the resources of a cluster of computers.

In order to understand how to use Spark, let's take a little time and understand the basics of Spark's architecture.

Spark Applications

Spark Applications consist of a *driver* process and a set of *executor* processes. The driver process, Figure 1-2, sits on the *driver node* and is responsible for three things: maintaining information about the Spark application, responding to a user's program, and analyzing, distributing, and scheduling work across the executors. As suggested by figure 1-1, the driver process is absolutely essential - it's the heart of a Spark Application and maintains all relevant information during the lifetime of the application.



An executor is responsible for two things: executing code assigned to it by the driver and reporting the state of the computation back to the driver node.

The last piece relevant piece for us is the cluster manager. The cluster manager controls physical machines and allocates resources to Spark applications. This can be one of several core cluster managers: Spark's standalone cluster manager, YARN, or Mesos. This means that there can be multiple Spark appliications running on a cluster at the same time.

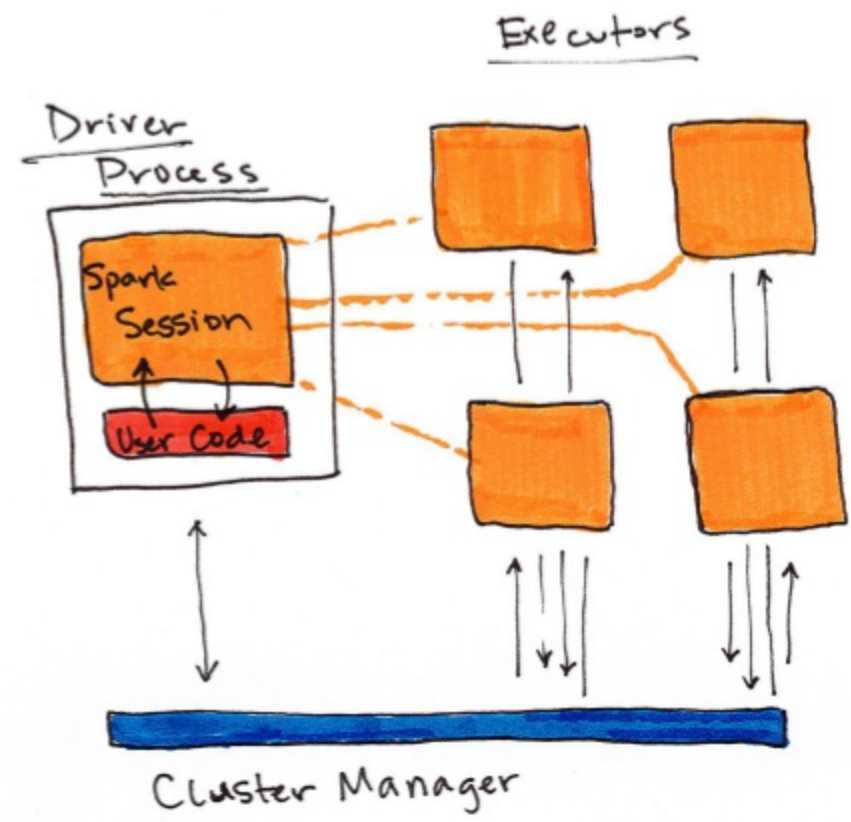


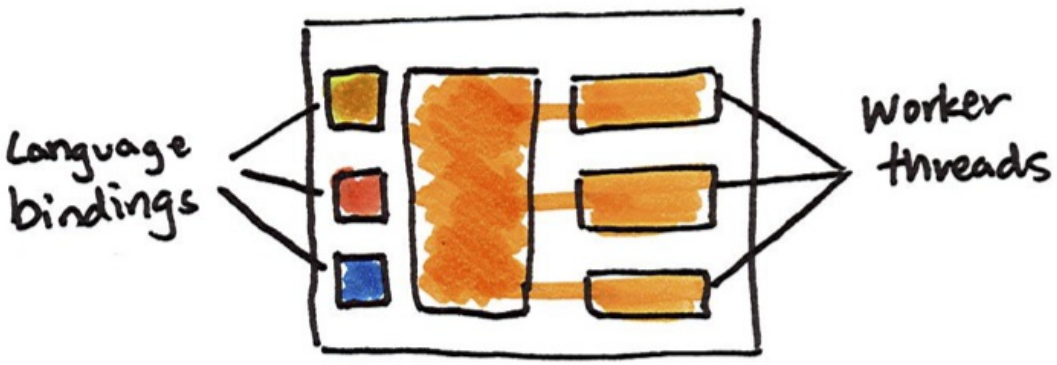
Figure 1-1 shows, on the left, our driver and on the right the four worker nodes on the right.

NOTE:

Spark, in addition to its cluster mode, also has a *local mode*. Remember how the driver and executors are processes? This means that Spark does not dictate where these processes live. In local mode, these processes run on your individual computer instead of a cluster. See figure 1-3 for a high level diagram of this architecture. This is the easiest way to get started with Spark and what the demonstrations in this book should run on.

*Need fix

Local Mode



Using Spark from Scala, Java, SQL, Python, or R

As you likely noticed in the previous figures, Spark works with multiple languages. These language APIs allow you to run Spark code from another language. When using the Structured APIs, code written in any of Spark's supported languages should perform the same, there are some caveats to this but in general this is the case. Before diving into the details, let's just touch a bit on each of these langauges and their integration with Spark.

Scala

Spark is primarily written in Scala, making it Spark's "default" language. This book will include examples of Scala where ever there are code samples.

Python

Python supports nearly everything that Scala supports. This book will include Python API examples wherever possible.

Java

Even though Spark is written in Scala, Spark's authors have been careful to ensure that you can write Spark code in Java. This book will focus primarily on Scala but will provide Java examples where relevant.

SQL

Spark supports user code written in ANSI 2003 Compliant SQL. This makes it easy for analysts and non-programmers to leverage the big data powers of Spark. This book will include numerous SQL examples.

R

Spark supports the execution of R code through a project called SparkR. We

will cover this in the Ecosystem section of the book along with other interesting projects that aim to do the same thing like Sparklyr.

Key Concepts

Now we have not exhaustively explored every detail about Spark's architecture because at this point it's not necessary to get us closer to running our own Spark code. The key points are that:

- Spark has some cluster manager that maintains an understanding of the resources available.
- The driver process is responsible for executing our driver program's commands accross the executors in order to complete our task.
- There are two modes that you can use, cluster mode (on multiple machines) and local mode (on a single machine).

Starting Spark

Now in the previous chapter we talked about what you need to do to get started with Spark by setting your Java, Scala, and Python versions. Now it's time to start Spark's local mode, this means running `./bin/spark-shell`. Once you start that you will see a console, into which you can enter commands. If you would like to work in Python you would run `./bin/pyspark`.

SparkSession

From the beginning of this chapter we know that we leverage a driver process to maintain our Spark Application. This driver process manifests itself to the user as something called the SparkSession. The *SparkSession* instance is the entrance point to executing code in Spark, in any language, and is the user-facing part of a Spark Application. In Scala and Python the variable is available as `spark` when you start up the Spark console. Let's go ahead and look at the `SparkSession` in both Scala and/or Python.

```
%scala

spark

%python

spark
```

In Scala, you should see something like:

```
res0: org.apache.spark.sql.SparkSession = org.apache.spark.sql.
```

In Python you'll see something like:

```
<pyspark.sql.session.SparkSession at 0x7efda4c1ccd0>
```

Now you need to understand how to submit commands to the SparkSession. Let's do that by performing one of the simplest tasks that we can - creating a range of numbers. This range of numbers is just like a named column in a spreadsheet.

```
%scala

val myRange = spark.range(1000).toDF("number")

%python

myRange = spark.range(1000).toDF("number")
```

You just ran your first Spark code! We created a DataFrame with one column containing 1000 rows with values from 0 to 999. This range of number represents a *distributed collection*. Running on a cluster, each part of this range of numbers would exist on a different executor. You'll notice that the value of *myRange* is a DataFrame, let's introduce DataFrames!

DataFrames

A *DataFrame* is a table of data with rows and columns. We call the list of columns and their types a *schema*. A simple analogy would be a spreadsheet with named columns. The fundamental difference is that while a spreadsheet sits on one computer in one specific location, a Spark DataFrame can span potentially thousands of computers. The reason for putting the data on more than one computer should be intuitive: either the data is too large to fit on one machine or it would simply take too long to perform that computation on one machine.

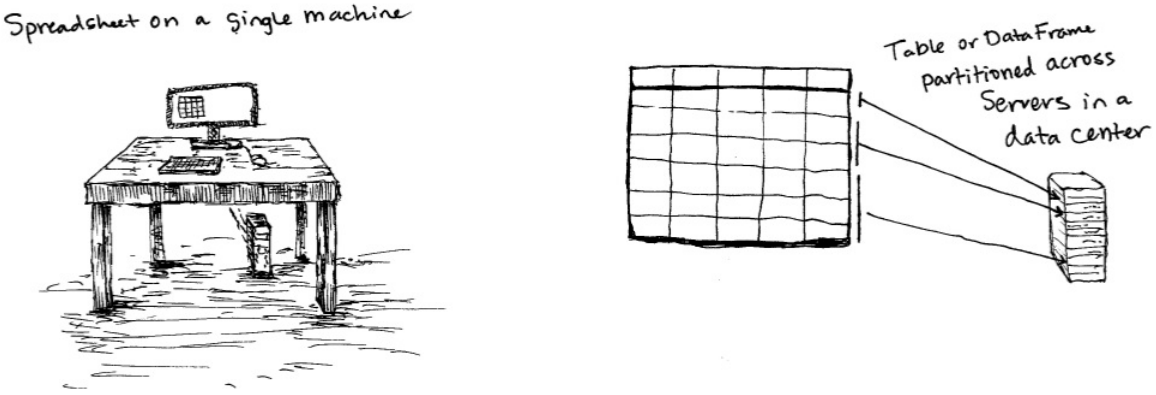
The DataFrame concept is not unique to Spark. The R Language has a similar concept as do certain libraries in the Python programming language. However, Python/R DataFrames (with some exceptions) exist on one machine rather than multiple machines. This limits what you can do with a given DataFrame in python and R to the resources that exist on that specific machine. However, since Spark has language interfaces for both Python and R, it's quite easy to convert to Pandas (Python) DataFrames to Spark DataFrames and R DataFrames to Spark DataFrames (in R).

Note

Spark has several core abstractions: Datasets, DataFrames, SQL Tables, and Resilient Distributed Datasets (RDDs). These abstractions all represent distributed collections of data however they have different interfaces for working with that data. The easiest and most efficient are DataFrames, which are available in all languages. We cover Datasets in Section II, Chapter 8 and RDDs in depth in Section III Chapter 2 and 3. The following concepts apply to all of the core abstractions.

Partitions

In order to leverage the the resources of the machines in cluster, Spark breaks up the data into chunks, called partitions. A *partition* is a collection of rows that sit on one physical machine in our cluster. A DataFrame consists of zero or more partitions.



When we perform some computation, Spark will operate on each partition in parallel unless an operation calls for a *shuffle*, where multiple partitions need to share data. Think about it this way, if you need to run some errands you typically have to do those one by one, or serially. What if you could instead give one errand to a worker who would then complete that task and then report back to you? In that scenario, the key is to break up errands efficiently so that you can get as much work done in as little time as possible. In the Spark world an “errand” is equivalent to computation + data and a “worker” is equivalent to an executor.

Now with DataFrames, we do not manipulate partitions individually, Spark gives us the DataFrame interface for doing that. Now when we ran the above code, you’ll notice there was no list of numbers, only a type signature. This is because Spark organizes computation into two categories, transformations and actions. When we create a DataFrame, we perform a transformation.

Transformations

In Spark, the core data structures are *immutable* meaning they cannot be changed once created. This might seem like a strange concept at first, if you cannot change it, how are you supposed to use it? In order to "change" a DataFrame you will have to instruct Spark how you would like to modify the DataFrame you have into the one that you want. These instructions are called *transformations*. Transformations are how you, as user, specify how you would like to transform the DataFrame you currently have to the DataFrame that you want to have. Let's show an example. To computer whether or not a number is divisible by two, we use the modulo operation to see the remainder left over from dividing one number by another.

We can use this operation to perform a *transformation* from our current DataFrame to a DataFrame that only contains numbers divisible by two. To do this, we perform the modulo operation on each row in the data and filter out the results that do not result in zero. We can specify this filter using a `where` clause.

```
%scala

val divisBy2 = myRange.where("number % 2 = 0")

%python

divisBy2 = myRange.where("number % 2 = 0")
```

Note

Now if you worked with any relational databases in the past, this should feel quite familiar. You might say, aha! I know the exact expression I should use if this was a table.

```
SELECT * FROM myRange WHERE number % 2 = 0
```

When we get to the next part of this chapter to discuss Spark SQL, you will find out that this expression is perfectly valid. We'll show you how to turn any

DataFrame into a table.

These operations create a new DataFrame but do not execute any computation. The reason for this is that DataFrame transformations do not trigger Spark to execute your code, they are lazily evaluated.

Lazy Evaluation

Lazy evaulation means that Spark will wait until the very last moment to execute your transformations. In Spark, instead of modifying the data quickly, we build up a *plan* of the transformations that we would like to apply. Spark, by waiting for the last minute to execute your code, can try and make this plan run as efficiently as possible across the cluster.

Actions

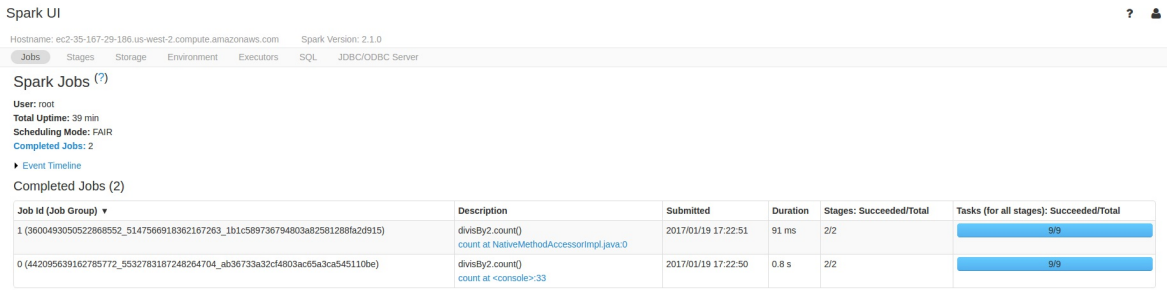
To trigger the computation, we run an *action*. An *action* instructs Spark to compute a result from a series of *transformations*. The simplest action is `count` which gives us the total number of records in the DataFrame.

```
%scala

divisBy2.count()

%python

divisBy2.count()
```

We now see a result! There are 500 number divisible by two from o to 999 (big surprise!). Now `count` is not the only action. There are three kinds of actions: actions to view data in the console, actions to collect data to native objects in the respective language, and actions to write to output data sources.

Spark UI

During Spark's execution of the previous code block, users can monitor the progress of their job through the Spark UI. The Spark UI is available on port 4040 of the driver node. If you are running in local mode this will just be the `http://localhost:4040`. The Spark UI maintains information on the state of our Spark jobs, environment, and cluster state. It's very useful, especially for tuning and debugging. In this case, we can see one Spark job with one stage and nine tasks were executed.



In this chapter we will avoid the details of Spark jobs and the Spark UI, at this point you should understand that a Spark job represents a set of transformations triggered by an individual action. We talk in depth about the Spark UI and the breakdown of a Spark job in Section IV.

A Basic Transformation Data Flow

In the previous example, we created a DataFrame from a range of data. Interesting, but not exactly applicable to industry problems. Let's create some DataFrames with real data in order to better understand how they work. We'll be using some flight data from the United States Bureau of Transportation statistics.

We touched briefly on the SparkSession as the interface the entry point to performing work on the Spark cluster. the SparkSession can do much more than simply parallelize an array it can create DataFrames directly from a file or set of files. In this case, we will create our DataFrames from a JavaScript Object Notation (JSON) file that contains some summary flight information as collected by the United States Bureau of Transport Statistics. In the folder provided, you'll see that we have one file per year.

```
%fs ls /mnt/defg/chapter-1-data/json/
```

This file has one JSON object per line and is typically refered to as line-delimited JSON.

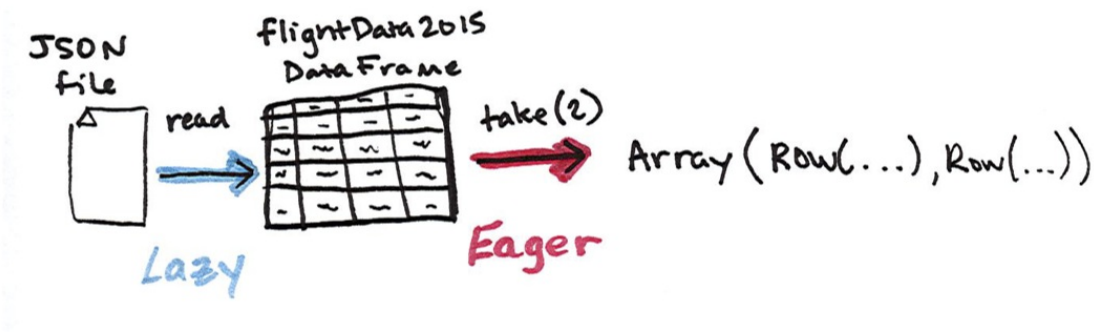
```
%fs head /mnt/defg/chapter-1-data/json/2015-summary.json
```

What we'll do is start with one specific year and then work up to a larger set of data. Let's go ahead and create a DataFrame from 2015. To do this we will use the `DataFrameReader` (via `spark.read`) interface, specify the format and the path.

```
%scala

val flightData2015 = spark
  .read
  .json("/mnt/defg/chapter-1-data/json/2015-summary.json")

%python

flightData2015 = spark\
  .read\
```

```
  .json("/mnt/defg/chapter-1-data/json/2015-summary.json")

flightData2015
```

You'll see that our two DataFrames (in Scala and Python) each have a set of columns with an unspecified number of rows. Let's take a peek at the data with a new action, `take`, which allows us to view the first couple of rows in our DataFrame. Figure 1-7 illustrates the conceptual actions that we perform in the process. We lazily create the DataFrame then call an action to take the first two values.




```
%scala

flightData2015.take(2)

%python

flightData2015.take(2)
```

Remember how we talked about Spark building up a plan, this is not just a conceptual tool, this is actually what happens under the hood. We can see the actual plan built by Spark by running the `explain` method.

```
flightData2015.explain()

%python

flightData2015.explain()
```

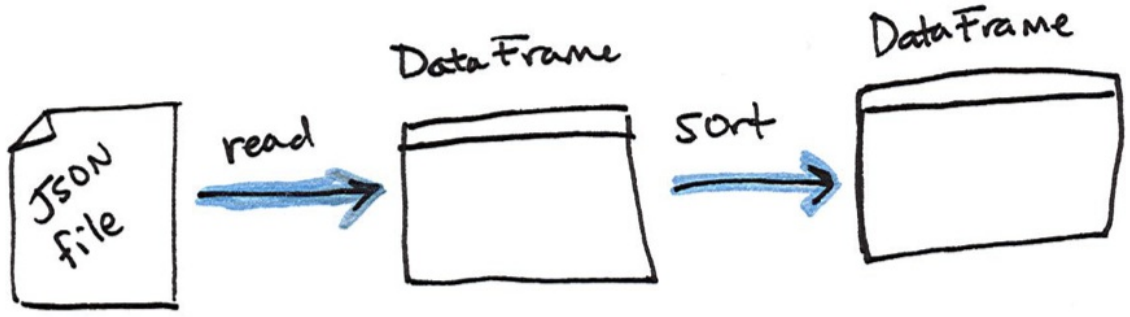
Congratulations, you've just read your first explain plan! This particular plan just describes reading data from a certain location however as we continue, you will start to notice patterns in the explain plans. Without going into too much detail at this point, the explain plan represents the logical combination of

transformations Spark will run on the cluster. We can use this to make sure that our code is as optimized as possible. We will not cover that in this chapter, but will touch on it in the optimization chapter.

Now in order to gain a better understanding of transformations and plans, let's create a slightly more complicated plan. We will specify an intermediate step which will be to sort the `DataFrame` by the values in the first column. We can tell from our DataFrame's column types that it's a string so we know that it will sort the data from A to Z.

Note

Remember, we cannot modify this DataFrame by specifying the `sort` transformation, we can only create a new DataFrame by transforming that previous DataFrame. We can see that even though we're seeming to ask for computation to be completed Spark doesn't yet execute this command, we're just building up a plan. The illustration in figure 1-8 represents the spark plan we see in the explain plan for that DataFrame.

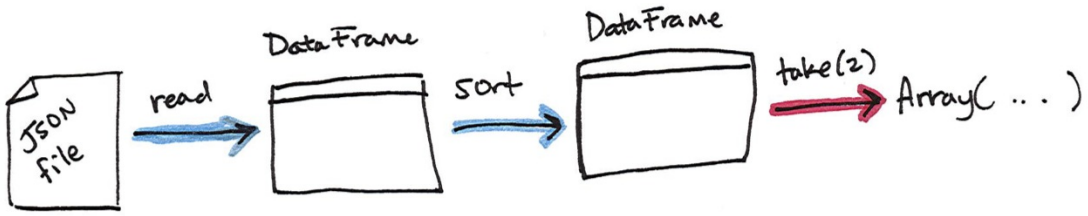



```
%scala

val sortedFlightData2015 = flightData2015.sort("count")
sortedFlightData2015.explain()

%python

sortedFlightData2015 = flightData2015.sort("count")
sortedFlightData2015.explain()
```

Now, just like we did before, we can specify an action in order to kick off this plan.

```
%scala

sortedFlightData2015.take(2)

%python

sortedFlightData2015.take(2)
```

The conceptual plan that we executed previously is illustrated in Figure-9.



Now this planning process is essentially defining *lineage* for the DataFrame so that at any given point in time Spark knows how to recompute any partition of a given DataFrame all the way back to a robust data source be it a file or database. Now that we performed this action, remember that we can navigate to the Spark UI (port 4040) and see the information about this jobs stages and tasks.

Now hopefully you have grasped the basics but let's just reinforce some of the core concepts with another data pipeline. We're going to be using the same flight data used except that this time we'll be using a copy of the data in comma seperated value (CSV) format.

If you look at the previous code, you'll notice that the column names appeared in our results. That's because each line is a json object that has a defined structure or schema. As mentioned, the schema defines the column names and types. This is a term that is used in the database world to describe what types are in every column of a table and it's no different in Spark. In this case the schema defines `ORIGIN_COUNTRY_NAME` to be a string. JSON and CSVs qualify as semi-structured data formats and Spark supports a range of data sources in its APIs and ecosystem.

Let's go ahead and define our DataFrame just like we did before however this time we're going to specify an `option` for our DataFrameReader. Options

allow you to control how you read in a given file format and tell Spark to take advantage of some of the structures or information available in the files. In this case we're going to use two popular options `inferSchema` and `header`.

```
%scala

val flightData2015 = spark.read
  .option("inferSchema", "true")
  .option("header", "true")
  .csv("/mnt/defg/chapter-1-data/csv/2015-summary.csv")
flightData2015

%python

flightData2015 = spark.read\
  .option("inferSchema", "true")\
  .option("header", "true")\
  .csv("/mnt/defg/chapter-1-data/csv/2015-summary.csv")
flightData2015
```

After running the code you should notice that we've basically arrived at the same DataFrame that we had when we read in our data from json with the correct looking column names and types. However, we had to be more explicit when it came to reading in the CSV file as opposed to json because json provides a bit more structure than CSVs because JSON has a notion of types.

Looking at them, the `header` option should feel like it makes sense. The first row in our csv file is the header (column names) and because CSV files are not guaranteed to have this information we must specify it manually. The `inferSchema` option might feel a bit more unfamiliar. JSON objects provides a bit more structure than csvs because JSON has a notion of types. We can get past this by infering the schema of the csv file we are reading in. Now it cannot do this magically, it must scan (read in) some of the data in order to infer this, but this saves us from having to specify the types for each column manually at the risk of Spark potentially making an errorneous guess as to what the type for a column should be.

A discerning reader might notice that the schema returned by our CSV reader does not exactly match that of the json reader.

```
val csvSchema = spark.read.format("csv")
  .option("inferSchema", "true")
```

```
  .option("header", "true")
  .load("/mnt/defg/chapter-1-data/csv/2015-summary.csv")
  .schema

val jsonSchema = spark
  .read.format("json")
  .load("/mnt/defg/chapter-1-data/json/2015-summary.json")
  .schema

println(csvSchema)
println(jsonSchema)

%python

csvSchema = spark.read.format("csv")\
  .option("inferSchema", "true")\
  .option("header", "true")\
  .load("/mnt/defg/chapter-1-data/csv/2015-summary.csv")\
  .schema

jsonSchema = spark.read.format("json")\
  .load("/mnt/defg/chapter-1-data/json/2015-summary.json")\
  .schema

print(csvSchema)
print(jsonSchema)
```

The csv schema:

```
StructType(StructField(DEST_COUNTRY_NAME,StringType,true),
StructField(ORIGIN_COUNTRY_NAME,StringType,true),
StructField(count,IntegerType,true))
```

The JSON schema:

```
StructType(StructField(DEST_COUNTRY_NAME,StringType,true),
StructField(ORIGIN_COUNTRY_NAME,StringType,true),
StructField(count,LongType,true))
```

For our purposes the difference between a `LongType` and an `IntegerType` is of little consequence however this may be of greater significance in production scenarios. Naturally we can always explicitly set a schema (rather than inferring it) when we read in data as well. These are just a few of the options we have when we read in data, to learn more about these options see the chapter on reading and writing data.

```
%scala

val flightData2015 = spark.read
  .schema(jsonSchema)
  .option("header", "true")
  .csv("/mnt/defg/chapter-1-data/csv/2015-summary.csv")

%python

flightData2015 = spark.read\
  .schema(jsonSchema)\
  .option("header", "true")\
  .csv("/mnt/defg/chapter-1-data/csv/2015-summary.csv")
```

DataFrames and SQL

Spark provides another way to query and operate on our DataFrames, and that's with SQL! Spark SQL allows you as a user to register any DataFrame as a table or view (a temporary table) and query it using pure SQL. There is no performance difference between writing SQL queries or writing DataFrame code, they both "compile" to the same underlying plan that we specify in DataFrame code.

Any DataFrame can be made into a table or view with one simple method call.

```
%scala

flightData2015.createOrReplaceTempView("flight_data_2015")

%python

flightData2015.createOrReplaceTempView("flight_data_2015")
```

Now we can query our data in SQL. To execute a SQL query, we'll use the `spark.sql` function (remember `spark` is our SparkSession variable?) that conveniently, returns a new DataFrame. While this may seem a bit circular in logic - that a SQL query against a DataFrame returns another DataFrame, it's actually quite powerful. As a user, you can specify transformations in the manner most convenient to you at any given point in time and not have to trade any efficiency to do so! To understand that this is happening, let's take a look at two explain plans.

```
Vi%scala

val sqlWay = spark.sql("""
SELECT DEST_COUNTRY_NAME, count(1)
FROM flight_data_2015
GROUP BY DEST_COUNTRY_NAME
""")

val dataFrameWay = flightData2015
  .groupBy('DEST_COUNTRY_NAME)
  .count()
```

```
sqlWay.explain
dataFrameWay.explain

%python

sqlWay = spark.sql("""
SELECT DEST_COUNTRY_NAME, count(1)
FROM flight_data_2015
GROUP BY DEST_COUNTRY_NAME
""")

dataFrameWay = flightData2015\
  .groupBy("DEST_COUNTRY_NAME")\
  .count()

sqlWay.explain()
dataFrameWay.explain()
```

We can see that these plans compile to the exact same underlying plan!

To reinforce the tools available to us, let's pull out some interesting stats from our data. Our first question will use our first imported function, the `max` function, to find out what the maximum number of flights to and from any given location are. This just scans each value in relevant column the DataFrame and sees if it's bigger than the previous values that have been seen. This is a transformation, as we are effectively filtering down to one row. Let's see what that looks like.

```
// scala or python
spark.sql("SELECT max(count) from flight_data_2015").take(1)

%scala

import org.apache.spark.sql.functions.max

flightData2015.select(max("count")).take(1)

%python

from pyspark.sql.functions import max

flightData2015.select(max("count")).take(1)
```

Let's move onto something a bit more complicated. What are the top five

destination countries in the data set? This is a our first multi-transformation query so we'll take it step by step. We will start with a fairly straightforward SQL aggregation.

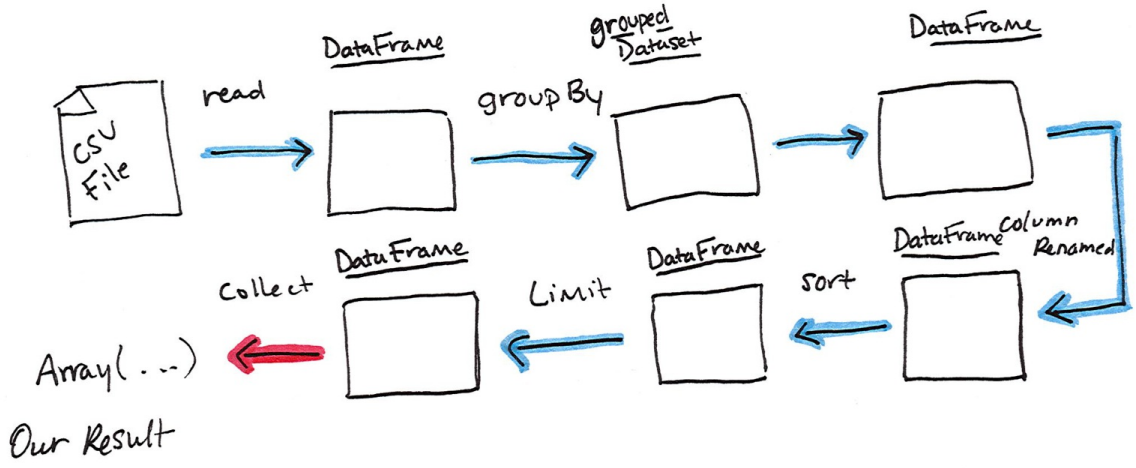
```
%scala

val maxSql = spark.sql("""
SELECT DEST_COUNTRY_NAME, sum(count) as destination_total
  FROM flight_data_2015
GROUP BY DEST_COUNTRY_NAME
ORDER BY sum(count) DESC
LIMIT 5""")

maxSql.collect()

%python

maxSql = spark.sql("""
SELECT DEST_COUNTRY_NAME, sum(count) as destination_total
  FROM flight_data_2015
GROUP BY DEST_COUNTRY_NAME
ORDER BY sum(count) DESC
LIMIT 5""")

maxSql.collect()
```

Now let's move to the `DataFrame` syntax that is semantically similar but slightly different in implementation and ordering. But, as we mentioned, the underlying plans for both of them are the same. Let's execute the queries and see their results as a sanity check.

```
%scala
import org.apache.spark.sql.functions.desc

flightData2015
  .groupBy("DEST_COUNTRY_NAME")
  .sum("count")
  .withColumnRenamed("sum(count)", "destination_total")
  .sort(desc("destination_total"))
  .limit(5)
  .collect()

%python
from pyspark.sql.functions import desc
```

```
flightData2015\
  .groupBy("DEST_COUNTRY_NAME")\
  .sum("count")\
  .withColumnRenamed("sum(count)", "destination_total")\
  .sort(desc("destination_total"))\
  .limit(5)\
  .collect()
```

Now there are 7 steps that take us all the way back to the source data. Illustrated below are the set of steps that we perform in "code". The true execution plan (the one visible in explain) will differ from what we have below because of optimizations in physical execution, however the illustration is as good of a starting point as any. With Spark, we are always building up a directed acyclic graph of transformations resulting in immutable objects that we can subsequently call an action on to see a result.



The first step is to read in the data. We defined the DataFrame previously but, as a reminder, Spark does not actually read it in until an action is called on that DataFrame or one derived from the original DataFrame.

The second step is our grouping, technically when we call "groupBy" we end up with a RelationalGroupedDataset which is a fancy name for a DataFrame that has a grouping specified but needs a user to specify an aggregation before it can be queried further. We can see this by trying to perform an action on it (which will not work). We still haven't performed any computation (besides

relational algebra) - we're simply passing along information about the layout of the data.

Therefore the third step is to specify the aggregation. Let's use the `sum` aggregation method. This takes as input a column expression or simply, a column name. The result of the sum method call is a new dataFrame. You'll see that it has a new schema but that it does know the type of each column. It's important to reinforce (again!) that no computation has been performed. This is simply another transformation that we've expressed and Spark is simply able to trace the type information we have supplied.

The fourth step is a simple renaming, we use the `withColumnRenamed` method that takes two arguments, the original column name and the new column name. Of course, this doesn't perform computation - this is just another transformation!

The fifth step sorts the data such that if we were to take results off of the top of the DataFrame, they would be the largest values found in the `destination_total` column.

You likely noticed that we had to import a function to do this, the `desc` function. You might also notice that `desc` does not return a string but a `Column`. In general, many DataFrame methods will accept Strings (as column names) or `Column` types or expressions. Columns and expressions are actually the exact same thing

The final step is just a limit. This just specifies that we only want five values. This is just like a filter except that it filters by position (lazily) instead of by value. It's safe to say that it basically just specifies a `DataFrame` of a certain size.

The last step is our action! Now we actually begin the process of collecting the results of our DataFrame above and Spark will give us back a list or array in the language that we're executing. Now to reinforce all of this, let's look at the explain plan for the above query.

```
flightData2015
  .groupBy("DEST_COUNTRY_NAME")
  .sum("count")
```

```
  .withColumnRenamed("sum(count)", "destination_total")
  .sort(desc("destination_total"))
  .limit(5)
  .explain()

== Physical Plan ==
TakeOrderedAndProject(limit=5, orderBy=[destination_total#1619
+- *HashAggregate(keys=[DEST_COUNTRY_NAME#7323], functions=[sur
   +- Exchange hashpartitioning(DEST_COUNTRY_NAME#7323, 5)
      +- *HashAggregate(keys=[DEST_COUNTRY_NAME#7323], functio
         +- InMemoryTableScan [DEST_COUNTRY_NAME#7323, count#7
               +- InMemoryRelation [DEST_COUNTRY_NAME#7323, ORI
                     +- *Scan csv [DEST_COUNTRY_NAME#7578,ORIG
```

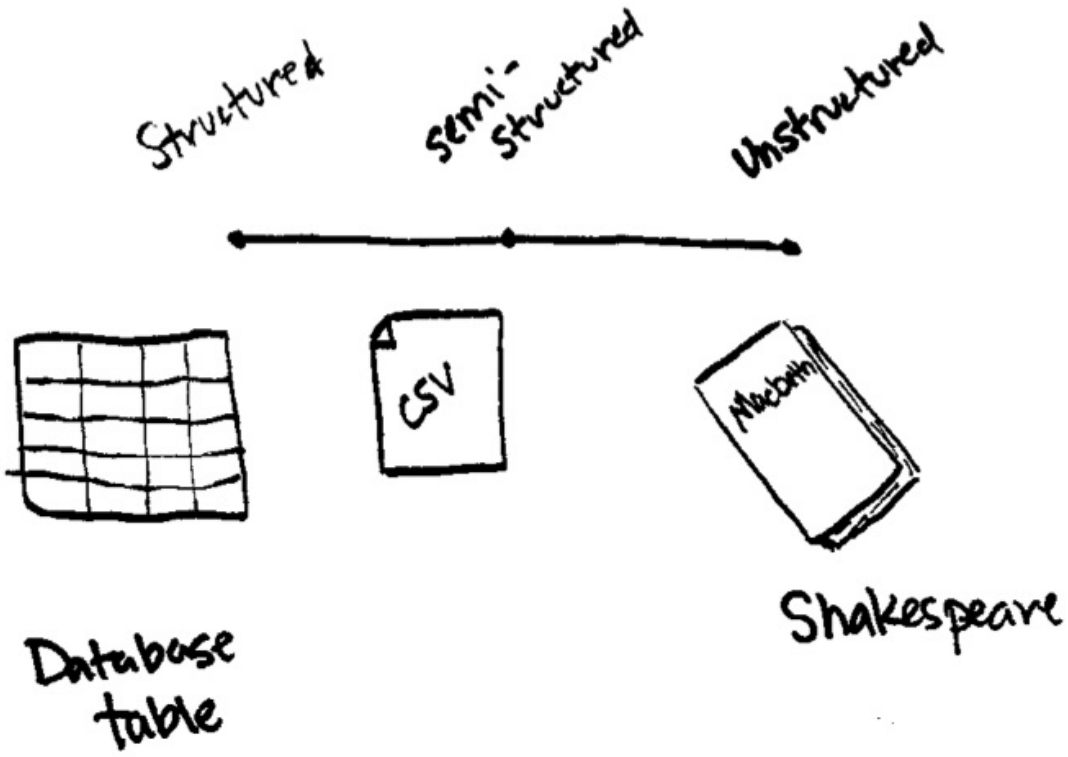
While this explain plan doesn't match our exact "conceptual plan" all of the pieces are there. You can see the limit statement as well as the `orderBy` (in the first line). You can also see how our aggregation happens in two phases, in the `partial_sum` calls. This is because summing a list of numbers is commutative and Spark can perform the sum, partition by partition. Of course we can see how we read in the DataFrame as well.

You are now equipped with the Spark knowledge to writing your own Spark code. In the next chapter we will explore some of Spark's more advanced features.

Chapter 2. Structured API Overview

Spark's Structured APIs

For our purposes there is a spectrum of types of data. The two extremes of the spectrum are *structured* and *unstructured*. Structured and semi-structured data refer to to data that have structure that a computer can understand relatively easily. Unstructured data, like a poem or prose, is much harder to a computer to understand. Spark's Structured APIs allow for transformations and actions on structured and semi-structured data.



The Structured APIs specifically refer to operations on DataFrames, Datasets, and in Spark SQL and were created as a high level interface for users to manipulate big data. This section will cover all the principles of the Structured APIs. Although distinct in the book, the vast majority of these user-facing operations apply to both *batch* as well as *streaming* computation.

The Structured API is the fundamental abstraction that you will leverage to write your data flows. Thus far in this book we have taken a tutorial-based approach, meandering our way through much of what Spark has to offer. In this section, we will perform a deeper dive into the Structured APIs. This introductory chapter will introduce the fundamental concepts that you should understand: the typed and untyped APIs (and their differences); how to work with different kinds of data using the structured APIs; and deep dives into different data flows with Spark.

BOX

> Before proceeding, let's review the fundamental concepts and definitions that we covered in the previous section. Spark is a distributed programming model where the user specifies *transformations*, which build up a directed-acyclic-graph of instructions, and *actions*, which begin the process of executing that graph of instructions, as a single job, by breaking it down into stages and tasks to execute across the cluster. The way we store data on which to perform transformations and actions are DataFrames and Datasets. To create a new DataFrame or Dataset, you call a transformation. To start computation or convert to native language types, you call an action.

DataFrames and Datasets

In Section I, we talked all about DataFrames. Spark has two notions of "structured" data structures: DataFrames and Datasets. We will touch on the (nuanced) differences shortly but let's define what they both represent first.

To the user, DataFrames and Datasets are (distributed) tables with rows and columns. Each column must have the same number of rows as all the other columns (although you can use null to specify the lack of a value) and columns have type information that tells the user what exists in each column.

To Spark, DataFrames and Datasets represent by immutable, lazily evaluated plans that specify how to perform a series of transformations to generate the correct output. When we perform an action on a DataFrame we instruct Spark to perform the actual transformations that represent that DataFrame. These represent plans of how to manipulate rows and columns to compute the user's desired result. Let's go over rows and column to more precisely define those concepts.

Schemas

One core concept that differentiates the Structured APIs from the lower level APIs is the concept of a *schema*. A schema defines the column names and types of a DataFrame. Users can define schemas manually or users can read a schema from a data source (often called *schema on read*). Now that we know what defines DataFrames and Datasets and how they get their structure, via a Schema, let's see an overview of all of the types.

Overview of Structured Spark Types

Spark is effectively a programming language of its own. When you perform operations with Spark, it maintains its own type information throughout the process. This allows it to perform a wide variety of optimizations during the execution process. These types correspond to the types that Spark connects to in each of Scala, Java, Python, SQL, and R. Even if we use Spark's Structured APIs from Python, the majority of our manipulations will operate strictly on *Spark types*, not Python types. For example, the below code does not perform addition in Scala or Python, it actually performs addition *purely in Spark*.

```
%scala

val df = spark.range(500).toDF("number")
df.select(df.col("number") + 10)
// org.apache.spark.sql.DataFrame = [(number + 10): bigint]

%python

df = spark.range(500).toDF("number")
df.select(df["number"] + 10)
# DataFrame[(number + 10): bigint]
```

This is because, as mentioned, Spark maintains its own type information, stored as a *schema*, and through some magic in each languages bindings, can convert an expression in one language to Spark's representation of that.

NOTE

> There are two distinct APIs within the In the Structured APIs. There is the API that goes across languages, more commonly referred to as the DataFrame or "untyped API". THe second API is the "typed API" or "Dataset API", that is only available to JVM based languages (Scala and Java). This is a bit of a misnomer because the "untyped API" does have types but it only operates on *Spark* types at *run time*. The "typed API" allows you to define your own types to represent each record in your

dataset with “case classes or Java Beans” and types are checked at *compile time*. Each record (or row) in the “untyped API” consists of a `Row` object that are available across languages and still have types, but only Spark types, not native types. The “typed API” is covered in the Datasets Chapter at the end of Section II. The majority of Section II will cover the “untyped API” however all of this still applies to the “typed API”.

Notice how the following code produces a `Dataset` of type `Long`, but also has an internal Spark type (bigint).

```
%scala

spark.range(500)
```

Notice how the following code produces a `DataFrame` with an internal Spark type (bigint).

```
%python

spark.range(500)
```

Columns

For now, all you need to understand about columns is that they can represent a *simple type* like an integer or string, a *complex types* like an array or map, or a null value. Spark tracks all of this type information to you and has a variety of ways that you can transform columns. Columns are discussed extensively in the next chapter but for the most part you can think about Spark `Column` types as columns in a table.

Rows

There are two ways of getting data into Spark, through Rows and Encoders. *Row* objects are the most general way of getting data into, and out of, Spark and are available in all languages. Each record in a DataFrame must be of `Row` type as we can see when we collect the following DataFrames.

```
%scala

spark.range(2).toDF().collect()

%python

spark.range(2).collect()
```

Spark Value Types

On the next page you will find a large table of all Spark types along with the corresponding language specific types. Caveats and details are included for the reader as well to make it easier to reference.

To work with the correct Scala types:

```
import org.apache.spark.sql.types._
val b = ByteType()
```

To work with the correct Java types you should use the factory methods in the following package:

```
import org.apache.spark.sql.types.DataTypes;
ByteType x = DataTypes.ByteType();
```

Python types at time have certain requirements (like the listed requirement for `ByteType` below.To work with the correct Python types:

```
from pyspark.sql.types import *
b = byteType()
```

Spark Type	Scala Value Type	Scala API
ByteType	Byte	`ByteType`
ShortType	Short	`ShortType`
IntegerType	Int	`IntegerType`
LongType	Long	`LongType`

FloatType	Float	`FloatType`
DoubleType	Double	`DoubleType`
DecimalType	java.math.BigDecimal	`DecimalType`
StringType	String	`StringType`
BinaryType	Array[Byte]	`BinaryType`
TimestampType	java.sql.Timestamp	`TimestampType`
DateType	java.sql.Date	`DateType`
ArrayType	scala.collection.Seq	`ArrayType(elementType, [valueContainsNull])` **
MapType	scala.collection.Map	`MapType(keyType, valueType, [valueContainsNull])` **
StructType	org.apache.spark.sql.Row	`StructType(Seq(StructFields)` *
StructField	StructField with DataType contents.	`StructField(name, dataType, nullable)`

- Numbers will be converted to 1-byte signed integer numbers at runtime. Make sure that numbers are within the range of -128 to 127.
    - Numbers will be converted to 2-byte signed integer numbers at runtime. Please make sure that numbers are within the range of -32768 to 32767.
        - Numbers will be converted to 8-byte signed integer numbers at runtime. Please make sure that numbers are within the range of -9223372036854775808 to 9223372036854775807. Otherwise, please convert data to decimal.Decimal and use DecimalType.
            - valueContainsNull is true by default.
                - No two fields can have the same name.

Encoders

Using Spark from Scala and Java allows you to define your own JVM types to use in place of Rows that consist of the above data types. To do this, we use an *Encoder*. Encoders are only available in Scala, with case classes, and Java, with JavaBeans. For some types, like Long, Spark already includes an Encoder. For instance we can collect a `Dataset` of type `Long` and get native Scala types back. We will cover encoders in the Datasets chapter.

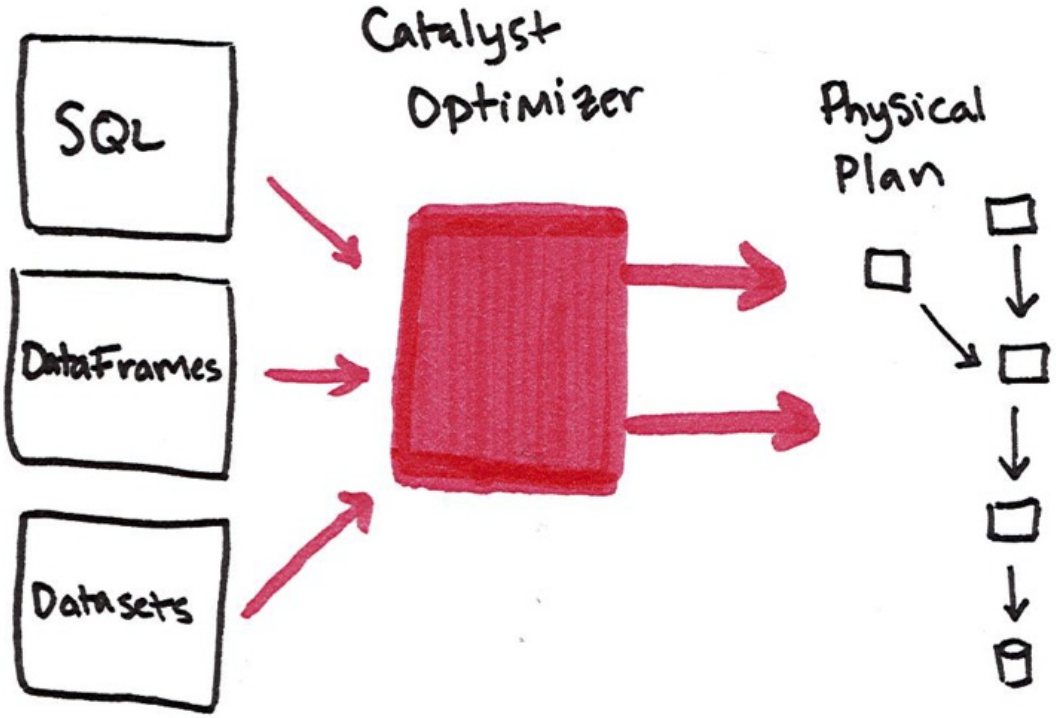
```
spark.range(2).collect()
```

Overview of Spark Execution

In order to help you understand (and potentially debug) the process of writing and executing code on clusters, let's walk through the execution of a single structured API query from user code to executed code. As an overview the steps are:

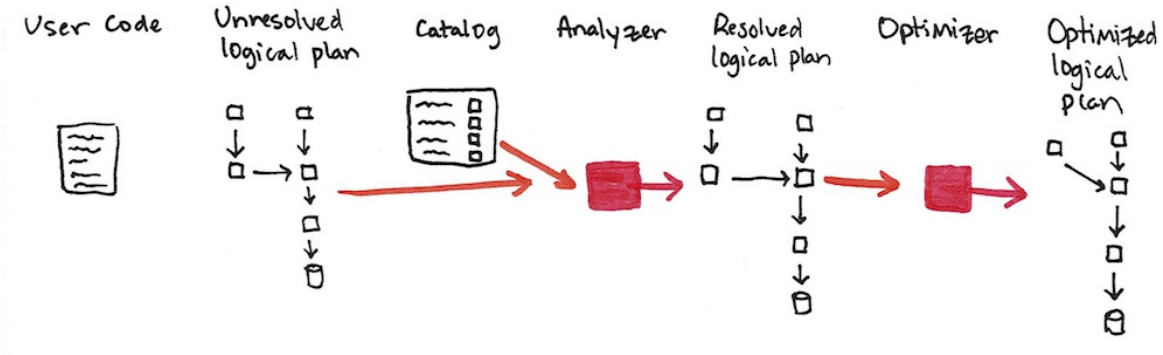
1. Write DataFrame/Dataset/SQL Code
2. If valid code, Spark converts this to a *Logical Plan*
3. Spark transforms this *Logical Plan* to a *Physical Plan*
4. Spark then executes this *Physical Plan* on the cluster

To execute code, we have to write code. This code is then submitted to Spark either through the console or via a submitted job. This code then passes through the Catalyst Optimizer which decides how the code should be executed and lays out a plan for doing so, before finally the code is run and the result is returned to the user.


SQL
DataFrames
Datasets
Catalyst
Optimizer
Physical
Plan

Logical Planning

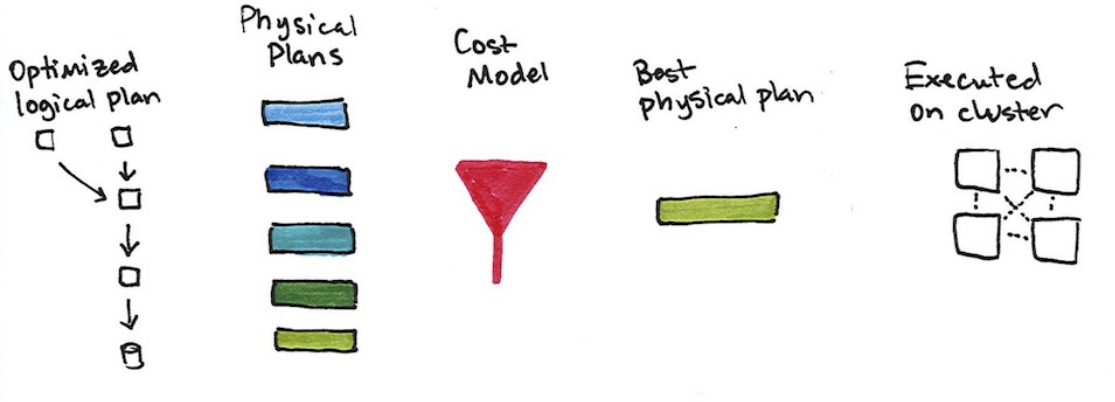
The first phase of execution is meant to take user code and convert it into a logical plan. This process in illustrated in the next figure.



This logical plan only represents a set of abstract transformations that do not refer to executors or drivers, it's purely to convert the user's set of expressions into the most optimized version. It does this by converting user code into an *unresolved logical plan*. This unresolved because while your code may be valid, the tables or columns that it refers to may or may not exist. Spark uses the *catalog*, a repository of all table and DataFrame information, in order to *resolve* columns and tables in the *analyzer*. The analyzer may reject the unresolved logical plan if it the required table or column name does not exist in the catalog. If it can resolve it, this result is passed through the optimizer, a collection of rules, which attempts to optimize the logical plan by pushing down predicates or selections.

Physical Planning

After successfully creating an optimized logical plan, Spark then begins the physical planning process. The *physical plan*, often called a Spark plan, specifies how the logical plan will execute on the cluster by generating different physical execution strategies and comparing them through a cost model. An example of the cost comparison might be choosing how to perform a given join by looking at the physical attributes of a given table (how big the table is or how big its partitions are.)



Physical planning results in a series of RDDs and transformations. This result is why you may have heard Spark referred to as a compiler, it takes queries in DataFrames, Datasets, and SQL and compiles them into RDD transformations for you.

Execution

Upon selecting a physical plan, Spark runs all of this code over RDDs, the lower-level programming interface of Spark covered in Part III. Spark performs further optimizations by, at runtime, generating native Java Bytecode that can remove whole tasks or stages during execution. Finally the result is returned to the user.

Chapter 3. Basic Structured Operations

Chapter Overview

In the previous chapter we introduced the core abstractions of the Structured API. This chapter will move away from the architectural concepts and towards the tactical tools you will use to manipulate DataFrames and the data within them. This chapter will focus exclusively on single DataFrame operations and avoid aggregations, window functions, and joins which will all be discussed in depth later in this section.

Definitionally, a DataFrame consists of a series of *records* (like rows in a table), that are of type `Row`, and a number of *columns* (like columns in a spreadsheet) that represent an computation expression that can performed on each individual record in the dataset. The *schema* defines the name as well as the type of data in each column. The *partitioning* of the DataFrame defines the layout of the DataFrame or Dataset's physical distribution across the cluster. The *partitioning scheme* defines how that is broken up, this can be set to be based on values in a certain column or non-deterministically.

Let's define a DataFrame to work with.

```
%scala

val df = spark.read.format("json")
  .load("/mnt/defg/flight-data/json/2015-summary.json")

%python

df = spark.read.format("json")\
  .load("/mnt/defg/flight-data/json/2015-summary.json")
```

We discussed that a DataFame will have columns, and we use a "schema" to view all of those. We can run the following command in Scala or in Python.

```
df.printSchema()
```

The schema ties the logical pieces together and is the starting point to better understand DataFrames.

Schemas

A schema defines the column names and types of a DataFrame. We can either let a data source define the schema (called *schema on read*) or we can define it explicitly ourselves.

NOTE

> Deciding whether or not you need to define a schema prior to reading in your data depends your use case. Often times for ad hoc analysis, schema on read works just fine (although at times it can be a bit slow with plain text file formats like csv or json). However, this can also lead to precision issues like a long type incorrectly set as an integer when reading in a file. When using Spark for production ETL, it is often a good idea to define your schemas manually, especially when working with untyped data sources like csv and json because schema inference can vary depending on the type of data that you read in.

Let's start with a simple file we saw in the previous chapter and let the semi-structured nature of line-delimited JSON define the structure. This data is flight data from the United States Bureau of Transportation statistics.

```
%scala

spark.read.format("json")
  .load("/mnt/defg/flight-data/json/2015-summary.json")
  .schema
```

Scala will return:

```
org.apache.spark.sql.types.StructType = ...
StructType(StructField(DEST_COUNTRY_NAME,StringType,true),
StructField(ORIGIN_COUNTRY_NAME,StringType,true),
StructField(count,LongType,true))

%python

spark.read.format("json")\
  .load("/mnt/defg/flight-data/json/2015-summary.json")\
```

```
  .schema
```

Python will return:

```
StructType(List(StructField(DEST_COUNTRY_NAME,StringType,true),
StructField(ORIGIN_COUNTRY_NAME,StringType,true),
StructField(count,LongType,true)))
```

A schema is a `StructType` made up of a number of fields, `StructFields`, that have a name, type, and a boolean flag which specifies whether or not that column can contain missing or `null` values. Schemas can also contain other `StructType` (Spark's complex types). We will see this in the next chapter when we discuss working with complex types.

Here's out to create, and enforce a specific schema on a DataFrame. If the types in the data (at runtime), do not match the schema. Spark will throw an error.

```
%scala

import org.apache.spark.sql.types.{StructField, StructType, Str

val myManualSchema = new StructType(Array(
  new StructField("DEST_COUNTRY_NAME", StringType, true),
  new StructField("ORIGIN_COUNTRY_NAME", StringType, true),
  new StructField("count", LongType, false) // just to illustra
))

val df = spark.read.format("json")
  .schema(myManualSchema)
  .load("/mnt/defg/flight-data/json/2015-summary.json")
```

Here's how to do the same in Python.

```
%python

from pyspark.sql.types import StructField, StructType, StringTy

myManualSchema = StructType([
  StructField("DEST_COUNTRY_NAME", StringType(), True),
  StructField("ORIGIN_COUNTRY_NAME", StringType(), True),
  StructField("count", LongType(), False)
])
df = spark.read.format("json")\
```

```
  .schema(myManualSchema)\
  .load("/mnt/defg/flight-data/json/2015-summary.json")
```

As discussed in the previous chapter, we cannot simply set types via the per language types because Spark maintains its own type information. Let's now discuss what schemas define, columns.

Columns and Expressions

To users, columns in Spark are similar to columns in a spreadsheet, R dataframe, pandas DataFrame. We can select, manipulate, and remove columns from DataFrames and these operations are represented as *expressions*.

To Spark, columns are logical constructions that simply represent a value computed on a per-record basis by means of an *expression*. This means, in order to have a real value for a column, we need to have a row, and in order to have a row we need to have a DataFrame. This means that we cannot manipulate an actual column outside of a DataFrame, we can only manipulate a logical column's expressions then perform that expression within the context of a DataFrame.

Columns

There are a lot of different ways to construct and or refer to columns but the two simplest ways are with the `col` or `column` functions. To use either of these functions, we pass in a column name.

```
%scala

import org.apache.spark.sql.functions.{col, column}

col("someColumnName")
column("someColumnName")

%python

from pyspark.sql.functions import col, column

col("someColumnName")
column("someColumnName")
```

We will stick to using `col` throughout this book. As mentioned, this column may or may not exist in our of our DataFrames. This is because, as we saw in the previous chapter, columns are not *resolved* until we compare the column names with those we are maintaining in the *catalog*. Column and table resolution happens in the *analyzer* phase as discussed in the first chapter in this section.

NOTE

> Above we mentioned two different ways of referring to columns. Scala has some unique language features that allow for more shorthand ways of referring to columns. These bits of syntactic sugar perform the exact same thing as what we have already, namely creating a column, and provide no performance improvement.

```
%scala

$"myColumn"
'myColumn
```

The `$` allows us to designate a string as a special string that should refer to an expression. The tick mark `'` is a special thing called a symbol, that is Scala-specific construct of referring to some identifier. They both perform the same thing and are shorthand ways of referring to columns by name. You'll likely see all the above references when you read different people's spark code. We leave it to the reader for you to use whatever is most comfortable and maintainable for you.

Explicit Column References

If you need to refer to a specific DataFrame's column, you can use the `col` method on the specific DataFrame. This can be useful when you are performing a join and need to refer to a specific column in one DataFrame that may share a name with another column in the joined DataFrame. We will see this in the joins chapter. As an added benefit, Spark does not need to resolve this column itself (during the *analyzer* phase) because we did that for Spark.

```
df.col("count")
```

Expressions

Now we mentioned that columns are expressions, so what is an expression? An *expression* is a set of transformations on one or more values in a record in a DataFrame. Think of it like a function that takes as input one or more column names, resolves them and then potentially applies more expressions to create a single value for each record in the dataset. Importantly, this "single value" can actually be a complex type like a Map type or Array type.

In the simplest case, an expression, created via the `expr` function, is just a DataFrame column reference.

```
import org.apache.spark.sql.functions.{expr, col}
```

In this simple instance, `expr("someCol")` is equivalent to `col("someCol")`.

Columns as Expressions

Columns provide a subset of expression functionality. If you use `col()` and wish to perform transformations on that column, you must perform those on that column reference. When using an expression, the `expr` function can actually parse transformations and column references from a string and can subsequently be passed into further transformations. Let's look at some examples.

`expr("someCol - 5")` is the same transformation as performing `col("someCol") - 5` or even `expr("someCol") - 5`. That's because Spark compiles these to a logical tree specifying the order of operations. This might be a bit confusing at first, but remember a couple of key points.

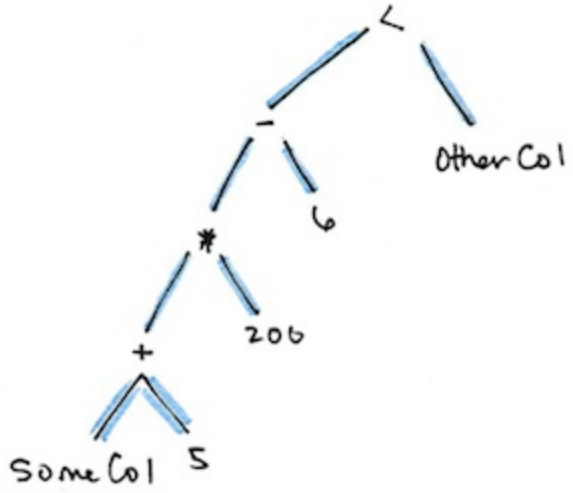
1. Columns are just expressions.

2. Columns and transformations of those column compile to the same logical plan as parsed expressions.

Let's ground this with an example.

```
(((col("someCol") + 5) * 200) - 6) < col("otherCol")
```

Figure 1 shows an illustration of that logical tree.



This might look familiar because it's a directed acyclic graph. This graph is represented equivalently with the following code.

```
%scala

import org.apache.spark.sql.functions.expr

expr("(((someCol + 5) * 200) - 6) < otherCol")

%python

from pyspark.sql.functions import expr

expr("(((someCol + 5) * 200) - 6) < otherCol")
```

This is an extremely important point to reinforce. Notice how the previous expression is actually valid SQL code as well, just like you might put in a `SELECT` statement? That's because this SQL expression and the previous DataFrame code compile to the same underlying logical tree prior to execution. This means you can write your expressions as DataFrame code or as SQL expressions and get the exact same benefits. You likely saw all of this in the first chapters of the book and we covered this more extensively in the

Overview of the Structured APIs chapter.

Accessing a DataFrame's Columns

Sometimes you'll need to see a DataFrame's columns, you can do this by doing something like printSchema however if you want to programmatically access columns, you can use the `columns` method to see all columns listed.

```
spark.read.format("json")
  .load("/mnt/defg/flight-data/json/2015-summary.json")
  .columns
```

Records and Rows

In Spark, a record or row makes up a “row” in a DataFrame. A logical record or row is an object of type `Row`. `Row` objects are the objects that column expressions operate on to produce some usable value. `Row` objects represent physical byte arrays. The byte array interface is never shown to users because we only use column expressions to manipulate them.

You’ll notice collections that return values will always return one or more `Row` types.

Note

we will use lowercase “row” and “record” interchangeably in this chapter, with a focus on the latter. A capitalized “Row” will refer to the Row object.

We can see a row by calling `first` on our DataFrame.

```
%scala

df.first()

%python

df.first()
```

Creating Rows

You can create rows by manually instantiating a `Row` object with the values that below in each column. It's important to note that only DataFrames have schema. Rows themselves do not have schemas. This means if you create a `Row` manually, you must specify the values in the same order as the schema of the DataFrame they may be appended to. We will see this when we discuss creating DataFrames.

```
%scala

import org.apache.spark.sql.Row

val myRow = Row("Hello", null, 1, false)

%python

from pyspark.sql import Row

myRow = Row("Hello", None, 1, False)
```

Accessing data in rows is equally as easy. We just specify the position. However because Spark maintains its own type information, we will have to manually coerce this to the correct type in our respective language.

For example in Scala, we have to either use the helper methods or explicitly coerce the values.

```
%scala

myRow(0) // type Any
myRow(0).asInstanceOf[String] // String
myRow.getString(0) // String
myRow.getInt(2) // String
```

There exist one of these helper functions for each corresponding Spark and Scala type. In Python, we do not have to worry about this, Spark will automatically return the correct type by location in the Row Object.

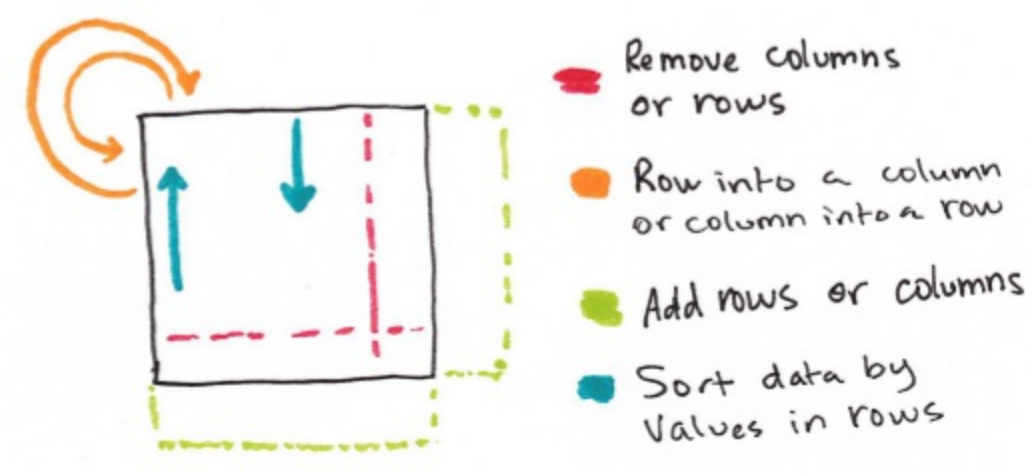
```
%python
```

```
myRow[0]
myRow[2]
```

You can also explicitly return a set of Data in the corresponding JVM objects by leverage the Dataset APIs. This is covered at the end of the Structured API section.

DataFrame Transformations

Now that we briefly defined the core parts of a DataFrame, we will move onto manipulating DataFrames. When working with individual DataFrames there are some fundamental objectives. These break down into several core operations.



- We can add rows or columns
- We can remove rows or columns
- We can transform a row into a column (or vice versa)
- We can change the order of rows based on the values in columns

Luckily we can translate all of these into simple transformations, the most common being those that take one column, change it row by row, and then return our results.

Creating DataFrames

As we saw previously, we can create DataFrames from raw data sources. This is covered extensively in the Data Sources chapter however we will use them now to create an example DataFrame. For illustration purposes later in this chapter, we will also register this as a temporary view so that we can query it with SQL.

```
%scala

val df = spark.read.format("json")
  .load("/mnt/defg/flight-data/json/2015-summary.json")

df.createOrReplaceTempView("dfTable")

%python

df = spark.read.format("json")\
  .load("/mnt/defg/flight-data/json/2015-summary.json")

df.createOrReplaceTempView("dfTable")
```

We can also create DataFrames on the fly by taking a set of rows and converting them to a DataFrame.

```
%scala

import org.apache.spark.sql.Row
import org.apache.spark.sql.types.{StructField, StructType,
                                   StringType, LongType}

val myManualSchema = new StructType(Array(
  new StructField("some", StringType, true),
  new StructField("col", StringType, true),
  new StructField("names", LongType, false) // just to illustra
))

val myRows = Seq(Row("Hello", null, 1L))
val myRDD = spark.sparkContext.parallelize(myRows)

val myDf = spark.createDataFrame(myRDD, myManualSchema)
myDf.show()
```

Note

In Scala we can also take advantage of Spark's implicits in the console (and if you import them in your jar code), by running `toDF` on a `Seq` type. This does not play well with null types, so it's not necessarily recommended for production use cases.

```
%scala

val myDF = Seq(("Hello", 2, 1L)).toDF()

%python

from pyspark.sql import Row
from pyspark.sql.types import StructField, StructType,\
                              StringType, LongType

myManualSchema = StructType([
  StructField("some", StringType(), True),
  StructField("col", StringType(), True),
  StructField("names", LongType(), False)
])

myRow = Row("Hello", None, 1)
myDf = spark.createDataFrame([myRow], myManualSchema)
myDf.show()
```

Now that we know how to create DataFrames, let's go over their most useful methods that you're going to be using are: the `select` method when you're working with columns or expressions and the `selectExpr` method when you're working with expressions in strings. Naturally some transformations are not specified as a methods on columns, therefore there exists a group of functions found in the `org.apache.spark.sql.functions` package.

With these three tools, you should be able to solve the vast majority of transformation challenges that you may encourage in DataFrames.

Select & SelectExpr

`Select` and `SelectExpr` allow us to do the DataFrame equivalent of SQL queries on a table of data.

```
SELECT * FROM dataFrameTable
SELECT columnName FROM dataFrameTable
SELECT columnName * 10, otherColumn, someOtherCol as c FROM dat
```

In the simplest possible terms, it allows us to manipulate columns in our DataFrames. Let's walk through some examples on DataFrames to talk about some of the different ways of approaching this problem. The easiest way is just to use the `select` method and pass in the column names as string that you would like to work with.

```
%scala

df.select("DEST_COUNTRY_NAME").show(2)

%python

df.select("DEST_COUNTRY_NAME").show(2)

%sql

SELECT DEST_COUNTRY_NAME
FROM dfTable
LIMIT 2
```

You can select multiple columns using the same style of query, just add more column name strings to our `select` method call.

```
%scala

df.select(
  "DEST_COUNTRY_NAME",
  "ORIGIN_COUNTRY_NAME")
  .show(2)

%python

df.select(
```

```
  "DEST_COUNTRY_NAME",
  "ORIGIN_COUNTRY_NAME")\
  .show(2)

%sql

SELECT
  DEST_COUNTRY_NAME,
  ORIGIN_COUNTRY_NAME
FROM
  dfTable
LIMIT 2
```

As covered in Columns and Expressions, we can refer to columns in a number of different ways; as a user all you need to keep in mind is that we can use them interchangeably.

```
%scala

import org.apache.spark.sql.functions.{expr, col, column}

df.select(
  df.col("DEST_COUNTRY_NAME"),
  col("DEST_COUNTRY_NAME"),
  column("DEST_COUNTRY_NAME"),
  'DEST_COUNTRY_NAME,
  $"DEST_COUNTRY_NAME",
  expr("DEST_COUNTRY_NAME")
).show(2)

%python

from pyspark.sql.functions import expr, col, column

df.select(
    expr("DEST_COUNTRY_NAME"),
    col("DEST_COUNTRY_NAME"),
    column("DEST_COUNTRY_NAME"))\
  .show(2)
```

One common error is attempting to mix `Column` objects and strings. For example, the below code will result in a compiler error.

```
df.select(col("DEST_COUNTRY_NAME"), "DEST_COUNTRY_NAME")
```

As we've seen thus far, `expr` is the most flexible reference that we can use. It

can refer to a plain column or a string manipulation of a column. To illustrate, let's change our column name, then change it back as an example using the `AS` keyword and then the `alias` method on the column.

```
%scala

df.select(expr("DEST_COUNTRY_NAME AS destination"))

%python

df.select(expr("DEST_COUNTRY_NAME AS destination"))

%sql

SELECT
  DEST_COUNTRY_NAME as destination
FROM
  dfTable
```

We can further manipulate the result of our expression as another expression.

```
%scala

df.select(
  expr("DEST_COUNTRY_NAME as destination").alias("DEST_COUNTRY_
)

%python

df.select(
  expr("DEST_COUNTRY_NAME as destination").alias("DEST_COUNTRY_
)
```

Because `select` followed by a series of `expr` is such a common pattern, Spark has a shorthand for doing so efficiently: `selectExpr`. This is probably the most convenient interface for everyday use.

```
%scala

df.selectExpr(
  "DEST_COUNTRY_NAME as newColumnName",
  "DEST_COUNTRY_NAME")
  .show(2)

%python
```

```
df.selectExpr(
  "DEST_COUNTRY_NAME as newColumnName",
  "DEST_COUNTRY_NAME"
).show(2)
```

This opens up the true power of Spark. We can treat `selectExpr` as a simple way to build up complex expressions that create new DataFrames. In fact, we can add any valid non-aggregating SQL statement and as long as the columns resolve - it will be valid! Here's a simple example that adds a new column `withinCountry` to our DataFrame that specifies whether or not the destination and origin are the same.

```
%scala

df.selectExpr(
  "*", // all original columns
  "(DEST_COUNTRY_NAME = ORIGIN_COUNTRY_NAME) as withinCountry"
).show(2)

%python

df.selectExpr(
  "*", # all original columns
  "(DEST_COUNTRY_NAME = ORIGIN_COUNTRY_NAME) as withinCountry")
  .show(2)

%sql

SELECT
  *,
  (DEST_COUNTRY_NAME = ORIGIN_COUNTRY_NAME) as withinCountry
FROM
  dfTable
```

Now we've learning about select and select expression. With these we can specify aggregations over the entire DataFrame by leveraging the functions that we have. These look just like what we have been showing so far.

```
%scala

df.selectExpr("avg(count)", "count(distinct(DEST_COUNTRY_NAME))

%python
```

```
df.selectExpr("avg(count)", "count(distinct(DEST_COUNTRY_NAME))

%sql

SELECT
  avg(count),
  count(distinct(DEST_COUNTRY_NAME))
FROM
  dfTable
```

Converting to Spark Types (Literals)

Sometimes we need to pass explicit values into Spark that aren't a new column but are just a value. This might be a constant value or something we'll need to compare to later on. The way we do this is through literals. This is basically a translation from a given programming language's literal value to one that Spark understands. Literals are expressions and can be used in the same way.

```
%scala

import org.apache.spark.sql.functions.lit

df.select(
  expr("*"),
  lit(1).as("something")
).show(2)

%python

from pyspark.sql.functions import lit

df.select(
  expr("*"),
  lit(1).alias("One")
).show(2)
```

In SQL, literals are just the specific value.

```
%sql

SELECT
  *,
  1 as One
FROM
  dfTable
LIMIT 2
```

This will come up when you might need to check if a date is greater than some constant or some value.

Adding Columns

There's also a more formal way of adding a new column to a DataFrame using the `withColumn` method on our DataFrame. For example, let's add a column that just adds the number one as a column.

```
%scala

df.withColumn("numberOne", lit(1)).show(2)

%python

df.withColumn("numberOne", lit(1)).show(2)

%sql

SELECT
  1 as numberOne
FROM
  dfTable
LIMIT 2
```

Let's do something a bit more interesting and make it an actual expression. Let's set a boolean flag for when the origin country is the same as the destination country.

```
%scala

df.withColumn(
  "withinCountry",
  expr("ORIGIN_COUNTRY_NAME == DEST_COUNTRY_NAME")
).show(2)

%python

df.withColumn(
  "withinCountry",
  expr("ORIGIN_COUNTRY_NAME == DEST_COUNTRY_NAME"))\
  .show(2)
```

You should notice that the `withColumn` function takes two arguments: the column name and the expression that will create the value for that given row in

the DataFrame. Interestingly, we can also rename a column this way.

```
%scala

df.withColumn(
  "Destination",
  df.col("DEST_COUNTRY_NAME"))
  .columns
```

Renaming Columns

Although we can rename a column in the above manner, it's often much easier (and readable) to use the `withColumnRenamed` method. This will rename the column with the name of the string in the first argument, to the string in the second argument.

```
%scala

df.withColumnRenamed("DEST_COUNTRY_NAME", "dest").columns

%python

df.withColumnRenamed("DEST_COUNTRY_NAME", "dest").columns
```

Reserved Characters and Keywords in Column Names

One thing that you may come across is reserved characters like spaces or dashes in column names. Handling these means escaping column names appropriately. In Spark this is done with backtick (`) characters. Let's use the `withColumn` that we just learned about to create a Column with reserved characters.

```
%scala

import org.apache.spark.sql.functions.expr

val dfWithLongColName = df
  .withColumn(
    "This Long Column-Name",
    expr("ORIGIN_COUNTRY_NAME"))

%python

dfWithLongColName = df\
  .withColumn(
    "This Long Column-Name",
    expr("ORIGIN_COUNTRY_NAME"))
```

We did not have to escape the column above because the first argument to `withColumn` is just a string for the new column name. We only have to use backticks when referencing a column in an expression.

```
%scala

dfWithLongColName
  .selectExpr(
    "`This Long Column-Name`",
    "`This Long Column-Name` as `new col`")
  .show(2)

%python

dfWithLongColName\
  .selectExpr(
```

```
    "`This Long Column-Name`",
    "`This Long Column-Name` as `new col`")\
  .show(2)

dfWithLongColName.createOrReplaceTempView("dfTableLong")

%sql

SELECT `This Long Column-Name` FROM dfTableLong
```

We can refer to columns with reserved characters (and not escape them) if doing an explicit string to column reference, which gets interpreted as a literal instead of an expression. We only have to escape expressions that leverage reserved characters or keywords. The following two examples both result in the same DataFrame.

```
%scala

dfWithLongColName.select(col("This Long Column-Name")).columns

%python

dfWithLongColName.select(expr("`This Long Column-Name`")).colur
```

Removing Columns

Now that we've created this column, let's take a look at how we can remove columns from DataFrames. You likely already noticed that we can do this with `select`. However there is also a dedicated method called `drop`.

```
df.drop("ORIGIN_COUNTRY_NAME").columns
```

We can drop multiple columns by passing in multiple columns as arguments.

```
dfWithLongColName.drop("ORIGIN_COUNTRY_NAME", "DEST_COUNTRY_NAM
```

Changing a Column's Type (cast)

Sometimes we may need to convert from one type to another, for example if we have a set of `StringType` that should be integers. We can convert columns from one type to another by casting the column from one type to another. For instance let's convert our count column from an integer to a Long type.

```
df.printSchema()

df.withColumn("count", col("count").cast("int")).printSchema()

%sql

SELECT
  cast(count as int)
FROM
  dfTable
```

Filtering Rows

To filter rows we create an expression that evaluates to true or false. We then filter out the rows that have expression that is equal to false. The most common way to do this with DataFrames is to create either an expression as a String or build an expression with a set of column manipulations. There are two methods to perform this operation, we can use `where` or `filter` and they both will perform the same operation and accept the same argument types when used with DataFrames. The Dataset API has slightly different options and please refer to the Dataset chapter for more information.

The following filters are equivalent.

```
%scala

val colCondition = df.filter(col("count") < 2).take(2)
val conditional = df.where("count < 2").take(2)

%python

colCondition = df.filter(col("count") < 2).take(2)
conditional = df.where("count < 2").take(2)

%sql

SELECT
  *
FROM dfTable
WHERE
  count < 2
```

Instinctually you may want to put multiple filters into the same expression. While this is possible, it is not always useful because Spark automatically performs all filtering operations at the same time. This is called pipelining and helps make Spark very efficient. As a user, that means if you want to specify multiple AND filters, just chain them sequentially and let Spark handle the rest.

```
%scala

df.where(col("count") < 2)
```

```
  .where(col("ORIGIN_COUNTRY_NAME") =!= "Croatia")
  .show(2)

%python

df.where(col("count") < 2)\
  .where(col("ORIGIN_COUNTRY_NAME") != "Croatia")\
  .show(2)

%sql

SELECT
  *
FROM dfTable
WHERE
  count < 2 AND
  ORIGIN_COUNTRY_NAME != "Croatia"
```

Getting Unique Rows

A very common use case is to get the unique or distinct values in a DataFrame. These values can be in one or more columns. The way we do this is with the `distinct` method on a DataFrame that will allow us to deduplicate any rows that are in that DataFrame. For instance let's get the unique origins in our dataset. This of course is a transformation that will return a new DataFrame with only unique rows.

```
%scala

df.select("ORIGIN_COUNTRY_NAME", "DEST_COUNTRY_NAME").count()

%python

df.select("ORIGIN_COUNTRY_NAME", "DEST_COUNTRY_NAME").count()

%sql

SELECT
  COUNT(DISTINCT ORIGIN_COUNTRY_NAME, DEST_COUNTRY_NAME)
FROM dfTable

%scala

df.select("ORIGIN_COUNTRY_NAME").distinct().count()

%python

df.select("ORIGIN_COUNTRY_NAME").distinct().count()

%sql

SELECT
  COUNT(DISTINCT ORIGIN_COUNTRY_NAME)
FROM dfTable
```

Random Samples

Sometimes you may just want to sample some random records from your DataFrame. This is done with the `sample` method on a DataFrame that allows you to specify a fraction of rows to extract from a DataFrame and whether you'd like to sample with or without replacement.

```
val seed = 5
val withReplacement = false
val fraction = 0.5

df.sample(withReplacement, fraction, seed).count()

%python

seed = 5
withReplacement = False
fraction = 0.5

df.sample(withReplacement, fraction, seed).count()
```

Random Splits

Random splits can be helpful when you need to break up your DataFrame, randomly, in such a way that sampling random cannot guarantee that all records are in one of the DataFrames that you're sampling from. This is often used with machine learning algorithms to create training, validation, and test sets. In this example we'll split our DataFrame into two different DataFrames by setting the weights by which we will split the DataFrame (these are the arguments to the function). Since this method involves some randomness, we will also specify a seed. It's important to note that if you don't specify a proportion for each DataFrame that adds up to one, they will be normalized so that they do.

```
%scala

val dataFrames = df.randomSplit(Array(0.25, 0.75), seed)
dataFrames(0).count() > dataFrames(1).count()

%python

dataFrames = df.randomSplit([0.25, 0.75], seed)
dataFrames[0].count() > dataFrames[1].count()
```

Concatenating and Appending Rows to a DataFrame

As we learned in the previous section, DataFrames are immutable. This means users cannot append to DataFrames because that would be changing it. In order to append to a DataFrame, you must union the original DataFrame along with the new DataFrame. This just concatenates the two DataFrames together. To union two DataFrames, you have to be sure that they have the same schema and number of columns, else the union will fail.

```
%scala

import org.apache.spark.sql.Row

val schema = df.schema

val newRows = Seq(
  Row("New Country", "Other Country", 5L),
  Row("New Country 2", "Other Country 3", 1L)
)
val parallelizedRows = spark.sparkContext.parallelize(newRows)

val newDF = spark.createDataFrame(parallelizedRows, schema)

df.union(newDF)
  .where("count = 1")
  .where($"ORIGIN_COUNTRY_NAME" =!= "United States")
  .show() // get all of them and we'll see our new rows at the

%python

from pyspark.sql import Row

schema = df.schema

newRows = [
  Row("New Country", "Other Country", 5L),
  Row("New Country 2", "Other Country 3", 1L)
]
parallelizedRows = spark.sparkContext.parallelize(newRows)
newDF = spark.createDataFrame(parallelizedRows, schema)
```

```
%python

df.union(newDF)\
  .where("count = 1")\
  .where(col("ORIGIN_COUNTRY_NAME") != "United States")\
  .show()
```

As expected, you'll have to use this new DataFrame reference in order to refer to the DataFrame with the newly appended rows. A common way to do this is to make the DataFrame into a view or register it as a table so that you can reference it more dynamically in your code.

Sorting Rows

When we sort the values in a DataFrame, we always want to sort with either the largest or smallest values at the top of a DataFrame. There are two equivalent operations to do this `sort` and `orderBy` that work the exact same way. They accept both column expressions and strings as well as multiple columns. The default is to sort in ascending order.

```
%scala

df.sort("count").show(5)
df.orderBy("count", "DEST_COUNTRY_NAME").show(5)
df.orderBy(col("count"), col("DEST_COUNTRY_NAME")).show(5)

%python

df.sort("count").show(5)
df.orderBy("count", "DEST_COUNTRY_NAME").show(5)
df.orderBy(col("count"), col("DEST_COUNTRY_NAME")).show(5)
```

To more explicit specify sort direction we have to use the `asc` and `desc` functions if operating on a column. These allow us to specify the order that a given column should be sorted in.

```
%scala

import org.apache.spark.sql.functions.{desc, asc}

df.orderBy(expr("count desc")).show(2)
df.orderBy(desc("count"), asc("DEST_COUNTRY_NAME")).show(2)

%python

from pyspark.sql.functions import desc, asc

df.orderBy(expr("count desc")).show(2)
df.orderBy(desc(col("count")), asc(col("DEST_COUNTRY_NAME"))).s

%sql

SELECT *
FROM dfTable
```

```
ORDER BY count DESC, DEST_COUNTRY_NAME ASC
```

For optimization purposes, it can sometimes be advisable to sort within each partition before another set of transformations. We can do this with the `sortWithinPartitions` method.

```
%scala

spark.read.format("json")
  .load("/mnt/defg/flight-data/json/*-summary.json")
  .sortWithinPartitions("count")

%python

spark.read.format("json")\
  .load("/mnt/defg/flight-data/json/*-summary.json")\
  .sortWithinPartitions("count")
```

We will discuss this more when discussing tuning and optimization in Section 3.

Limit

Often times you may just want the top ten of some DataFrame. For example, you might want to only work with the top 50 of some dataset. We do this with the `limit` method.

```
%scala

df.limit(5).show()

%python

df.limit(5).show()

%scala

df.orderBy(expr("count desc")).limit(6).show()

%python

df.orderBy(expr("count desc")).limit(6).show()

%sql

SELECT *
FROM dfTable
LIMIT 6
```

Repartition and Coalesce

Another important optimization opportunity is to partition the data according to some frequently filtered columns which controls the physical layout of data across the cluster including the partitioning scheme and the number of partitions.

Repartition will incur a full shuffle of the data, regardless of whether or not one is necessary. This means that you should typically only repartition when the future number of partitions is greater than your current number of partitions or when you are looking to partition by a set of columns. C

```
%scala

df.rdd.getNumPartitions

%python

df.rdd.getNumPartitions()

%scala

df.repartition(5)

%python

df.repartition(5)
```

If we know we are going to be filtering by a certain column often, it can be worth repartitioning based on that column.

```
%scala

df.repartition(col("DEST_COUNTRY_NAME"))

%python

df.repartition(col("DEST_COUNTRY_NAME"))
```

We can optionally specify the number of partitions we would like too.

```
%scala

df.repartition(5, col("DEST_COUNTRY_NAME"))

%python

df.repartition(5, col("DEST_COUNTRY_NAME"))
```

Coalesce on the other hand will not incur a full shuffle and will try to combine partitions. This operation will shuffle our data into 5 partitions based on the destination country name, then coalesce them (without a full shuffle).

```
%scala

df.repartition(5, col("DEST_COUNTRY_NAME")).coalesce(2)

%python

df.repartition(5, col("DEST_COUNTRY_NAME")).coalesce(2)
```

Collecting Rows to the Driver

As we covered in the previous chapters. Spark has a Driver that maintains cluster information and runs user code. This means that when we call some method to collect data, this is collected to the Spark Driver.

Thus far we did not talk explicitly about this operation however we used several different methods for doing that that are effectively all the same. `collect` gets all data from the entire DataFrame, `take` selects the first `N` rows, `show` prints out a number of rows nicely. See the appendix for collecting data for the complete list.

```
%scala

val collectDF = df.limit(10)
collectDF.take(5) // take works with an Integer count
collectDF.show() // this prints it out nicely
collectDF.show(5, false)
collectDF.collect()

%python

collectDF = df.limit(10)
collectDF.take(5) # take works with an Integer count
collectDF.show() # this prints it out nicely
collectDF.show(5, False)
collectDF.collect()
```

Chapter 4. Working with Different Types of Data

Chapter Overview

In the previous chapter, we covered basic DataFrame concepts and abstractions. this chapter will cover building expressions, which are the bread and butter of Spark's structured operations. This chapter will cover working with a variety of different kinds of data including:

- Booleans
- Numbers
- Strings
- Dates and Timestamps
- Handling Null
- Complex Types
- User Defined Functions

Where to Look for APIs

Before we get started, it's worth explaining where you as a user should start looking for transformations. Spark is a growing project and any book (including this one) is a snapshot in time. Therefore it is our priority to educate you as a user as to where you should look for functions in order to transform your data. The key places to look for transformations are:

`DataFrame` (`Dataset`) Methods. This is actually a bit of a trick because a DataFrame is just a Dataset of `Row` types so you'll actually end up looking at the `Dataset` methods. These are available at: *http://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.s*

`Dataset` sub-modules like `DataFrameStatFunctions` and `DataFrameNaFunctions` that have more methods. These are usually domain specific sets of functions and methods that only make sense in a certain context. For example, `DataFrameStatFunctions` holds a variety of statistically related functions while `DataFrameNaFunctions` refers to functions that are relevant when working with null data.

Null Functions:
http://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.s

Stat Functions:
http://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.s

`Column` Methods. These were introduced for the most part in the previous chapter are hold a variety of general column related methods like `alias` or `contains`. These are available at:
http://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.s

`org.apache.spark.sql.functions` contains a variety of functions for a variety of different data types. Often you'll see the entire package imported because they are used so often. These are available at:
http://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.s

Now this may feel a bit overwhelming but have no fear, the majority of these functions are ones that you will find in SQL and analytics systems. All of these tools exist to achieve one purpose, to transform rows of data in one format or structure to another. This may create more rows or reduce the number of rows available. To get stated, let's read in the `DataFrame` that we'll be using for this analysis.

```
%scala

val df = spark.read.format("csv")
  .option("header", "true")
  .option("inferSchema", "true")
  .load("/mnt/defg/retail-data/by-day/2010-12-01.csv")

df.printSchema()

df.createOrReplaceTempView("dfTable")

%python

df = spark.read.format("csv")\
  .option("header", "true")\
  .option("inferSchema", "true")\
  .load("/mnt/defg/retail-data/by-day/2010-12-01.csv")

df.printSchema()

df.createOrReplaceTempView("dfTable")
```

These will print the schema nicely.

```
root
 |-- InvoiceNo: string (nullable = true)
 |-- StockCode: string (nullable = true)
 |-- Description: string (nullable = true)
 |-- Quantity: integer (nullable = true)
 |-- InvoiceDate: timestamp (nullable = true)
 |-- UnitPrice: double (nullable = true)
 |-- CustomerID: double (nullable = true)
 |-- Country: string (nullable = true)
```

Working with Booleans

Booleans are foundational when it comes to data analysis because they are the foundation for all filtering. Boolean statements consist of four elements: `and`, `or`, `true` and `false`. We use these simple structures to build logical statements that evaluate to either `true` or `false`. These statements are often used as conditional requirements where a row of data must either pass this test (evaluate to true) or else it will be filtered out.

Let's use our retail dataset to explore working with booleans. We can specify equality as well as less or greater than.

```
%scala

import org.apache.spark.sql.functions.col

df.where(col("InvoiceNo").equalTo(536365))
  .select("InvoiceNo", "Description")
  .show(5, false)
```

NOTE

> Scala has some particular semantics around the use of == and ===. In Spark, if you wish to filter by equality you should use === (equal) or =!= (not equal). You can also use `not` function and the `equalTo` method.

```
%scala

import org.apache.spark.sql.functions.col

df.where(col("InvoiceNo") === 536365)
  .select("InvoiceNo", "Description")
  .show(5, false)
```

Python keeps a more conventional notation.

```
%python

from pyspark.sql.functions import col
```

```
df.where(col("InvoiceNo") != 536365)\
  .select("InvoiceNo", "Description")\
  .show(5, False)
```

Now we mentioned that we can specify boolean expressions with multiple parts when we use `and` or `or`. In Spark you should always chain together `and` filters as a sequential filter.

The reason for this is that even if boolean expressions are expressed serially (one after the other) Spark will flatten all of these filters into one statement and perform the filter at the same time, creating the `and` statement for us. While you may specify your statements explicitly using `and` if you like, it's often easier to reason about and to read if you specify them serially. `or` statements need to be specified in the same statement.

```
%scala

val priceFilter = col("UnitPrice") > 600
val descripFilter = col("Description").contains("POSTAGE")

df.where(col("StockCode").isin("DOT"))
  .where(priceFilter.or(descripFilter))
  .show(5)

%python

from pyspark.sql.functions import instr

priceFilter = col("UnitPrice") > 600
descripFilter = instr(df.Description, "POSTAGE") >= 1

df.where(df.StockCode.isin("DOT"))\
  .where(priceFilter | descripFilter)\
  .show(5)

%sql

SELECT
  *
FROM dfTable
WHERE
  StockCode in ("DOT") AND
  (UnitPrice > 600 OR
    instr(Description, "POSTAGE") >= 1)
```

Boolean expressions are not just reserved to filters. In order to filter a `DataFrame` we can also just specify a boolean column.

```
val DOTCodeFilter = col("StockCode") === "DOT"
val priceFilter = col("UnitPrice") > 600
val descripFilter = col("Description").contains("POSTAGE")

df.withColumn("isExpensive",
    DOTCodeFilter.and(priceFilter.or(descripFilter)))
  .where("isExpensive")
  .select("unitPrice", "isExpensive")
  .show(5)

%python

from pyspark.sql.functions import instr
DOTCodeFilter = col("StockCode") == "DOT"
priceFilter = col("UnitPrice") > 600
descripFilter = instr(col("Description"), "POSTAGE") >= 1

df.withColumn("isExpensive",
    DOTCodeFilter & (priceFilter | descripFilter))\
  .where("isExpensive")\
  .select("unitPrice", "isExpensive")\
  .show(5)

%sql

SELECT
  UnitPrice,
  (StockCode = 'DOT' AND
  (UnitPrice > 600 OR
    instr(Description, "POSTAGE") >= 1)) as isExpensive
FROM dfTable
WHERE
  (StockCode = 'DOT' AND
  (UnitPrice > 600 OR
    instr(Description, "POSTAGE") >= 1))
```

Notice how we did not have to specify our filter as an expression and how we could use a column name without any extra work.

If you're coming from a SQL background all of these statements should seem quite familiar. Indeed, all of them can be expressed as a `where` clause. In fact, it's often easier to just express filters as SQL statements than using the

programmatic `DataFrame` interface and Spark SQL allows us to do this without paying any performance penalty. For example, the two following statements are equivalent.

```
import org.apache.spark.sql.functions.{expr, not, col}

df.withColumn("isExpensive", not(col("UnitPrice").leq(250)))
  .filter("isExpensive")
  .select("Description", "UnitPrice").show(5)

df.withColumn("isExpensive", expr("NOT UnitPrice <= 250"))
  .filter("isExpensive")
  .select("Description", "UnitPrice").show(5)

%python

from pyspark.sql.functions import expr

df.withColumn("isExpensive", expr("NOT UnitPrice <= 250"))\
  .where("isExpensive")\
  .select("Description", "UnitPrice").show(5)
```

Working with Numbers

When working with big data, the second most common task you will do after filtering things is counting things. For the most part, we simply need to express our computation and that should be valid assuming we're working with numerical data types.

To fabricate a contrived example, let's imagine that we found out that we mis-recorded the quantity in our retail dataset and true quantity is equal to (the current quantity * the unit price) ^ 2 + 5. This will introduce our first numerical function as well the `pow` function that raises a column to the expressed power.

```
%scala

import org.apache.spark.sql.functions.{expr, pow}

val fabricatedQuantity = pow(col("Quantity") * col("UnitPrice")

df.select(
    expr("CustomerId"),
    fabricatedQuantity.alias("realQuantity"))
  .show(2)

%python

from pyspark.sql.functions import expr, pow

fabricatedQuantity = pow(col("Quantity") * col("UnitPrice"), 2)

df.select(
    expr("CustomerId"),
    fabricatedQuantity.alias("realQuantity"))\
  .show(2)
```

You'll notice that we were able to multiply our columns together because they were both numerical. Naturally we can add and subtract as necessary as well. In fact we can do all of this a SQL expression as well.

```
%scala
```

```
df.selectExpr(
  "CustomerId",
  "(POWER((Quantity * UnitPrice), 2.0) + 5) as realQuantity")
  .show(2)

%python

df.selectExpr(
  "CustomerId",
  "(POWER((Quantity * UnitPrice), 2.0) + 5) as realQuantity")\
  .show(2)

%sql

SELECT
  customerId,
  (POWER((Quantity * UnitPrice), 2.0) + 5) as realQuantity
FROM dfTable
```

Another common numerical task is rounding. Now if you'd like to just round to a whole number, often times you can cast it to an integer and that will work just fine. However Spark also has more detailed functions for performing this explicitly and to a certain level of precision. In this case we will round to one decimal place.

```
%scala

import org.apache.spark.sql.functions.{round, bround}

df.select(
    round(col("UnitPrice"), 1).alias("rounded"),
    col("UnitPrice"))
  .show(5)
```

By default, the `round` function will round up if you're exactly in between two numbers. You can round down with the `bround`.

```
%scala

import org.apache.spark.sql.functions.lit

df.select(
    round(lit("2.5")),
    bround(lit("2.5")))
  .show(2)
```

```
%python

from pyspark.sql.functions import lit, round, bround

df.select(
    round(lit("2.5")),
    bround(lit("2.5")))\
  .show(2)

%sql

SELECT
  round(2.5),
  bround(2.5)
```

Another numerical task is to compute the correlation of two columns. For example, we can see the Pearson Correlation Coefficient for two columns to see if cheaper things are typically bought in greater quantities. We can do this through a function as well as through the DataFrame statistic methods.

```
%scala

import org.apache.spark.sql.functions.{corr}

df.stat.corr("Quantity", "UnitPrice")
df.select(corr("Quantity", "UnitPrice")).show()

%python

from pyspark.sql.functions import corr

df.stat.corr("Quantity", "UnitPrice")
df.select(corr("Quantity", "UnitPrice")).show()

%sql

SELECT
  corr(Quantity, UnitPrice)
FROM
  dfTable
```

A common task is to compute summary statistics for a column or set of columns. We can use the `describe` method to achieve exactly this. This will take all numeric columns and calculate the count, mean, standard deviation, min, and max. This should be used primarily for viewing in the console as the

schema may change in the future.

```
%scala

df.describe().show()

%python

df.describe().show()
```

```
+-------+------------------+------------------+----------------
|summary|          Quantity|         UnitPrice|        Custome
+-------+------------------+------------------+----------------
|  count|              3108|              3108|              1
|   mean| 8.627413127413128| 4.151946589446603|15661.388719512
| stddev|26.371821677029203|15.638659854603892|1854.4496996893
|    min|               -24|               0.0|           1243
|    max|               600|            607.49|           1822
+-------+------------------+------------------+----------------
```

If you need these exact numbers you can also perform this as an aggregation yourself by importing the functions and applying them to the columns that you need.

```
%scala

import org.apache.spark.sql.functions.{count, mean, stddev_pop,

%python

from pyspark.sql.functions import count, mean, stddev_pop, min,
```

There are a number of statistical functions available in the StatFunctions Package. These are DataFrame methods that allow you to calculate a vareity of different things. For instance, we can calculate either exact or approximate quantiles of our data using the `approxQuantile` method.

```
%scala

val colName = "UnitPrice"
val quantileProbs = Array(0.5)
val relError = 0.05
df.stat.approxQuantile("UnitPrice", quantileProbs, relError)

%python
```

```
colName = "UnitPrice"
quantileProbs = [0.5]
relError = 0.05
df.stat.approxQuantile("UnitPrice", quantileProbs, relError)
```

We can also use this to see a cross tabulation or frequent item pairs (Be careful, this output will be large).

```
%scala

df.stat.crosstab("StockCode", "Quantity").show()

%python

df.stat.crosstab("StockCode", "Quantity").show()

%scala

df.stat.freqItems(Seq("StockCode", "Quantity")).show()

%python

df.stat.freqItems(["StockCode", "Quantity"]).show()
```

Spark is home to a variety of other features and functionality. For example, you can use Spark to construct a Bloom Filter or Count Min Sketch using the `stat` sub-package. There are also a multitude of other functions available that are self-explanatory and need not be explained individually.

Working with Strings

String manipulation shows up in nearly every data flow and its worth explaining what you can do with strings. You may be manipulating log files performing regular expression extraction or substitution, or checking for simple string existence, or simply making all strings upper or lower case.

We will start with the last task as it's one of the simplest. The `initcap` function will capitalize every word in a given string when that word is separated from another via whitespace.

```
%scala

import org.apache.spark.sql.functions.{initcap}

df.select(initcap(col("Description"))).show(2, false)

%python

from pyspark.sql.functions import initcap

df.select(initcap(col("Description"))).show()

%sql

SELECT
  initcap(Description)
FROM
  dfTable
```

As mentioned above, we can also quite simply lower case and upper case strings as well.

```
%scala

import org.apache.spark.sql.functions.{lower, upper}

df.select(
    col("Description"),
    lower(col("Description")),
    upper(lower(col("Description"))))
```

```
  .show(2)

%python

from pyspark.sql.functions import lower, upper

df.select(
    col("Description"),
    lower(col("Description")),
    upper(lower(col("Description"))))\
  .show(2)

%sql

SELECT
  Description,
  lower(Description),
  Upper(lower(Description))
FROM
  dfTable
```

Another trivial task is adding or removing whitespace around a string. We can do this with `lpad`, `ltrim`, `rpad` and `rtrim`, `trim`.

```
%scala

import org.apache.spark.sql.functions.{lit, ltrim, rtrim, rpad,

df.select(
    ltrim(lit("    HELLO    ")).as("ltrim"),
    rtrim(lit("    HELLO    ")).as("rtrim"),
    trim(lit("    HELLO    ")).as("trim"),
    lpad(lit("HELLO"), 3, " ").as("lp"),
    rpad(lit("HELLO"), 10, " ").as("rp"))
  .show(2)

%python

from pyspark.sql.functions import lit, ltrim, rtrim, rpad, lpa

df.select(
    ltrim(lit("    HELLO    ")).alias("ltrim"),
    rtrim(lit("    HELLO    ")).alias("rtrim"),
    trim(lit("    HELLO    ")).alias("trim"),
    lpad(lit("HELLO"), 3, " ").alias("lp"),
    rpad(lit("HELLO"), 10, " ").alias("rp"))\
  .show(2)
```

```
%sql

SELECT
  ltrim('    HELLLOOOO  '),
  rtrim('    HELLLOOOO  '),
  trim('    HELLLOOOO  '),
  lpad('HELLOOOO  ', 3, ' '),
  rpad('HELLOOOO  ', 10, ' ')
FROM
  dfTable
```

```
+---------+---------+-----+---+----------+
|    ltrim|    rtrim| trim| lp|        rp|
+---------+---------+-----+---+----------+
|HELLO    |    HELLO|HELLO| HE|HELLO     |
|HELLO    |    HELLO|HELLO| HE|HELLO     |
+---------+---------+-----+---+----------+
only showing top 2 rows
```

You'll notice that if `lpad` or `rpad` takes a number less than the length of the string, it will always remove values from the right side of the string.

Regular Expressions

Probably one of the most frequently performed tasks is searching for the existance of one string on another or replacing all mentions of a string with another value. This is often done with a tool called “Regular Expressions” that exist in many programming languages. Regular expressions give the user an ability to specify a set of rules to use to either extract values from a string or replace them with some other values.

Spark leverages the complete power of Java Regular Expressions. The syntax departs slightly from other programming languages so it is worth reviewing before putting anything into production.. There are two key functions in Spark that you’ll need to perform regular expression tasks: `regexp_extract` and `regexp_replace`. These functions extract values and replace values respectively.

Let’s explore how to use the `regexp_replace` function to replace substitute colors names in our description column.

```
%scala

import org.apache.spark.sql.functions.regexp_replace

val simpleColors = Seq("black", "white", "red", "green", "blue"
val regexString = simpleColors.map(_.toUpperCase).mkString("|")
// the | signifies `OR` in regular expression syntax

df.select(
     regexp_replace(col("Description"), regexString, "COLOR")
      .alias("color_cleaned"),
     col("Description"))
  .show(2)

%python

from pyspark.sql.functions import regexp_replace

regex_string = "BLACK|WHITE|RED|GREEN|BLUE"

df.select(
```

```
    regexp_replace(col("Description"), regex_string, "COLOR")
     .alias("color_cleaned"),
    col("Description"))\
  .show(2)

%sql

SELECT
  regexp_replace(Description, 'BLACK|WHITE|RED|GREEN|BLUE', 'C(
  Description
FROM
  dfTable

+--------------------+--------------------+
|       color_cleaned|         Description|
+--------------------+--------------------+
|COLOR HANGING HEA...|WHITE HANGING HEA...|
| COLOR METAL LANTERN| WHITE METAL LANTERN|
+--------------------+--------------------+
```

Another task may be to replace given characters with other characters. Building this as regular expression could be tedious so Spark also provides the translate function to replace these values. This is done at the character level and will replace all instances of a character with the indexed character in the replacement string.

```
%scala

import org.apache.spark.sql.functions.translate

df.select(
    translate(col("Description"), "LEET", "1337"),
    col("Description"))
  .show(2)

%python

from pyspark.sql.functions import translate

df.select(
    translate(col("Description"), "LEET", "1337"),
    col("Description"))\
  .show(2)

%sql
```

```
SELECT
  translate(Description, 'LEET', '1337'),
  Description
FROM
  dfTable
```

```
+----------------------------------+--------------------+
|translate(Description, LEET, 1337)|         Description|
+----------------------------------+--------------------+
|              WHI73 HANGING H3A...|WHITE HANGING HEA...|
|               WHI73 M37A1 1AN73RN| WHITE METAL LANTERN|
+----------------------------------+--------------------+
```

We can also perform something similar like pulling out the first mentioned color.

```
%scala

import org.apache.spark.sql.functions.regexp_extract

val regexString = simpleColors
  .map(_.toUpperCase)
  .mkString("(", "|", ")")
// the | signifies OR in regular expression syntax

df.select(
     regexp_extract(col("Description"), regexString, 1)
       .alias("color_cleaned"),
     col("Description"))
  .show(2)

%python

from pyspark.sql.functions import regexp_extract

extract_str = "(BLACK|WHITE|RED|GREEN|BLUE)"
df.select(
     regexp_extract(col("Description"), extract_str, 1)
       .alias("color_cleaned"),
     col("Description"))\
  .show(2)

%sql

SELECT
  regexp_extract(Description, '(BLACK|WHITE|RED|GREEN|BLUE)', 1
  Description
```

```
FROM
  dfTable
```

Sometimes, rather than extracting values, we simply want to check for existence. We can do this with the `contains` method on each column. This will return a boolean declaring whether it can find that string in the column's string.

```
%scala

val containsBlack = col("Description").contains("BLACK")
val containsWhite = col("DESCRIPTION").contains("WHITE")

df.withColumn("hasSimpleColor", containsBlack.or(containsWhite)
  .filter("hasSimpleColor")
  .select("Description")
  .show(3, false)
```

In Python we can use the `instr` function.

```
%python

from pyspark.sql.functions import instr

containsBlack = instr(col("Description"), "BLACK") >= 1
containsWhite = instr(col("Description"), "WHITE") >= 1

df.withColumn("hasSimpleColor", containsBlack | containsWhite)\
  .filter("hasSimpleColor")\
  .select("Description")\
  .show(3, False)

%sql

SELECT
  Description
FROM
  dfTable
WHERE
  instr(Description, 'BLACK') >= 1 OR
  instr(Description, 'WHITE') >= 1

+----------------------------------+
|Description                       |
+----------------------------------+
|WHITE HANGING HEART T-LIGHT HOLDER|
|WHITE METAL LANTERN               |
```

```
|RED WOOLLY HOTTIE WHITE HEART.    |
+----------------------------------+
only showing top 3 rows
```

This is trivial with just two values but gets much more complicated with more values.

Let's work through this in a more dynamic way and take advantage of Spark's ability to accept a dynamic number of arguments. When we convert a list of values into a set of arguments and pass them into a function, we use a language feature called varargs. This feature allows us to effectively unravel an array of arbitrary length and pass it as arguments to a function. This, coupled with `select` allows us to create arbitrary numbers of columns dynamically.

```
%scala

val simpleColors = Seq("black", "white", "red", "green", "blue'

val selectedColumns = simpleColors.map(color => {
   col("Description")
    .contains(color.toUpperCase)
    .alias(s"is_$color")
}):+expr("*") // could also append this value

df
  .select(selectedColumns:_*)
  .where(col("is_white").or(col("is_red")))
  .select("Description")
  .show(3, false)

+----------------------------------+
|Description                       |
+----------------------------------+
|WHITE HANGING HEART T-LIGHT HOLDER|
|WHITE METAL LANTERN               |
|RED WOOLLY HOTTIE WHITE HEART.    |
+----------------------------------+
```

We can also do this quite easily in Python. In this case we're going to use a different function `locate` that returns the integer location (1 based location). We then convert that to a boolean before using it as a the same basic feature.

```
%python
```

```
from pyspark.sql.functions import expr, locate

simpleColors = ["black", "white", "red", "green", "blue"]

def color_locator(column, color_string):
  """This function creates a column declaring whether or
  not a given pySpark column contains the UPPERCASED
  color.

  Returns a new column type that can be used
  in a select statement.
  """
  return locate(color_string.upper(), column)\
          .cast("boolean")\
          .alias("is_" + c)

selectedColumns = [color_locator(df.Description, c) for c in s
selectedColumns.append(expr("*")) # has to a be Column type

df\
  .select(*selectedColumns)\
  .where(expr("is_white OR is_red"))\
  .select("Description")\
  .show(3, False)
```

This simple feature is often one that can help you programmatically generate columns or boolean filters in a way that is simple to reason about and extend. We could extend this to calculating the smallest common denominator for a given input value or whether or not a number is a prime.

Working with Dates and Timestamps

Dates and times are a constant challenge in programming languages and databases. It's always necessary to keep track of timezones and make sure that formats are correct and valid. Spark does its best to keep things simple by focusing explicitly on two kinds of time related information. There are dates, which focus exclusively on calendar dates, and timestamps that include both date and time information.

Now as we hinted at above, working with dates and timestamps closely relates to working with strings because we often store our timestamps or dates as strings and convert them into date types at runtime. This is less common when working with databases and structured data but much more common when we are working with text and csv files.

Now Spark, as we saw with our current dataset, will make a best effort to correctly identify column types, including dates and timestamps when we enable `inferSchema`. We can see that this worked quite well with our current dataset because it was able to identify and read our date format without us having to provide some specification for it.

```
df.printSchema()
```

```
root
 |-- InvoiceNo: string (nullable = true)
 |-- StockCode: string (nullable = true)
 |-- Description: string (nullable = true)
 |-- Quantity: integer (nullable = true)
 |-- InvoiceDate: timestamp (nullable = true)
 |-- UnitPrice: double (nullable = true)
 |-- CustomerID: double (nullable = true)
 |-- Country: string (nullable = true)
```

While Spark will do this on a best effort basis, sometimes there will be no getting around working with strangely formatted dates and times. Now the key to reasoning about the transformations that you are going to need to apply is to

ensure that you know exactly what type and format you have at each given step of the way. Another common gotcha is that Spark's TimestampType only supports second-level precision, this means that if you're going to be working with milliseconds or microseconds, you're going to have to work around this problem by potentially operating on them as longs. Any more precision when coercing to a TimestampType will be removed.

Spark can be a bit particular about what format you have at any given point in time. It's important to be explicit when parsing or converting to make sure there are no issues in doing so. At the end of the day, Spark is working with Java dates and timestamps and therefore conforms to those standards. Let's start with the basics and get the current date and the current timestamps.

```
%scala

import org.apache.spark.sql.functions.{current_date, current_t

val dateDF = spark.range(10)
  .withColumn("today", current_date())
  .withColumn("now", current_timestamp())

dateDF.createOrReplaceTempView("dateTable")

%python

from pyspark.sql.functions import current_date, current_timesta

dateDF = spark.range(10)\
  .withColumn("today", current_date())\
  .withColumn("now", current_timestamp())

dateDF.createOrReplaceTempView("dateTable")

dateDF.printSchema()
```

Now that we have a simple DataFrame to work with, let's add and subtract 5 days from today. These functions take a column and then the number of days to either add or subtract as the arguments.

```
%scala

import org.apache.spark.sql.functions.{date_add, date_sub}
```

```
dateDF
  .select(
    date_sub(col("today"), 5),
    date_add(col("today"), 5))
  .show(1)

%python

from pyspark.sql.functions import date_add, date_sub

dateDF\
  .select(
    date_sub(col("today"), 5),
    date_add(col("today"), 5))\
  .show(1)

%sql

SELECT
  date_sub(today, 5),
  date_add(today, 5)
FROM
  dateTable
```

Another common task is to take a look at the difference between two dates. We can do this with the `datediff` function that will return the number of days in between two dates. Most often we just care about the days although since months can have a strange number of days there also exists a function `months_between` that gives you the number of months between two dates.

```
%scala

import org.apache.spark.sql.functions.{datediff, months_betwee

dateDF
  .withColumn("week_ago", date_sub(col("today"), 7))
  .select(datediff(col("week_ago"), col("today")))
  .show(1)

dateDF
  .select(
    to_date(lit("2016-01-01")).alias("start"),
    to_date(lit("2017-05-22")).alias("end"))
  .select(months_between(col("start"), col("end")))
  .show(1)
```

```
%python

from pyspark.sql.functions import datediff, months_between, to_

dateDF\
  .withColumn("week_ago", date_sub(col("today"), 7))\
  .select(datediff(col("week_ago"), col("today")))\
  .show(1)

dateDF\
  .select(
    to_date(lit("2016-01-01")).alias("start"),
    to_date(lit("2017-05-22")).alias("end"))\
  .select(months_between(col("start"), col("end")))\
  .show(1)

%sql

SELECT
  to_date('2016-01-01'),
  months_between('2016-01-01', '2017-01-01'),
  datediff('2016-01-01', '2017-01-01')
FROM
  dateTable
```

You'll notice that I introduced a new function above, the `to_date` function. This function allows us to convert a date of the format `"2017-01-01"` to a Spark date. Of course, for this to work our date must be in the year-month-day format. You'll notice that in order to perform this I'm also using the `lit` function which ensures that we're returning a literal value in our expression not trying to evaluate subtraction.

```
%scala

import org.apache.spark.sql.functions.{to_date, lit}

spark.range(5).withColumn("date", lit("2017-01-01"))
  .select(to_date(col("date")))
  .show(1)

%python

from pyspark.sql.functions import to_date, lit

spark.range(5).withColumn("date", lit("2017-01-01"))\
  .select(to_date(col("date")))\
```

```
  .show(1)
```

WARNING

> Spark will not throw an error if it cannot parse the date, it'll just return `null`. This can be a bit tricky in larger pipelines because you may be expecting your data in one format and getting it in another. To illustrate, let's take a look at the date format that has switched from year-month-day to year-day-month. Spark will fail to parse this date and silently return `null` instead.

```
dateDF.select(to_date(lit("2016-20-12")),to_date(lit("2017-12-1
```

```
+-------------------+-------------------+
|to_date(2016-20-12)|to_date(2017-12-11)|
+-------------------+-------------------+
|               null|         2017-12-11|
+-------------------+-------------------+
```

We find this to be an especially tricky situation for bugs because some dates may match the correct format while others do not. See how above, the second date is show to be Decembers 11th instead of the correct day, November 12th? Spark doesn't throw an error because it cannot know whether the days are mixed up or if that specific row is incorrect.

Let's fix this pipeline, step by step and come up with a robust way to avoid these issues entirely. The first step is to remember that we need to specify our date format according to the Java `SimpleDateFormat` standard as documented in *https://docs.oracle.com/javase/8/docs/api/java/text/SimpleDateFormat.html*.

By using the `unix_timestamp` we can parse our date into a `bigInt` that specifies the Unix timestamp in seconds. We can then cast that to a literal `timestamp` before passing that into the `to_date` format which accepts timestamps, strings, and other dates.

```
import org.apache.spark.sql.functions.{unix_timestamp, from_un
```

```
val dateFormat = "yyyy-dd-MM"
```

```
val cleanDateDF = spark.range(1)
```

```
  .select(
    to_date(unix_timestamp(lit("2017-12-11"), dateFormat).cast
      .alias("date"),
    to_date(unix_timestamp(lit("2017-20-12"), dateFormat).cast
      .alias("date2"))

cleanDateDF.createOrReplaceTempView("dateTable2")

%python

from pyspark.sql.functions import unix_timestamp, from_unixtime

dateFormat = "yyyy-dd-MM"

cleanDateDF = spark.range(1)\
  .select(
    to_date(unix_timestamp(lit("2017-12-11"), dateFormat).cast
      .alias("date"),
    to_date(unix_timestamp(lit("2017-20-12"), dateFormat).cast
      .alias("date2"))

cleanDateDF.createOrReplaceTempView("dateTable2")

%sql

SELECT
  to_date(cast(unix_timestamp(date, 'yyyy-dd-MM') as timestamp)
  to_date(cast(unix_timestamp(date2, 'yyyy-dd-MM') as timestamp
  to_date(date)
FROM
  dateTable2
```

The above example code also shows us how easy it is to cast between timestamps and dates.

```
%scala

cleanDateDF
  .select(
    unix_timestamp(col("date"), dateFormat).cast("timestamp"))
  .show()

%python

cleanDateDF\
  .select(
    unix_timestamp(col("date"), dateFormat).cast("timestamp"))\
```

```
  .show()
```

Once we've gotten our date or timestamp into the correct format and type,Comparing between them is actually quite easy. We just need to be sure to either use a date/timestamp type or specify our string according to the right format of `yyyy-MM-dd` if we're comparing a date.

```
cleanDateDF.filter(col("date2") > lit("2017-12-12")).show()
```

One minor point is that we can also set this as a string which Spark parses to a literal.

```
cleanDateDF.filter(col("date2") > "'2017-12-12'").show()
```

Working with Nulls in Data

As a best practice, you should always use nulls to represent missing or empty data in your DataFrames. Spark can optimize working with null values more than it can if you use empty strings or other values. The primary way of interacting with null values, at DataFrame scale, is to use the `.na` subpackage on a DataFrame.

In Spark there are two things you can do with null values. You can explicitly drop nulls or you can fill them with a value (globally or on a per column basis).

Let's experiment with each of these now.

Drop

The simplest is probably drop, which simply removes rows that contain nulls. The default is to drop any row where any value is null.

```
df.na.drop()
df.na.drop("any")
```

In SQL we have to do this column by column.

```
%sql

SELECT
  *
FROM
  dfTable
WHERE
  Description IS NOT NULL
```

Passing in “any” as an argument will drop a row if any of the values are null. Passing in “all” will only drop the row if all values are null or NaN for that row.

```
df.na.drop("all")
```

We can also apply this to certain sets of columns by passing in an array of columns.

```
%scala

df.na.drop("all", Seq("StockCode", "InvoiceNo"))

%python

df.na.drop("all", subset=["StockCode", "InvoiceNo"])
```

Fill

Fill allows you to fill one or more columns with a set of values. This can be done by specifying a map, specific value and a set of columns.

For example to fill all null values in String columns I might specify.

```
df.na.fill("All Null values become this string")
```

We could do the same for integer columns with `df.na.fill(5:Integer)` or for Doubles `df.na.fill(5:Double)`. In order to specify columns, we just pass in an array of column names like we did above.

```
%scala

df.na.fill(5, Seq("StockCode", "InvoiceNo"))

%python

df.na.fill("all", subset=["StockCode", "InvoiceNo"])
```

We can also do with with a Scala `Map` where the key is the column name and the value is the value we would like to use to fill null values.

```
%scala

val fillColValues = Map(
  "StockCode" -> 5,
  "Description" -> "No Value"
)

df.na.fill(fillColValues)

%python

fill_cols_vals = {
  "StockCode": 5,
  "Description" : "No Value"
}

df.na.fill(fill_cols_vals)
```

Replace

In addition to replacing null values like we did with `drop` and `fill`, there are more flexible options that we can use with more than just null values. Probably the most common use case is to replace all values in a certain column according to their current value. The only requirement is that this value be the same type as the original value.

```
%scala

df.na.replace("Description", Map("" -> "UNKNOWN"))

%python

df.na.replace([""], ["UNKNOWN"], "Description")
```

Working with Complex Types

Complex types can help you organize and structure your data in ways that make more sense for the problem you are hoping to solve. There are three kinds of complex types, structs, arrays, and maps.

Structs

You can think of structs as DataFrames within DataFrames. A worked example will illustrate this more clearly. We can create a struct by wrapping a set of columns in parenthesis in a query.

```
df.selectExpr("(Description, InvoiceNo) as complex", "*")

df.selectExpr("struct(Description, InvoiceNo) as complex", "*")

%scala
import org.apache.spark.sql.functions.struct

val complexDF = df
  .select(struct("Description", "InvoiceNo").alias("complex"))

complexDF.createOrReplaceTempView("complexDF")

%python

from pyspark.sql.functions import struct

complexDF = df\
  .select(struct("Description", "InvoiceNo").alias("complex"))

complexDF.createOrReplaceTempView("complexDF")
```

We now have a DataFrame with a column `complex`. We can query it just as we might another DataFrame, the only difference is that we use a dot syntax to do so.

```
complexDF.select("complex.Description")
```

We can also query all values in the struct with `*`. This brings up all the columns to the top level DataFrame.

```
complexDF.select("complex.*")

%sql

SELECT
  complex.*
```

```
FROM
  complexDF
```

Arrays

To define arrays, let's work through a use case. With our current data, our object is to take every single word in our `Description` column and convert that into a row in our DataFrame.

The first task is to turn our Description column into a complex type, an array.

split

We do this with the split function and specify the delimiter.

```
%scala

import org.apache.spark.sql.functions.split

df.select(split(col("Description"), " ")).show(2)

%python

from pyspark.sql.functions import split

df.select(split(col("Description"), " ")).show(2)

%sql

SELECT
 split(Description, ' ')
FROM
  dfTable
```

This is quite powerful because Spark will allow us to manipulate this complex type as another column. We can also query the values of the array with a python-like syntax.

```
%scala

df.select(split(col("Description"), " ").alias("array_col"))
  .selectExpr("array_col[0]")
  .show(2)

%python

df.select(split(col("Description"), " ").alias("array_col"))\
  .selectExpr("array_col[0]")\
  .show(2)

%sql

SELECT
 split(Description, ' ')[0]
```

```
FROM
  dfTable
```

Array Contains

For instance we can see if this array contains a value.

```
import org.apache.spark.sql.functions.array_contains

df.select(array_contains(split(col("Description"), " "), "WHITE
```

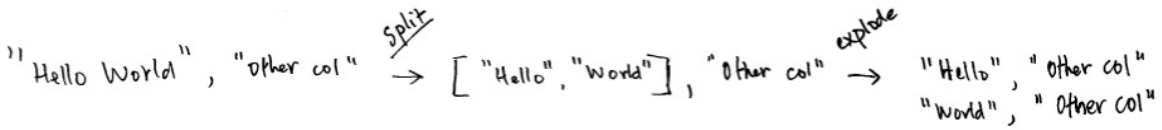
```
%python

from pyspark.sql.functions import array_contains

df.select(array_contains(split(col("Description"), " "), "WHITE
```

```
%sql

SELECT
 array_contains(split(Description, ' '), 'WHITE')
FROM
  dfTable
```

However this does not solve our current problem. In order to convert a complex type into a set of rows (one per value in our array), we use the explode function.

Explode

The explode function takes a column that consists of arrays and creates one row (with the rest of the values duplicated) per value in the array. The following figure illustrates the process.




```
%scala

import org.apache.spark.sql.functions.{split, explode}

df.withColumn("splitted", split(col("Description"), " "))
  .withColumn("exploded", explode(col("splitted")))
  .select("Description", "InvoiceNo", "exploded")

%python

from pyspark.sql.functions import split, explode

df.withColumn("splitted", split(col("Description"), " "))\
  .withColumn("exploded", explode(col("splitted")))\
  .select("Description", "InvoiceNo", "exploded")\
```

Maps

Maps are used less frequently but are still important to cover. We create them with the map function and key value pairs of columns. Then we can select them just like we might select from an array.

```
import org.apache.spark.sql.functions.map

df.select(map(col("Description"), col("InvoiceNo")).alias("comp
  .selectExpr("complex_map['Description']")

%sql

SELECT
  map(Description, InvoiceNo) as complex_map
FROM
  dfTable
WHERE
  Description IS NOT NULL
```

We can also explode map types which will turn them into columns.

```
import org.apache.spark.sql.functions.map

df.select(map(col("Description"), col("InvoiceNo")).alias("comp
  .selectExpr("explode(complex_map)")
  .take(5)
```

Working with JSON

Spark has some unique support for working with JSON data. You can operate directly on strings of JSON in Spark and parse from JSON or extract JSON objects. Let's start by creating a JSON column.

```
%scala

val jsonDF = spark.range(1)
  .selectExpr("""
  '{"myJSONKey" : {"myJSONValue" : [1, 2, 3]}}' as jsonString
  """)

%python

jsonDF = spark.range(1)\
  .selectExpr("""
  '{"myJSONKey" : {"myJSONValue" : [1, 2, 3]}}' as jsonString
  """)
```

We can use the `get_json_object` to inline query a JSON object, be it a dictionary or array. We can use `json_tuple` if this object has only one level of nesting.

```
%scala

import org.apache.spark.sql.functions.{get_json_object, json_tu

jsonDF.select(
    get_json_object(col("jsonString"), "$.myJSONKey.myJSONValue
    json_tuple(col("jsonString"), "myJSONKey"))
  .show()

%python

from pyspark.sql.functions import get_json_object, json_tuple

jsonDF.select(
    get_json_object(col("jsonString"), "$.myJSONKey.myJSONValue
    json_tuple(col("jsonString"), "myJSONKey"))\
  .show()
```

The equivalent in SQL would be.

```
jsonDF.selectExpr("json_tuple(jsonString, '$.myJSONKey.myJSONVa
```

We can also turn a StructType into a JSON string using the `to_json` function.

```
%scala

import org.apache.spark.sql.functions.to_json

df.selectExpr("(InvoiceNo, Description) as myStruct")
  .select(to_json(col("myStruct")))

%python

from pyspark.sql.functions import to_json

df.selectExpr("(InvoiceNo, Description) as myStruct")\
  .select(to_json(col("myStruct")))
```

This function also accepts a dictionary (map) of parameters that are the same as the JSON data source. We can use the `from_json` function to parse this (or other json) back in. This naturally requires us to specify a schema and optionally we can specify a Map of options as well.

```
%scala

import org.apache.spark.sql.functions.from_json
import org.apache.spark.sql.types._

val parseSchema = new StructType(Array(
  new StructField("InvoiceNo",StringType,true),
  new StructField("Description",StringType,true)))

df.selectExpr("(InvoiceNo, Description) as myStruct")
  .select(to_json(col("myStruct")).alias("newJSON"))
  .select(from_json(col("newJSON"), parseSchema), col("newJSON'

%python

from pyspark.sql.functions import from_json
from pyspark.sql.types import *

parseSchema = StructType((
  StructField("InvoiceNo",StringType(),True),
  StructField("Description",StringType(),True)))
```

```
df.selectExpr("(InvoiceNo, Description) as myStruct")\
  .select(to_json(col("myStruct")).alias("newJSON"))\
  .select(from_json(col("newJSON"), parseSchema), col("newJSON'
```

User-Defined Functions

One of the most powerful things that you can do in Spark is define your own functions. These allow you to write your own custom transformations using Python or Scala and even leverage external libraries like numpy in doing so. These functions are called `user defined functions` or `UDFs` and can take and return one or more columns as input. Spark UDFs are incredibly powerful because they can be written in several different programming languages and do not have to be written in an esoteric format or DSL. They're just functions that operate on the data, record by record.

While we can write our functions in Scala, Python, or Java, there are performance considerations that you should be aware of. To illustrate this, we're going to walk through exactly what happens when you create UDF, pass that into Spark, and then execute code using that UDF.

The first step is the actual function, we'll just a take a simple one for this example. We'll write a `power3` function that takes a number and raises it to a power of three.

```
%scala

val udfExampleDF = spark.range(5).toDF("num")

def power3(number:Double):Double = {
  number * number * number
}
power3(2.0)

%python

udfExampleDF = spark.range(5).toDF("num")

def power3(double_value):
  return double_value ** 3

power3(2.0)
```

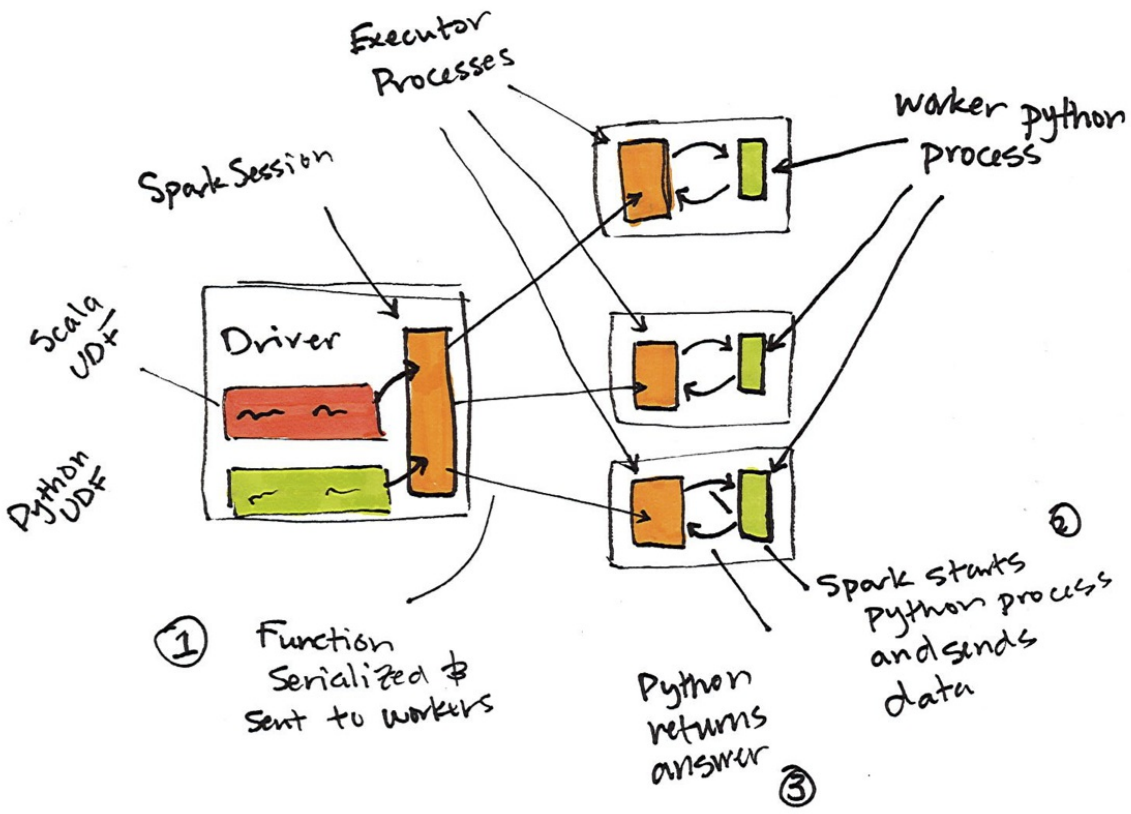
In this trivial example, we can see that our functions work as expected. We are

able to provide an individual input and produce the expected result (with this simple test case). Thus far our expectations for the input are high, it must be a specific type and cannot be a null value. See the section in this chapter titled "Working with Nulls in Data".

Now that we've created these functions and tested them, we need to register them with Spark so that we can used them on all of our worker machines. Spark will serialize the function on the driver and transfer it over the network to all executor processes. This happens regardless of language.

Once we go to use the function, there are essentially two different things that occur. If the function is written in Scala or Java then we can use that function within the JVM. This means there will be little performance penalty aside from the fact that we can't take advantage of code generation capabilities that Spark has for built-in functions. There can be performance issues if you create or use a lot of objects which we will cover in the optimization section.

If the function is written in Python, something quite different happens. Spark will start up a python process on the worker, serialize all of the data to a format that python can understand (remember it was in the JVM before), execute the function row by row on that data in the python process, before finally returning the results of the row operations to the JVM and Spark.



Warning

Starting up this Python process is expensive but the real cost is in serializing the data to Python. This is costly for two reasons, it is an expensive computation but also once the data enters Python, Spark cannot manage the memory of the worker. This means that you could potentially cause a worker to fail if it becomes resource constrained (because both the JVM and python are competing for memory on the same machine). We recommend that you write your UDFs in Scala - the small amount of time it should take you to write the function in Scala will always yield significant speed ups and on top of that, you can still use the function from Python!

Now that we have an understanding of the process, let's work through our example. First we need to register the function to be available as a DataFrame function.

```
%scala

import org.apache.spark.sql.functions.udf
```

```
val power3udf = udf(power3(_:Double):Double)
```

Now we can use that just like any other DataFrame function.

```
%scala

udfExampleDF.select(power3udf(col("num"))).show()
```

The same applies to Python, we first register it.

```
%python

from pyspark.sql.functions import udf

power3udf = udf(power3)
```

Then we can use it in our DataFrame code.

```
%python

from pyspark.sql.functions import col

udfExampleDF.select(power3udf(col("num"))).show()
```

Now as of now, we can only use this as DataFrame function. That is to say, we can't use it within a string expression, only on an expression. However, we can also register this UDF as a Spark SQL function. This is valuable because it makes it simple to use this function inside of SQL as well as across languages.

Let's register the function in Scala.

```
%scala

spark.udf.register("power3", power3(_:Double):Double)
udfExampleDF.selectExpr("power3(num)").show()
```

Now because this function is registered with Spark SQL, and we've learned that any Spark SQL function or epxression is valid to use as an expression when working with DataFrames, we can turn around and use the UDF that we wrote in Scala, in Python. However rather than using it as a DataFrame function we use it as a SQL expression.

```
%python

udfExampleDF.selectExpr("power3(num)").show()
# registered in Scala
```

We can also register our Python function to be available as SQL function and use that in any language as well.

One thing we can also do to make sure that our functions are working correctly is specify a return type. As we saw in the beginning of this section, Spark manages its own type information that does not align exactly with Python's types. Therefore it's a best practice to define the return type for your function when you define it. It is important to note that specifying the return type is not necessary but is a best practice.

If you specify the type that doesn't align with the actual type returned by the function - Spark will not error but rather just return `null` to designate a failure. You can see this if you were to switch the return type in the below function to be a `DoubleType`.

```
%python

from pyspark.sql.types import IntegerType, DoubleType

spark.udf.register("power3py", power3, DoubleType())

%python

udfExampleDF.selectExpr("power3py(num)").show()
# registered via Python
```

This is because the range above creates Integers. When Integers are operated on in Python, Python won't convert them into floats (the corresponding type to Spark's Double type), therefore we see null. We can remedy this by ensuring our Python function returns a float instead of an Integer and the function will behave correctly.

Naturally we can use either of these from SQL too once we register them.

```
%sql

SELECT
```

```
power3py(12), -- doesn't work because of return type
power3(12)
```

This chapter demonstrated how easy it is to extend Spark SQL to your own purposes and do so in a way that is not some esoteric, domain-specific language but rather simple functions that are easy to test and maintain without even using Spark! This is an amazingly powerful tool we can use to specify sophisticated business logic that can run on 5 rows on our local machines or on terabytes of data on a hundred node cluster!

Chapter 5. Aggregations

What are aggregations?

Aggregating is the act of collecting something together and is a cornerstone of big data analytics. In an aggregation you will specify a *key* or *grouping* and an *aggregation function* that specifies how you should transform one or more columns. This function must produce one result for each group given multiple input values. Spark's aggregation capabilities sophisticated and mature, with a variety of different use cases and possibilities. In general, we use aggregations to summarize numerical data usually by means of some grouping. This might be a summation, a product, or simple counting. Spark also allows us aggregate any kind of value into an array, list or map as we will see in the complex types part of this chapter.

In addition to working with any types of values, Spark also allows us to create a variety of different groupings types.

- The simplest grouping is to just summarize a complete DataFrame by performing an aggregation in a select statement.
- A "group by" allows us to specify one or more keys as well as one or more aggregation functions to transform the value columns.
- A "roll up" allows us to specify one or more keys as well as one or more aggregation functions to transform the value columns which will be summarized hierarchically.
- a "cube" allows us to specify one or more keys as well as one or more aggregation functions to transform the value columns which will be summarized across all combinations of columes.
- a "window" allows us to specify one or more keys as well as one or more aggregation functions to transform the value columns. However the rows input to the function are somehow related to the current row.

Each grouping returns a `RelationalGroupedDataset` on which we specify our aggregations.

Let's get started by reading in our data on purchases, repartitioning the data to have far fewer partitions (because we know it's small data stored in a lot of small files), and caching the results for rapid access.

```
%scala

val df = spark.read.format("csv")
  .option("header", "true")
  .option("inferSchema", "true")
  .load("dbfs:/mnt/defg/streaming/*.csv")
  .coalesce(5)

df.cache()

df.createOrReplaceTempView("dfTable")

%python

df = spark.read.format("csv")\
  .option("header", "true")\
  .option("inferSchema", "true")\
  .load("dbfs:/mnt/defg/streaming/*.csv")\
  .coalesce(5)

df.cache()

df.createOrReplaceTempView("dfTable")
```

As mentioned, basic aggregations apply to an entire DataFrame. The simplest example is the `count` method.

```
df.count()
```

If you read chapter by chapter you will know that `count` is actually an action as opposed to a transformation and so it returns immediately. You can use `count` to get an idea of the total size of your dataset but another common pattern is to use it to cache an entire DataFrame in memory, just like we did in this example.

Now this method is a bit of an outlier because it exists as a method (in this case) as opposed to a function and is eagerly evaluated instead of a lazy transformation. In the next part of this chapter we will see count used as lazy function as well.

Aggregation Functions

All aggregations are available as functions, in addition to the special cases that can appear on DataFrames or sub-packages themselves. Most aggregations are functions that can be found in the `org.apache.spark.sql.functions` package.

count

The first function worth going over is count, except this will perform count as a transformation instead of an action. In this case we can do one of two things, we can specify a specific column to count, all the columns (with `count(*)`) or `count(1)` to represent that we want to count every row as the literal one.

```
%scala

import org.apache.spark.sql.functions.count
df.select(count("StockCode")).collect()

%python

from pyspark.sql.functions import count
df.select(count("StockCode")).collect()

%sql

SELECT COUNT(*) FROM dfTable
```

Count Distinct

Sometimes the total number is not relevant, but rather the number of unique groups. To get this number we can use the `countDistinct` function. This is a bit more relevant for individual columns.

```
%scala

import org.apache.spark.sql.functions.countDistinct
df.select(countDistinct("StockCode")).collect()

%python

from pyspark.sql.functions import countDistinct
df.select(countDistinct("StockCode")).collect()

%sql

SELECT COUNT(DISTINCT *) FROM DFTABLE
```

Approximate Count Distinct

However often times we are working with really large datasets and the exact distinct count is irrelevant. In fact, getting the distinct count is a very expensive operation and for large datasets it might take a very long time to calculate the exact result. There are times when an approximation to a certain degree of accuracy will work just fine.

```
%scala

import org.apache.spark.sql.functions.approx_count_distinct
df.select(approx_count_distinct("StockCode", 0.1)).collect()

%python

from pyspark.sql.functions import approx_count_distinct
df.select(approx_count_distinct("StockCode", 0.1)).collect()

%sql

SELECT approx_count_distinct(StockCode, 0.1) FROM DFTABLE
```

You will notice that `approx_count_distinct` took another parameter that allows you to specify the maximum estimation error allowed. In this case, we specified a rather large error and thus receive an answer that is quite far off but does complete more quickly than `countDistinct`. You will see much greater gains with much larger datasets.

First and Last

We can get the first and last values from a DataFrame with the obviously named functions. This will be based on the rows in the DataFrame, not on the values in the DataFrame.

```
%scala

import org.apache.spark.sql.functions.{first, last}
df.select(first("StockCode"), last("StockCode")).collect()

%python

from pyspark.sql.functions import first, last
df.select(first("StockCode"), last("StockCode")).collect()

%sql

SELECT first(StockCode), last(StockCode) FROM dfTable
```

Min and Max

We can get the minimum and maximum values from a DataFrame with the relevant functions.

```
%scala

import org.apache.spark.sql.functions.{min, max}
df.select(min("Quantity"), max("Quantity")).collect()

%python

from pyspark.sql.functions import min, max
df.select(min("Quantity"), max("Quantity")).collect()

%sql

SELECT min(Quantity), max(Quantity) FROM dfTable
```

Sum

Another simple task is to sum up all the values in a row.

```
%scala

import org.apache.spark.sql.functions.sum
df.select(sum("Quantity")).show()

%python

from pyspark.sql.functions import sum
df.select(sum("Quantity")).show()

%sql

SELECT sum(Quantity) FROM dfTable
```

sumDistinct

In addition to summing up a total, we can also sum up a distinct set of values with the `sumDistinct` function.

```
%scala

import org.apache.spark.sql.functions.sumDistinct
df.select(sumDistinct("Quantity")).show()

%python

from pyspark.sql.functions import sumDistinct
df.select(sumDistinct("Quantity")).show()

%sql

SELECT SUM(DISTINCT Quantity) FROM dfTable
```

Average

Now the average is the calculation of the sum over the total number of items. While we can run that calculation using the previous counts and sums, Spark also allows us to calculate that with the `avg` or `mean` functions. We will use alias in order to more easily reuse these columns later.

```
%scala

import org.apache.spark.sql.functions.{sum, count, avg, expr}

df.select(
    count("Quantity").alias("total_transactions"),
    sum("Quantity").alias("total_purchases"),
    avg("Quantity").alias("avg_purchases"),
    expr("mean(Quantity)").alias("mean_purchases"))
  .selectExpr(
    "total_purchases/total_transactions",
    "avg_purchases",
    "mean_purchases")
  .collect()

%python

from pyspark.sql.functions import sum, count, avg, expr

df.select(
    count("Quantity").alias("total_transactions"),
    sum("Quantity").alias("total_purchases"),
    avg("Quantity").alias("avg_purchases"),
    expr("mean(Quantity)").alias("mean_purchases"))\
  .selectExpr(
    "total_purchases/total_transactions",
    "avg_purchases",
    "mean_purchases")\
  .collect()
```

Variance and Standard Deviation

Calculating the mean naturally brings up questions about the variance and standard deviation. These are both measures of the spread of the data around the mean. The variance is the average of the squared differences from the mean and the standard deviation is the square root of the variance. These can be calculated in Spark with their respective functions, however something to note is that Spark has both the formula for the sample standard deviation as well as the formula for the population standard deviation. These are fundamental different statistical formulae that it is important to differentiate between. By default, Spark will perform the formula for the sample standard deviation or variance if you use the `variance` or `stddev` functions.

You can also specify these explicitly or refer to the population standard deviation or variance.

```
%scala

import org.apache.spark.sql.functions.{var_pop, stddev_pop}
import org.apache.spark.sql.functions.{var_samp, stddev_samp}

df.select(
    var_pop("Quantity"),
    var_samp("Quantity"),
    stddev_pop("Quantity"),
    stddev_samp("Quantity"))
  .collect()

%python

from pyspark.sql.functions import var_pop, stddev_pop
from pyspark.sql.functions import var_samp, stddev_samp

df.select(
    var_pop("Quantity"),
    var_samp("Quantity"),
    stddev_pop("Quantity"),
    stddev_samp("Quantity"))\
  .collect()

%sql
```

```
SELECT
  var_pop(Quantity),
  var_samp(Quantity),
  stddev_pop(Quantity),
  stddev_samp(Quantity)
FROM
  dfTable
```

Skewness and Kurtosis

Skewness and kurtosis are both measurements of extreme points in your data. Skewness measures the asymmetry the values in your data around the mean while kurtosis is a measure of the tail of data. These are both relevant specifically when modeling yuor data as a probability distribution of a random variable. While we won't go into the math behind these specifically, you can look up definitions quite easily on the internet. We can calculate these by the functions of the same name.

```
import org.apache.spark.sql.functions.{skewness, kurtosis}

df.select(
    skewness("Quantity"),
    kurtosis("Quantity"))
  .collect()

%python

from pyspark.sql.functions import skewness, kurtosis

df.select(
    skewness("Quantity"),
    kurtosis("Quantity"))\
  .collect()

%sql

SELECT
  skewness(Quantity),
  kurtosis(Quantity)
FROM
  dfTable
```

Covariance and Correlation

We discussed single column aggregations but some functions compare the interactions of the values in two difference columns together. Two of these functions are the covariance and correlation. Correlation measures the Pearson correlation coefficient, which is scaled between -1 and +1. The covariance is scaled according to the inputs in the data.

Covariance, like variance above, can be calculated either as the sample covariance or the population covariance. Therefore it can be important to specify which formula you want to be using. Correlation has no notion of this and therefore does not have calculations for population or sample.

```
%scala

import org.apache.spark.sql.functions.{corr, covar_pop, covar_s

df.select(
    corr("InvoiceNo", "Quantity"),
    covar_samp("InvoiceNo", "Quantity"),
    covar_pop("InvoiceNo", "Quantity"))
  .show()

%python

from pyspark.sql.functions import corr, covar_pop, covar_samp

df.select(
    corr("InvoiceNo", "Quantity"),
    covar_samp("InvoiceNo", "Quantity"),
    covar_pop("InvoiceNo", "Quantity"))\
  .show()

%sql

SELECT
  corr(InvoiceNo, Quantity),
  covar_samp(InvoiceNo, Quantity),
  covar_pop(InvoiceNo, Quantity)
FROM
  dfTable
```

Aggregating to Complex Types

Spark allows users to perform aggregations not just of numerical values using formulas but also to Spark's complex types. For example, we can collect a list of values present in a given column or only the unique values by collecting to a set.

This can be used to perform some more programmatic access later on in the pipeline or pass the entire collection in a UDF.

```
%scala

import org.apache.spark.sql.functions.{collect_set, collect_lis

df.agg(
    collect_set("Country"),
    collect_list("Country"))
  .show()

%python

from pyspark.sql.functions import collect_set, collect_list

df.agg(
    collect_set("Country"),
    collect_list("Country"))\
  .show()

%sql

SELECT
  collect_set(Country),
  collect_set(Country)
FROM
  dfTable
```

Grouping

Thus far we only performed DataFrame level aggregations. A more common task is to perform calculations based on *groups* in the data. This is most commonly performed on categorical data where we group our data on one column and perform some calculations on the other columns that end up in that group.

The best explanation for this is probably to start performing some groupings. The first we will perform will be a count, just as we did before. We will group by each unique invoice number and get the count of items on that invoice. Notice that this returns another DataFrame and is lazily performed.

When we perform this grouping we do it in two phases. First we specify the column(s) that we would like to group on, then we specify our aggregation(s). The first step returns a `RelationalGroupedDataset` and the second step returns a `DataFrame`.

```
df.groupBy("invoiceNo").count().show()
```

As mentioned, we can specify any number of columns that we want to group on.

```
df.groupBy("InvoiceNo", "CustomerId")
  .count()
  .show()

%sql

SELECT
  count(*)
FROM
  dfTable
GROUP BY
  InvoiceNo, CustomerId
```

Grouping with expressions

Now counting, as we saw previously, is a bit of a special case because it exists as a method. Usually we prefer to use the count function (the same function that we saw earlier in this chapter). However rather than passing that function as an expression into a `select` statement, we specify it as inside of `agg`. This allows for passing in arbitrary expressions that just need to have some aggregation specified. We can even do things like `alias` a column after transforming it for later use in our data flow.

```
import org.apache.spark.sql.functions.count

df.groupBy("InvoiceNo")
  .agg(
    count("Quantity").alias("quan"),
    expr("count(Quantity)"))
  .show()

%python

from pyspark.sql.functions import count

df.groupBy("InvoiceNo")\
  .agg(
    count("Quantity").alias("quan"),
    expr("count(Quantity)"))\
  .show()
```

Grouping with Maps

Sometimes it can be easier to specify your transformations as a series of `Maps` where the key is the column and the value is the aggregation function (as a string) that you would like to perform. You can reuse multiple column names if you specify them inline as well.

```
%scala

df.groupBy("InvoiceNo")
  .agg(
    "Quantity" ->"avg",
    "Quantity" -> "stddev_pop")
  .show()

%python

df.groupBy("InvoiceNo")\
  .agg(expr("avg(Quantity)"),
       expr("stddev_pop(Quantity)"))\
  .show()

%sql

SELECT
  avg(Quantity),
  stddev_pop(Quantity),
  InvoiceNo
FROM
  dfTable
GROUP BY
  InvoiceNo
```

Window Functions

Window functions allow us to perform some unique aggregations by either computing some aggregation on a specific "window" of data where we define the window with reference to the current data. This window specification determines which rows will be passed into this function. Now this is a bit abstract and probably similar to a standard group by so lets differentiate them a bit more.

A group by takes data and every row can only go into one grouping. A window function calculates a return value for every input row of a table based on a group of rows, called a frame. A common use case is to take a look at a rolling average of some value where each row represents one day. If we were to do this, each row ends up in seven different frames. We will cover defining frames below but for your reference, spark supports three kinds of window functions: ranking functions, analytic functions, and aggregate functions.

In order to demonstrate, we will add a date column that will convert our invoice date into a column that contains only date information (not time information too).

```
%scala

import org.apache.spark.sql.functions.col

val dfWithDate = df.withColumn("date", col("InvoiceDate").cast

dfWithDate.createOrReplaceTempView("dfWithDate")

%python

from pyspark.sql.functions import col

dfWithDate = df.withColumn("date", col("InvoiceDate").cast("dat
dfWithDate.createOrReplaceTempView("dfWithDate")
```

The first step to a window function is the creation of a window specification. The `partition by` is unrelated to the partitioning scheme that we have

covered thus far. It's just a similar concept that describes how we will be breaking up our group. The ordering determines the ordering within a given partition and the finally the frame specification (the `rowsBetween` statement) states which rows will be included in the frame based on its reference to the current input row. In our case we look at all previous rows up to the current row.

```
%scala

import org.apache.spark.sql.expressions.Window
import org.apache.spark.sql.functions.col

val windowSpec = Window
  .partitionBy("CustomerId", "date")
  .orderBy(col("Quantity").desc)
  .rowsBetween(Window.unboundedPreceding, Window.currentRow)

%python

from pyspark.sql.window import Window
from pyspark.sql.functions import desc

windowSpec = Window\
  .partitionBy("CustomerId", "date")\
  .orderBy(desc("Quantity"))\
  .rowsBetween(Window.unboundedPreceding, Window.currentRow)
```

Now we want to use an aggregation function to learn more about each specific customer. For instance we might want to know the max purchase quantity over all time. We use aggregation functions in much the same way that we saw above, we passing a column name or expression. However in addition we also specify the window specification that this function show apply over.

```
import org.apache.spark.sql.functions.max

val maxPurchaseQuantity = max(col("Quantity"))
  .over(windowSpec)

%python

from pyspark.sql.functions import max

maxPurchaseQuantity = max(col("Quantity"))\
  .over(windowSpec)
```

You will notice that this returns a column (or expressions). We can now use this in a DataFrame select statement. However before doing so, we will create the purchase quantity rank. To do that we will use the dense_rank rank function to determine which date had the max purchase quantity for every customer. We will use dense_rank as opposed to rank to avoid gaps in the ranking sequence when there are tied values (or in our case, duplicate rows).

```
%scala

import org.apache.spark.sql.functions.{dense_rank, rank}

val purchaseDenseRank = dense_rank()
  .over(windowSpec)
val purchaseRank = rank()
  .over(windowSpec)

%python

from pyspark.sql.functions import dense_rank, rank

purchaseDenseRank = dense_rank()\
  .over(windowSpec)
purchaseRank = rank()\
  .over(windowSpec)
```

This also returns a column that we can use in select statements. Now we can perform a select and we will see our calculated window values.

```
%scala

import org.apache.spark.sql.functions.col

dfWithDate
  .where("CustomerId IS NOT NULL")
  .orderBy("CustomerId")
  .select(
    col("CustomerId"),
    col("date"),
    col("Quantity"),
    purchaseRank.alias("quantityRank"),
    purchaseDenseRank.alias("quantityDenseRank"),
    maxPurchaseQuantity.alias("maxPurchaseQuantity"))
  .show()

%python
```

```
from pyspark.sql.functions import col

dfWithDate\
  .where("CustomerId IS NOT NULL")\
  .orderBy("CustomerId")\
  .select(
    col("CustomerId"),
    col("date"),
    col("Quantity"),
    purchaseRank.alias("quantityRank"),
    purchaseDenseRank.alias("quantityDenseRank"),
    maxPurchaseQuantity.alias("maxPurchaseQuantity"))\
  .show()

%sql

SELECT
  CustomerId,
  date,
  Quantity,
  rank(Quantity) OVER (PARTITION BY CustomerId, date
                       ORDER BY Quantity DESC NULLS LAST
                       ROWS BETWEEN
                         UNBOUNDED PRECEDING AND
                         CURRENT ROW) as rank,

  dense_rank(Quantity) OVER (PARTITION BY CustomerId, date
                             ORDER BY Quantity DESC NULLS LAST
                             ROWS BETWEEN
                               UNBOUNDED PRECEDING AND
                               CURRENT ROW) as dRank,

  max(Quantity) OVER (PARTITION BY CustomerId, date
                      ORDER BY Quantity DESC NULLS LAST
                      ROWS BETWEEN
                        UNBOUNDED PRECEDING AND
                        CURRENT ROW) as maxPurchase
FROM
  dfWithDate
WHERE
  CustomerId IS NOT NULL
ORDER BY
  CustomerId
```

Rollups

Now thus far we've been looking at explicit groupings. When we set our grouping keys of multiple columns, Spark will look at those and look at the actual combinations that are visible in the dataset. A Rollup is a multi-dimensional aggregation that performs a variety of group by style calculations for us.

Now that we prepared our data, we can perform our rollup. This rollup will look across time (with our new date column) and space (with the Country column) and will create a new DataFrame that includes the grand total over all dates, the grand total for each date in the DataFrame, and the sub total for each country on each date in the dataFrame.

```
val rolledUpDF = dfWithDate.rollup("Date", "Country")
  .agg(sum("Quantity"))
  .selectExpr("Date", "Country", "`sum(Quantity)` as total_quar
  .orderBy("Date")

rolledUpDF.show(20)

%python

rolledUpDF = dfWithDate.rollup("Date", "Country")\
  .agg(sum("Quantity"))\
  .selectExpr("Date", "Country", "`sum(Quantity)` as total_quar
  .orderBy("Date")

rolledUpDF.show(20)
```

Now where you see the `null` values is where you'll find the grand totals. A `null` in both rollup columns specifies the grand total across both of those column.

```
rolledUpDF.where("Country IS NULL").show()

rolledUpDF.where("Date IS NULL").show()
```

Cube

A cube takes the rollup takes a rollup to a level deeper. Rather than treating things hierarchically a cube does the same thing across all dimensions. This means that it won't just go by date over the entire time period but also the country. To pose this as a question again,

Can you make a table that includes:

- The grand total across all dates and countries
- The grand total for each date across all countries
- The grand total for each country on each date
- The grand total for each country across all dates

The method call is quite similar, instead of calling `rollup`, we call `cube`.

```
%scala

dfWithDate.cube("Date", "Country")
  .agg(sum(col("Quantity")))
  .select("Date", "Country", "sum(Quantity)")
  .orderBy("Date")
  .show(20)

%python

dfWithDate.cube("Date", "Country")\
  .agg(sum(col("Quantity")))\
  .select("Date", "Country", "sum(Quantity)")\
  .orderBy("Date")\
  .show(20)
```

This is a quick and easily accessible summary of nearly all summary information in our table and is a great way of creating a quick summary table that others can use later on.

Pivot

Pivots allow you to convert a row into a column. For example, in our current data we have a country column. With a pivot we can aggregate according to some function for each of those given countries and display them in an easy to query way.

```
%scala

val pivoted = dfWithDate
  .groupBy("date")
  .pivot("Country")
  .agg("quantity" -> "sum")

%python

pivoted = dfWithDate\
  .groupBy("date")\
  .pivot("Country")\
  .agg({"quantity":"sum"})
```

This DataFrame will now have a column for each Country in the dataset.

```
pivoted.columns

pivoted.where("date > '2011-12-05'").select("USA").show()
```

Now all of the can be calculated with single groupings, but the value of a pivot comes down to how you or users would like to explore the data. It can be useful, if you have low enough cardinality in a certain column to transform it into columns so that users can see the schema and immediately know what to query for.

User-Defined Aggregation Functions

User-Defined Aggregation Functions or UDAFs are a way for users to define their own aggregation functions based on custom formulae or business rules. These UDAFs can be used to compute custom calculations over groups of input data (as opposed to single rows). Spark maintains a single AggregationBuffer to store intermediate results for every group of input data.

To create a UDAF you must inherit from the base class `UserDefinedAggregateFunction` and implement the following methods.

- `inputSchema` represents input arguments as a `StructType`.
- `bufferSchema` represents intermediate UDAF results as a `StructType`.
- `dataType` represents the return DataType.
- `deterministic` is a boolean value that describes whether or not this UDAF will return the same result for a given input.
- `initialize` allows you to initialize values of an aggregation buffer.
- `update` describes how you should update the internal buffer based on a given row.
- `merge` describes how two aggregation buffers should be merged.
- `evaluate` will generate the final result of the aggregation.

The below example implements a `Boolean And` which will tell us if all the rows (for a given column) are True or else it will return false.

```
import org.apache.spark.sql.expressions.MutableAggregationBuffe
import org.apache.spark.sql.expressions.UserDefinedAggregateFur
import org.apache.spark.sql.Row
import org.apache.spark.sql.types._
```

```
class BoolAnd extends UserDefinedAggregateFunction {

  def inputSchema: org.apache.spark.sql.types.StructType =
    StructType(StructField("value", BooleanType) :: Nil)

  def bufferSchema: StructType = StructType(
    StructField("result", BooleanType) :: Nil
  )

  def dataType: DataType = BooleanType

  def deterministic: Boolean = true

  def initialize(buffer: MutableAggregationBuffer): Unit = {
    buffer(0) = true
  }

  def update(buffer: MutableAggregationBuffer, input: Row): Uni
    buffer(0) = buffer.getAs[Boolean](0) && input.getAs[Boolean
  }

  def merge(buffer1: MutableAggregationBuffer, buffer2: Row): U
    buffer1(0) = buffer1.getAs[Boolean](0) && buffer2.getAs[Boo
  }

  def evaluate(buffer: Row): Any = {
    buffer(0)
  }

}
```

Now we simply instantiate our class and/or register it as a function.

```
val ba = new BoolAnd
spark.udf.register("booland", ba)

import org.apache.spark.sql.functions._

spark.range(1)
  .selectExpr("explode(array(TRUE, TRUE, TRUE)) as t")
  .selectExpr("explode(array(TRUE, FALSE, TRUE)) as f", "t")
  .select(ba(col("t")), expr("booland(f)"))
  .show()
```

UDAFs are currently only available in Scala or Java.

Chapter 6. Joins

Joins will be an essential part of your Spark workloads. Spark's ability to talk to a variety of data sources means your ability to tap into a variety of data sources across your company.

What is a join?

Join Expressions

A *join* brings together two sets of data, the *left* and the *right*, by comparing the value of one or more *keys* of the left and right and evaluating the result of a *join expression* that determines whether or not Spark should join the left set of data with the right set of data on that given row. The most common join expression is that of an equi-join, where we compare whether or not the keys are equal, however there are other join expressions that we can specify like whether or not a value is greater than or equal to another value. Join expressions can be a variety of different things, we can even leverage complex types and perform something like checking whether or not key exists inside of an array.

Join Types

While the join expressions determines whether or not two rows should join, the join type determines how the join should be performed. There are a variety of different joins types available in Spark for you to use. These include:

- inner joins (keep rows with keys that exist in the left and right datasets),
- outer joins (keep rows with keys in either the left or right datasets),
- left outer joins (keep rows with keys in the left dataset),
- right outer joins (keep rows with keys in the right dataset),
- left semi joins (keep the rows in the left (and only the left) dataset where the key appears in the right dataset),
- left anti joins (keep the rows in the left (and only the left) dataset where they does not appear in the right dataset)
- cross (or cartesian) joins (match every row in the left dataset with every row in the right dataset).

Now that we defined a baseline definition for each type of join, we will create a dataset with which we can see the behavior of each kind of join.

```
val person = Seq(
    (0, "Bill Chambers", 0, Seq(100)),
    (1, "Matei Zaharia", 1, Seq(500, 250, 100)),
    (2, "Michael Armbrust", 1, Seq(250, 100)))
  .toDF("id", "name", "graduate_program", "spark_status")

val graduateProgram = Seq(
    (0, "Masters", "School of Information", "UC Berkeley"),
    (2, "Masters", "EECS", "UC Berkeley"),
    (1, "Ph.D.", "EECS", "UC Berkeley"))
  .toDF("id", "degree", "department", "school")

val sparkStatus = Seq(
```

```
    (500, "Vice President"),
    (250, "PMC Member"),
    (100, "Contributor"))
  .toDF("id", "status")

%python

person = spark.createDataFrame([
    (0, "Bill Chambers", 0, [100]),
    (1, "Matei Zaharia", 1, [500, 250, 100]),
    (2, "Michael Armbrust", 1, [250, 100])])\
  .toDF("id", "name", "graduate_program", "spark_status")

graduateProgram = spark.createDataFrame([
    (0, "Masters", "School of Information", "UC Berkeley"),
    (2, "Masters", "EECS", "UC Berkeley"),
    (1, "Ph.D.", "EECS", "UC Berkeley")])\
  .toDF("id", "degree", "department", "school")

sparkStatus = spark.createDataFrame([
    (500, "Vice President"),
    (250, "PMC Member"),
    (100, "Contributor")])\
  .toDF("id", "status")

person.createOrReplaceTempView("person")
graduateProgram.createOrReplaceTempView("graduateProgram")
sparkStatus.createOrReplaceTempView("sparkStatus")
```

Inner Joins

Inner joins will look at the keys in both of the DataFrames or tables and only include (and join together) the rows that evaluate to true. In this case we will join the graduate program to the person to create a DataFrame that graduate program information joined to the individual's information.

```
%scala

val joinExpression = person.col("graduate_program") === graduat

%python

joinExpression = person["graduate_program"] == graduateProgram
```

Keys that do not exist in both DataFrames will not show in the resulting DataFrame. For example the following expression would result in zero values in the resulting DataFrame.

```
%scala

val wrongJoinExpression = person.col("name") === graduateProgra

%python

wrongJoinExpression = person["name"] == graduateProgram["schoo
```

Inner joins are the default when we perform a join, so we just need to specify our left DataFrame and join the right on the join expression.

```
person.join(graduateProgram, joinExpression).show()

%sql

SELECT
  *
FROM
  person
  JOIN graduateProgram
  ON person.graduate_program = graduateProgram.id
```

We can also specify this explicitly by passing in a third parameter, the join type.

```
%scala

var joinType = "inner"

%python

joinType = "inner"

person.join(graduateProgram, joinExpression, joinType).show()

%sql

SELECT
  *
FROM
  person
  INNER JOIN graduateProgram
  ON person.graduate_program = graduateProgram.id
```

Outer Joins

Outer joins will look at the keys in both of the DataFrames or tables and will include (and join together) the rows that evaluate to true or false. “Null” values will be filled in where there is not a equivalent row in the left or right DataFrames.

```
joinType = "outer"

person.join(graduateProgram, joinExpression, joinType).show()

%sql

SELECT
  *
FROM
  person
  OUTER JOIN graduateProgram
  ON graduate_program = graduateProgram.id
```

Left Outer Joins

Left outer joins will look at the keys in both of the DataFrames or tables and will include all rows from the left DataFrame as well as any rows in the right DataFrame that have a match in the left DataFrame. “Null” values will be filled in where there is not a equivalent row in the right DataFrame.

```
joinType = "left_outer"

graduateProgram.join(person, joinExpression, joinType).show()
```

```
%sql

SELECT
  *
FROM
  graduateProgram
  JOIN person
  ON person.graduate_program = graduateProgram.id
```

Right Outer Joins

Right outer joins will look at the keys in both of the DataFrames or tables and will include all rows from the right DataFrame as well as any rows in the left DataFrame that have a match in the right DataFrame. “Null” values will be filled in where there is not a equivalent row in the left DataFrame.

```
joinType = "right_outer"

person.join(graduateProgram, joinExpression, joinType).show()
```

```
%sql

SELECT
  *
FROM
  person
  RIGHT OUTER JOIN graduateProgram
  ON person.graduate_program = graduateProgram.id
```

Left Semi Joins

Semi joins are a bit of a departure from our other joins. They do not actually include any values from the right DataFrame, they only compare values to see if the value exists in the second DataFrame. If they do those rows will be kept in the result even if there are duplicate keys in the left DataFrame. Left semi joins can be thought of as filters on a DataFrame and less of a conventional join.

```
joinType = "left_semi"

graduateProgram.join(person, joinExpression, joinType).show()

%scala

val gradProgram2 = graduateProgram
  .union(Seq(
    (0, "Masters", "Duplicated Row", "Duplicated School")).toDF

gradProgram2.createOrReplaceTempView("gradProgram2")

%python

gradProgram2 = graduateProgram\
  .union(spark.createDataFrame([
    (0, "Masters", "Duplicated Row", "Duplicated School")]))

gradProgram2.createOrReplaceTempView("gradProgram2")

gradProgram2.join(person, joinExpression, joinType).show()

%sql

SELECT
  *
FROM
  gradProgram2
  LEFT SEMI JOIN person
  ON gradProgram2.id = person.graduate_program
```

Left Anti Joins

Left anti joins are the opposite of left semi joins. Like left semi joins, they do not actually include any values from the right DataFrame, they only compare values to see if the value exists in the second DataFrame. However rather than keeping the values that exist in the second DataFrame, they only keep the values that do not have a corresponding key in the second DataFrame. They can be thought of as a not in filter.

```
joinType = "left_anti"
graduateProgram.join(person, joinExpression, joinType).show()
```

```
%sql

SELECT
  *
FROM
  graduateProgram
  LEFT ANTI JOIN person
  ON graduateProgram.id = person.graduate_program
```

Cross (Cartesian) Joins

The last of our joins are cross joins or cartesian products. Cross joins in simplest terms are inner joins that do not specify a predicate. Cross joins will join every single row in the left DataFrame to ever single row in the right DataFrame. This will cause an absolute explosion in the number of rows that the resulting DataFrame will have. For example if you have 1,000 rows in two different DataFrames. The cross join of these will result in 1,000,000 (1000 x 1000) rows. If we specify a join condition, but still specify cross it will be the same as an inner join.

```
joinType = "cross"
graduateProgram.join(person, joinExpression, joinType).show()
```

```
%sql

SELECT
  *
FROM
  graduateProgram
  CROSS JOIN person
  ON graduateProgram.id = person.graduate_program
```

If we truly intend to have a cross join, we can call that out explicitly.

```
person.crossJoin(graduateProgram).show()
```

```
%sql

SELECT
  *
FROM
  graduateProgram
  CROSS JOIN person
```

WARNING

> Only use cross joins if you are absolutely, 100% sure that this is the join you need. There is a reason in Spark that they must be explicitly stated as a cross join. They're dangerous!

Challenges with Joins

When performing joins, there are some specific challenges that can come up. This part of the chapter aims to help you resolve these.

Joins on Complex Types

While this may seem like a challenge, it's actually not. Any expression is a valid join expression assuming it returns a boolean.

```
import org.apache.spark.sql.functions.expr

person
  .withColumnRenamed("id", "personId")
  .join(sparkStatus, expr("array_contains(spark_status, id)"))
  .take(5)

%python

from pyspark.sql.functions import expr

person\
  .withColumnRenamed("id", "personId")\
  .join(sparkStatus, expr("array_contains(spark_status, id)"))\
  .take(5)

%sql

SELECT
*
FROM
  (select id as personId, name, graduate_program, spark_status
  INNER JOIN sparkStatus
  on array_contains(spark_status, id)
```

Handling Duplicate Column Names

Arguably one of the most nuisance things that comes up is duplicate column names in your results DataFrame. In a DataFrame, each column has a unique ID inside of Spark's SQL Engine, Catalyst. This unique ID is purely internal and not something that user can directly reference. That means when you have a DataFrame with duplicate column names, referring to one column can be quite difficult.

This arises in two distinct situations:

- the join expression that you specify does not remove one key from one of the input DataFrames and the keys have the same column name or,
- two columns that you are not performing the join on have the same name.

Let's create a problem dataset that we can use to illustrate these problems.

```
val gradProgramDupe = graduateProgram.withColumnRenamed("id", '

val joinExpr = gradProgramDupe.col("graduate_program") === pers
```

We will now see that there are two `graduate_program` columns even though we joined on that key.

```
person.join(gradProgramDupe, joinExpr).show()
```

The challenge is that when we go to refer to one of these columns, we will receive an error. I this case the following code with generate

```
org.apache.spark.sql.AnalysisException: Reference
'graduate_program' is ambiguous, could be:
graduate_program#40, graduate_program#1079.;.
```

```
person
  .join(gradProgramDupe, joinExpr)
  .select("graduate_program")
  .show()
```

Approach 1: Different Join Expression

When you have two keys that have the same name, probably the easiest fix is to change the join expression from a boolean expression to a string or sequence. This will automatically remove one of the columns for you during the join.

```
person
  .join(gradProgramDupe, "graduate_program")
  .select("graduate_program")
  .show()
```

Approach 2: Dropping the Column After the Join

Another approach is to drop the offending column after the join. When doing this we have to refer to the column via the original source DataFrame. We can do this if the join uses the same key names or if the source DataFrames have columns that simply have the same name.

```
person
  .join(gradProgramDupe, joinExpr)
  .drop(person.col("graduate_program"))
  .select("graduate_program")
  .show()

val joinExpr = person.col("graduate_program") === graduateProgr

person
  .join(graduateProgram, joinExpr)
  .drop(graduateProgram.col("id"))
  .show()
```

This is an artifact of Spark's SQL analysis process where an explicitly referenced column will pass analysis because Spark has no need to resolve the column. Notice how the column uses the `.col` method instead of a column function. That allows us to implicitly specify that column with its specific id.

Approach 3: Renaming a Column Before the Join

This issue does not arise, at least in an unmanageable way, if we rename one of

our columns before the join.

```
val gradProgram3 = graduateProgram
  .withColumnRenamed("id", "grad_id")

val joinExpr = person.col("graduate_program") === gradProgram3.

person
  .join(gradProgram3, joinExpr)
  .show()
```

How Spark Performs Joins

Understanding how Spark performs joins means understanding the two core resources at play, the *node-to-node communication strategy* and *per node computation strategy*. These internals are likely irrelevant to your business problem, however understanding how Sparrk performs joins can mean the difference between a job that completely quickly or never completes at all.

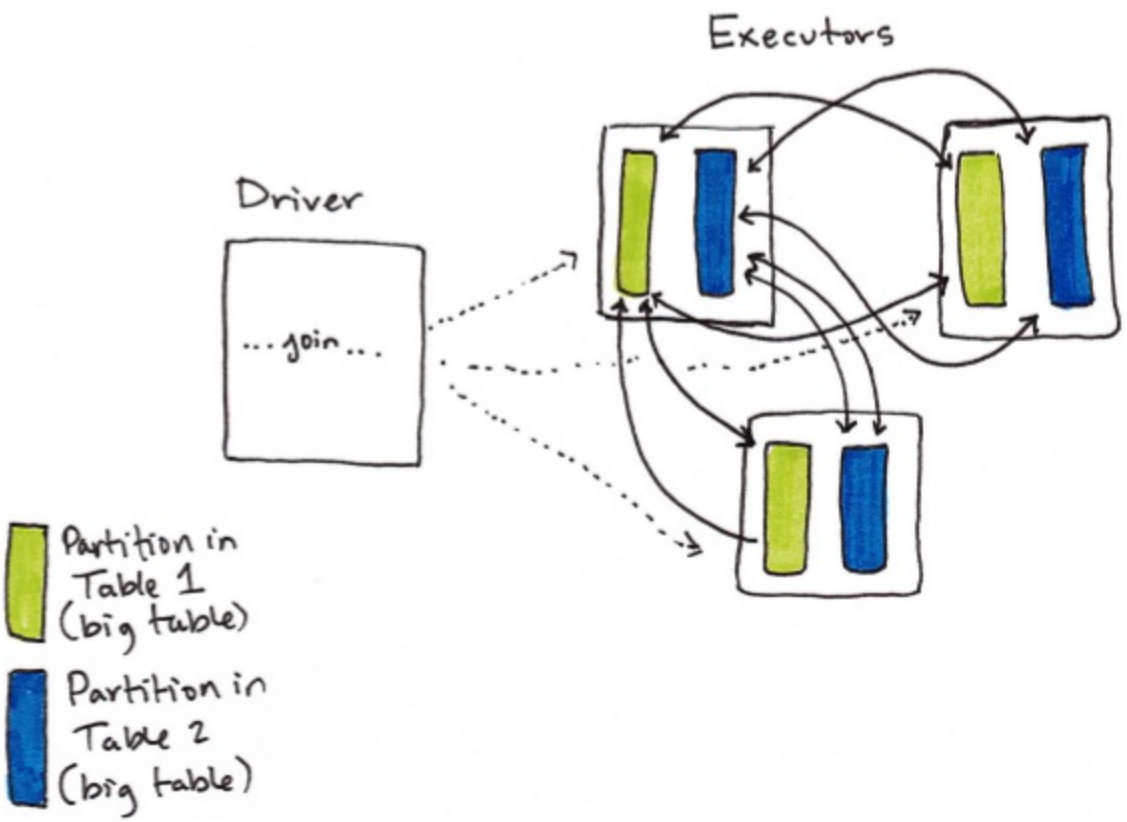
Node-to-Node Communication Strategies

There are two different approachs Spark can take when it comes to communication. Spark will either incur a *shuffle join*, which results in an all-to-all communication or a *broadcast join* where one of the DataFrames you work with is duplicated around the cluster which, in general, results in lower total communication that a shuffle join. Let's talk through these in a little bit less abstract terms.

In Spark you will have either a big table or a small table. While this is obviously a spectrum, it can help to be binary about the distinction.

Big Table to Big Table

When you join a big table to another big table, you end up with a shuffle join.



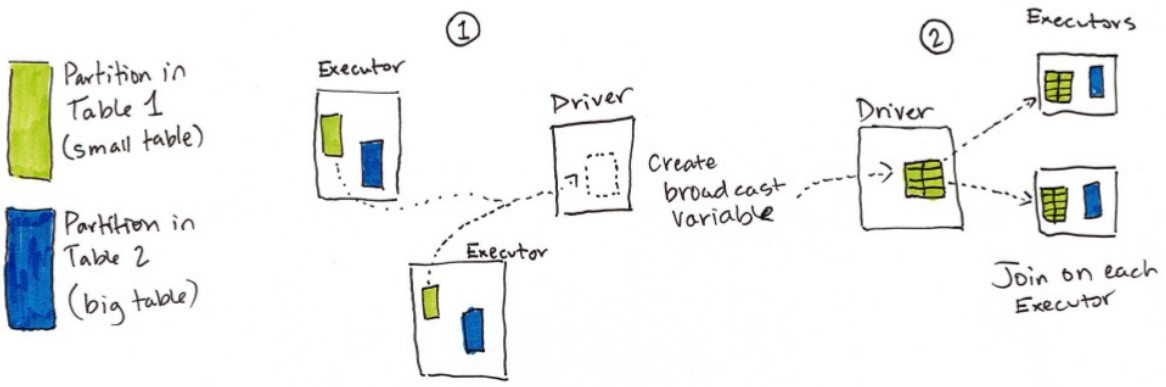
In a shuffle join, every node will talk to every other node and they will share data according to which node has a certain key or set of keys (that you are joining on). These joins are expensive because the network can get congested with traffic, especially if your data is not partitioned well.

This join describes taking a large table of data and joining it to another large table of data. An example of this might be that a company receive trillions of internet-of-things messages every day. You need to compare day over day change by joining on `deviceId`, `messageType` and `date` in one column and `date - 1 day` in order to see changes in day over day traffic and message types.

Referring to our image above, in this example DataFrame one and DataFrame two are both large DataFrames. This means that all worker nodes (and potentially every partition) will have to communicate with one another during the *entire* join process (with no intelligent partitioning of data). We can see this in the previous figure.

Big Table to Small Table

When the table is small enough to fit into a single worker nodes memory, with some breathing room of course, we can optimize our join. While we can use a large table to large table communication strategy it can often be more efficient to use a broadcast join. What this means is that we will replicate our small DataFrame onto every worker node in the cluster (be it located on one machine or many currently). Now this sounds expensive, however what this does is prevent us from performing the all to all communication during the *entire* join process, instead we only perform it once at the beginning and then let each individual worker node perform the work without having to wait or communicate with any other worker node.



At the beginning of the join will be a large communication, just like in the previous type of join however immediately after that first set up there will be no communication happening between nodes. This means that joins will be performed on every single node individually, making cpu the biggest bottleneck. For our current set of data, we can see that Spark has automatically set this up as a broadcast join by looking at the explain plan.

```
val joinExpr = person.col("graduate_program") === graduateProgr

person
  .join(graduateProgram, joinExpr)
  .explain()

== Physical Plan ==
*BroadcastHashJoin [graduate_program#40], [id#56], Inner, Build
:- LocalTableScan [id#38, name#39, graduate_program#40, spark_s
+- BroadcastExchange HashedRelationBroadcastMode(List(cast(inpu
   +- LocalTableScan [id#56, degree#57, department#58, school#5
```

We can force a broadcast join too by using the correct function around the small DataFrame in question. In this example, these result in the same physical plan, however it can be more consequential for other tables.

```
import org.apache.spark.sql.functions.broadcast


val joinExpr = person.col("graduate_program") === graduateProgr

person
  .join(broadcast(graduateProgram), joinExpr)
  .explain()
```

Little Table to Little Table

When performing joins with small tables, it's usually best to let Spark decide how to join them, however you can employ both of the strategies above.

```
CODE TK
```

Chapter 7. Data Sources

The Data Source APIs

One of the reasons for Spark's immense popularity is its ability to read and write to a variety of data sources. Thus far in this book we read data in CSV and JSON file format. This chapter will formally introduce the variety of other data sources that you can use with Spark.

Spark has six "core" data sources and hundreds of external data sources written by the community. Spark's core Data Sources are:

- CSV,
- JSON,
- Parquet,
- ORC,
- JDBC/ODBC Connections,
- and plain text files.

As mentioned Spark has numerous community-created data sources including:

- Cassandra
- HBase
- MongoDB
- AWS Redshift
- and many others.

This chapter will not cover writing your own data sources but rather the core concepts that you will need to work with any of the above data sources. After

introducing the the core concepts, we will move onto demonstrations of each of Spark's core data sources.

Basics of Reading Data

The foundation for reading data in Spark is the `DataFrameReader`. We access this through our instantiated `SparkSession` via the `read` attribute.

Once we have a DataFrame reader, we specify several values: the *format* (1), the *schema* (2), the *read mode* (3), a series of *options* (4) and finally the *path* (5). At a minimum, you must supply a format and a path. the format, options, and schema each return a `DataFrameReader` that can undergo further transformations. Each data source has a specific set of options that determine how the data is read into Spark. We will cover these options shortly.

```
spark.read.format("csv")
  .schema(someSchema)
  .option("mode", "FAILFAST")
  .option("inferSchema", "true")
  .load("path/to/file(s)")
```

Read Mode

Read modes what will happen when Spark encounters malformed records. These modes are:

readMode	Description
`permissive`	Sets all fields to null when it encounters a corrupted record.
`dropMalformed`	Drops the row that contains malformed records.
`failFast`	Fails immediately upon encountering malformed records.

The default is permissive.

Basics of Writing Data

The foundation for reading data in Spark is the `DataFrameWriter`. We access this through a given `DataFrame` via the `write` attribute.

```
dataFrame.write
```

Once we have a DataFrameWritier, we specify several values: the *format* (1), the *save mode* (2), a series of *options* (3) and finally the *path* (4). At a minimum, you must supply a path. We will cover the required options afterwards.

```
dataframe.write.format("csv")
  .option("mode", "OVERWRITE")
  .option("dateFormat", "yyyy-MM-dd")
  .save("path/to/file(s)")
```

Save Mode

Save modes specify what will happen if Spark finds data at the specified location (assuming all else equal). These modes are:

saveMode	Description
`append`	Appends the output files to the list of files that already exist at that location.
`overwrite`	Will completely overwrite any data that already exists there.
`errorIfExists`	Throws an error and fails the write if data or files already exist at the specified location.
	If data or files exist at the location, do nothing with the

`ignore`	current DataFrame.

The default is error if exists.

Options

Now every data source has a set of options that can be used to control how the data is read or written. Each set of options varies based on the data source. We will cover the options for each specific data source as we go through them.

CSV Files

CSV stands for commma-separated values and is common text file format where each line represents a single record consisting of a variety of columns. CSV files, while seeming well structured, are actually one of the trickiest file formats you will encounter because not many assumptions can be made in production scenarios about what they contain or how they are structured. For this reason, the CSV reader has the largest number of options.

This allows us to work around issues like certain characters needing to be escaped like commas inside of columns when the file is also comma delimited or null values labelled in an unconventional way.

CSV Options

Read/Write	Key	Potential Values	Defa
both	sep	any single string character	,
both	header	TRUE, FALSE	FALSE
read	escape	any string character	\

read	inferSchema	TRUE, FALSE	FALSE
read	ignoreLeadingWhiteSpace	TRUE, FALSE	FALSE
read	ignoreTrailingWhiteSpace	TRUE, FALSE	FALSE
both	nullValue	any string character	“”

both	nanValue	any string character	NaN
both	positiveInf	any string or character	Inf
both	negativeInf	any string or character	-Inf
both	compression or codec	none, uncompressed, bzip2, deflate, gzip, lz4, or snappy	none

both	dateFormat	Any string or character that conforms to java's `SimpleDataFormat`.	yyyy-MM-dd
both	timestampFormat	Any string or character that conforms to java's `SimpleDataFormat`.	yyyy-MM-dd'T'HH:mm
read	maxColumns	Any integer	20480
read	maxCharsPerColumn	Any integer	1000000
read	escapeQuotes	TRUE, FALSE	TRUE

read	maxMalformedLogPerPartition	Any integer	10
	quoteAll	TRUE, FALSE	FALSE

Reading CSV Files

To read a csv file, like any other format, we must first create a DataFrameReader for that specific format to do that. We specify the format to be CSV.

```
spark.read.format("csv")
```

After this we have the option of specifying a schema as well as modes an options. Let's set a couple of options, some that we saw from the beginning of the book and others that we haven't seen so far. We'll set the `header` to be true for our csv file, we'll set the `mode` to be `FAILFAST`, and we will flag on `inferSchema`.

```
spark.read.format("csv")
  .option("header", "true")
  .option("mode", "FAILFAST")
  .option("inferSchema", "true")
  .load("some/path/to/file.csv")
```

As mentioned, the mode allows us to specify how much tolerance we have for malformed data. For example, we can use these modes and the schema that we created in Chapter two of this section to ensure that our file(s) conform to the data that we expected.

```
import org.apache.spark.sql.types.{StructField, StructType, St

val myManualSchema = new StructType(Array(
  new StructField("DEST_COUNTRY_NAME", StringType, true),
  new StructField("ORIGIN_COUNTRY_NAME", StringType, true),
  new StructField("count", LongType, false)
))
myManualSchema

spark.read.format("csv")
  .option("header", "true")
  .option("mode", "FAILFAST")
  .schema(myManualSchema)
  .load("dbfs:/mnt/defg/flight-data/csv/2010-summary.csv")
  .take(5)
```

Things get tricky when we don't expect data to be in a certain format. For example, Let's take our current schema and change all column types to `LongType`. this does not match the *actual* schema but Spark has no problem with us doing this. The problem will only manifest itself once Spark actually goes to read the data. Once we trigger our Spark job, Spark will immediately fail (once we execute a job) due to the data not conforming to the specified schema.

```
val myManualSchema = new StructType(Array(
  new StructField("DEST_COUNTRY_NAME", LongType, true),
  new StructField("ORIGIN_COUNTRY_NAME", LongType, true),
  new StructField("count", LongType, false)
))

spark.read.format("csv")
  .option("header", "true")
  .option("mode", "FAILFAST")
  .schema(myManualSchema)
  .load("dbfs:/mnt/defg/chapter-1-data/csv/2010-summary.csv")
  .take(5)
```

In general, Spark will only fail at job execution time rather than DataFrame definition time - even if for example we point to a file that does not exist.

Writing CSV Files

Just like with reading data there are a variety of options (listed previously in this chapter) for writing data when we write CSV files. This is a subset of the reading options because many do not apply when writing data (like `maxColumns` and `inferSchema`).

```
val csvFile = spark.read.format("csv")
  .option("header", "true")
  .option("mode", "FAILFAST")
  .schema(myManualSchema)
  .load("dbfs:/mnt/defg/chapter-1-data/csv/2010-summary.csv")
```

For example we can take our csv file and write it out as a tsv file quite easily.

```
csvFile.write.format("csv")
  .mode("overwrite")
  .option("sep", "\t")
  .save("/tmp/my-tsv-file.tsv")
```

When you list the destination directory, you can see that my-tsv-file is actually a folder with numerous files inside of it. This actually reflects the number of partitions at write time. If we were to repartition our data before then, we would end up with a larger number of files. We discuss this tradeoff at the end of this chapter.

```
%fs ls /tmp/my-tsv-file.tsv/
```

JSON Files

Those coming from the world of JavaScript are likely familiar with JSON notation (JavaScript Object Notation). There are some catches when working with this kind of data that are worth considering before hand. In Spark when we refer to JSON files we refer to line-delimited JSON files. This contrasts with files that have a large JSON object or array per file.

The line-delimited vs. whole file trade off is controlled by a single option `wholeFile`.[NOTE: This isn't merged as of the time of this writing but will be in by 2.2] When you set this to true, you can read an entire file as one json object and Spark will go through the work of parsing that into a DataFrame. With that being said, line-delimited JSON is actually a much more stable format because it allows you to append to a file with a new record (rather than having to read in a whole file and then write it out). Another key reason for the popularity of line-delimited JSON is because JSON objects have structure and JavaScript (on which JSON is based) has types. This makes it easier to work with because Spark can make more assumptions on our behalf about the data. You'll noitice that there are significantly less options than we saw for CSV because of the objects.

JSON Options

Read/Write	Key	Potential Values	
both	compression or codec	none, uncompressed, bzip2, deflate, gzip, lz4, or snappy	none
both	dateFormat	Any string or character that conforms to java's `SimpleDataFormat`.	yyyy
both	timestampFormat	Any string or character that conforms to java's `SimpleDataFormat`.	yyyy
read	primitiveAsString	TRUE, FALSE	FALS

read	allowComments	TRUE, FALSE	FALS
read	allowUnquotedFieldNames	TRUE, FALSE	FALS
read	allowSingleQuotes	TRUE, FALSE	TRU
read	allowNumericLeadingZeros	TRUE, FALSE	FALS
read	allowBackslashEscapingAnyCharacter	TRUE, FALSE	FALS

read	columnNameOfCorruptRecord	Any string	value spark
read	wholeFile	TRUE, FALSE	FALS

Now reading a line-delimited JSON file only varies in the format and the options that we specify.

```
spark.read.format("json")
```

Reading JSON Files

Let's have an example of reading a JSON file and compare the options that we're seeing.

```
spark.read.format("json")
  .option("mode", "FAILFAST")
  .schema(myManualSchema)
  .load("dbfs:/mnt/defg/flight-data/json/2010-summary.json")
  .show(5)
```

Writing JSON Files

Now writing JSON files is just as simple as reading them and as you might expect, the data source does not matter. Therefore we can reuse the CSV DataFrame that we created above in order to write out our JSON file. This too follows the rules that we specified above, one file per partition will be written out and the entire DataFrame will be written out as a folder. It will also have one JSON object per line.

```
csvFile.write.format("json")
  .mode("overwrite")
  .save("/tmp/my-json-file.json")
```

```
%fs ls /tmp/my-json-file.json/
```

Parquet Files

Apache Parquet is an open source column-oriented data store that provides a variety of storage optimizations, especially for analytics workloads. It provides columnar compression in order to save storage space and allows for reading individual columns instead of entire files. It is a file format that works exceptionally well with Apache Spark and is the default file format. We recommend writing data out to Parquet for long-term storage as reading from a parquet file always be more efficient than json or csv. Another advantage of Parquet is that it supports complex types. That means that if your column is an array (which would fail with a csv file for example), map, or struct - you'll still be able to read and write that file without issue.

```
spark.read.format("parquet")
```

Reading Parquet Files

Parquet has exceptionally few options because it enforces its own schema when storing data. Additionally all we have to set is the format and we are good to go. We can set the schema if we have strict requirements for what our DataFrame should look like, however often times this is not necessary because we can leverage schema on read which is similar to the `inferSchema` of csv files however it is more powerful because the schema is built into the file itself (so no inference needed).

Parquet Options

There are few parquet options because it has a well defined specification that aligns well with the concepts in Spark.

The only options are:

Read/Write	Key	Potential Values	Default	De
write	compression or codec	none, uncompressed, bzip2, deflate, gzip, lz4, or snappy	none	Dec wha com cod shou reac the
				sets we mer sche coll

read	mergeSchema	TRUE, FALSE	value of spark.sql.parquet.mergeSchema	fron Par files will ove con valu

Even though there are few options, there can be conflict where different versions of Parquet files are incompatible with one another. Be careful when you write out Parquet files with different versions of Spark (especially older ones) because this can cause significant headache.

```
spark.read.format("parquet")
```

```
spark.read.format("parquet")
  .load("/mnt/defg/flight-data/parquet/2010-summary.parquet")
  .show(5)
```

Writing Parquet Files

Writing parquet is as easy as reading it. We simply specify the location for the file. The same partitioning rules apply.

```
csvFile.write.format("parquet")
  .mode("overwrite")
  .save("/tmp/my-parquet-file.parquet")
```

ORC Files

ORC or Optimized Row Columnar file format is an efficient file format borrowed from Hive. Orc actually has no options to for reading in data as Spark understands the file format quite well. An often asked question is, what is the difference between ORC and Parquet and for the most part, they're quite similar. The fundamental difference is that Parquet is further optimized for use with Spark.

Reading Orc Files

```
spark.read.format("orc")
  .load("/mnt/defg/flight-data/orc/2010-summary.orc")
  .show(5)
```

Writing Orc Files

At this point in the chapter you should feel pretty comfortable taking a guess at how to write out orc files. It really follows the exact same pattern that we have seen so far where we specify the format and then save the file.

```
csvFile.write.format("orc")
  .mode("overwrite")
  .save("/tmp/my-json-file.orc")
```

SQL Databases

SQL datasources are one of the more powerful connectors because they allow you to connect to a variety of systems (as long as that system speaks SQL). For instance you can connect to a MySQL database, a PostgreSQL Database, or an Oracle database. We can also connect to SQLite which we'll be doing in this example.

NOTE

> a primer on SQLite. SQLite is the most used database engine in the entire world and then are some pretty amazing use cases for it. Personally I think it is an amazing companion to Spark because it allows you to span the spectrum of big and little data and when things are small enough to be placed on a local machine, then we can write them to a SQLite database and report on them from there.

Now because databases aren't just a set of raw files, there are some more options to consider around *how* you connect to the database. Namely you're going to have to start considering things like authentication and connectivity (is the network of your Spark cluster connected to the network of your database system). SQLite is going to allow us to skip a lot of these details because it should work with minimal setup on your local machine.

Reading from SQL Databases

Let's get started with out example, SQLite isn't a file format at all, therefore it lacks the `format` option. What we do is instead set a list of properties that specify how we will be connecting to our data source. In this case I'm just going to declare these as variables to make it apparent what is happening where.

```
val props = new java.util.Properties
props.setProperty("driver", "org.sqlite.JDBC")

val path = "/dbfs/mnt/defg/flight-data/jdbc/my-sqlite.db"
val url = s"jdbc:sqlite:/${path}"
val tablename = "flight_info"
```

If this were a more complex database like MySQL, we might need to set some more sophisticated parameters.

```
val props = new java.util.Properties
props.setProperty("driver", "org.sqlite.JDBC") // set to postgr
// dbProperties.setProperty("username", "some-username")
// dbProperties.setProperty("password", "some-password")
val hostname = "192.168.1.5"
val port = "2345"

// we would set a username and a password in the properties fi
val dbDatabase = "DATABASE"
val dbTable = "test"
```

Once we have defined our connection properties, we can test our connection to the database itself to make sure that it is functional. This is an excellent troubleshooting technique to ensure that your database is available to (at the very least) the Spark driver. This is much less relevant for SQLite because it is a file on our machine but if we were using something like MySQL we could test our connection with code like.

```
import java.sql.DriverManager
val connection = DriverManager.getConnection(url)
connection.isClosed()
connection.close()
```

If we can see that this connection succeeds, we should have a robust connection to our database. Now let's go ahead and read in a DataFrame from our table.

```
val dbDataFrame = spark.read.jdbc(url, tablename, props)
```

As we create this DataFrame it is no different from any other, we can query it, transform it, and join it without issue. You'll also notice that we already have a schema as well. That's because Spark just gets this information from the table itself and maps the types to Spark data types. Let's just get the distinct locations to verify that we can query it as expected.

```
dbDataFrame.select("DEST_COUNTRY_NAME").distinct().show(5)
```

Awesome, we can query our database! Now there are a couple of nuanced details that are worth understanding.

Query Pushdown

Firstly, Spark will make a best effort to try and filter data in the database itself before creating the DataFrame. For example in our above query, we can see from the query plan that it only selects the relevant column name from the table.

```
dbDataFrame.select("DEST_COUNTRY_NAME").distinct().explain
```

```
== Physical Plan ==
*HashAggregate(keys=[DEST_COUNTRY_NAME#8108], functions=[])
+- Exchange hashpartitioning(DEST_COUNTRY_NAME#8108, 200)
   +- *HashAggregate(keys=[DEST_COUNTRY_NAME#8108], functions=
      +- *Scan JDBCRelation(flight_info) [numPartitions=1] [DES
```

Spark can actually do better than this on certain queries. For example if we were to specify a filter on our DataFrame, then Spark will be able to ask the database to do that for us. This is conveniently called predicate pushdown. We can again see this in the explain plan.

```
dbDataFrame
  .filter("DEST_COUNTRY_NAME in ('Anguilla', 'Sweden')")
  .explain
```

Spark can't translate all of its own functions into the functions available in the SQL database that you're working with. Therefore sometimes you're going to want to pass an entire query into your SQL which will return the results as a DataFrame. Now this seems like it might be a bit complicated but it's actually quite straightforward. Rather than specifying a table name, we just specify a SQL query. Now we do have to specify this in a special way as we can see below. We have to wrap our query in parenthesis and rename it to something - in this case I just gave it the same table name.

```
val pushdownQuery = """
(SELECT DISTINCT(DEST_COUNTRY_NAME)
  FROM flight_info) as flight_info
"""
val dbDataFrame = spark.read.jdbc(url, pushdownQuery, props)
```

Now when we query this table, we'll actually be querying the results of that

query. We can see this in the explain plan. Now Spark doesn't even know about the actual schema of the table, just the one that results from our query above.

```
dbDataFrame.explain
```

Reading from Databases in Parallel

All throughout this book we have talked about partitioning and its importance in data processing. When we read in a set of parquet files for example, we will get one Spark partition per file. When we reading from SQL databases, we by default will always get one partition. Now this can be helpful if that dataset is small and we'd like to broadcast it out to all other workers but if it's a larger dataset sometimes it is better to read it into multiple partitions and even control what the keys of those partitions are.

Partitioning Via Predicates

One way is to specify an array of predicates that determine what should go in a particular partition. For example, say we wanted one partition to have all the flights to Sweden and another to the United States (and no others) Then we would speciy these predicates and pass them into our JDBC connection.

```
?val predicates = Array(
  "DEST_COUNTRY_NAME = 'Sweden'",
  "DEST_COUNTRY_NAME = 'United States'")

val dbDataFrame = spark.read.jdbc(url, tablename, predicates, p
```

We can see that this will result in exactly what we expect, two partitions and the country names that we specified above.

```
dbDataFrame.rdd.getNumPartitions

dbDataFrame.select("DEST_COUNTRY_NAME").distinct().show()
```

Now we don't have to specify predicates that are disjoint from one another. This would mean that we would get rows from our database duplicated into multiple partitions. For example, we have a total of 255 rows in our database.

```
spark.read.jdbc(url, tablename, props).count()
```

If we specify predicates that are not disjoint we can end up with lots of duplicate rows.

```
val predicates = Array(
  "DEST_COUNTRY_NAME != 'Sweden'",
  "Origin_COUNTRY_NAME != 'United States'")

spark.read.jdbc(url, tablename, predicates, props).count()
```

Partitioning Based on a Sliding Window

Now we saw how we can partition based on predicates, let's partition based on our numerical `count` column. What we do here is specify a minimum, a maximum for our first partition and our last partition. Anything outside of these bounds will be in the first partition or final partition. Then we set the number of partitions we would like total (this is the level of parallelism). Spark will then query our database in parallel and return `numPartitions` partitions. We simply modify the upper and lower bounds in order to place certain values in certain partitions. No filtering is taking place like we saw in the previous example.

```
val colName = "count"
val lowerBound = 0L
val upperBound = 348113L // this is the max count in our databa
val numPartitions = 10
```

This will will distribute the intervals equally from low to high.

```
spark.read.jdbc(url,
                tablename,
                colName,
                lowerBound,
                upperBound,
                numPartitions,
                props)
  .count()
```

Writing to SQL Databases

Now writing out to SQL Database is just as easy as before. We simply specify our URI and write out the data according to the specified write mode we would like. In this case I'm going to specify overwrite, which will overwrite the entire table. I'll be using the CSV DataFrame that we defined above in order to do this.

```
val newPath = "jdbc:sqlite://tmp/my-sqlite.db"

csvFile.write.mode("overwrite").jdbc(newPath, tablename, props)
```

Now we can see the results.

```
spark.read.jdbc(newPath, tablename, props).count()
```

Of course we can append to the table that we just created just as easily.

```
csvFile.write.mode("append").jdbc(newPath, tablename, props)
```

And naturally see the count increase.

```
spark.read.jdbc(newPath, tablename, props).count()
```

Text Files

Spark also allows you to read in plain text files. For the most part you shouldn't really need to do this, however if you do you will then have to parse the text file as a set of strings. For the most part this is only relevant for Datasets which will be covered in the next chapter.

Reading Text Files

Reading text files is simple, we just specify the type to be `textFile`.

```
spark.read.textFile("/tmp/five-csv-files.csv")
  .map(stringRow => stringRow.split(","))
  .show()
```

Writing Out Text Files

When we write out a text file, we need to be sure to only have one column, otherwise the write will fail.

```
spark.read.textFile("/tmp/five-csv-files.csv")
  .write.text("/tmp/my-text-file.txt")
```

Advanced IO Concepts

We saw previously that we can control the parallelism of files that we write by controlling the partitions prior to a write. We can also control specific data layout by controlling two things, bucketing and partitioning.

Reading Data in Parallel

While multiple executors cannot read from the same file as the same time, they can read different files at the same time. This means when you read from a folder with multiple files in it, each one of those files will become a partition in your DataFrame and be read in by available executors in parallel (with the remaining queueing up behind the others).

Writing Data in Parallel

The number of files that are written is a function of the number of partitions the DataFrame at the time your look to write it out. One file is written out per partition of the data by default meaning that although we specify a "file" it's actually a number of files inside of a folder with the name of the specified file with a file per each partition that is written out.

For example the following code.

```
csvFile.repartition(5).write.format("csv").save("/tmp/multiple
```

Will end up with five files inside of that folder. As you can see from the list call.

```
ls /tmp/multiple.csv
```

```
/tmp/multiple.csv/_SUCCESS
/tmp/multiple.csv/part-00000-767df509-ec97-4740-8e15-4e173d365a
/tmp/multiple.csv/part-00001-767df509-ec97-4740-8e15-4e173d365a
/tmp/multiple.csv/part-00002-767df509-ec97-4740-8e15-4e173d365a
/tmp/multiple.csv/part-00003-767df509-ec97-4740-8e15-4e173d365a
/tmp/multiple.csv/part-00004-767df509-ec97-4740-8e15-4e173d365a
```

Bucketing and Partitioning

Now one other thing we do is control even more specifically the layout. We can write out files in a given partitioning scheme which basically encodes the files into a certain folder structure. We will go into why you want to do this in the optimizations chapter but the core reason is that you're able to filter out data when you read it in later much more easily, reducing the amount of data you need to handle in the first place. These are supported for all file-based data sources.

```
csvFile.write
  .mode("overwrite")
  .partitionBy("DEST_COUNTRY_NAME")
  .save("/tmp/partitioned-files.parquet")
```

```
%fs ls /tmp/partitioned-files.json

%fs ls /tmp/partitioned-files.json/DEST_COUNTRY_NAME=Australia/
```

Rather than partitioning on a specific column (which might write out a ton of files), it's probably more worth it to explore bucketing the data. This will create a certain number of files and organize our data into those "buckets".

```
val numberBuckets = 10
val columnToBucketBy = "count"

csvFile.write.format("parquet")
  .mode("overwrite")
  .bucketBy(numberBuckets, columnToBucketBy)
  .saveAsTable("bucketedFiles")

%fs ls "dbfs:/user/hive/warehouse/bucketedfiles/"
```

The above write will give us one file per partition because the number of DataFrame partitions was less than the total number of output partitions. Now as is, this can get even worse if we were to have a higher number of partitions in our DataFrame and were writing out to a partitioning scheme that had fewer total partitions. This is because we could end up with many files per partition - and if we have a small DataFrame then reading this data back in will be very slow.

Controlling partitioning in-flight as well as at read and write time is the source of almost all Spark optimizations. We will cover this in Part IV of the book.

Writing Complex Types

As we covered in the “Working with Different Types of Data” Chapter, Spark as a variety of different internal types. While Spark can work with all of these types, not every single type works well with every data format. For instance, CSV files do not support complex types while Parquet and ORC do.

Chapter 8. Spark SQL

Spark SQL Concepts

Spark SQL is arguably one of the most important and powerful concepts in Spark. This chapter will introduce the core concepts in Spark SQL that you need to understand. This chapter will not rewrite the ANSI-SQL specification or enumerate every single kind of SQL expression. If you read any other parts of this book, you will notice that we try to include SQL code wherever we include DataFrame code to make it easy to cross reference with code examples. Other examples are available in the appendix and reference sections.

In a nutshell, Spark SQL allows the user to execute *SQL queries* against *views* or *tables* organized into *databases*. Users can also use *system functions* or define *user functions* and analyze *query plans* in order to optimize their workloads.

What is SQL?

SQL or *Structured Query Language* is a domain specific language for expressing relational operations over data. It is used in all relational databases and many "NoSQL" databases create their SQL dialect in order to make working with their databases easier. SQL is everywhere and even though tech pundits prophesized its death, it is an extremely resilient data tool that many business depend on. Spark implements a subset of the ANSI SQL:2003 Standard. This SQL standard is one that is available in the majority of SQL databases and this support means that Spark successfully runs the popular benchmark TPC-DS.

Big Data and SQL: Hive

Before Spark's rise, Hive was the de facto big data SQL access layer. Originally developed at Facebook, Hive became an incredibly popular tool across industry for performing SQL operations on big data. In many ways it helped propel Hadoop into different industries because analysts could run SQL queries. While Spark began as a general processing engine with RDDs, and was successful when doing so, Spark took off further when it because supporting a subset of SQL with the `sqlContext` and nearly all of the capabilities of Hive with the `HiveContext` in Spark 1.x.

Big Data and SQL: Spark SQL

With Spark 2.0's release the authors of Spark created a superset of Hive's support, writing a native SQL parser that supports both ANSI-SQL as well as Hive QL queries. In late 2016, Facebook announced that they would be throwing their weight behind Spark SQL and put Spark SQL into production in place of Hive (and seeing huge benefits in doing so).

The power of Spark SQL derives from several key facts: SQL analysts can now leverage Spark's computation abilities by plugging into the Thrift Server or Spark's SQL interface while Data Engineers and Scientists can use Spark's programmatic SQL interface in any of Spark's supported languages via the method `sql` on the `SparkSession` object. This code then can be manipulated as a DataFrame, passed into one of Spark MLlibs large scale machine learning algorithms, written out to another data source and everything in between.

Spark SQL is intended to operate as a OLAP (online analytic processing) database, not an OLTP (online transaction processing) database. This means that it is not intended very extremely low latency queries.

How to Run Spark SQL Queries

Spark provides several interfaces to execute SQL queries.

SparkSQL Thrift JDBC/ODBC Server

Spark provides a JDBC interface by which either you or a remote program connects to the Spark driver into order to execute Spark SQL queries. A common use case might be a for a business analyst to connect a business intelligence software like Tableau to Spark. The Thrift JDBC/ODBC server implemented here corresponds to the HiveServer2 in Hive 1.2.1 You can test the JDBC server with the beeline script that comes with either Spark or Hive 1.2.1.

To start the JDBC/ODBC server, run the following in the Spark directory:

```
./sbin/start-thriftserver.sh
```

This script accepts all `bin/spark-submit` command line options. Run `./sbin/start-thriftserver.sh --help` to see all available options for configuring this Thrift Server. By default, the server listens on localhost:10000. You may override this behavior through environmental variables or system properties.

For environment configuration:

```
export HIVE_SERVER2_THRIFT_PORT=<listening-port>
export HIVE_SERVER2_THRIFT_BIND_HOST=<listening-host>
./sbin/start-thriftserver.sh \
  --master <master-uri> \
  ...
```

For system properties:

```
./sbin/start-thriftserver.sh \
  --hiveconf hive.server2.thrift.port=<listening-port> \
  --hiveconf hive.server2.thrift.bind.host=<listening-host> \
  --master <master-uri>
  ...
```

You can then test this connect by running the commands below.

```
./bin/beeline
```

```
beeline> !connect jdbc:hive2://localhost:10000
```

Beeline will ask you for a username and password. In non-secure mode, simply enter the username on your machine and a blank password. For secure mode, please follow the instructions given in the beeline documentation.

To learn more about the Thrift server see the Spark SQL Appendix.

Spark SQL CLI

The Spark SQL CLI is a convenient tool to run the Hive metastore service in local mode and execute queries input from the command line. Note that the Spark SQL CLI cannot talk to the Thrift JDBC server. To start the Spark SQL CLI, run the following in the Spark directory:

```
./bin/spark-sql
```

Configuration of Hive is done by placing your *hive-site.xml*, *core-site.xml* and *hdfs-site.xml* files in `conf/`. You may run `./bin/spark-sql --help` for a complete list of all available options.

Spark's Programmatic SQL Interface

In addition to setting up a server, you can also execute sql in an ad hoc manner via any of Spark's language. This is done via the method `sql` on the `SparkSession` object. This will return a DataFrame as we will see later in this chapter. For example in Scala, we can run.

```
%scala

spark.sql("SELECT 1 + 1").collect()
```

The python interface is essentially the exact same.

```
%python

spark.sql("SELECT 1 + 1").collect()
```

The command `spark.sql("SELECT 1 + 1")` will return a `DataFrame` that we can then evaluate programmatically. Just like other transformations, this will not be executed eagerly but lazily. This is an immensely powerful interface because there are some transformations that are much simpler to express in SQL code as opposed to DataFrames.

You can express multi-line queries quite simply, just pass a multi-line string into the function. For example we could execute something like the following code in Python or Scala.

```
spark.sql("""
  SELECT
    user_id,
    department,
    first_name
  FROM
    professors
  WHERE
    department IN
      (SELECT name
       FROM department
       WHERE created_date >= '2016-01-01')
""")
```

For the remainder of this chapter will only show the SQL being executed, just keep in mind if you're using the programmatic interface that you need to wrap everything in a `spark.sql` function call in order to execute the relevant code.

Tables

To do anything useful with Spark SQL, we first need to define tables. Tables are logically equivalent to a DataFrame in that they are a structure of data that we execute commands against. We can join tables, filter then, aggregate them and many different manipulations that we saw in previous chapters. The core difference between tables and DataFrames is that while we define DataFrames in the scope of a programming language, we define tables inside of a database. This means when you create a table (assuming you never changed the database), it will belong to the *default* database. We will discuss databases more later on in the chapter.

We can see the already defined tables by running the following command.

```
%sql

SHOW TABLES
```

```
case class Table(database:String, tableName:String, isTemporary
spark.sql("SHOW TABLES").as[Table].collect().map {t =>
  try {
    spark.sql(s"DROP TABLE IF EXISTS ${t.tableName}").collect()
  }
  catch {
    case e: org.apache.spark.sql.AnalysisException => {
         spark.sql(s"DROP VIEW IF EXISTS ${t.tableName}").colle
    }
  }

}
// will delete this, just to help me iterate on all these table
```

You will notice in the results that a database is listed. We discuss databases later in this chapter but it is of note that we can also see tables in a Specific database with the following query `show tables IN databaseName` where `databaseName` represents the name of the database we'd like to query.

If you are running on a new cluster or local mode, this should return zero results.

Creating Tables

Tables can be created from a variety of sources. Something fairly unique to Spark is the capability of reusing the entire Data Source API within SQL. This means that you do not have to define a table and then load data into it, Spark let's you create one on the fly. We can even specify all sorts of sophisticated options when we read in a file. For example, here's a simple way to read our flights data in from previous chapters.

```
%sql

CREATE TABLE flights (
  DEST_COUNTRY_NAME STRING,
  ORIGIN_COUNTRY_NAME STRING,
  count LONG)
USING JSON
OPTIONS (
  path '/mnt/defg/chapter-1-data/json/2015-summary.json')
```

We can also add comments to certain columns in a table, this can help other people understand the data in the tables.

```
%sql

CREATE TABLE  flights_csv (
  DEST_COUNTRY_NAME STRING,
  ORIGIN_COUNTRY_NAME STRING COMMENT "remember that the most pı
  count LONG)
USING csv
OPTIONS (
  inferSchema true,
  header true,
  path '/mnt/defg/chapter-1-data/csv/2015-summary.csv')
```

We can also create a table from a query.

```
%sql

CREATE TABLE flights_from_select
AS
  SELECT * FROM flights
```

We can also specify to create a table only if it does not currently exist as we see in the following snippet.

```
%sql

CREATE TABLE IF NOT EXISTS flights_from_select
AS
  SELECT * FROM flights
  LIMIT 5
```

We can also control the layout of the data by writing out a partitioned dataset as we saw in the previous chapter.

```
%sql

CREATE TABLE partitioned_flights
USING parquet
PARTITIONED BY (DEST_COUNTRY_NAME)
AS
  SELECT DEST_COUNTRY_NAME, ORIGIN_COUNTRY_NAME, count FROM fl
  LIMIT 5 -- so we don't create a ton of files
```

These tables will be available in Spark even through sessions, temporary tables do not currently exist in Spark. You must create a temporary view as we will demonstrate later in this chapter.

Inserting Into Tables

Insertions follow the standard SQL syntax.

```
%sql

INSERT INTO flights_from_select
  SELECT DEST_COUNTRY_NAME, ORIGIN_COUNTRY_NAME, count FROM fl
  LIMIT 20
```

We can optionally provide a partition specification if we only want to write into a certain partition. Note that a write will respect a partitioning scheme as well (which may cause the above query to run quite slowly), however it will only add additional files into the end partitions.

```
%fs ls /user/hive/warehouse/partitioned_flights/

%sql

INSERT INTO partitioned_flights
  PARTITION (DEST_COUNTRY_NAME="UNITED STATES")
  SELECT count, ORIGIN_COUNTRY_NAME FROM flights
  WHERE DEST_COUNTRY_NAME='UNITED STATES'
  LIMIT 12
```

Now that we created our tables, we can query them and see our results.

```
%sql

SELECT * FROM flights_csv

%sql

SELECT * FROM flights
```

Describing Table Metadata

We saw above that we can add a comment when we create a table, we can view this by describing the table metadata which will show us the relevant comment.

```
%sql

DESCRIBE TABLE flights_csv
```

We can also see the partitioning scheme for the data with the following command, however this only works on partitioned tables.

```
%sql

SHOW PARTITIONS partitioned_flights
```

Refreshing Table Metadata

There are two commands to refresh table metadata.

REFRESH TABLE will refresh all cached entries associated with the table. If the table was previously cached, then it would be cached lazily the next time it is scanned.

```
%sql

REFRESH table partitioned_flights

%sql

MSCK REPAIR TABLE partitioned_flights
```

Dropping Tables

Tables cannot be deleted, they are only “dropped”. We can drop a table with the `DROP` keyword. If we are dropping a managed table (e.g., `flights_csv`), both the data and the table definition will be removed.

> WARNING This can and will delete your data, be care when you are dropping tables.

```
%sql

DROP TABLE flights_csv;
```

If you try to drop a table that does not exist, you will receive an error. To only delete a table if it already exists use `DROP TABLE IF EXISTS`.

```
%sql

DROP TABLE IF EXISTS flights_csv;
```

Views

Now that we created a table another thing we can define a view. A view specifies a set of transformations on top of an existing table. Views can be either just a saved query plan to be executed against the source table or they can be materialized which means that the results are precomputed (at the risk of going stable if the underlying table changes).

Spark has several different notions of views. Views can be global, set to a database, or per session.

Creating Views

To an end user, views are displayed as tables except rather than rewriting all of the data to a new location, they simply perform a transformation on the source data at query time. this might be a `filter`, `select`, or potentially an even larger `GROUP BY` or `ROLLUP`. For example, we can create a view where the destination must be `United States` in order to see only flights to the `USA`.

```
%sql

CREATE VIEW just_usa_view AS
  SELECT *
  FROM flights
  WHERE dest_country_name = 'United States'
```

We can make it global by leveraging the `GLOBAL` keyword.

```
%sql

CREATE VIEW just_usa_global AS
  SELECT *
  FROM flights
  WHERE dest_country_name = 'United States'
```

Views, like tables, can be created as temporary views which will only be available during the current Spark Session and are not registered to a database.

```
%sql

CREATE TEMP VIEW just_usa_view_temp AS
  SELECT *
  FROM flights
  WHERE dest_country_name = 'United States'
```

Or it can be a global temp view. Global temp views are resolved regardless of database and are viewable across the entire Spark application but are removed at the end of the session.

```
%sql
```

```
CREATE GLOBAL TEMP VIEW just_usa_global_view_temp AS
  SELECT *
  FROM flights
  WHERE dest_country_name = 'United States'

%sql SHOW TABLES
```

We can also specify that we would like to overwite a view if one already exists with the following keywords. We can overwrite both temp views and regular view.

```
%sql

CREATE OR REPLACE TEMP VIEW just_usa_view_temp AS
  SELECT *
  FROM flights
  WHERE dest_country_name = 'United States'
```

Now we can query this view just as if it were another table.

```
%sql

SELECT * FROM just_usa_view
```

A view is effectively a transformation and Spark will only perform it at query time. This means that it will only apply that filter once we actually go to query the table and (and not earlier). Effectively, views are equivalent to creating a new DataFrame from an existing DataFrame.

In fact we can see this by comparing the query plans generated by Spark DataFrames and Spark SQL. In DataFrames we would write.

```
val flights = spark.read.format("json")
  .load("/mnt/defg/chapter-1-data/json/2015-summary.json")
val just_usa_df = flights
  .where("dest_country_name = 'United States'")

just_usa_df
  .selectExpr("*")
  .explain
```

In SQL we would write (querying from our view).

```
%sql
```

```
EXPLAIN SELECT * FROM just_usa_view
```

Or equivalently.

```
%sql

EXPLAIN
  SELECT *
  FROM flights
  WHERE dest_country_name = 'United States'
```

Due to this fact, you should feel comfortable in writing your logic either on DataFrames or SQL - which ever is most comfortable and maintainable for you.

Dropping Views

You can drop views in the same way that you drop tables but specify that what you intend to drop is a *view* instead of a table. If we are dropping a `view` no underlying data will be removed, only the view definition itself.

```
%sql

DROP VIEW IF EXISTS just_usa_view;
```

Databases

Databases are a tool for organizing tables. As mentioned above, if you do not define a database Spark will use the default one. Any SQL statements you execute from within Spark (including DataFrame commands) execute within the context of a database. That means if you change the database, any user defined tables will remain in the previous database and will have to be queried different.

WARNING

> this can be a source of confusion for your co-workers so make sure to set your databases appropriately.

We can see all databases with the following command.

```
%sql

SHOW DATABASES
```

Creating Databases

Creating databases follows the same patterns we saw previously in this chapter, we use the `CREATE DATABASE` keywords.

```
%sql

CREATE DATABASE some_db
```

Setting The Database

You may want to set a database to perform a certain query. To do this use the `USE` keyword followed by the database name.

```
%sql

USE some_db
```

Once we set this database, all queries will try to resolve tables names to this database. Queries that were working just fine will now may fail or give different results because we are in a different database.

```
%sql

SHOW tables
```

```
%sql

SELECT * FROM flights
```

However we can query different databases by using the correct prefix.

```
%sql

SELECT * FROM default.flights
```

We can see what database we are currently using with the following command.

```
%sql

SELECT current_database()
```

We can, of course, switch back to the default database.

```
%sql

USE default;
```

Dropping Databases

Dropping or removing databases is equally as easy. We simply use the `DROP DATABASE` keyword.

```
%sql

DROP DATABASE IF EXISTS some_db;
```

Select Statements

Queries in Spark support follow ANSI SQL requirements. The follow lists the layout of `SELECT` expression.

```
SELECT [ALL|DISTINCT] named_expression[, named_expression, ...]
    FROM relation[, relation, ...]
    [lateral_view[, lateral_view, ...]]
    [WHERE boolean_expression]
    [aggregation [HAVING boolean_expression]]
    [ORDER BY sort_expressions]
    [CLUSTER BY expressions]
    [DISTRIBUTE BY expressions]
    [SORT BY sort_expressions]
    [WINDOW named_window[, WINDOW named_window, ...]]
    [LIMIT num_rows]

named_expression:
    : expression [AS alias]

relation:
    | join_relation
    | (table_name|query|relation) [sample] [AS alias]
    : VALUES (expressions)[, (expressions), ...]
          [AS (column_name[, column_name, ...])]

expressions:
    : expression[, expression, ...]

sort_expressions:
    : expression [ASC|DESC][, expression [ASC|DESC], ...]
```

Case When Then Statements

Often times you may need to conditionally replace values in your SQL queries. This can be achieved with a `case...when...then...end` style statement. This are essentially the equivalent of programmatic if statements.

```
%sql

SELECT
  CASE WHEN DEST_COUNTRY_NAME = 'UNITED STATES' THEN 1
       WHEN DEST_COUNTRY_NAME = 'Egypt' THEN 0
       ELSE -1 END
FROM
  partitioned_flights
```

Advanced Topics

Now that we defined where data lives and how to organize it, let's move onto querying data. A SQL query is a SQL statement that requests that some set of commands be executed. SQL statements can define manipulations, definitions, or controls. The most common case are the manipulations which is what we will primarily be focusing on. We can execute these statements without necessarily pointing to a set of data to execute our statement on.

While we do not want to define the entire SQL standard over again. We encourage you to look through the entire structured API section, in this we have included a SQL query in almost every location that we included a DataFrame manipulation. Or pick up a SQL language book as it will provide nearly all the information that you need in order to leverage Spark SQL.

Complex Types

Complex types are a departure from standard SQL and are an incredibly powerful feature that does not exist in standard SQL. Understanding how to manipulate them appropriately in SQL is essential. There are three core complex types in Spark SQL, sets, lists, and structs.

Structs

Structs on the other hand are more akin to maps. They provide a way of creating or querying nested data in Spark. To create one, you simply need to wrap a set of columns (or expressions in parentheses).

```
%sql

CREATE VIEW IF NOT EXISTS
  nested_data
AS
  SELECT
    (DEST_COUNTRY_NAME, ORIGIN_COUNTRY_NAME) as country,
    count
  FROM flights
```

Now we can query this data to see what it looks like.

```
%sql

SELECT * FROM nested_data
```

We can even query individual columns within a struct, all we have to do is use dot syntax.

```
%sql

SELECT country.DEST_COUNTRY_NAME, count
FROM nested_data
```

We can also select all the sub-values from a struct if we like by using the struct's name and select all of the sub-columns. While these aren't truly sub-

columns it does provide a simpler way to think about them because we can do everything that we like with them as if they were a column.

```
%sql

SELECT country.*, count
FROM nested_data
```

Sets and Lists

Sets and lists are the same that you should be familiar with in programming languages. Sets have no ordering and no duplicates, lists can have both. We create sets and lists with the `collect_set` and `collect_list` functions, respectively. However we must do this within an aggregation because these are aggregation functions.

```
%sql

SELECT
  DEST_COUNTRY_NAME as new_name,
  collect_list(count) as flight_counts,
  collect_set(ORIGIN_COUNTRY_NAME) as origin_set
FROM
  flights
GROUP BY
  DEST_COUNTRY_NAME
```

We can also query these types by position by using a python like array query syntax.

```
%sql

SELECT
  DEST_COUNTRY_NAME as new_name,
  collect_list(count)[0]
FROM
  flights
GROUP BY
  DEST_COUNTRY_NAME
```

We can also do things like convert an array back into rows. The way we do this is with the `explode` function. To demonstrate, let's create a new view as

our aggregation.

```
%sql

CREATE OR REPLACE TEMP VIEW flights_agg
AS
  SELECT
    DEST_COUNTRY_NAME,
    collect_list(count) as collected_counts
  FROM
    flights
  GROUP BY
    DEST_COUNTRY_NAME
```

Now let's explode the complex type to one row in our result for every value in the array. The DEST_COUNTRY_NAME will duplicate for every value in the array, performing the exact opposite of the original collect and returning us to the original DataFrame.

```
%sql

SELECT explode(collected_counts), DEST_COUNTRY_NAME
FROM flights_agg
```

Functions

In addition to complex types, Spark SQL provides a variety of sophisticated functions. Most of these functions can be found in the DataFrames function reference however it is worth understanding how to find these functions in SQL as well. To see a list of functions in Spark SQL, you simply need to use the `SHOW FUNCTIONS` statement in order to see a list of all available functions.

```
%sql

SHOW FUNCTIONS
```

You can also more specifically specify whether or not you would like to see the system functions (i.e., those built into Spark) as well as user functions.

```
%sql

SHOW SYSTEM FUNCTIONS
```

User functions are those that you, or someone else sharing your Spark environment, defined. These are the same User-Defined Functions that we talked about in previous chapters. We will discuss how to create them later on in this chapter.

```
%sql

SHOW USER FUNCTIONS
```

All `SHOW` commands can be filtered by passing a string with wildcard (`*`) characters. We can see all functions that start with “s”.

```
%sql

SHOW FUNCTIONS "s*";
```

Optionally, you can include the `LIKE` keyword although this is not necessary.

```
%sql
```

```
SHOW FUNCTIONS LIKE "collect*";
```

While listing functions is certain useful, often times you may want to know more about specific functions themselves. Use the `DESCRIBE` keyword in order to return the documentation for a specific function.

User Defined Functions

As we saw in Section two, Chapters three and four, Spark allows you to define your own functions and use them in a distributed manner. We define functions and register them, just as we would do before, writing the function in the language of our choice and then registering it appropriately.

```
def power3(number:Double):Double = {
  number * number * number
}

spark.udf.register("power3", power3(_:Double):Double)

%sql

SELECT count, power3(count)
FROM flights
```

Spark Managed Tables

One important note is the concept of *managed* vs *unmanaged* tables. Tables store two important pieces of information. The data within the tables as well as the data about the tables, that is the *metadata*. You can have Spark manage the metadata for a set of files, as well as the data. When you define a table from files on disk, you are defining an unmanaged table. When you use `saveAsTable` on a `DataFrame` you are creating a managed table where Spark will keep track of all of the relevant information for you.

This will read in our table and write it out to a new location in Spark format. We can see this reflected in the new explain plan. In the explain plan you will also notice that this writes to the default hive warehouse location. You can set this by setting the `spark.sql.warehouse.dir` configuration to the directory of your choosing at SparkSession creation time. By default Spark sets this to `/user/hive/warehouse`.

Creating External Tables

Now as we mentioned in the beginning of this chapter, Hive was one of the first big data SQL systems and Spark SQL is completely compatible with Hive SQL (HiveQL) statements. One of the use cases you may have here will be to port your legacy hive statements to Spark SQL. Luckily you can just copy and paste your Hive statements directly into Spark SQL. For example below I am creating an *unmanaged table*. Spark will manage the metadata about this table however, the files are not managed by Spark at all. We create this table with the `CREATE EXTERNAL TABLE` statement.

```
%sql

CREATE EXTERNAL TABLE hive_flights (
  DEST_COUNTRY_NAME STRING,
  ORIGIN_COUNTRY_NAME STRING,
  count LONG)
ROW FORMAT DELIMITED FIELDS TERMINATED BY ','
LOCATION '/mnt/defg/flight-data-hive/'
```

You can also create an external table from a select clause.

```
%sql

CREATE EXTERNAL TABLE hive_flights_2
ROW FORMAT DELIMITED FIELDS TERMINATED BY ','
LOCATION '/mnt/defg/flight-data-hive/'
AS SELECT * FROM flights

%sql

SELECT * FROM hive_flights
```

Dropping Unmanaged Tables

If we are dropping an unmanaged table (e.g., `hive_flights`) no data will be removed but we won't be able to refer to this data by the table name any longer.

Subqueries

Subqueries allow you to specify queries within other queries. This can allow you to specify some sophisticated logic inside of your SQL. In Spark there are two fundamental subqueries. *Correlated Subqueries* use some information from the outer scope of the query in order to supplement information in the subquery. *Uncorrelated subqueries* include no information from the outer scope. Each of these queries can return one (scalar subquery) or more values. Spark also includes support for *predicate subqueries* which allow for filtering based on values.

Uncorrelated Predicate Subqueries

For example, let's take a look at a predicate subquery. This is going to be composed of two *uncorrelated* queries. The first query is just to get the top five country destinations based on the data we have.

```
%sql

SELECT dest_country_name
FROM flights
GROUP BY dest_country_name
ORDER BY sum(count) DESC
LIMIT 5
```

This gives us the result:

```
+-----------------+
|dest_country_name|
+-----------------+
|    United States|
|           Canada|
|           Mexico|
|   United Kingdom|
|            Japan|
+-----------------+
```

Now we place this subquery inside of the filter and check to see if our origin

country exists in that list.

```
%sql

SELECT *
FROM flights
WHERE
  origin_country_name IN (
                          SELECT dest_country_name
                          FROM flights
                          GROUP BY dest_country_name
                          ORDER BY sum(count) DESC
                          LIMIT 5)
```

This query is uncorrelated because it does not include any information from the outer scope of the query. It's a query that can be executed on its own.

Correlated Predicated Subqueries

Correlated predicate subqueries allows us to use information from the outer scope in our inner query. For example, if we want to see whether or not we have a flight that will take you back from your destination country we could do so by checking whether or not there was a flight that had the destination country as an origin and a flight that had the origin country as a destination.

```
%sql

SELECT *
FROM   flights f1
WHERE  EXISTS (
            SELECT 1
            FROM flights f2
            WHERE f1.dest_country_name = f2.origin_country_name
AND    EXISTS (
            SELECT 1
            FROM flights f2
            WHERE f2.dest_country_name = f1.origin_country_name
```

`EXISTS` just checks for some existence in the subquery and returns true if there is a value. We can flip this by placing the `NOT` operator in front of it. This would be equivalent to finding a flight that you won't be able to get back from!

Uncorrelated Scalar Queries

Uncorrelated scalar queries allows us to bring in some supplemental information that we might not have previously. For example if we wanted to include the maximum value as its own column from the entire counts dataset in order to

```
%sql

SELECT *,
  (SELECT max(count) FROM flights) AS maximum
FROM flights
```

Conclusion

Many concepts in Spark SQL transfer directly to DataFrames (and vice versa) you should be able to leverage many of the examples through this book, and with a little manipulation, get them to work in any of Spark's supported languages.

Chapter 9. Datasets

What are Datasets?

Datasets are the foundational type of the Structured APIs. Earlier in this section we worked with DataFrames, which are Datasets of Type `Row`, and are available across Spark's different languages. Datasets are a strictly JVM language feature that only work with Scala and Java. Datasets allow you to define the object that each row in your Dataset will consist of. In Scala this will be a case class object that essentially defines a schema that you can leverage and in Java you will define a Java Bean. Experienced users often refer to Datasets as the "typed set of APIs" in Spark. See the Structured API Overview Chapter for more information.

In the introduction to the Structured APIs we discussed that Spark has types like `StringType`, `BigIntType`, `StructType` and so on. Those Spark specific types map to types available in each of Spark's languages like `String`, `Integer`, `Double`. When you use the DataFrame API, you do not create Strings or Integers but Spark manipulates the data for you by manipulating the Row. When you use the Dataset API, for every row it touches with user code (not Spark code), Spark converts the Spark Row format to the case class object you specify when you create your Dataset. This will slow down your operations but can provide more flexibilty. You will notice a performance difference but this is a far different order of magnitude from what you might see from something like a Python UDF because the performance costs are not as extreme as switching programming languages but it is an important thing to keep in mind.

Encoders

As mentioned in the Structured API Overview, when working with JVM languages, we can define specific types in order to operate on user defined types instead of JVM Types. To do this, we use an *Encoder*. Encoders are only available in Scala, with case classes, and Java, with JavaBeans. For some types, like `Long` or `Integer`, Spark already includes an Encoder. For instance we can collect a `Dataset` of type `Long` and get native Scala types back.

As of early 2017, users cannot define their own *arbitrary types* like a custom Scala class.

Creating Datasets

Case Classes

To create Datasets in Scala, we define a Scala `case class`.

A case class is a regular class that is:

- immutable,
- decomposable through pattern matching,
- allows for comparison based on structure instead of reference, and
- easy to use and operate on.

These traits make it quite valuable for data analysis because it is quite easy to reason about a case class. Probably the most important feature is that case classes are immutable and allow for comparison by structure instead of value.

According to the Scala Documentation:

- Immutability frees you from needing to keep track of where and when things are mutated
- Comparison-by-value allows you compare instances as if they are primitive values - no more uncertainty regarding whether instances of a class is compared by value or reference
- Pattern matching simplifies branching logic, which leads to less bugs and more readable code.

http://docs.scala-lang.org/tutorials/tour/case-classes.html

These advantages carry over to their usage within Spark as well.

To get started creating a Dataset let's define a case class for one of our datasets.

```
case class Flight(DEST_COUNTRY_NAME: String, ORIGIN_COUNTRY_NAM
```

Now that we defined a case class, this will represent a single record in our dataset. More succintly, we now have a Dataset of Flights. This doesn't define any methods for us but simply the schema. Now when we read in our data we'll get a DataFrame However we simply use the `as` method to cast it to our specified row type.

```
val flightsDF = spark.read.parquet("/mnt/defg/chapter-1-data/pa
val flights = flightsDF.as[Flight]
```

Actions

While we can see the power of Datasets what's important to understand is that actions like `collect`, `take`, and `count` apply to whether we are using Datasets or DataFrames.

```
flights.take(2)
```

You'll also notice that when we actually go to access one of the case classes we have to do no type coercion, we simply specify the named attribute of the case class and get back, not just the expected value but the expected type as well.

```
flights.first.DEST_COUNTRY_NAME
```

Transformations

Now transformations on Datasets are the same as those that we saw on DataFrames. Any transformation that you read about in this section is valid on a Dataset and we encourage you to look through the specific sections on relevant aggregations or joins.

In addition to those transformations, Datasets allow us to specify more complex and strongly typed transformations than we could perform on DataFrames alone because we can manipulate raw JVM types. Let's look at an example with filtering down or dataset.

Filtering

Let's look at a simple example by creating a simple function that accepts a Flight and returns a boolean value that describes whether or not the origin and destination are the same. This is not a UDF (at least in the way that Spark SQL defines UDF) but a generic function.

```
def originIsDestination(flight_row: Flight): Boolean = {
  return flight_row.ORIGIN_COUNTRY_NAME == flight_row.DEST_COUI
}
```

We can now pass this function into the filter method specifying that for each row it should verify that this function returns true and in the process will filter our Dataset down accordingly.

```
flights.filter(flight_row => originIsDestination(flight_row)).
```

As we saw above, this function does not need to execute in Spark code at all. Similar to our UDFs, we can use it and test it on data on our local machines before using it within Spark.

For example, this dataset is small enough for us to collect to the driver (as an Array of Flights) on which we can operate and perform the exact same filtering operation.

```
flights.collect().filter(flight_row => originIsDestination(fli
```

We can see that we get the exact same answer as before.

Mapping

Now filtering is a simple transformation but sometimes you need to map one value to another value. We did this with our function above, it accepts a flight and returns a boolean, but other times we may actually need to perform something more sophisticated like extract a value, compare a set of values, or something similar.

The simplest example is manipulating our Dataset such that we extract one value from each row. This is effectively performing a DataFrame like `select` on our Dataset. Let's extract the destination.

```
val destinations = flights.map(f => f.DEST_COUNTRY_NAME)
```

You'll notice that we end up with a Dataset of type String. That is because Spark already knows the JVM type that that result should return and allows us to benefit from compile time checking if, for some reason, it is invalid.

We can collect this and get back an array of strings on the driver.

```
val localDestinations = destinations.take(10)
```

Now this may feel trivial and unnecessary, we can do the majority of this right on DataFrames. We in fact recommend that you do this because you gain so many benefits from doing so. You will gain advantages like code generation that are simply not possible with arbitrary user-defined functions. However this can come in handy with much more sophisticated row-by-row manipulation.

Joins

Joins, as we covered earlier in this section, apply just the same as they did for DataFrames. However Datasets also provide a more sophisticated method, the `joinWith` method. The joinWith method is roughly equal to a co-group (in RDD terminology) and you basically end up with two nested Datasets inside of one. Each column represents one Dataset and these can be manipulated accordingly. This can be useful when you need to maintain more information in the join or perofrm some more sophisticated manipulation on the entire result like performing an advanced map or filter.

Let's create a fake flight metadata dataset to demonstrate joinWith.

```
case class FlightMetadata(count: BigInt, randomData: BigInt)

val flightsMeta = spark.range(500)
  .map(x => (x, scala.util.Random.nextLong))
  .withColumnRenamed("_1", "count")
  .withColumnRenamed("_2", "randomData")
  .as[FlightMetadata]

val flights2 = flights
  .joinWith(flightsMeta,
    flights.col("count") === flightsMeta.col("count"))
```

Now you will notice taht we end up with a Dataset of a sort of key value pair, where each row represents a Flight and the Flight Metadata. We can of course query these as a Dataset or a DataFrame with complex types.

```
flights2.selectExpr("_1.DEST_COUNTRY_NAME")
```

We can collect them just as we did before.

```
flights2.take(2)
```

Of course a "regular" join would work quite well too although we'll notice in this case that we end up with a DataFrame (and thus lose our JVM type information).

```
val flights2 = flights.join(flightsMeta, Seq("count"))
```

We can, of course, define another Dataset in order to gain this back. Now it's also important to note that there are no problems joining a DataFrame and a Dataset, we will end up with the same result.

```
val flights2 = flights.join(flightsMeta.toDF(), Seq("count"))
```

Grouping and Aggregations

Grouping and aggregations follow the same fundamental standards that we saw in the previous aggregation chapter, so `groupBy` `rollup` and `cube` still apply but these return DataFrames instead of datasets (you lose type information).

```
s"${sc.uiWebUrl.get}/api/v1/applications/${sc.applicationId}"
```

```
flights.groupBy("DEST_COUNTRY_NAME").count()
```

This often is not too big of a deal but if you want to keep type information around there are other groupings and aggregations that you can perform. An excellent example is the `groupByKey` method. This will allow you to group by a specific key in the Dataset and get a typed Dataset in return. This function however doesn't accept a specific column name but rather a function. This allows you to specific more sophisticated grouping functions that are much more akin to something

```
flights.groupByKey(x => x.DEST_COUNTRY_NAME).count()
```

Now although this provides flexibility, it's a tradeoff because now we are introducing JVM types as well as functions that cannot be optimized by Spark. This means that you will see a performance difference and we can see this once we inspect the explain plan. Belo we can see that we are effectivelly appending a new column to the DataFrame (the result of our function) and then performing the grouping on that.

```
flights.groupByKey(x => x.DEST_COUNTRY_NAME).count().explain
```

However this doesn't just apply to standard functions. We can now operate on the Key Value Dataset with functions that will manipulate the groupings as raw objects.

```
def grpSum(countryName:String, values: Iterator[Flight]) = {
  values.dropWhile(_.count < 5).map(x => (countryName, x))
}
flights.groupByKey(x => x.DEST_COUNTRY_NAME).flatMapGroups(grpS
```

```
def grpSum2(f:Flight):Integer = {
  1
}
flights.groupByKey(x => x.DEST_COUNTRY_NAME).mapValues(grpSum2)

def sum2(left:Flight, right:Flight) = {
  Flight(left.DEST_COUNTRY_NAME, null, left.count + right.count
}
flights.groupByKey(x => x.DEST_COUNTRY_NAME).reduceGroups((l, r
```

it should be straightfoward enough to understand that this is a more expensive process than aggregating immediately after scanning, especially since it ends up in the same end result.

```
flights.groupBy("DEST_COUNTRY_NAME").count().explain
```

When to use Datasets

You might ponder, if I am going to pay a performance penalty when I use Datasets, why should I use Datasets at all?

There are several reasons that are worth considering when you use the Dataset API. One consideration is that operations that are invalid, say subtracting two String types, will fail at compilation time not at runtime because Datasets are strongly typed. If correctness and bulletproof code is your highest priority at the sacrifice of performance, this can be a great choice for you.

Another time you may want to use Datasets is when you would like to reuse a variety of transformations of entire rows between single node workloads and Spark workloads. If you have some experience with Scala, you may notice that Spark's APIs reflect those of Native Scala Sequence Types, but in a distributed fashion. If you define all of your data and transformations as accepting case classes it is trivial to reuse them for both distributed and local workloads. Additionally when you collect your DataFrames to local disk they will be of the correct class and type, sometimes making further manipulation easier.

It's also worth considering that you can use both DataFrames and Datasets, using whatever is most convenient for you at the time. For instance one common pattern one of the authors uses is to write their core ETL workflow in DataFrames and then when finally collecting some data to the driver, creating a Dataset in order to do so.

```
case class Transaction(customerId: BigInt, amount: Integer, uni

case class Receipt(customerId: BigInt, totalCost: Double)

val localTransactions = Seq(
  Transaction(1, 5, 5.5, 37),
  Transaction(1, 10, 8.24, 67),
  Transaction(1, 1, 3.5, 22)
)
val SparkTransactions = localTransactions.toDF().as[Transactior

def isBigTransaction(transaction: Transaction) = {
```

```
  (transaction.amount * transaction.unitCost) > 15
}
```

Now that we defined our filter function, we can reuse it with ease.

```
localTransactions.filter(isBigTransaction(_))
SparkTransactions.filter(isBigTransaction(_))
```

Also, when we go to collect our data, say for more local manipulation, you will be able to get that as a sequence or array of that specific data type, not of a Spark row. This, just as operating on the case classes you define, can help you reuse code and logic in both distributed and non-distributed settings.

A recommended approach if you don't have significant logical that requires you to manipulate raw JVM objects is to perform all of your manipulations inside of Spark's DataFrames and finally collecting the final dataset as a `Dataset` that can fit on a local machine. This allows you to manipulate the results using strong typing.

Chapter 10. Low Level API Overview

The Low Level APIs

In the previous section we presented Spark's Structured APIs which are what most users should be using regularly to manipulate their data. There are times where this high level manipulation will not fit the business or engineering problem you are trying to solve. In those cases you may need to use Spark's lower level APIs specifically the Resilient Distributed Dataset (RDD), the SparkContext, and shared variables like accumulators and broadcast variables. These lower level APIs should be used for two core reasons:

1. If you need some functionality that you cannot find in the higher level APIs. For the most part this case should be the exception.

2. You need to maintain some legacy codebase that runs on RDDs.

While those are the reasons you should *use* these lower level tools, it is well worth *understanding* these tools because all Spark workloads compile now to this fundamental primitives. When you're calling a DataFrame transformation - it actually just becomes a set of RDD transformations. It can be useful to understand how these parts of Spark work in order to debug and troubleshoot your jobs.

This part of the book will introduce these tools and teach you how to leverage them for your work.

When to use the low level APIs?

Warning

If you are brand new to Spark, this is not the place to start. Start with the Structured APIs, you'll be more productive more quickly!

If you are an advanced developer hoping to get the most out of Spark, we still recommend focusing on the Structured APIs. However there are sometimes when you may want to "drop down" to some of the lower level tools in order to complete your task. These tools give you more fine-grained control at the expense of preventing you from shooting yourself in the foot. You may need to drop down to these APIs in order to use some legacy code, implement some custom partitioner, leverage a Broadcast variable or an Accumulator.

The SparkConf

The SparkConf manages all of the configurations for our environment. We create one via the import below.

```
import org.apache.spark.SparkConf

val myConf = new SparkConf().setAppName("My Application")
```

The SparkContext

A SparkContext represents the connection to a Spark cluster, and can be used to create RDDs, accumulators and broadcast variables on that cluster.

Prior to the consolidation of the SparkSession, the entrance point to executing Spark code that we used in previous chapters, Spark had two different contexts. Spark had a `SparkContext` and a `SQLContext`. The former focused on more fine grained control of Spark's central abstractions while the latter focused on the higher level tools like Spark SQL. The creators of Spark, in the version two of Spark, combined the two APIs into the centralized SparkSession that we have today. With that being said, both of these APIs can still be found in Spark today. We access both of them through the SparkSession variable. It is important to note that you should never need to use the SQLContext and rarely need to use the SparkContext. Here's how we access it.

```
spark.sparkContext
```

It is also of note that we can create the SparkContext if we need to. However because of the variety of environments your Spark workloads may run in, it is worth creating the SparkContext in the most general way. The way to do this is with the getOrCreate method.

```
import org.apache.spark.SparkContext

val sc = SparkContext.getOrCreate()
```

Resilient Distributed Datasets

Resilient Distributed Datasets (RDDs) are Spark's oldest and lowest level abstraction made available to users. They were the primary API in the 1.X Series and are still available in 2.X, but much less commonly used. An important fact to note, however, is that virtually all Spark code you run, where DataFrames or Datasets, "compiles" down to an RDD. While many users forego RDDs because virtually all functionality they provide is available in Datasets and DataFrames, users can still use RDDs. A *Resilient Distributed Dataset (RDD)* represents an immutable, partitioned collection of elements that can be operated on in parallel.

Broadcast Variables

Broadcast variables are immutable constants that Spark can replicate across every node in the cluster from the driver node. The use case for doing this would be to replicate some non-trivialy sized constant (like a look up table) around the cluster such that Spark does not have to serialize it in a function to every node itself. This is commonly referred to as a Map-Side Join and can provide immense speed ups when used correctly. We will touch on the implementation and use cases in the Distributed Variables Chapter.

Accumulators

Accumulators, in a sense, are the opposite of a Broadcast Variable. Instead of replicating an immutable variable to all the nodes in the cluster, Accumulators create a mutable variable that each executor can update accordingly. This allows you to update a raw variable from each partition in the dataset in a safe way while even visualizing the results along the way in the Spark UI. We will touch on the implementation and use cases in the Distributed Variables Chapter.

Chapter 11. Basic RDD Operations

RDD Overview

Resilient Distributed Datasets (RDDs) are Spark's oldest and lowest level abstraction made available to users. They were the primary API in the 1.X Series and are still available in 2.X, but are not commonly used by end users. An important fact to note, however, is that virtually all Spark code you run, where DataFrames or Datasets, compiles down to an RDD. The Spark UI, mentioned in later chapters, also describes things in terms of RDDs and therefore it behooves users to have at least a basic understanding of what an RDD is and how to use it. While many users forego RDDs because virtually all functionality they provide is available in Datasets and RDDs, users can still use RDDs if they are handling legacy code. A Resilient Distributed Dataset (RDD), the basic abstraction in Spark, represents an immutable, partitioned collection of elements that can be operated on in parallel.

RDDs give the user complete control because every row in an RDD is a just a Java object. Therefore RDDs do not need to have a Schema defined, or frankly anything defined. This gives the user great power but also makes manipulating data much more manual as a user has to "reinvent the wheel" for whatever task they are hoping to achieve. for example, users have to make sure that their Java objects have an efficient memory representation. Users will also have to implement their own filtering and mapping functions even to perform simple tasks like compute and average. Spark SQL obviates the need for the vast majority of this kind of work and does so in a highly optimized and efficient manner.

Internally, each RDD is characterized by five main properties.

- A list of partitions.
- A function for computing each split.
- A list of dependencies on other RDDs.
- Optionally, a `Partitioner` for key-value RDDs (e.g., to say that the RDD

is hash-partitioned).

- Optionally, a list of preferred locations to compute each split on (e.g., block locations for an HDFS file).

note

The Partitioner is probably one of the core motivations for why you might want to use RDDs in your code. Specifying your own custom partitioner can give you significant performance and stability improvements if used correctly. These are discussed towards the end of the next Chapter when we introduce Key-Value Pair RDDs.

These properties determine all of Spark's ability to schedule and execute the user program. Different kinds of RDDs implement their own versions of each of the above properties allow you to define new data sources.

RDDs follow the exact same Spark programming paradigms that we discussed in earlier chapters. We define *transformations*, which evaluate lazily, and *actions*, which evaluate eagerly, to manipulate data in a distributed fashion. The transformations and actions that we defined previously apply conceptually to RDDs however in a much lower level interface. There is no concept of a "row" in RDDs, individual records are actually raw Java/Scala/Python objects and we manipulate those manually instead of tapping into the repository of functions that we have in the structured APIs. This chapter will show examples in Scala but the APIs are quite similar across languages and there are countless examples across the web.

The whole point of RDDs is they provide a way for users to gain more control of exactly how data is distributed and operated on upon the cluster.

Python vs Scala/Java

For Scala and Java, the performance is largely the same, the large costs are going to be incurred in manipulating the raw objects. Python however suffers greatly when you use RDDs. This is because each function is essentially a UDF where data and code must get serialized to the python process running with each executor. This causes stability problems and serious challenges. If you're going to write code using RDDs, you should definitely do it using Scala or Java.

Creating RDDs

From a Collection

To create an RDD from a list, we leverage the `parallelize` method on a SparkContext (within a SparkSession). This will turn a single node collection into a parallel collection. We can explicitly set the number of partitions that we would like to distribute this array (in this case that number is two).

```
val myCollection = "Spark The Definitive Guide : Big Data Proce
val words = spark.sparkContext.parallelize(myCollection, 2)
```

An additional feature is that we can then name this RDD to show up in the Spark UI according to a given name.

```
words.setName("myWords")

words.name
```

From Data Sources

While you can create RDDs from data sources or text files. It's often preferable to use the Data Source APIs. RDDs do not have a notion of "Data Source APIs" like DataFrames do, they primarily define their dependency structures and lists of partitions. If you are reading from any sort of Structured or Semi-Structured data source, we recommend using the Data Source API. This is assuming that a data source connector already exists for your data source. You can also create RDDs from plain-text files (either line-by-line or as a complete file) is quite simple.

To do this we use the `SparkContext` that we defined previously and specify that we would like to read a file line by line.

```
sc.textFile("/some/path/withTextFiles")
```

Or alternatively that each partition should consist of an entire text file. The use case here would be where each file is a file that consists of a large JSON object or some document that you will operate on as an individual.

```
sc.wholeTextFiles("/some/path/withTextFiles")
```

Manipulating RDDs

We manipulate RDDs in much the same way that we manipulate DataFrames. As mentioned, the core difference being that we manipulate raw Java or Scala objects instead of Spark types. There are also a dearth of "helper" methods or functions that we can draw upon to simple calculations. We must define filter functions, map functions, and other manipulations manually instead of leveraging those that already exist like we do in the Structured APIs.

Let's use the simple RDD (myCollection) we created previously to define some more details.

Transformations

Let's walk through some of the transformations on RDDs. For the most part, these will mirror functionality that we find in the Structured APIs. Just as we do with DataFrames and Datasets, we specify *transformations* on one RDD to create another. In doing so, we define a RDD as a dependency to another along with some manipulation of the data contained in that RDD.

Distinct

a distinct method call on an RDD will remove duplicates from the RDD.

```
words.distinct().count()
```

Filter

Filtering is equivalent to creating a SQL like `where` clase. We look through our records in our RDD and see which ones match some predicate function. This function just needs to return a boolean type to be used as a filter function. The input should be whatever our given row is. Let's filter our RDD to only keep the words that start with the letter "S".

```
def startsWithS(individual:String) = {
  individual.startsWith("S")
}
```

Now that we defined the function, let's filter the data. This should feel quite familiar if you read the Dataset Chapter in the Structured APIs section because we simply use a function that operates record by record in the RDD. The function is defined to work on each record in the RDD individually.

```
val onlyS = words.filter(word => startsWithS(word))
```

We can see our results with a simple action.

```
onlyS.collect()
```

We can see, like the Dataset API, that this returns native types. That is because we never coerce our data into type Row, nor do we need to convert the data after collecting it. This means that we lose efficiency by operating on native types but gain some flexibility.

Map

Mapping is again the same operation that you can read about in the Datasets Chapter. We specify a function that returns the value that we want, given the correct input. We then apply that record by record. Let's perform something similar to what we did above. Map our current word, to the word, its starting letter, and whether or not it starts with "S".

You will notice that in this instance we define our functions completely inline using the relevant lambda syntax.

```
val words2 = words.map(word => (word, word(0), word.startsWith
```

We can subsequently filter on this by selecting the relevant boolean value in a new function

```
words2.filter(record => record._3).take(5)
```

FlatMap

FlatMap provides a simple extension of the map function we see above. Sometimes each current row should return multiple rows instead. For example we might want to take our set of words and flatmap it into a set of characters. Since each word has multiple characters, we should use flatmap to expand it. Flatmap requires that the ouput of the map function be an iterable that can be expanded.

```
val characters = words.flatMap(word => word.toSeq)
characters.take(5)
```

Sorting

To sort an RDD you must use the `sortBy` method and just like any other RDD operation we do this by specifying a function to extract a value from the objects in our RDDs and then sorting based on that. For example, let's sort by word length from longest to shortest.

```
words.sortBy(word => word.length() * -1).take(2)
```

Random Splits

We can also randomly split an RDD into an Array of RDDs through the randomSplit method which accepts an Array of weights and a random seed.

```
val fiftyFiftySplit = words.randomSplit(Array[Double](0.5, 0.5)
```

This returns an array of RDDs that we can manipulate individually.

Actions

Just as we do with DataFrames and Datasets, we specify *actions* to kick off our specified transformations. This action will either write to an external Data source or collect some value to the driver.

Reduce

Reduce allows us to specify a function to “reduce” an RDD of any kind of value to one value. For instance, given a set of numbers, we can reduce this to their sum in this way.

```
sc.parallelize(1 to 20).reduce(_ + _)
```

We can also use this to get something like the longest word in our set of words that we defined above. The key is just to define the correct function.

```
def wordLengthReducer(leftWord:String, rightWord:String): Strir
  if (leftWord.length >= rightWord.length)
    return leftWord
  else
    return rightWord
}

words.reduce(wordLengthReducer)
```

Count

This method is fairly self explanatory, we could the number of rows in the RDD.

```
words.count()
```

countApprox

While the return signature for this type is a bit strange, it's quite sophisticated. This is an approximation of the above count that must execute within a timeout (and may return incomplete results if it exceeds the timeout).

The confidence is the probability that the error bounds of the result will contain the true value. That is, if countApprox were called repeatedly with confidence 0.9, we would expect 90% of the results to contain the true count. The confidence must be in the range [0,1] or an exception will be thrown.

```
val confidence = 0.95
val timeoutMilliseconds = 400
words.countApprox(timeoutMilliseconds, confidence)
```

countApproxDistinct

There are two implementations of this, both based on streamlib's implementation of "HyperLogLog in Practice: Algorithmic Engineering of a State of The Art Cardinality Estimation Algorithm".

In the first implementation, the argument we pass into the function is the relative accuracy. Smaller values create counters that require more space. The value must be greater than 0.000017.

```
words.countApproxDistinct(0.05)
```

The other implementation allows you a bit more control, you specify the relative accuracy based on two parameters one for "regular" data and another

for a sparse representation.

The two arguments are “p” and “sp” where p is precision and “sp” is sparse precision. The relative accuracy is approximately `1.054 / sqrt(2^p)`. Setting a nonzero (sp > p) triggers sparse representation of registers, which may reduce the memory consumption and increase accuracy when the cardinality is small. Both values are integers where

```
words.countApproxDistinct(4, 10)
```

countByValue

This method counts the number of values in a given RDD. However it does so by finally loading the result set into the memory of the driver. This method should only be used if the resulting map is expected to be small because the whole thing is loaded into the driver’s memory. Thus, this method only makes sense in a scenario where either the total number of rows is low or the number of distinct items is low.

```
words.countByValue()
```

countByValueApprox

This performs the same as the previous function but does so as an approximation. This must execute within the specified timeout (first parameter) (and may return incomplete results if it exceeds the timeout).

The confidence is the probability that the error bounds of the result will contain the true value. That is, if countApprox were called repeatedly with confidence 0.9, we would expect 90% of the results to contain the true count. The confidence must be in the range [0,1] or an exception will be thrown.

```
words.countByValueApprox(1000, 0.95)
```

First

The first method returns the first value in the dataset.

```
words.first()
```

Max and Min

Max and min return the maximum values and minimum values respectively.

```
sc.parallelize(1 to 20).max()
sc.parallelize(1 to 20).min()
```

Take

Take and its derivative methods take a number of values from our RDD. This works by first scanning one partition, and use the results from that partition to estimate the number of additional partitions needed to satisfy the limit.

There are various variations on this function to like `takeOrdered`, `takeSample`, and `top`. We can use `takeSample` to specify a fixed-size random sample from our RDD. We can specify whether or not this should be done withReplacement, the number of values, as well as the random seed. Top is effectively the opposite of `takeOrdered` and selects the top values according to the implicit ordering.

```
words.take(5)
words.takeOrdered(5)
words.top(5)

val withReplacement = true
val numberToTake = 6
val randomSeed = 100L

words.takeSample(withReplacement, numberToTake, randomSeed)
```

Saving Files

Saving files means writing to plain-text files. With RDDs, you cannot actually "save" to a data source in the conventional sense. You have to iterate over the partitions in order to save the contents of each partition to some external database.

saveAsTextFile

If order to save to a text file however we just specify a path and optionally a compression codec.

```
%fs rm -r file:/tmp/bookTitle*

words.saveAsTextFile("file:/tmp/bookTitle")
```

To set a compression codec, we have to import the proper codec from Hadoop. These can be found in the `org.apache.hadoop.io.compress` library.

```
import org.apache.hadoop.io.compress.BZip2Codec
words.saveAsTextFile("file:/tmp/bookTitleCompressed", classOf[B
```

SequenceFiles

Spark originally grew out of the Hadoop Ecosystem so it has a fairly tight integration with a variety of Hadoop tools. A SequenceFile is a flat file consisting of binary key/value pairs. It is extensively used in MapReduce as input/output formats.

Spark can write to SequenceFiles using the `saveAsObjectFile` method or by writing explicitly key value pairs as described in the next chapter.

```
words.saveAsObjectFile("file:/tmp/my/sequenceFilePath")
```

Hadoop Files

There are a variety of different hadoop file formats that you can save two. These allow you to specify classes, output formats, hadoop configurations, and compression schemes. Please see Hadoop: The Definitive Guide for information on these formats. These are largely irrelevant except if you're working deeply in the hadoop ecosystem or with some legacy mapreduce jobs.

Caching

The same principles for caching DataFrames and Datasets. We can either cache or persist an RDD. Cache and persist by default only cache data in memory.

```
words.cache()
```

We can specify a storage level as any of the storage levels in the singleton object: `org.apache.spark.storage.StorageLevel` which are combinations of memory only, disk only, and separately, off heap.

We can subsequently query for this storage level.

```
words.getStorageLevel
```

Interoperating between DataFrames, Datasets, and RDDs

There may be times when you need to drop down to a RDD in order to perform some very specific sampling, operation, or specific MLlib algorithm not available in the DataFrame API. Doing this is simple, simply leverage the RDD property on any structured data types. You'll notice that if we do a conversion from a Dataset to an RDD, you'll get the appropriate native type back.

```
spark.range(10).rdd
```

However if we convert from a DataFrame to a RDD, we will get an RDD of type `Row`.

```
spark.range(10).toDF().rdd
```

In order to operate on this data, you will have to convert this `Row` object to the correct data type or extract values out of it like you see below.

```
spark.range(10).toDF().rdd.map(rowObject => rowObject.getLong(0
```

This same methodology allows us to create a DataFrame or Dataset from a RDD. All we have to do is call the `toDF` method on the RDD.

```
spark.range(10).rdd.toDF()
```

```
%python
```

```
spark.range(10).rdd.toDF()
```

When to use RDDs?

In general RDDs should not be manually created by users unless you have a very, very specific reason for doing so. They are a much lower-level API that provides a lot of power but also lacks a lot of the optimizations that are available in the Structured APIs. For the vast majority of use cases, DataFrames will be more efficient, more stable, and more expressive that RDDs.

The most likely candidate for why you need to use RDDs is because you need fine grained control of the physical distribution of data.

Performance Considerations: Scala vs Python

Running Python RDDs equates to running Python UDFs row by row. Just as we saw in Chapter 3 of Part 2. We serialize the data to the python process, operate on it in Python, then serialize it back to the JVM. This causes an immense overhead for Python RDD manipulations. While many people ran production code with them in the past, we recommend building on the Structured APIs and only dropping down to RDDs if absolutely necessary. If you do drop down to RDDs, do so in Scala or Java and not Python.

RDD of Case Class VS Dataset

We noticed this question on the web and found it to be an interesting question. The difference between RDDs of Case Classes and Datasets is that Datasets can still take advantage of the wealth of functions that the Structured APIs have to offer. With Datasets, we do not have to choose between only operating on JVM types or on Spark types, we can choose whatever is either easiest to do or most flexible. We get the both of best worlds.

Chapter 12. Advanced RDDs Operations

The previous chapter explored RDDs, which are Spark's most stable API. This chapter will include relevant examples and point to the documentation for others. There is a wealth of information available about RDDs across the web and because the APIs have not changed for years, we will focus on the core concepts as opposed to just API examples.

Advanced RDD operations revolve around three main concepts:

- Advanced single RDD Partition Level Operations
- Aggregations and Key-Value RDDs
- Custom Partitioning
- RDD Joins

Advanced “Single RDD” Operations

Pipe RDDs to System Commands

The `pipe` method is probably one of the more interesting methods that Spark has. It allows you to return an RDD created by piping elements to a forked external process. The resulting RDD is computed by executing the given process once per partition. All elements of each input partition are written to a process's stdin as lines of input separated by a newline. The resulting partition consists of the process's stdout output, with each line of stdout resulting in one element of the output partition. A process is invoked even for empty partitions.

The print behavior can be customized by providing two functions.

```
%scala

val myCollection = "Spark The Definitive Guide : Big Data Proce
val words = spark.sparkContext.parallelize(myCollection, 2)
```

mapPartitions

You may notice that the return signature of a `map` function on an RDD is actually `MapPartitionsRDD`. That is because `map` is just a row-wise alias for `mapPartitions` which allows you to map an individual partition (represented as an iterator). That's because physically on the cluster we operate on each partition individually (and not a specific row). A simple example creates the value "1" for every partition in our data and the sum of the following expression will count the number of Partitions we have.

```
words.mapPartitions(part => Iterator[Int](1)).sum()
```

This also allows you to perform partition level operations. The value of this would be that you could pipe this through some custom machine learning algorithm and train an individual model for that given portion of the dataset.

Other functions like mapPartitions include mapPartitionsWithIndex. With this you specify a function that accepts an index (within the partition) and an iterator that goes through all items within the partition.

```
def indexedFunc(partitionIndex:Int, withinPartIterator: Iterat
  withinPartIterator.toList.map(value => s"Partition: $partiti
}
words.mapPartitionsWithIndex(indexedFunc).collect()
```

foreachPartition

While map partitions will result in a return value, `foreachPartition` will simply iterate over all the partitions of the data except the function that we pass into `foreachPartition` is not expected to have a return value. This makes it great for doing something with each partition like writing it out to a database. In fact, this is how many data source connectors are written. We can create our own text file source if we want by specifying outputs to the temp directory with a random id.

```
words.foreachPartition { iter =>
  import java.io._
  import scala.util.Random
  val randomFileName = new Random().nextInt()
  val pw = new PrintWriter(new File(s"/tmp/random-file-${randor
  while (iter.hasNext) {
      pw.write(iter.next())
  }

  pw.close()
}
```

You'll find these two files if you scan your `/tmp` directory.

glom

Glom is an interesting function. Rather than trying to break apart data, it's a way of gather data back up. Glom takes every partition in your dataset and turns it into an array of the values in that partition. For example, if we create a RDD with two partitions and two values, we can then glom the RDD to see what is in each partition. In this case we have our two words in a separate partition!

```
sc.parallelize(Seq("Hello", "World"), 2).glom().collect()
```

Key Value Basics (Key-Value RDDs)

There are many methods that require us to do something `byKey` whenever you see this in the API, that means you have to create a `PairRDD` in order to perform this operation. The easiest is to just map over your current RDD to a key-value structure.

```
words
  .map(word => (word.toLowerCase, 1))
```

keyBy

Creating keys from your data is relatively straightforward with a map but Spark RDDs have a convenience function to key an RDD by a given function that we pass in. In this case we are keying by the first letter in the word. This will keep the current value as the value for that row.

```
words
  .keyBy(word => word.toLowerCase.toSeq(0))
```

Mapping over Values

We can map over the values, ignoring the keys.

```
words
  .map(word => (word.toLowerCase.toSeq(0), word))
  .mapValues(word => word.toUpperCase)
  .collect()
```

Or flatMap over the values if we hope to expand the number of rows.

```
words
  .map(word => (word.toLowerCase.toSeq(0), word))
  .flatMapValues(word => word.toUpperCase)
  .collect()
```

Extracting Keys and Values

We can also extract individual RDDs of the keys or values with the below methods.

```
words
  .map(word => (word.toLowerCase.toSeq(0), word))
  .keys
  .collect()

words
  .map(word => (word.toLowerCase.toSeq(0), word))
  .values
  .collect()
```

Lookup

You can look up the value in a key-pair RDD as well.

```
words
  .map(word => (word.toLowerCase, 1))
  .lookup("spark")
```

Aggregations

Aggregations can be performed on plain RDDs or on PairRDDs, depending on the method that you are using. Let's leverage some of our datasets to demonstrate this.

```
// we created words at the beginning of this chapter
val chars = words
  .flatMap(word => word.toLowerCase.toSeq)

val KVcharacters = chars
  .map(letter => (letter, 1))

def maxFunc(left:Int, right:Int) = math.max(left, right)
def addFunc(left:Int, right:Int) = left + right
val nums = sc.parallelize(1 to 30, 5)
```

Once we have this we can do something like `countByKey` which will count the items per each key.

countByKey

Count the number of elements for each key, collecting the results to a local Map. We can also do this with an approximation which allows us to specify a timeout and confidence.

```
KVcharacters.countByKey()
val timeout = 1000L //milliseconds
val confidence = 0.95

KVcharacters.countByKeyApprox(timeout, confidence)
```

Understanding Aggregation Implementations

There are several ways to create your Key-Value PairRDDs however the implementation is actually quite important for job stability. Let's compare the two fundamental choices, groupBy and reduce. We'll do these in the context of a key, but the same basic principles apply to the `groupBy` and `reduce` methods.

groupByKey

Looking at the API documentation, you might think `groupByKey` with a map over each grouping is the best way to sum up the counts for each key.

```
KVcharacters
  .groupByKey()
  .map(row => (row._1, row._2.reduce(addFunc)))
  .collect()
```

This is the incorrect way to approach this problem. The issue here is that for the grouping, Spark has to hold all key-value pairs for any given key in memory. If a key has too many values, it can result in an `OutOfMemoryError`. This obviously doesn't cause an issue with our current dataset but can cause serious problems at scale.

There are obviously use cases for this grouping and given properly partitioned data, you can perform it in a stable manner.

reduceByKey

Since we are performing a simple count, a much more stable approach is to perform the same flatMap, however then we just perform a map to map each letter instance to the number one, then perform a reduceByKey with a summation in order to collect back the array. This implementation is much more stable because the reduce happens inside of each partition and doesn't

have to put everything in memory. Additionally, there is no incurred shuffle during this operation, everything happens at each worker individually. This greatly enhances the speed at which we can perform the operation as well as the stability of the operation.

```
KVcharacters.reduceByKey(addFunc).collect()
```

This method returns an RDD of a group and an array of values. Each group consists of a key and a sequence of elements mapping to that key. The ordering of elements within each group is not guaranteed, and may even differ each time the resulting RDD is evaluated. While this operation is completely valid, it may be *very* inefficient based on the end result computation that you'd like to perform.

aggregate

First we specify a null / start value, then we specify two functions. The first will aggregate within partitions, the second will aggregate across partitions. The start value will be used at both aggregation levels.

```
nums.aggregate(0)(maxFunc, addFunc)
```

`treeAggregate` follows the same pattern except that it has a multi-level tree pattern implementation and allows us to specify the depth of the tree that we would like to use. The initial value is not used in the across partition aggregation as well.

```
nums.treeAggregate(0)(maxFunc, addFunc)
```

AggregateByKey

This function does the same as above but instead of doing it partition by partition, it does it by key. The start value and functions follow the same properties.

```
KVcharacters.aggregateByKey(0)(addFunc, maxFunc).collect()
```

CombineByKey

Instead of specifying a n aggregation function, we specify a combiner. This combiner operates on a given key and merges the values according to some function. It then goes to merge the different outputs of the combiners to give us our result. We can specify the number of output partitions as well as a custom output partitioner as well.

```
val valToCombiner = (value:Int) => List(value)
val mergeValuesFunc = (vals:List[Int], valToAppend:Int) => val
val mergeCombinerFunc = (vals1:List[Int], vals2:List[Int]) =>
// not we define these as function variables
val outputPartitions = 6

KVcharacters
  .combineByKey(
    valToCombiner,
    mergeValuesFunc,
    mergeCombinerFunc,
    outputPartitions)
  .collect()
```

foldByKey

Merge the values for each key using an associative function and a neutral “zero value” which may be added to the result an arbitrary number of times, and must not change the result (e.g., Nil for list concatenation, 0 for addition, or 1 for multiplication.).

```
KVcharacters
  .foldByKey(0)(addFunc)
  .collect()
```

sampleByKey

There are two ways to sample an RDD by a set of keys. First we can do it via an approximation or exactly. Both operations can do so with or without replacement, as well as sampling by a Franction by a given key. This is done via simple random sampling with one pass over the RDD, to produce a sample of size that's approximately equal to the sum of `math.ceil(numItems * samplingRate)` over all key values.

```
val distinctChars = words
  .flatMap(word => word.toLowerCase.toSeq)
  .distinct
  .collect()
import scala.util.Random
val sampleMap = distinctChars.map(c => (c, new Random().nextDou

words
  .map(word => (word.toLowerCase.toSeq(0), word))
  .sampleByKey(true, sampleMap, 6L)
  .collect()
```

This method differs from sampleByKey in that we make additional passes over the RDD to create a sample size that's exactly equal to the sum of math.ceil(numItems * samplingRate) over all key values with a 99.99% confidence. When sampling without replacement, we need one additional pass over the RDD to guarantee sample size; when sampling with replacement, we need two additional passes.

```
words
  .map(word => (word.toLowerCase.toSeq(0), word))
  .sampleByKeyExact(true, sampleMap, 6L)
  .collect()
```

CoGroups

CoGroups allow you as a user to group together up to three key-value RDDs together. When doing this we can also specify a number of output partitions or a custom Partitioner.

```
import scala.util.Random

val distinctChars = words
  .flatMap(word => word.toLowerCase.toSeq)
  .distinct

val charRDD = distinctChars.map(c => (c, new Random().nextDoubl
val charRDD2 = distinctChars.map(c => (c, new Random().nextDoub
val charRDD3 = distinctChars.map(c => (c, new Random().nextDoub
charRDD.cogroup(charRDD2, charRDD3).take(5)
```

The result is a group with our key on one side and all of the relevant values on the other side.

Joins

RDDs have much the same joins as we saw in the Structured API although naturally they are a bit more manual to perform. They all follow the same basic format: the two RDDs we would like to join and optionally either the number of output partitions or the customer Partitioner that they should output to.

Inner Join

We'll demonstrate an inner join now.

```
val keyedChars = sc.parallelize(distinctChars.map(c => (c, new

val outputPartitions = 10

KVcharacters.join(keyedChars).count()
KVcharacters.join(keyedChars, outputPartitions).count()
```

We won't provide an example for the other joins but they all follow the same function signature. You can learn about these join types in the Structured API chapter.

- `fullOuterJoin`
- `leftOuterJoin`
- `rightOuterJoin`
- `cartesian` (this, again, is very dangerous! It does not accept a join key and can have a massive output.)

zips

The final type of join isn't really a join at all, but it does combine two RDDs so it's worth labelling as a join. Zip allows you to "zip" together two RDDs assuming they have the same length. This creates a `PairRDD`. The two RDDs must have the same number of partitions as well as the same number of elements.

```
val numRange = sc.parallelize(0 to 9, 2)
words.zip(numRange).collect()
```

Controlling Partitions

coalesce

Coalesce effectivelly collapses partitions on the same worker in order to avoid a shuffle of the data when repartitioning. For instance our words RDD is currently two partitions, we can collapse that to one partition with coalesce without bringing about a shuffle of the data.

```
words.coalesce(1)
```

Repartition

Repartition allows us to repartition our data up or down but performs a shuffle across nodes in the process. Increasing the number of partitions can increase the level of parallelism when operating in map and filter type operations.

```
words.repartition(10)
```

repartitionAndSortWithinPartitions

Custom Partitioning

To perform custom partitioning you need to implement your own own class that extends `Partitioner`. You only need to do this when you have lots of domain knowledge about your problem space, if you're just looking to partition on a value, it's worth just doing it in the DataFrame API. The canonical use case for this operation is PageRank where we seek to control the layout of the data on the cluster and avoid shuffles. In our shopping dataset, this might mean partitioning by each customerId.

```
val df = spark.read
  .option("header", "true")
  .option("inferSchema", "true")
  .csv("dbfs:/mnt/defg/streaming/*.csv")

val rdd = df.coalesce(10).rdd
```

Spark has two built in Partitioners, a `HashPartitioner` for discrete values and a `RangePartitioner`. These two work for discrete values and continuous values respectively. Spark's Structured APIs will already leverage these although we can use the same thing in RDDs.

```
rdd.map(r => r(6)).take(5).foreach(println)

val keyedRDD = rdd.keyBy(row => row(6).asInstanceOf[Double])

import org.apache.spark.{HashPartitioner}

keyedRDD
  .partitionBy(new HashPartitioner(10))
```

However at times we might have more information, for example say that the first two digits of our CustomerID dictate something like original purchase location. We could partition by these values explicitly using something like a HashPartitioner like what we saw above but we could also do the same by implementing our own customer partitioner.

```
import org.apache.spark.{Partitioner}
```

```
class DomainPartitioner extends Partitioner {
 def numPartitions = 20
 def getPartition(key: Any): Int = {
   (key.asInstanceOf[Double] / 1000).toInt
 }
}

val res = keyedRDD
  .partitionBy(new DomainPartitioner)
```

Now we can see how many values are in each partition by gloming each partition and counting the values. This won't work for big data because it'll be too many values in each partition but it does help with the explanation! This also shows us that some partitions are skewed. Handling skew will be a topic in the optimization section.

```
res
  .glom()
  .collect()
.map(arr => {
  if (arr.length > 0) {
      arr.map(_._2(6)).toSet.toSeq.length
  }
})
```

When we have a custom partitioner, we can do all kinds of cool things!

repartitionAndSortWithinPartitions

This will repartition our data and sort it according to the keys in each partition.

```
keyedRDD.repartitionAndSortWithinPartitions(new DomainPartitior
```

Serialization

The last advanced topic that is worth talking about is the issue of Kryo Serialization. Any object that you hope to parallelize (or function) must be serializable.

```
class SomeClass extends Serializable {
  var someValue = 0
  def setSomeValue(i:Int) = {
    someValue = i
    this
  }
}

sc.parallelize(1 to 10).map(num => new SomeClass().setSomeValue
```

The default serialization is actually quite slow. To speed things up, you need to register your classes with Kryo propr to using them.

Chapter 13. Distributed Variables

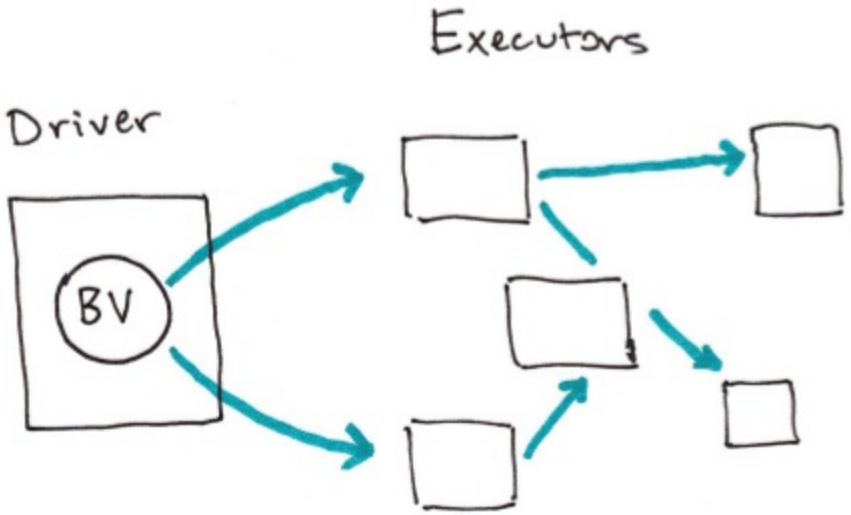
Chapter Overview

Spark, in addition to the RDD interface, maintains two level level variable types that you can leverage to make your processing more efficient. These are broadcast variables and accumulator variables.

These variables serve two opposite purposes.

Broadcast Variables

Broadcast variables intend to share an immutable value efficiently around the cluster. This might be to share some immutable value and use it around the cluster without having to serialize it in a function to every node. We demonstrate this tool in the following figure.



Now you might

Broadcast variables are shared, immutable variables that is cached on every machine in the cluster instead of serialized with every single task. A use case might be a look up table accessed by an RDD. Serializing this lookup table with every task is wasteful because the driver must perform all of this work. You can achieve the same result with a broadcast variable.

For example, let's imagine that we have a list of words or values.

```
%scala

val myCollection = "Spark The Definitive Guide : Big Data Proce
val words = spark.sparkContext.parallelize(myCollection, 2)

%python
```

```
my_collection = "Spark The Definitive Guide : Big Data Process
words = spark.sparkContext.parallelize(my_collection, 2)
```

And we would like to supplement these values with some information. Now this is technically a right outer join (if we thought in terms of SQL) but sometimes this can be a bit inefficient. Therefore we can take advantage of something that we call a Map-Side join, where Data is sent to each worker and Spark performs the join there instead of incurring an all-to-all communication.

Let's suppose that our values are sitting in a Map structure.

```
val supplementalData = Map(
  "Spark" -> 1000,
  "Definitive" -> 200,
  "Big" -> -300,
  "Simple" -> 100
)
```

We can broadcast this structure across Spark and reference it using `suppBroadcast`. This value is immutable and is lazily replicated across all nodes in the cluster when we trigger an action.

```
val suppBroadcast = spark.sparkContext.broadcast(supplementalDa
```

We reference this variable via the `value` method which will return the exact value that we had before. This method is accessible within serialized functions without having to serialize the data. This can save you a great deal of serialization and deserialization costs as Spark transfers data more efficiently around the cluster using broadcasts.

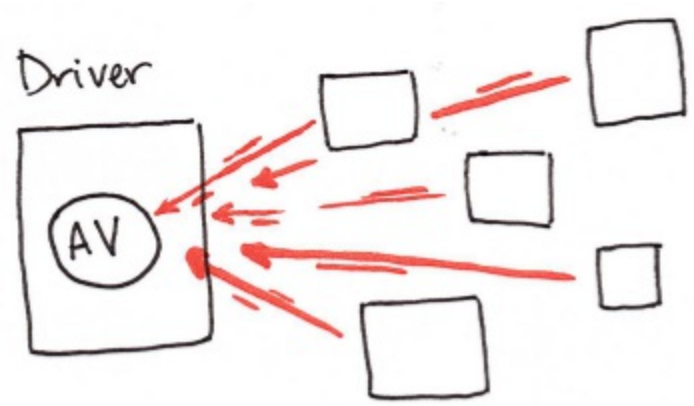
```
suppBroadcast.value
```

Now we could transform our RDD using this value. In this instance we will create a key-value pair according to the value we may have in the map. If we lack the value we will simple replace it with 0.

```
val suppWords = words.map(word => (word, suppBroadcast.value.ge

suppWords.sortBy(wordPair => wordPair._2).collect()
```

Accumulators

Accumulator variables on the other hand are a way of updating a value inside of a variety of transformations and propagating that value to the driver node at the end in an efficient and faul-tolerant way. We demonstrate accumulators in the following figure.



Accumulators provide a mutable variable that can be updated safely on a per row basis by a Spark cluster. These can be used for debugging purposes (say to track the values of a certain variable per partition in order to intelligently leverage it over time) or to create low level aggregation. Accumulators are variables that are only “added"”” to through an associative and commutative operation and can therefore be efficiently supported in parallel. They can be used to implement counters (as in MapReduce) or sums. Spark natively supports accumulators of numeric types, and programmers can add support for new types.

For accumulator updates performed inside *actions only*, Spark guarantees that each task’s update to the accumulator will only be applied once, i.e. restarted tasks will not update the value. In transformations, users should be aware of that each task’s update may be applied more than once if tasks or job stages are re-executed.

Accumulators do not change the lazy evaluation model of Spark. If they are being updated within an operation on an RDD, their value is only updated once

that RDD is computed as part of an action. Consequently, accumulator updates are not guaranteed to be executed when made within a lazy transformation like map().

Accumulators can be both named and unnamed. Named accumulators will display their running results in the Spark UI while unnamed ones will not.

Basic Example

Let's experiment by performing a custom aggregation on our Flight dataset. In this example, we will use the Dataset API as opposed to the RDD API, but the extension is quite similar.

```
case class Flight(DEST_COUNTRY_NAME: String, ORIGIN_COUNTRY_NAI
val flights = spark.read
  .parquet("/mnt/defg/chapter-1-data/parquet/2010-summary.parqu
  .as[Flight]
```

Now let's create an accumulator that will count the number of flights to or from China. While we could do this in a fairly straightfoward manner in SQL, many things may not be so straightfoward. Accumulators provide a programmatic way of allowing for us to do these sorts of counts. The following demonstrates creating an unnamed accumulator.

```
import org.apache.spark.util.LongAccumulator

val accUnnamed = new LongAccumulator
sc.register(accUnnamed)
```

However for our use case it is better to give the accumulator a name. There are two ways to do this, one short hand and one long hand. The simplest is just to use the `SparkContext`, equivalently we can instantiate the accumulator and register it with a name.

```
val accChina = new LongAccumulator

sc.register(accChina, "China")

val accChina2 = sc.longAccumulator("China")
```

We specify the name of the accumulator in the String value that we pass into the function, or as the second parameter into the `register` function. Named accumulators will display in the Spark UI, while unnamed ones will not.

The next step is to define the way we add to our accumulator. This is a fairly straight forward function.

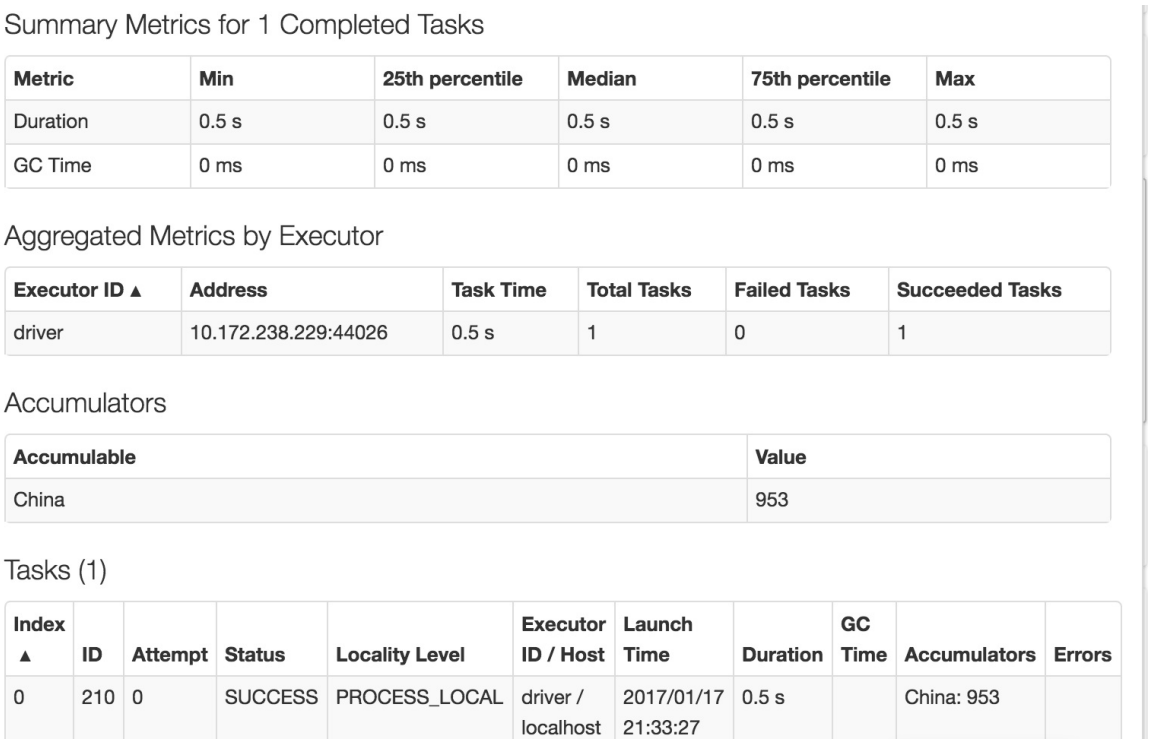
```
def accChinaFunc(flight_row: Flight) = {
  val destination = flight_row.DEST_COUNTRY_NAME
  val origin = flight_row.ORIGIN_COUNTRY_NAME
  if (destination == "China") {
    accChina.add(flight_row.count.toLong)
  }
  if (origin == "China") {
    accChina.add(flight_row.count.toLong)
  }
}
```

Now let's iterate over every row in our flights dataset via the `foreach` method. The reason for this is because `foreach` is an action, and the Spark can only provide guarantees that perform inside of actions.

The `foreach` method will run once for each row in the input DataFrame (assuming we did not filter it) and will run our function against each row. Incrementing the accumulator accordingly.

```
flights.foreach(flight_row => accChinaFunc(flight_row))
```

This will completely fairly quickly but if you navigate to the Spark UI, you can see the relevant value, on a per Executor level even before querying it programmatically.



Summary Metrics for 1 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	0.5 s	0.5 s	0.5 s	0.5 s	0.5 s
GC Time	0 ms	0 ms	0 ms	0 ms	0 ms

Aggregated Metrics by Executor

Executor ID ▲	Address	Task Time	Total Tasks	Failed Tasks	Succeeded Tasks
driver	10.172.238.229:44026	0.5 s	1	0	1

Accumulators

Accumulable	Value
China	953

Tasks (1)

Index ▲	ID	Attempt	Status	Locality Level	Executor ID / Host	Launch Time	Duration	GC Time	Accumulators	Errors
0	210	0	SUCCESS	PROCESS_LOCAL	driver / localhost	2017/01/17 21:33:27	0.5 s		China: 953	

Of course we can query it programmatically as well, to do this we use the `value` property.

```
accChina.value
```

Custom Accumulators

While Spark does provide some default accumulator types. Sometimes you may want to build your own custom accumulator. To do this you need to subclass the `AccumulatorV2` class. There are several abstract methods that need to be implemented, as we can see below. In this example we will only add values that are even to the accumulator, while this is again simplistic, it should show you how easy it is to build up your own accumulators.

```
import scala.collection.mutable.ArrayBuffer
val arr = ArrayBuffer[BigInt]()

import scala.collection.mutable.ArrayBuffer
import org.apache.spark.util.AccumulatorV2

class EvenAccumulator extends AccumulatorV2[BigInt, BigInt] {

  private var num:BigInt = 0

  def reset(): Unit = {
    this.num = 0
  }

  def add(intValue: BigInt): Unit = {
    if (intValue % 2 == 0) {
        this.num += intValue
    }
  }

  def merge(other: AccumulatorV2[BigInt,BigInt]): Unit = {
    this.num += other.value
  }

  def value():BigInt = {
    this.num
  }

  def copy(): AccumulatorV2[BigInt,BigInt] = {
    new EvenAccumulator
  }

  def isZero():Boolean = {
    this.num == 0
```

```
  }
}

val acc = new EvenAccumulator
val newAcc = sc.register(acc, "evenAcc")

acc.value

flights.foreach(flight_row => acc.add(flight_row.count))

acc.value
```

Chapter 14. Advanced Analytics and Machine Learning

Spark is an incredible tool for a variety of different use cases. Beyond large scale SQL analysis and Streaming, Spark also provides mature support for large scale machine learning and graph analysis. This sort of computation is what is commonly referred to as “advanced analytics”. This part of the book will focus on how you can use Spark to perform advanced analytics, from linear regression, to connected components graph analysis, and deep learning. Before covering those topics, we should define advanced analytics more formally.

Gartner defines advanced analytics as follows:

> Advanced Analytics is the autonomous or semi-autonomous examination of data or content using sophisticated techniques and tools, typically beyond those of traditional business intelligence (BI), to discover deeper insights, make predictions, or generate recommendations. Advanced analytic techniques include those such as data/text mining, machine learning, pattern matching, forecasting, visualization, semantic analysis, sentiment analysis, network and cluster analysis, multivariate statistics, graph analysis, simulation, complex event processing, neural networks.

As their definition suggests, it is a bit of a grab bag of techniques to try and solve a core problem of deriving and potentially delivering insights and making predictions or recommendations. Spark provides strong tooling for nearly all of these different approaches and this part of the book will cover the different tools and tool areas available to end users to perform advanced analytics.

This part of the book will cover the different parts of Spark your organization can leverage for advanced analytics including:

- Preprocessing (Cleaning Data)

- Feature Engineering
- Supervised Learning
- Unsupervised Learning
- Recommendation Engines
- Graph Analysis

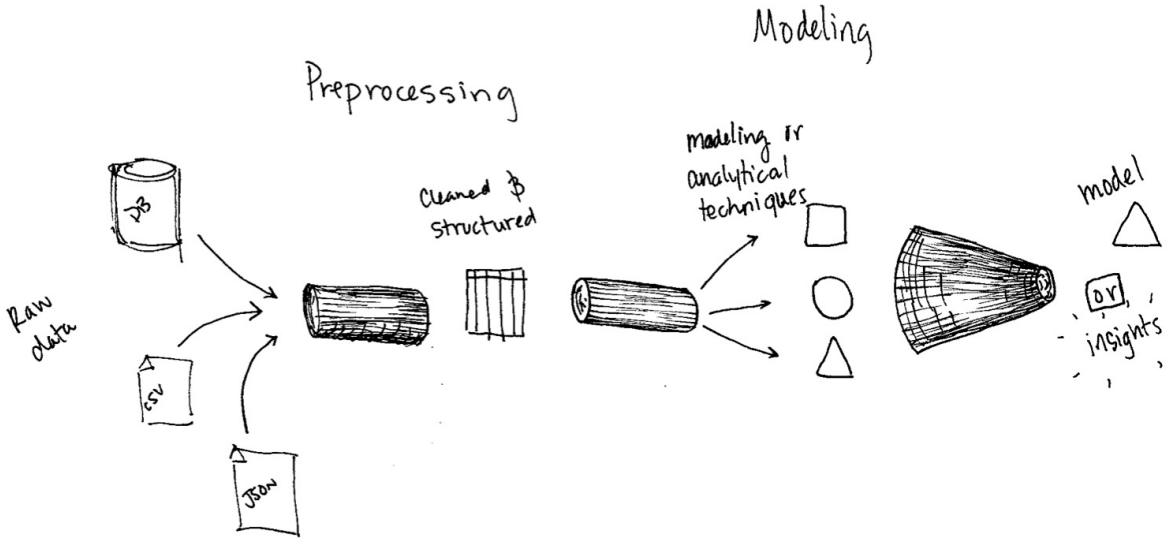
Before diving into these topics in depth, it is worth mentioning the goal of this part of the book as well as what it will and will not cover. This part of the book is not an algorithm guide that will teach you what every algorithm means via Spark. There is simply too much to cover the intricacies of each algorithm.

What this part of the book will cover is *how you can be successful using these algorithms in real world scenarios*. This means covering the scalability of individual algorithms and teaching you the high level concepts you will need to be successful. Unfortunately, this means eschewing strict mathematical definitions and formulations - not for lack of importance but simply because it's too much information to cover in this context.

We will reference three books for those of you that would like to understand more about the individual methods.

- An Introduction to Statistical Learning by Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani - available at: *http://www-bcf.usc.edu/~gareth/ISL/*. We will refer to this book as "ISL".
- Elements of Statistical Learning by Trevor Hastie, Robert Tibshirani, and Jerome Friedman- available at: *http://statweb.stanford.edu/~tibs/ElemStatLearn/*. We will refer to this book as "ESL".
- Deep Learning by Ian Goodfellow, Yoshua Bengio, and Aaron Courville - available at: *http://www.deeplearningbook.org/*. We will refer to this book as "DLB".

The Advanced Analytics Workflow



The first step of almost any advanced analytics task is to gather and clean data, data scientists report that this takes up the majority of their time and is one of the places that Spark performs extremely well (See part II of this book). Once you clean your data you may need to manipulate it according to the task you would like to complete. However the process does not end there, sometimes you may need to create new features including creating new ones, combining from other sources, or looking at interactions of variables. Once you performed all preparation of your data, it's time for the next step in the process: modeling. A model is just a simplified conceptual representation of some process. We can create different kinds of models according to our task. For instance, do you want to predict whether or not something will happen? Assign a probability to that happening? Do you simply want to understand what properties are associated with other properties?

Different Advanced Analytics Tasks

To build out a model, we first need to specify the task that we want to perform. At high level these fall into the following categories.

Supervised Learning

Supervised learning occurs when you train a model to predict a particular outcome based on historical information. This task might be *classification* where the dependent variable is a *categorical variable*, meaning the output consists of a finite set of values. This task might be a *regression*, where the output variable may take on one of an infinite number of values. In simplest terms, we know what we want to be predicting and have values that represent that in our dataset. Some examples of supervised learning include:

- Spam email detection - Spam detection systems leverage supervised learning to predict whether or not a message is spam or not. It does like by analzing the contents of a given email. An example dataset for doing this can be found at: *https://archive.ics.uci.edu/ml/datasets/Spambase*.

- Classifying handwritten digits - The United States Postal Service had a use case where they wanted to be able to read handwritten addresses on letters. To do this they leverage machine learning to train a classifier to them the value of a given digit. The canonical dataset for doing this can be found at: *http://yann.lecun.com/exdb/mnist/*

- Predicting heart disease - A doctor or hospital might want to predict the likelihood of a person's body characteristics or lifestyle leading to heart disease later in life. An example dataset for doing this can be found at: *https://archive.ics.uci.edu/ml/datasets/Heart+Disease*.

Recommendation

The task of recommendation is likely one of the most intuitive. By studying what people either explicitly state that they like and dislike (through ratings) or by what they implicitly state that they like and dislike (through observed behavior) you can make recommendations on what one user may like by drawing similarities between those individuals and other individuals. This use case is quite well suited to Spark as we will see in the coming chapter. Some examples of recommendations are:

- Movie Recommendations - Netflix uses Spark to make large scale movie recommendations to their users. More generally, movies can be recommended based on what you watch as well as what you rated previously.

- Product Recommendations - In order to promote high purchases, companies use product recommendations to suggest new products to buy to their customers. This can be based on previous purchases or simply viewing behavior.

Unsupervised Learning

Unsupervised learning occurs when you train a model on data that does not have a a specific outcome variable. The goal is to discover and describe some underlying structure or clusters in the data. We may use this to create a set of labels to use as output variables in a supervised learning situation later on or to find *outliers*, data points that are far away from most other data points. Some examples of unsupervised learning include:

- Clustering - Given some traits in plant types, we might want to cluster them by these attributes in order to try and find similiarities (or differences) between them. An example dataset for doing this can be found at: *https://archive.ics.uci.edu/ml/datasets/Iris/*.

- Anomaly Detection - Given some standard event type often occuring over time, we might want to report when a non-standard type of event occurs (non-standard being a potentially difficult term to define generally.) An example of this might be that a security officer would like to receive a notification when a strange object (think vehicle, skater or bicyclist) is observed on a pathway. An example dataset for doing this can be found at: *http://www.svcl.ucsd.edu/projects/anomaly/dataset.html*.

- Topic Modeling - Given a set of documents, we might want to infer some underlying structure in these documents like the latent topics that identify each document (or subset of documents) the best. An example dataset for doing this can be found at: *http://www.cs.cmu.edu/~enron/*.

note

We linked to a number of datasets that work well for these tasks. Many of the linked datasets are courtesy of the UCI Machine Learning Repository. Citation: Lichman, M. (2013). UCI Machine Learning Repository [*http://archive.ics.uci.edu/ml*]. Irvine, CA: University of California, School of Information and Computer Science.

Graph Analysis

Graph analysis is a bit more of a sophisticated analytical tool that can absorb aspects of all of the above. Graph analysis is effectively the study of relationships where we specify “vertices” which are objects and “edges” which represent relationships between those objects. Some examples of graph analysis include:

- Fraud Prediction - Capital One uses Spark’s graph analytics capabilities to better understand fraud networks. This includes assigning probabilities to certain bits of information to make a decision about whether or not a given piece of information suggests that a charge it fraudulent.

- Anomaly Detection - By looking at how networks of individuals connect with one another, outliers and anomalies can be flagged for manual analysis.

- Classification - Given some facts about certain vertices in the network, you can classify other vertices according to their connection to that original node. An example might be looking at classifying influencers in friend groups.

- Recommendation - Google’s original web recommendation algorithm, PageRank, is a graph algorithm that analyzed the relationships between certain web pages by looking at how they linked to one another.

Spark’s Packages for Advanced Analytics

Spark includes several core packages and many external packages for performing advanced analytics. The primary package is MLlib which provides an interface for bulding machine learning pipelines. We elaborate on other packages in later chapters.

What is MLlib?

MLlib is a package, built on and included in Spark, that provides interfaces for

1. gathering and cleaning data,
2. generating and selecting features,
3. training and tuning large scale supervised and unsupervised machine learning models,
4. and using those models in production.

This means that it helps with all three steps of the process although it really shines in steps one and two for reason that we will touch on shortly. MLlib consists of two packages that leverage different core data structures. The package `org.apache.spark.ml` maintains an interface for use with Spark DataFrames. This package also maintains a high level interface for building machine learning pipelines that help standardize the way in which you perform the above steps. The lower level package, `org.apache.spark.mllib`, maintains interfaces for Spark's Low-Level, RDD APIs. This book will focus on the DataFrame API because the RDD API is both well documented and is currently in maintenance mode (meaning it will only receive bug fixes, not new features) at the time of this writing.

When and why should you use MLlib (vs scikit learn or another package)?

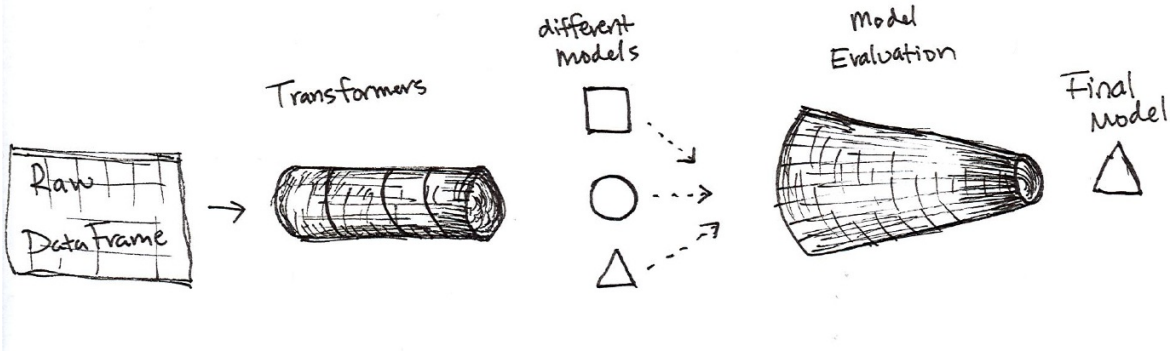
Now, at a high level, this sounds like a lot of other machine learning packages you have probably heard of like scikit-learn for Python or the variety of R packages for performing similar tasks. So why should you bother MLlib at all? The answer is simple, scale. There are numerous tools for performing machine learning on a single machine. They do quite well at this and will continue to be great tools. However they reach a limit, either in data size or processing time. This is where Spark excels. The fact that they hit a limit in terms of scale

makes them *complementary* tools, not competitive ones. When your input data or model size become too difficult or inconvenient to put on one machine, use Spark to do the heavy lifting. Spark makes big data machine learning simple.

An important caveat to the previous paragraph is that while training and data prep are made extremely simple, there are still some complexities that you will need to keep in mind. For example, some models like a recommender system end up being way too large for use on a single machine for prediction, yet we still need to make predictions to derive value from our model. Another example might be a logistic regression model trained in Spark. Spark's execution engine is not a low-latency execution engine and therefore making single predictions quickly (< 500ms) is still challenging because of the costs of starting up and executing a Spark jobs - even on a single machine. Some models have good answers to this problem, others are still open questions. We will discuss the state of the art at the end of this chapter. This is a fruitful research area and likely to change overtime as new systems come out to solve this problem.

High Level MLlib Concepts

In MLlib there are several fundamental architectural types: transformers, estimators, evaluator and pipelines. The following is a diagram of the overall workflow.



Transformers are just functions that convert raw data into another, usually more structured representation. Additionally they allow you to create new features from your data like interactions between variables. An example of a transformer is one converts string categorical variables into a better representation for our algorithms. Transformers are primarily used in the first step of the machine learning process we described previously. *Estimators* represent different models (or variations of the same model) that are trained and then tested using an evaluation. An *evaluator* allows us to see how a given estimator performs according to some criteria that we specify like a ROC curve. Once we select the best model from the ones that we tested, we can then use it to make predictions.

From a high level we can specify each of the above steps one by one however it is often more much easier to specify our steps as *stages* in a *pipeline*. This pipeline is similar to Scikit-learn's Pipeline concept where transformations and estimators are specified together.

This is not just a conceptual framework. These are the high level data types that we actually use to build our out advanced analytics pipelines.

Low Level Data Types

In addition to the high level architectural types, there are also several lower level primitives that you may need to leverage. The most common that you will come across is the `Vector`. Whenever we pass a set of features into a machine learning model, we must do it as a vector that consists of `Double`s. This vector can be either sparse (where most of the elements are zero) or dense (where there are many unique values). These are specified in different ways, one where we specify the exact values(dense) and the other where we specify the total size and which values are nonzero(sparse). Sparse is appropriate, as you might have guessed, when the majority of the values are zero as this is a more compressed representation that other formats.

```
%scala

import org.apache.spark.ml.linalg.Vectors

val denseVec = Vectors.dense(1.0, 2.0, 3.0)
val size = 3
val idx = Array(1,2) // locations in vector
val values = Array(2.0,3.0)
val sparseVec = Vectors.sparse(size, idx, values)
sparseVec.toDense
denseVec.toSparse

%python

from pyspark.ml.linalg import Vectors

denseVec = Vectors.dense(1.0, 2.0, 3.0)
size = 3
idx = [1, 2] # locations in vector
values = [2.0, 3.0]
sparseVec = Vectors.sparse(size, idx, values)
# sparseVec.toDense() # these two don't work, not sure why
# denseVec.toSparse() # will debug later
```

warning

Confusingly, there are similar types that refer to ones that can be used in DataFrames and others than can only be used in RDDs. The RDD implementations fall under the `mllib` package while the DataFrame implementations under `ml`.

MLlib in Action

Now we described some of the core pieces that we are going to come across, let's create a simple pipeline to demostrate each of the component parts. We'll use a small synthetic dataset that will help illustrate our point. This dataset consists of a categorical label, a categorical variable (color), and two numerical variables. You should immediately recognize that this will be a classification task where we hope to predict our binary output variable based on the inputs.

```
%scala

var df = spark.read.json("/mnt/defg/simple-ml")

%python

df = spark.read.json("/mnt/defg/simple-ml")

df.orderBy("value2").show()
```

Spark can also quickly read from LIBSVM formatted datasets. For more information on the LIBSVM format see the documentation here: *http://www.csie.ntu.edu.tw/~cjlin/libsvm/*.

```
%scala

val libsvmData = spark.read.format("libsvm")
  .load("/mnt/defg/sample_libsvm_data.txt")

%python

libsvmData = spark.read.format("libsvm")\
  .load("/mnt/defg/sample_libsvm_data.txt")
```

Transformers

Transformers exist to either cut down on the number of features, add more features, manipulate current ones or simply help us format our data correctly. All inputs to machine learning algorithms in Spark must consist of type `Double` (for labels) and `Vector[Double]` for features. Note that our current data does *not* meet that requirement and therefore we need to transform it to the proper format.

To achieve this, we are going to do this by specifying an `RFormula`. This is a declarative language for specifying machine learning models and is incredibly simple to use once you understand the syntax. Currently RFormula supports a limited subset of the R operators that in practice work quite well for simple models. The basic operators are:

- `~` separate target and terms
- `+` concat terms, "+ 0" means removing intercept
- `-` remove a term, "- 1" means removing intercept
- `:` interaction (multiplication for numeric values, or binarized categorical values)
- `.` all columns except target

In order to specify our transformations with this syntax, we need to import the relevant class.

```
%scala

import org.apache.spark.ml.feature.RFormula

%python

from pyspark.ml.feature import RFormula
```

Then we go through the process of defining our formula. In this case we want

to use all available variables (the .) and then specify a interactions between value1 and color and value2 and color.

```
val supervised = new RFormula()
  .setFormula("lab ~ . + color:value1 + color:value2")

%python

supervised = RFormula()\
  .setFormula("lab ~ . + color:value1 + color:value2")
```

At this point we created, but have not used out model. The above transformer object is actually a special kind of transformer that will modify itself according to the underlying data. Not all transformers have this requirement but because `RFormula` will automatically handle categorical variables for us, it needs to figure out which columns are categorical and which are now. For this reason, we have to call the `fit` method. Once we call fit, this returns a "trained" version of our transformer that we can then use to actually transform our data.

```
%scala

val fittedRF = supervised.fit(df)
val preparedDF = fittedRF.transform(df)

%python

fittedRF = supervised.fit(df)
preparedDF = fittedRF.transform(df)

preparedDF.show()
```

We used that to transform our data. What's happening behind the scenes is actually quite simple. `RFormula` inspects our data during the `fit` call and outputs an object that will transform our data according to the specified formula. This "trained" transformer always has the word `Model` in the type signature. When we use this transformer, you will notice that Spark automatically converts our categorical variable to `Doubles` so that we can input this into a (yet to be specified) machine learning model. It does this with several calls to the `StringIndexer`, `Interaction`, and `VectorAssembler` transformers covered in the next chapter. We then call `tranform` on that object in order to transform our input data into the expected output data.

After preparing our data for use in an estimator, we must now prepare a test set with which we can use to evaluate our model.

```
%scala

val Array(train, test) = preparedDF.randomSplit(Array(0.7, 0.3)

%python

train, test = preparedDF.randomSplit([0.7, 0.3])
```

Estimators

Now that we transformed our data into the correct format and created some valuable features. It's time to actually fit our model. In this case we will use logistic regression. To create our classifier we instantiate an instance of `LogisticRegression`, using the default hyperparameters. We then set the label columns and the feature columns. The values we are setting are actually the default labels for all Estimators in the DataFrame API in Spark MLlib and you will see in later chapters that we omit them.

```
%scala

import org.apache.spark.ml.classification.LogisticRegression

val lr = new LogisticRegression()
  .setLabelCol("label")
  .setFeaturesCol("features")

%python

from pyspark.ml.classification import LogisticRegression

lr = LogisticRegression()\
  .setLabelCol("label")\
  .setFeaturesCol("features")
```

Once we instantiate the model, we can train it. This is done with the `fit` method which returns a `LogisticRegressionModel`. This is just the trained version of logistic regression and is conceptually the same as fitting the `RFormula` that we saw above.

```
%scala

val fittedLR = lr.fit(train)

%python

fittedLR = lr.fit(train)
```

This previous code will kick off a spark job, fitting an ML model is always

eagerly performed.

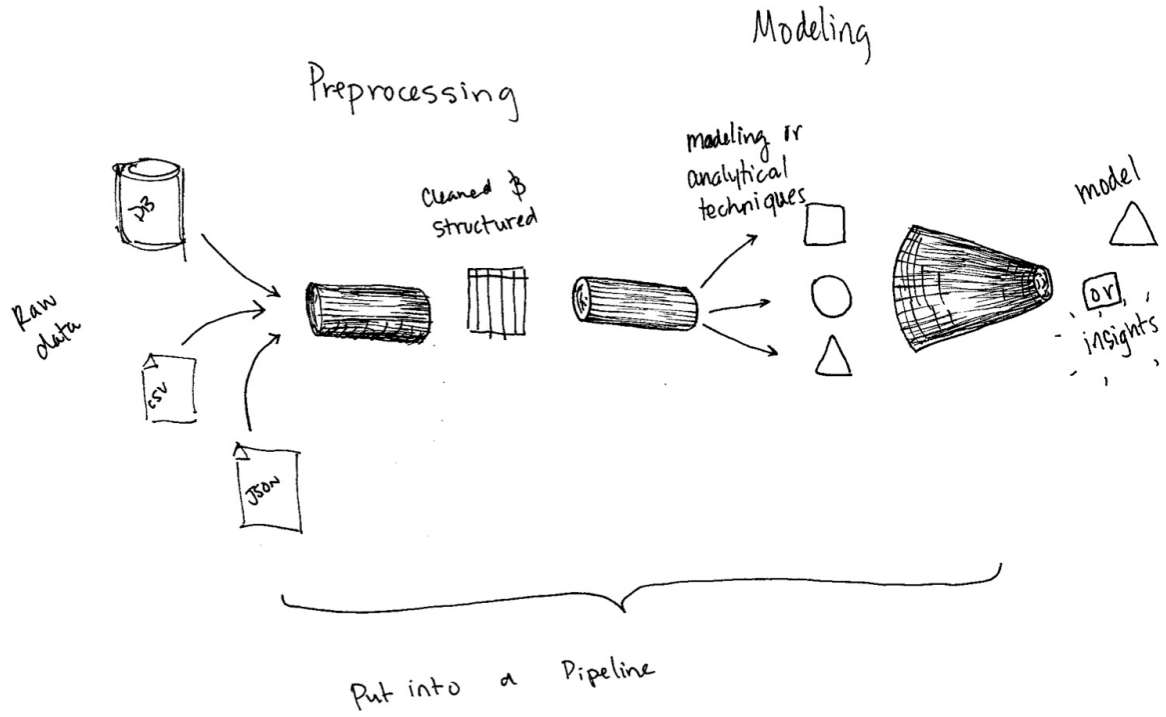
Now that we trained the model, we can use it to make predictions. Logically this represents a transformation of features into labels. We make predictions with the `transform` method. For example, we can transform our training dataset to see what labels our model assigned to the training data and how those compare to the true outputs. This, again, is just another DataFrame that we can manipulate.

```
fittedLR.transform(train).select("label", "prediction").show()
```

Our next step would be to manually evaluate this model and calculate the true positive rate, false negative rate, etc. We might then turn around and try a different set of parameters to see if those perform better. This process, while useful, is actually quite tedious and well defined. Spark helps you avoid this by allowing you to specify your workload as a declarative pipeline of work that includes all your transformations and includes tuning your hyperparameters.

Pipelining our Workflow

As you likely noticed above, if you are performing a lot of transformations, writing all the steps and keeping track of DataFrames ends up being quite tedious. That's why Spark includes the concept of a `Pipeline`. A pipeline allows you to set up a dataflow of the relevant transformations, ending with an estimator that is automatically tuned according to your specifications resulting a tuned model ready for a production use case. The following diagram illustrates this process.



One important detail is that it is essential that instances of transformers or models are *not* reused across pipelines or different models. Always create a new instance of a model before creating another pipeline.

In order to make sure that we don't overfit, we are going to create a holdout test set and tune our hyperparameters based on a validation set. Note that this is our raw dataset.

```
%scala

val Array(train, test) = df.randomSplit(Array(0.7, 0.3))

%python

train, test = df.randomSplit([0.7, 0.3])
```

While in this case we opt for just using the `RFormula` a common pattern is to set up a pipeline of many different transformations in conjunction with the RFormula (for the simpler features). We cover these preprocessing techniques in the following chapter, just keep in kind that there can be far more stages than just two. In this case we will not specify a formula.

```
%scala
```

```
val rForm = new RFormula()

val lr = new LogisticRegression()
  .setLabelCol("label")
  .setFeaturesCol("features")

%python

rForm = RFormula()

%python

lr = LogisticRegression()\
  .setLabelCol("label")\
  .setFeaturesCol("features")
```

Now instead of manually using our transformations and then tuning our model. Now we just make them stages in the overall pipeline. This makes them just logical transformations, or a specification for chain of commands for Spark to run in a pipeline.

```
import org.apache.spark.ml.Pipeline

val stages = Array(rForm, lr)
val pipeline = new Pipeline().setStages(stages)

%python

from pyspark.ml import Pipeline

stages = [rForm, lr]
pipeline = Pipeline().setStages(stages)
```

Evaluators

At this point we set up a set up our pipeline. The next step will be evaluating the performance of this pipeline. Spark does this by setting up a parameter grid of all the combinations of the parameters that you specify. You should immediately notice in the following code snippet that even our `RFormula` is tuning specific parameters. In a pipeline, we can modify more than just the model's hyperparameters, we can even modify the transformer's properties.

```
%scala

import org.apache.spark.ml.tuning.ParamGridBuilder

val params = new ParamGridBuilder()
  .addGrid(rForm.formula, Array(
    "lab ~ . + color:value1",
    "lab ~ . + color:value1 + color:value2"))
  .addGrid(lr.elasticNetParam, Array(0.0, 0.5, 1.0))
  .addGrid(lr.regParam, Array(0.1, 2.0))
  .build()

%python

from pyspark.ml.tuning import ParamGridBuilder

params = ParamGridBuilder()\
  .addGrid(rForm.formula, [
    "lab ~ . + color:value1",
    "lab ~ . + color:value1 + color:value2"])\
  .addGrid(lr.elasticNetParam, [0.0, 0.5, 1.0])\
  .addGrid(lr.regParam, [0.1, 2.0])\
  .build()
```

In our current grid there are three hyperparameters that will diverge from the defaults.

- two different options for the R formula
- three different options for the elastic net parameter
- two different options for the regularization parameter

This gives us a total of twelve different combinations of these parameters, which means we will be training twelve different versions of logistic regression.

With the grid built it is now time to specify our evaluation. There are evaluators for classifiers (binary and multilabel) and regression, which we cover in subsequent chapters however in this case we will be using the `BinaryClassificationEvaluator`. This evaluator allows us to automatically optimize our model training according to some specific criteria that we specify. In this case we will specify `areaUnderROC` which is the total area under the receiver operating characteristic. (CITE)

Now that we have a pipeline that specifies how our data should be transformed. Let's take it to the next level and automatically perform model selection by trying out different hyper-parameters in our logistic regression model. We do this by specifying a parameter grid, a splitting measuer, and lastly an Evaluator. An evaluator allows us to automatically optimize our model training according to some criteria (specified in the evaluator) however in order to leverage this we need a simple way of trying out different model parameters to see which ones perform best. We cover all the different evaluation metrics in each task's chapter.

```
%scala

import org.apache.spark.ml.evaluation.BinaryClassificationEvalu

val evaluator = new BinaryClassificationEvaluator()
  .setMetricName("areaUnderROC")
  .setRawPredictionCol("prediction")
  .setLabelCol("label")

%python

from pyspark.ml.evaluation import BinaryClassificationEvaluato

evaluator = BinaryClassificationEvaluator()\
  .setMetricName("areaUnderROC")\
  .setRawPredictionCol("prediction")\
  .setLabelCol("label")
```

As you may know, it is a best practice in machine learning to fit your

hyperparameters on a validation set (instead of your test set). The reasons for this are to prevent overfitting. Therefore we cannot use our holdout test set (that we created before) to tune these parameters. Luckily Spark provides two options for performing this hyperparameter tuning in an automated way. We can use a `TrainValidationSplit`, which will simply perform an arbitrary random split of our data into two different groups, or a `CrossValidator`, which performs K-fold cross validation by splitting the dataset into non-overlapping randomly partitioned folds.

```
%scala

import org.apache.spark.ml.tuning.TrainValidationSplit

val tvs = new TrainValidationSplit()
  .setTrainRatio(0.75) // also the default.
  .setEstimatorParamMaps(params)
  .setEstimator(pipeline)
  .setEvaluator(evaluator)

%python

from pyspark.ml.tuning import TrainValidationSplit

tvs = TrainValidationSplit()\
  .setTrainRatio(0.75)\
  .setEstimatorParamMaps(params)\
  .setEstimator(pipeline)\
  .setEvaluator(evaluator)
```

Now we can fit our entire pipeline. This will test out every version of the model against the validation set. You will notice that the the type of `tvsFitted` is `TrainValidationSplitModel`. Any time that we fit a given model, it outputs a "model" type.

```
%scala

val tvsFitted = tvs.fit(train)

%python

tvsFitted = tvs.fit(train)
```

And naturally evaluate how it performs on the test set!

```
evaluator.evaluate(tvsFitted.transform(test))
```

We can also see a training summary for particular models. To do this we extract it from the pipeline, cast it to the proper type and print our results. The metrics available depend on the models which are covered in some of the following chapters. The only key thing to understand is that an unfitted estimator has the same name as the estimator, e.g. LogisticRegression.

```
import org.apache.spark.ml.PipelineModel
import org.apache.spark.ml.classification.LogisticRegressionMo

val trainedPipeline = tvsFitted.bestModel.asInstanceOf[Pipeline
val TrainedLR = trainedPipeline.stages(1)
  .asInstanceOf[LogisticRegressionModel]
val summaryLR = TrainedLR.summary

summaryLR.objectiveHistory
```

Persisting and Applying Models

Now that we trained this model, we can persist it to disk to use it in an online predicting fashion later.

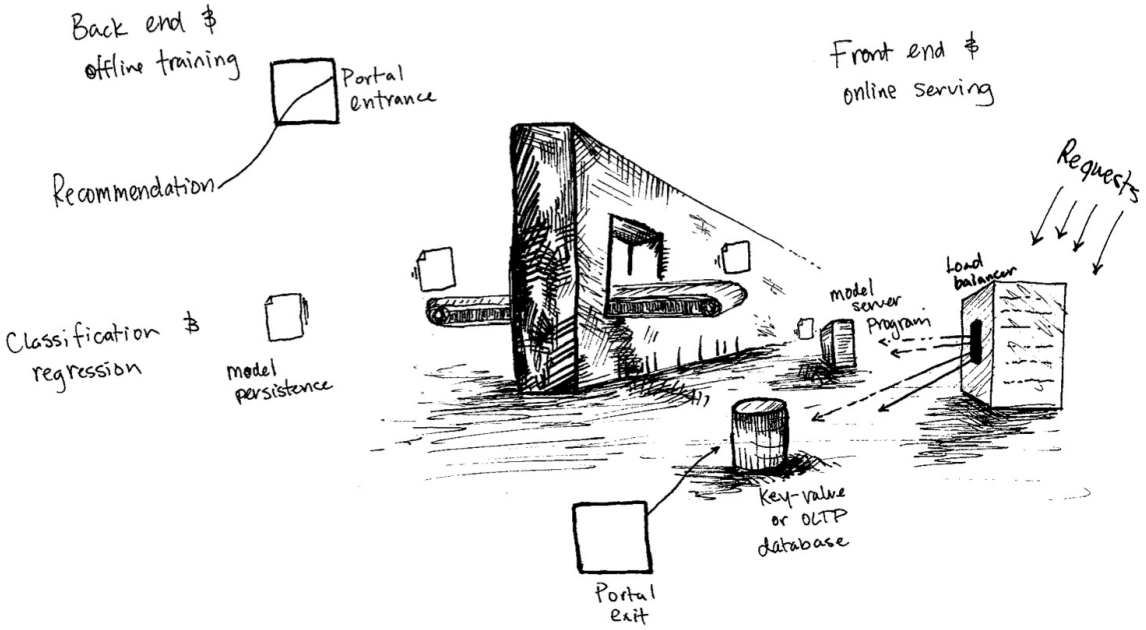
```
tvsFitted.write.overwrite().save("/tmp/modelLocation")
```

Now that we wrote out the model we can load it back into a program (potentially in a different location) in ordre to make predictions. In order to do this we need to use the companion object to the model, tuning class, or transformer that we originally used. In this case, we used `TrainValidationSplit` which outputs a `TrainValidationSplitModel`. We will now use the "model" version to load our persisted model. If we were to use a `CrossValidator`, we'd have to read in the persisted version as the `CrossValidatorModel` and if we were to use `LogisticRegression` manually we would have to use `LogisticRegressionModel`.

```
%scala

import org.apache.spark.ml.tuning.TrainValidationSplitModel

val model = TrainValidationSplitModel.load("/tmp/modelLocation'
model.transform(test)

%python

# not currently available in python but bet it's coming...
# will remove if not.
# from pyspark.ml.tuning import TrainValidationSplitModel

# model = TrainValidationSplitModel.load("/tmp/modelLocation")
# model.transform(test)
```

Deployment Patterns

When it comes to Spark there are several different deployment patterns for putting machine learning models into production in Spark. The following diagram aims to illustrate that.



1. Train your ML algorithm offline and then put the results into a database (usually a key-value store). This works well for something like recommendation but poorly for something like classification or regression where you cannot just lookup a value for a given user but must calculate one.

2. Train your ML algorithm offline, persist the model to disk, then use that for serving. This is not a low latency solution as the overhead of starting up a Spark job can be quite high - even if you're not running on a cluster. Additionally this does not parallelize well so you'll likely have to put a load balancer of multiple model replicas. There are some interesting

potential solutions to this problem, but nothing quite production ready yet.

3. Manually (or via some other software) convert your distributed model to one that can run much more quickly on a single machine. This works well when there is not too much manipulation of the raw data in Spark and can be hard to maintain over time. Again there are solutions that are working on this specification as well but nothing production ready. This cannot be found in the previous illustration because it's something that requires manual work.

4. Train your ML algorithm online and use it online, this is possible when used in conjunction like streaming but is quite sophisticated. This landscape will likely continue to mature as Structured Streaming development continues.

While these are some of the options, there are more potential ways of performing this deployment. This is a heavy area for development that is certainly likely to change and progress quickly.

Chapter 15. Preprocessing and Feature Engineering

Any data scientist worth her salt knows that one of the biggest challenges in advanced analytics is preprocessing. Not because it's particularly complicated work, it just requires deep knowledge of the data you are working with and an understanding of what your model needs in order to successfully leverage this data. This chapter will cover the details of how you can use Spark to perform preprocessing and feature engineering. We will walk through the core requirements that you're going to need to meet in order to train an MLlib model in terms of how your data is structured. We will then walk through the different tools Spark has to perform this kind of work.

Formatting your models according to your use case

To preprocess data for Spark's different advanced analytics tools, you must consider your end objective.

- In the case of classification and regression, you want to get your data into a column of type `Double` to represent the label and a column of type `Vector` (either dense or sparse) to represent the features.
- In the case of recommendation, you want to get your data into a column of users, a column of targets (say movies or books), and a column of ratings.
- In the case of unsupervised learning, a column of type `Vector` (either dense or sparse) to represent the features.
- In the case of graph analytics, you will want a DataFrame of vertices and a DataFrame of edges.

The best way to do this is through transformers. Transformers are function that accepts a DataFrame as an argument and returns a modified DataFrame as a response. These tools are well documented in Spark's ML Guide and the list of transformers continues to grow. This chapter will focus on what transformers are relevant for particular use cases rather than attempting to enumerate every possible transformer.

> **note**
>
> Spark provides a number of transformers under the `org.apache.spark.ml.feature` package. The corresponding package in Python is `pyspark.ml.feature`. The most up to date list can be found on the Spark documentation site. *http://spark.apache.org/docs/latest/ml-features.html*

Before we proceed, we're going to read in several different datasets. Each of

these have different properties that we will want to manipulate in this chapter.

```
%scala

val sales = spark.read.format("csv")
  .option("header", "true")
  .option("inferSchema", "true")
  .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")
  .coalesce(5)
  .where("Description IS NOT NULL")

val fakeIntDF = spark.read.parquet("/mnt/defg/simple-ml-intege
var simpleDF = spark.read.json("/mnt/defg/simple-ml")
val scaleDF = spark.read.parquet("/mnt/defg/simple-ml-scaling"

%python

sales = spark.read.format("csv")\
  .option("header", "true")\
  .option("inferSchema", "true")\
  .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")\
  .coalesce(5)\
  .where("Description IS NOT NULL")


fakeIntDF = spark.read.parquet("/mnt/defg/simple-ml-integers")
simpleDF = spark.read.json("/mnt/defg/simple-ml")
scaleDF = spark.read.parquet("/mnt/defg/simple-ml-scaling")

sales.cache()
```

warning

It is important to note that we filtered out null values above. MLlib does not play nicely with null values at this point in time. This is a frequent cause for problems and errors and a great first step when you are debugging.

Properties of Transformers

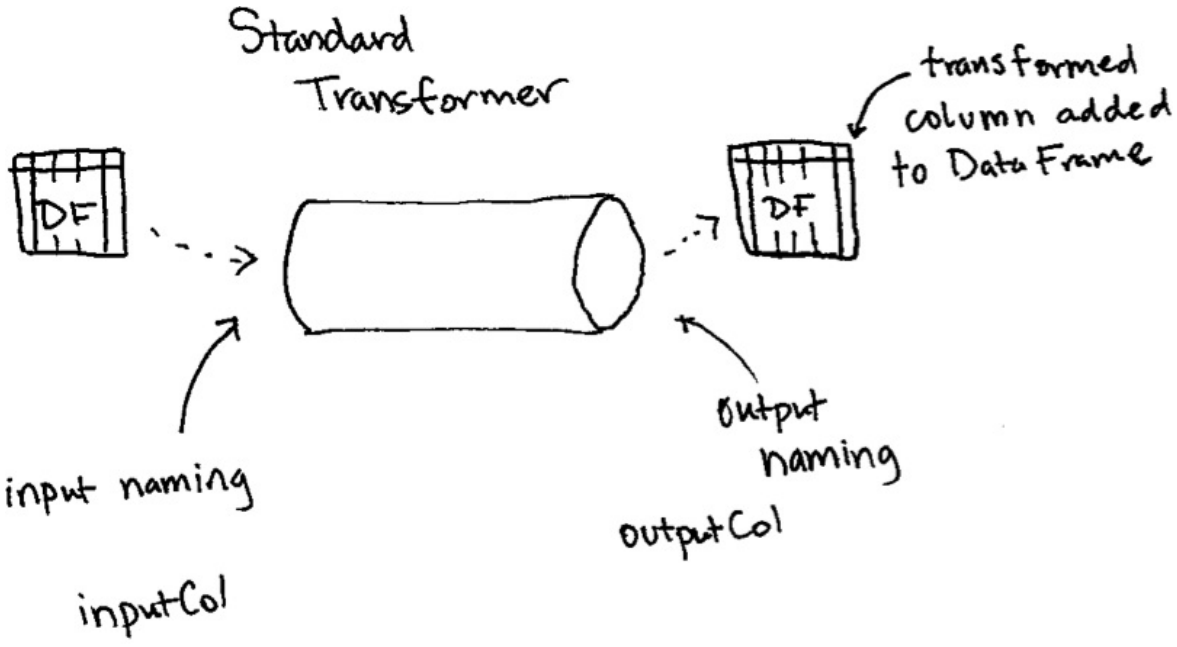
All transformers require you to specify, at a minimum the `inputCol` and the `outputCol`, obviously representing the column name of the input and output. You set these with the `setInputCol` and `setOutputCol`. At times there are defaults (you can find these in the documentation) but it is a best practice to manually specify them yourself for clarity. In addition to input and outpul columns, all transformers have different parameters that you can tune, whenever we mention a parameter in this chapter you must set it with `set<PARAMETER_NAME>`.

note

Spark MLlib stores metadata about the columns that it uses as an attribute on the column itself. This allows it to properly store (and annotate) that a column of doubles may actually represent a series of categorical variables which should not just blindly be used as numerical values. As demonstrated later on this chapter under the “Working with Categorical Variables Section”, this is why it’s important to index variables (and potentially one hot encode them) before inputting them into your model. One catch is that this will not show up when you print the schema of a column.

Different Transformer Types

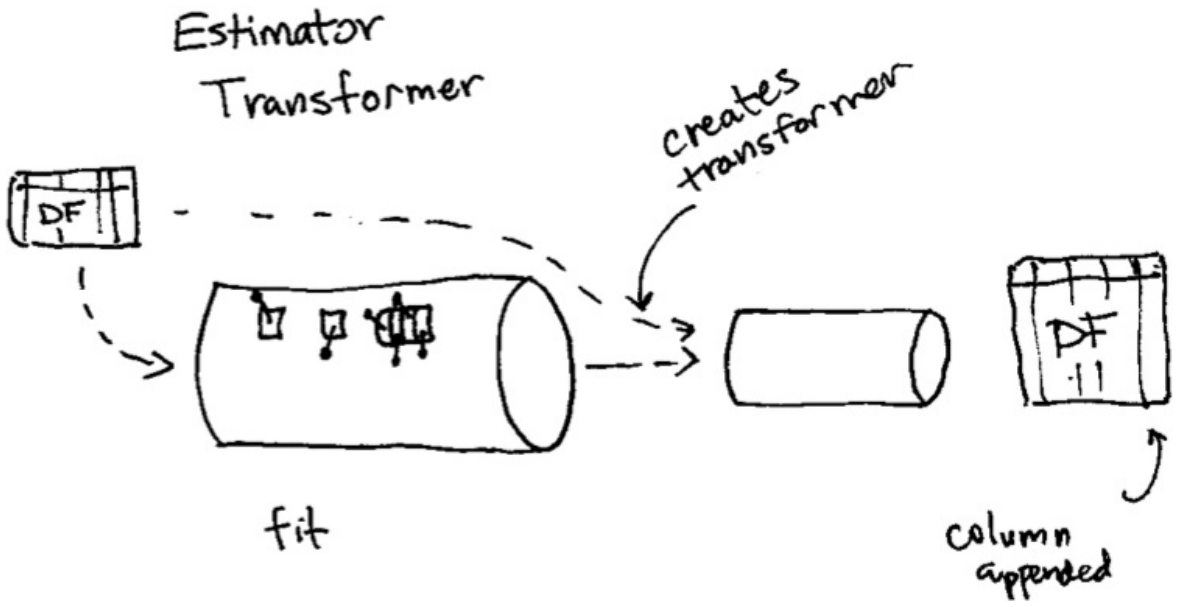
In the previous chapter we mentioned the simplified concept of "transformers" however there are actually two different kinds of tranformers. The "standard" transformer only includes a "transform" method, this is because it will not change based on the input data.



An example of this is the `Tokenizer` transformer. It has nothing to "learn" from out data.

```
import org.apache.spark.ml.feature.Tokenizer

val tkn = new Tokenizer().setInputCol("Description")
tkn.transform(sales).show()
```

The other kind of transformer is actually an *estimator*. This just means that it needs to be fit prior to being used as a transformer because it must tune itself according to the input data set. While technically incorrect, it can be helpful to think about this as simply generating a transformer at runtime based on the input data.



An example of this is the `StandardScaler` that must modify itself according to the numbers in the relevant column in order to scale the data appropriately.

```
import org.apache.spark.ml.feature.StandardScaler

val ss = new StandardScaler().setInputCol("features")
ss.fit(scaleDF).transform(scaleDF).show(false)
```

High Level Transformers

In general, you should try to use the highest level transformers that you can, this will minimize the risk of error and help you focus on the business problem instead of the smaller details of implementation. While this is not always possible, it's a good goal.

RFormula

You likely noticed in the previous chapter that the `RFormula` is the easiest transformer to use when you have "conventionally" formatted data. Spark borrows this transformer from the R language and makes it simple to declaratively specify a set of transformations for your data. What we mean by this is that values are either numerical or categorical and you do not need to extract values from the strings or manipulate them in anyway. This will automatically handle categorical inputs (specified as strings) by one hot encoding them. Numeric columns will be cast to `Double` but will *not* be one hot encoded. If the label column is of type string, it will be first transformed to double with `StringIndexer`.

> **warning**
>
> This has some strong implications. If you have numerically valued categorical variables, they will *only* be cast to `Double`, implicitly specifying an order. It is important to ensure that the input types correspond to the expected conversion. For instance, if you have categorical variables, they should be `String`. You can also manually index columns, see "Working with Categorical Variables" in this chapter.

`RFormula` also uses default columns of label and features respectively. This makes it very easy to pass it immediately into models which will require those exact column names by default.

```
%scala

import org.apache.spark.ml.feature.RFormula

val supervised = new RFormula()
  .setFormula("lab ~ . + color:value1 + color:value2")
supervised.fit(simpleDF).transform(simpleDF).show()

%python

from pyspark.ml.feature import RFormula
```

```
supervised = RFormula()\
  .setFormula("lab ~ . + color:value1 + color:value2")
supervised.fit(simpleDF).transform(simpleDF).show()
```

SQLTransformers

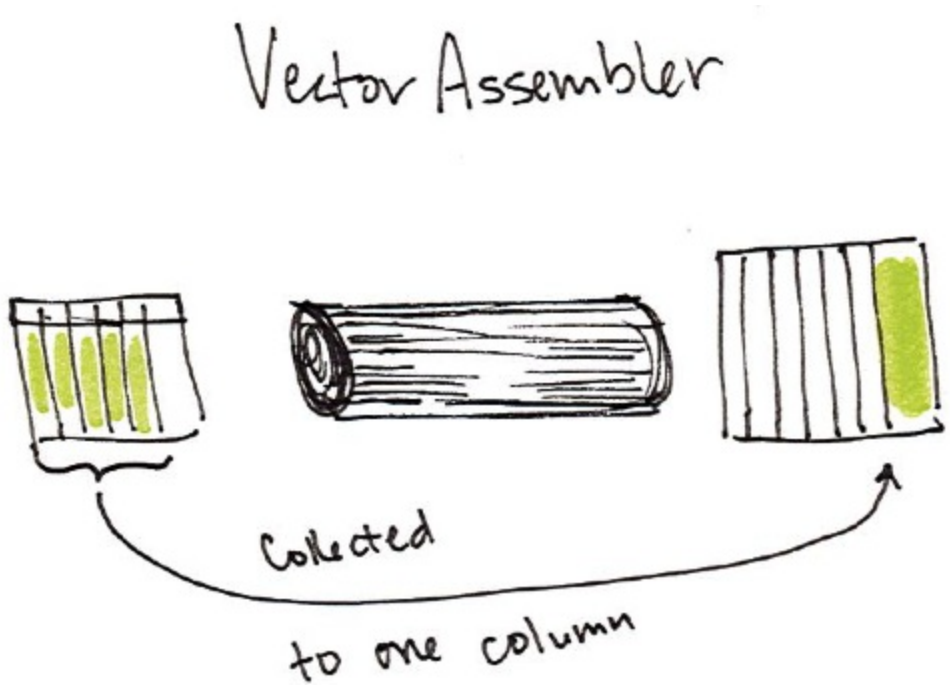
The `SQLTransformer` allows you to codify the SQL manipulations that you make as a ML transformation. Any SELECT statement is a valid transformation, the only thing that you need to change is that instead of using the table name, you should just use the keyword `__THIS__`. You might want to use this if you want to formally codify some DataFrame manipulation as a preprocessing step. One thing to note as well is that the output of this transformation will be appended as a column to the output DataFrame.

```
%scala

import org.apache.spark.ml.feature.SQLTransformer

val basicTransformation = new SQLTransformer()
  .setStatement("""
    SELECT sum(Quantity), count(*), CustomerID
    FROM __THIS__
    GROUP BY CustomerID
  """)

basicTransformation.transform(sales).show()

%python

from pyspark.ml.feature import SQLTransformer

basicTransformation = SQLTransformer()\
  .setStatement("""
    SELECT sum(Quantity), count(*), CustomerID
    FROM __THIS__
    GROUP BY CustomerID
  """)

basicTransformation.transform(sales).show()
```

For extensive samples of these transformations see Part II of the book.

VectorAssembler

The `VectorAssembler` is the tool that you'll use in every single pipeline that you generate. It helps gather all your features into one big vector that you can then pass into an estimator. It's used typically in the last step of a machine learning pipeline and takes as input a number of columns of `Double` or `Vector`.




```
import org.apache.spark.ml.feature.VectorAssembler

val va = new VectorAssembler()
  .setInputCols(Array("int1", "int2", "int3"))
va.transform(fakeIntDF).show()

%python

from pyspark.ml.feature import VectorAssembler

va = VectorAssembler().setInputCols(["int1", "int2", "int3"])
va.transform(fakeIntDF).show()
```

Text Data Transformers

Text is always a tricky input because it often requires lots of manipulation to conform to some input data that a machine learning model will be able to use effectively. There's generally two kinds of formats that you'll deal with, freeform text and text categorical variables. This section of the chapter primarily focuses on text while later on in this chapter we discuss categorical variables.

Tokenizing Text

Tokenization is the process of converting free form text into a list of "tokens" or individual words. The easiest way to do this is through the `Tokenizer`. This transformer will take a string of words, separated by white space, and convert them into an array of words. For example, in our dataset we might want to convert the Description field into a list of tokens.

```
import org.apache.spark.ml.feature.Tokenizer

val tkn = new Tokenizer()
  .setInputCol("Description")
  .setOutputCol("DescriptionOut")

val tokenized = tkn.transform(sales)
tokenized.show()

%python

from pyspark.ml.feature import Tokenizer

tkn = Tokenizer()\
  .setInputCol("Description")\
  .setOutputCol("DescriptionOut")

tokenized = tkn.transform(sales)
tokenized.show()
```

We can also create a tokenizer that is not just based off of white space but a regular expression with the `RegexTokenizer`. The format of the regular expression should conform to the Java Regular Expression Syntax.

```
%scala

import org.apache.spark.ml.feature.RegexTokenizer

val rt = new RegexTokenizer()
  .setInputCol("Description")
  .setOutputCol("DescriptionOut")
  .setPattern(" ") // starting simple
  .setToLowercase(true)
```

```
rt.transform(sales).show()

%python

from pyspark.ml.feature import RegexTokenizer

rt = RegexTokenizer()\
  .setInputCol("Description")\
  .setOutputCol("DescriptionOut")\
  .setPattern(" ")\
  .setToLowercase(True)

rt.transform(sales).show()
```

You can also have this match words (as opposed to splitting on a given value) by setting the `gaps` parameter to false.

Removing Common Words

A common task after tokenization is the filtering of common words or *stop words*. These words are not relevant for a particular analysis and should therefore be removed from our lists of words. Common stop words in English include “the”, “and”, “but” and other common words. Spark contains a list of default stop words which you can see by calling the method below. THis can be made case insensitive if necessary. Support languages for stopwords are: “danish”, “dutch”, “english”, “finnish”, “french”, “german”, “hungarian”, “italian”, “norwegian”, “portuguese”, “russian”, “spanish”, “swedish”, and “turkish” as of Spark 2.2.

```
%scala

import org.apache.spark.ml.feature.StopWordsRemover

val englishStopWords = StopWordsRemover
  .loadDefaultStopWords("english")
val stops = new StopWordsRemover()
  .setStopWords(englishStopWords)
  .setInputCol("DescriptionOut")

stops.transform(tokenized).show()

%python

from pyspark.ml.feature import StopWordsRemover

englishStopWords = StopWordsRemover\
  .loadDefaultStopWords("english")
stops = StopWordsRemover()\
  .setStopWords(englishStopWords)\
  .setInputCol("DescriptionOut")

stops.transform(tokenized).show()
```

Creating Word Combinations

Tokenizing our strings and filtering stop words leaves us with a clean set of words to use as features. Often time it is of interest to look at combinations of words, usually by looking at co-located words. Word combinations are technically referred to as *n-grams*. N-grams are sequences of words of length N. N-grams of length one are called unigrams, length two are bigrams, length three are trigrams. Anything above those are just four-gram, five-gram, etc. Order matters with N-grams, so a converting three words into bigrams would contain two bigrams. For example, the bigrams of "Bill Spark Matei" would be "Bill Spark", "Spark Matei".

We can see this below. The use case for ngrams is to look at what words commonly co-occur and potentially learn some machine learning algorithm based on those inputs.

```
import org.apache.spark.ml.feature.NGram

val unigram = new NGram()
  .setInputCol("DescriptionOut")
  .setN(1)

val bigram = new NGram()
  .setInputCol("DescriptionOut")
  .setN(2)

unigram.transform(tokenized).show()
bigram.transform(tokenized).show()
```

Converting Words into Numbers

Once we created word features, it's time to start counting instances of words and word combinations. The simplest way is just to include binary counts of the existence of a word in a given document (in our case, a row). However we can also count those up (`CountVectorizer`) as well as reweigh them according to the prevalence of a given word in all the documents `TF-IDF`.

A `CountVectorizer` operates on our tokenized data and does two things.

1. During the `fit` process it gathers information about the *vocabulary* in this dataset. For instance for our current data, it would look at all the tokens in each DescriptionOut column and then call that the vocabulary.

2. It then counts the occurrences of a given word in each row of the DataFrame column during the `transform` process and outputs a vector with the terms that occur in that row.

Conceptually this tranformer treats every row as a *document* and every word as a *term* and the total collection of all terms as the *vocabulary*. These are all tunable parameters, meaning we can set the minimum term frequency (`minTF`) for it to be included in the vocabulary (effectively removing rare words from the vocabulary), minimum number of documents a term must appear in (`minDF`) before being included in the vocabulary (another way to remove rare words from the vocabulary), and finally the total maximum vocabulary size (`vocabSize`). Lastly, by default the count vectorizer will output the counts of a term in a document. We can use `setBinary(true)` to have it output simple word existence instead.

```
%scala

import org.apache.spark.ml.feature.CountVectorizer

val cv = new CountVectorizer()
  .setInputCol("DescriptionOut")
  .setOutputCol("countVec")
  .setVocabSize(500)
  .setMinTF(1)
```

```
  .setMinDF(2)

val fittedCV = cv.fit(tokenized)
fittedCV.transform(tokenized).show()

%python

from pyspark.ml.feature import CountVectorizer

cv = CountVectorizer()\
  .setInputCol("DescriptionOut")\
  .setOutputCol("countVec")\
  .setVocabSize(500)\
  .setMinTF(1)\
  .setMinDF(2)

fittedCV = cv.fit(tokenized)
fittedCV.transform(tokenized).show()
```

TF-IDF

Another way to approach the problem in a bit more sophisticated way than simple counting is to use TF-IDF or term frequency-inverse document frequency. The complete explanation of TF-IDF beyond the scope of this book but in simplest terms it finds words that are most representative of certain rows by finding out how often those words are used and weighing a given term according to the number of documents those terms show up in. A more complete explanation can be found *http://billchambers.me/tutorials/2014/12/21/tf-idf-explained-in-python.html*. In practice, TF-IDF helps find documents that share similar topics. Let's see a worked example.

```
%scala

val tfIdfIn = tokenized
  .where("array_contains(DescriptionOut, 'red')")
  .select("DescriptionOut")
  .limit(10)
tfIdfIn.show(false)

%python

tfIdfIn = tokenized\
```

```
  .where("array_contains(DescriptionOut, 'red')")\
  .select("DescriptionOut")\
  .limit(10)
tfIdfIn.show(10, False)
```

```
+----------------------------------------+
|DescriptionOut                          |
+----------------------------------------+
|[gingham, heart, , doorstop, red]       |
...
|[red, retrospot, oven, glove]           |
|[red, retrospot, plate]                 |
+----------------------------------------+
```

We can see some overlapping words in these documents so those won't be perfect identifiers for individual documents but do identify that "topic" of sort across those documents. Now let's input that into TF-IDF. First we perform a hashing of each word then we perform the IDF weighting of the vocabulary.

```
%scala

import org.apache.spark.ml.feature.{HashingTF, IDF}

val tf = new HashingTF()
  .setInputCol("DescriptionOut")
  .setOutputCol("TFOut")
  .setNumFeatures(10000)

val idf = new IDF()
  .setInputCol("TFOut")
  .setOutputCol("IDFOut")
  .setMinDocFreq(2)

%python

from pyspark.ml.feature import HashingTF, IDF

tf = HashingTF()\
  .setInputCol("DescriptionOut")\
  .setOutputCol("TFOut")\
  .setNumFeatures(10000)

idf = IDF()\
  .setInputCol("TFOut")\
  .setOutputCol("IDFOut")\
  .setMinDocFreq(2)
```

```
%scala

idf.fit(tf.transform(tfIdfIn))
  .transform(tf.transform(tfIdfIn))
  .show(false)

%python

idf.fit(tf.transform(tfIdfIn))\
  .transform(tf.transform(tfIdfIn))\
  .show(10, False)
```

While the output is too large to include here what you will notice is that a certain value is assigned to "red" and that value appears in every document. You will then notice that this term is weighted extremely low because it appears in every document. The output format is a `Vector` that we can subsequently input into a machine learning model in a form like:

```
(10000,[2591,4291,4456],[1.0116009116784799,0.0,0.0])
```

This vector is composed of three different values, the total vocabulary size, the hash of every word appearing in the document, and the weighting of each of those terms.

Advanced Techniques

The last text manipulation tool we have at our disposal is Word2vec. Word2vec is a sophisticated neural network style natural language processing tool. Word2vec uses a technique called "skip-grams" to convert a sentence of words into an embedded vector representation. It does this by building a vocabulary, then for every sentence, removes a token and trains the model to predict the missing token in the "n-gram" representation. With the sentence, "the Queen of England" it might be trained to try to predict the missing token "Queen" in "the of England". Word2vec works best with continuous, free form text in the form of tokens, so we won't expect great results from our description field which does not include freeform text. Spark's Word2vec implementation includes a variety of tuning parameters that can be found on the documentation.

Working with Continuous Features

Continuous features are just values on the number line, from positive infinity to negative infinity. There are two transformers for continuous features. First you can convert continuous features into categorical features via a process called bucketing or you can scale and normalize your features according to several different requirements. These transformers will *only* work on `Double` types, so make sure that you've turned any other numerical values to `Double`.

```
%scala

val contDF = spark.range(500)
  .selectExpr("cast(id as double)")

%python

contDF = spark.range(500)\
  .selectExpr("cast(id as double)")
```

Bucketing

The most straightforward approach to bucketing or binning is the `Bucketizer`. This will split a given continuous feature into the buckets of your designation. You specify how buckets should be created via an array or list of `Double` values. This method is confusing because we specify bucket borders via the `splits` method, however these are not actually splits. They are actually bucket borders.

For example setting splits to `5.0, 10.0, 250.0` on our `contDF` because we don't cover all possible ranges input ranges. To specify your bucket points, the values you pass into `splits` must satisfy three requirements.

- The minimum value in your splits array must be less than the minimum value in your DataFrame.
- The maximum value in your splits array must be greater than the maximum value in your DataFrame.
- You need to specify at a minimum three values in the splits array, which creates two buckets.

To cover all possible ranges, Another split option could be `scala.Double.NegativeInfinity` and `scala.Double.PositiveInfinity` to cover all possible ranges outside of the inner splits. Or in python `float("inf"), float("-inf").`

In order to handle `null` or `NaN` values, we must specify the `handleInvalid` parameter to a certain value. We can either keep those values (`keep`), error on null `error`, or `skip` those rows.

```
%scala

import org.apache.spark.ml.feature.Bucketizer

val bucketBorders = Array(-1.0, 5.0, 10.0, 250.0, 600.0)
```

```
val bucketer = new Bucketizer()
  .setSplits(bucketBorders)
  .setInputCol("id")

bucketer.transform(contDF).show()

%python

from pyspark.ml.feature import Bucketizer

bucketBorders = [-1.0, 5.0, 10.0, 250.0, 600.0]

bucketer = Bucketizer()\
  .setSplits(bucketBorders)\
  .setInputCol("id")

bucketer.transform(contDF).show()
```

As opposed to splitting based on hardcoded values, another option is to split based on percentiles in our data. This is done with the `QuantileDiscretizer` which will bucket the values in the a number of user-specified buckets with the splits being determined by approximate quantiles values. You can control how finely the buckets should be split by setting the relative error for the approximate quantiles calculation using `setRelativeError`.

```
%scala

import org.apache.spark.ml.feature.QuantileDiscretizer

val bucketer = new QuantileDiscretizer()
  .setNumBuckets(5)
  .setInputCol("id")

val fittedBucketer = bucketer.fit(contDF)
fittedBucketer.transform(contDF).show()

%python

from pyspark.ml.feature import QuantileDiscretizer

bucketer = QuantileDiscretizer()\
  .setNumBuckets(5)\
  .setInputCol("id")

fittedBucketer = bucketer.fit(contDF)
fittedBucketer.transform(contDF).show()
```

Advanced Bucketing Techniques

There are other bucketing techniques like locality sensitive hashing. Conceptually these are no different from the above (in that they create buckets out of discrete variables) but do some according to different algorithms. Please see the documentation for more information on these techniques.

Scaling and Normalization

Bucketing is straightforward for creating groups out of continuous variables. The other frequent task is to scale and normalize continuous data such that large values do not overly emphasize one feature simply because their scale is different. This is a well studied process and the transformers available are routinely found in other machine learning libraries. Each of these transformers operate on a column of type `Vector` and for every row (of type `Vector`) in that column it will apply the normalization component wise to the values in the vector. It effectively treats every value in the vector as its own column.

Normalizer

Probably the simplest technique is that of the normalizer. This normalizes a an input vector to have unit norm to the user-supplied p-norm. For example we can get the taxicab norm with p = 1, Euclidean norm with p= 2, and so on.

```
%scala
import org.apache.spark.ml.feature.Normalizer

val taxicab = new Normalizer()
  .setP(1)
  .setInputCol("features")

taxicab.transform(scaleDF).show(false)

%python

from pyspark.ml.feature import Normalizer

taxicab = Normalizer()\
  .setP(1)\
  .setInputCol("features")

taxicab.transform(scaleDF).show()
```

StandardScaler

The `StandardScaler` standardizes a set of feature to have zero mean and unit standard deviation. the flag `withStd` will scale the data to unit standard deviation while the flag `withMean` (false by default) will center the data prior to scaling it.

> **warning**
>
> this centering can be very expensive on sparse vectors, so be careful before centering your data.

```
import org.apache.spark.ml.feature.StandardScaler

val sScaler = new StandardScaler()
  .setInputCol("features")

sScaler.fit(scaleDF).transform(scaleDF).show(false)
```

MinMaxScaler

The MinMaxScaler will scale the values in a vector (component wise) to the proportional values on a Scale from the min value to the max value. The min is 0 and the max is 1 by default, however we can change this as seen in the following example.

```
import org.apache.spark.ml.feature.MinMaxScaler

val minMax = new MinMaxScaler()
  .setMin(5)
  .setMax(10)
  .setInputCol("features")

val fittedminMax = minMax.fit(scaleDF)
fittedminMax.transform(scaleDF).show(false)

%python

from pyspark.ml.feature import MinMaxScaler
```

```
minMax = MinMaxScaler()\
  .setMin(5)\
  .setMax(10)\
  .setInputCol("features")

fittedminMax = minMax.fit(scaleDF)
fittedminMax.transform(scaleDF).show()
```

MaxAbsScaler

The max absolutely scales the data by dividing each value (component wise) by the maximum absolute value in each feature. It does not shift or center data.

```
import org.apache.spark.ml.feature.MaxAbsScaler

val maScaler = new MaxAbsScaler()
  .setInputCol("features")

val fittedmaScaler = maScaler.fit(scaleDF)

fittedmaScaler.transform(scaleDF).show(false)
```

ElementwiseProduct

This just performs component wise multiplication of a user specified vector and each vector in each row or your data. For example given the vector below and the row “1, 0.1, -1” the output will be “10, 1.5, -20”. Naturally the dimensions of the scaling vector must match the dimensions of the vector inside the relevant column.

```
%scala

import org.apache.spark.ml.feature.ElementwiseProduct
import org.apache.spark.ml.linalg.Vectors

val scaleUpVec = Vectors.dense(10.0, 15.0, 20.0)
val scalingUp = new ElementwiseProduct()
  .setScalingVec(scaleUpVec)
  .setInputCol("features")

scalingUp.transform(scaleDF).show()
```

```
%python

from pyspark.ml.feature import ElementwiseProduct
from pyspark.ml.linalg import Vectors

scaleUpVec = Vectors.dense(10.0, 15.0, 20.0)
scalingUp = ElementwiseProduct()\
  .setScalingVec(scaleUpVec)\
  .setInputCol("features")

scalingUp.transform(scaleDF).show()
```

Working with Categorical Features

The most common task with categorical features is indexing. This converts a categorical variable in a column to a numerical one that you can plug into Spark's machine learning algorithms. While this is conceptually simple, there are some catches that are important to keep in mind so that Spark can do this in a stable and repeatable manner.

What might come as a surprise is that you *should* use indexing with *every categorical variable* in your DataFrame. This is because it will ensure that all values not just the correct type but that the largest value in the output will represent the number of groups that you have (as opposed to just encoding business logic). This can also be helpful in order to maintain consistency as your business logic and representation may evolve and groups change.

StringIndexer

The simplest way to index is via the `StringIndexer`. Spark's `StringIndexer` creates metadata attached to the DataFrame that specify what inputs correspond to what outputs. This allows us later to get inputs back from their respective output values.

```
%scala

import org.apache.spark.ml.feature.StringIndexer

val labelIndexer = new StringIndexer()
  .setInputCol("lab")
  .setOutputCol("labelInd")

val idxRes = labelIndexer.fit(simpleDF).transform(simpleDF)
idxRes.show()

%python

from pyspark.ml.feature import StringIndexer

labelIndexer = StringIndexer()\
  .setInputCol("lab")\
  .setOutputCol("labelInd")

idxRes = labelIndexer.fit(simpleDF).transform(simpleDF)
idxRes.show()
```

As mentioned, we can apply `StringIndexer` to columns that are not strings.

```
%scala

val valIndexer = new StringIndexer()
  .setInputCol("value1")
  .setOutputCol("valueInd")

valIndexer.fit(simpleDF).transform(simpleDF).show()

%python

valIndexer = StringIndexer()\
  .setInputCol("value1")\
```

```
  .setOutputCol("valueInd")

valIndexer.fit(simpleDF).transform(simpleDF).show()
```

Keep in mind that the `StringIndexer` is a transformer that must be fit on the input data. This means that it must see all inputs to create a respective output. If you train a `StringIndexer` on inputs “a”, “b”, and “c” then go to use it against input “d”, it will throw an error by default. There is another option which is to skip the entire row if it has not seen that label before. We can set this before or after training. More options may be added to this in the future but as of Spark 2.2, you can only skip or error on invalid inputs.

```
valIndexer.setHandleInvalid("skip")
valIndexer.fit(simpleDF).setHandleInvalid("skip")
```

Converting Indexed Values Back to Text

When inspecting your machine learning results, you're likely going to want to map back to the original values. We can do this with IndexToString. You'll notice that we do not have to input our value to string key, Spark's MLlib maintains this metadata for you. You can optionally specify the outputs.

```
%scala

import org.apache.spark.ml.feature.IndexToString

val labelReverse = new IndexToString()
  .setInputCol("labelInd")

labelReverse.transform(idxRes).show()

%python

from pyspark.ml.feature import IndexToString

labelReverse = IndexToString()\
  .setInputCol("labelInd")

labelReverse.transform(idxRes).show()
```

Indexing in Vectors

`VectorIndexer` is a helpful tool for working with categorical variables that are already found inside of vectors in your dataset. It can automatically decide which features are categorical and then convert those categorical features into 0-based category indices for each categorical feature. For example, in the DataFrame below the first column in our Vector is a categorical variable with two different categories. By setting `maxCategories` to 2 we instruct the VectorIndexer that any column in our vector with less than two distinct values should be treated as categorical.

```
%scala

import org.apache.spark.ml.feature.VectorIndexer
import org.apache.spark.ml.linalg.Vectors

val idxIn = spark.createDataFrame(Seq(
  (Vectors.dense(1, 2, 3),1),
  (Vectors.dense(2, 5, 6),2),
  (Vectors.dense(1, 8, 9),3)
)).toDF("features", "label")

val indxr = new VectorIndexer()
  .setInputCol("features")
  .setOutputCol("idxed")
  .setMaxCategories(2)

indxr.fit(idxIn).transform(idxIn).show

%python

from pyspark.ml.feature import VectorIndexer
from pyspark.ml.linalg import Vectors

idxIn = spark.createDataFrame([
  (Vectors.dense(1, 2, 3),1),
  (Vectors.dense(2, 5, 6),2),
  (Vectors.dense(1, 8, 9),3)
]).toDF("features", "label")

indxr = VectorIndexer()\
  .setInputCol("features")\
```

```
  .setOutputCol("idxed")\
  .setMaxCategories(2)

indxr.fit(idxIn).transform(idxIn).show
```

One Hot Encoding

Now indexing categorical values gets our data into the correct data type however, it does not always represent our data in the correct format. When we index our “color” column you’ll notice that implicitly some colors will receive a higher number than others (in my case blue is 1 and green is 2).

```
%scala

val labelIndexer = new StringIndexer()
  .setInputCol("color")
  .setOutputCol("colorInd")

val colorLab = labelIndexer.fit(simpleDF).transform(simpleDF)

%python

labelIndexer = StringIndexer()\
  .setInputCol("color")\
  .setOutputCol("colorInd")

colorLab = labelIndexer.fit(simpleDF).transform(simpleDF)
```

Some algorithms will treat this as “green” being greater than “blue” - which does not make sense. To avoid this we use a `OneHotEncoder` which will convert each distinct value as a boolean flag (1 or 0) as a component in a vector. We can see this when we encode the color value that these are no longer ordered but a categorical representation in our vector.

```
%scala

import org.apache.spark.ml.feature.OneHotEncoder

val ohe = new OneHotEncoder()
  .setInputCol("colorInd")
ohe.transform(colorLab).show()

%python

from pyspark.ml.feature import OneHotEncoder

ohe = OneHotEncoder()\
```

```
  .setInputCol("colorInd")
ohe.transform(colorLab).show()
```

Feature Generation

While nearly every transformer in ML manipulates the feature space in some way, the following algorithms and tools are automated means of either expanding the input feature vectors or reducing them to ones that are more important.

PCA

PCA or Principal Components Analysis performs a decomposition of the input matrix (your features) into its component parts. This can help you reduce the number of features you have to the principal components (or the features that truly matter), just as the name suggests. Using this tool is straightforward, you simply specify the number of components, `k`, you would like.

```
%scala

import org.apache.spark.ml.feature.PCA

val pca = new PCA()
  .setInputCol("features")
  .setK(2)

pca.fit(scaleDF).transform(scaleDF).show(false)

%python

from pyspark.ml.feature import PCA

pca = PCA()\
  .setInputCol("features")\
  .setK(2)

pca.fit(scaleDF).transform(scaleDF).show()
```

Interaction

Often you might have some domain knowledge about specific variables in your dataset. For example, you might know that some interaction between the two is an important variable to include in a down stream estimator. The `Interaction` feature transformer allows you to create this manually. It just multiplies the two features together. This is currently only available in Scala and mostly used internally by the `RFormula`. We recommend users to just use `RFormula` from any language instead of manually creating interactions.

PolynomialExpansion

Polynomial expansion is used to generate interaction variables of all of the inputs. It's effectively taking every value in your feature vector, multiplying it by every other value, and then storing each of those results as features. In Spark, we can control the degree polynomial when we create the polynomial expansion.

> **warning**
>
> This can have a significant effect on your feature space and so it should be used with caution.

```
%scala

import org.apache.spark.ml.feature.PolynomialExpansion

val pe = new PolynomialExpansion()
  .setInputCol("features")
  .setDegree(2)

pe.transform(scaleDF).show(false)

%python

from pyspark.ml.feature import PolynomialExpansion

pe = PolynomialExpansion()\
  .setInputCol("features")\
  .setDegree(2)

pe.transform(scaleDF).show()
```

Feature Selection

ChisqSelector

In simplest terms, the Chi-Square Selector is a tool for performing feature selection of categorical data. It is often used to reduce the dimensionality of text data (in the form of frequencies or counts) to better aid the usage of these features in classification. Since this method is based on the Chi-Square test, there are several different ways that we can pick the "best" features. The methods are "numTopFeatures" which is ordered by p-value, "percentile" which takes a proportion of the input features (instead of just the top N features), "fpr" which sets a cut off p-value.

We will demonstrate this with the output of the `CountVectorizer` created previous in this chapter.

```
%scala

import org.apache.spark.ml.feature.ChiSqSelector

val prechi = fittedCV.transform(tokenized)
  .where("CustomerId IS NOT NULL")

val chisq = new ChiSqSelector()
  .setFeaturesCol("countVec")
  .setLabelCol("CustomerID")
  .setNumTopFeatures(2)

chisq.fit(prechi).transform(prechi).show()

%python

from pyspark.ml.feature import ChiSqSelector

prechi = fittedCV.transform(tokenized)\
  .where("CustomerId IS NOT NULL")

chisq = ChiSqSelector()\
  .setFeaturesCol("countVec")\
  .setLabelCol("CustomerID")\
  .setNumTopFeatures(2)

chisq.fit(prechi).transform(prechi).show()
```

Persisting Transformers

Once you've used an estimator, it can be helpful to write it to disk and simply load it when necessary. We saw this in the previous chapter were we persisted an entire pipeline. To persist a transformer we use the `write` method on the fitted transformer (or the standard transformer) and specify the location.

```
val fittedPCA = pca.fit(scaleDF)

fittedPCA.write.overwrite().save("/tmp/fittedPCA")
```

TODO: not sure why this isn't working right now…

```
val loadedPCA = PCA.load("/tmp/fittedPCA")
loadedPCA.transform(scaleDF).sow()
```

Writing a Custom Transformer

Writing a custom transformer can be valuable when you would like to encode some of your own business logic as something that other folks in your organization can use. In general you should try to use the built-in modules (e.g., `SQLTransformer`) as much as possible because they are optimized to run efficiently, however sometimes we do not have that luxury. Let's create a simple tokenizer to demonstrate.

```
import org.apache.spark.ml.UnaryTransformer
import org.apache.spark.ml.util.{DefaultParamsReadable, Default
import org.apache.spark.sql.types.{ArrayType, StringType, Data
import org.apache.spark.ml.param.{IntParam, ParamValidators}

class MyTokenizer(override val uid: String)
  extends UnaryTransformer[String, Seq[String], MyTokenizer] w

  def this() = this(Identifiable.randomUID("myTokenizer"))

  val maxWords: IntParam = new IntParam(this, "maxWords", "The
  ParamValidators.gtEq(0))

  def setMaxWords(value: Int): this.type = set(maxWords, value)

  def getMaxWords: Integer = $(maxWords)

  override protected def createTransformFunc: String => Seq[St
    inputString.split("\\s").take($(maxWords))
  }

  override protected def validateInputType(inputType: DataType)
    require(inputType == StringType, s"Bad input type: $inputTy
  }

  override protected def outputDataType: DataType = new ArrayTy
}

// this will allow you to read it back in by using this object.
object MyTokenizer extends DefaultParamsReadable[MyTokenizer]

val myT = new MyTokenizer()
  .setInputCol("someCol")
```

```
  .setMaxWords(2)

display(myT.transform(Seq("hello world. This text won't show.")

myT.write.overwrite().save("/tmp/something")
```

It is also possible to write a custom `Estimator` where you must customize the transformation based on the actual input data.

Chapter 16. Preprocessing

Any data scientist worth her salt knows that one of the biggest challenges in advanced analytics is preprocessing. Not because it's particularly complicated work, it just requires deep knowledge of the data you are working with and an understanding of what your model needs in order to successfully leverage this data.

Formatting your models according to your use case

To preprocess data for Spark's different advanced analytics tools, you must consider your end objective.

- In the case of classification and regression, you want to get your data into a column of type `Double` to represent the label and a column of type `Vector` (either dense or sparse) to represent the features.
- In the case of recommendation, you want to get your data into a column of users, a column of targets (say movies or books), and a column of ratings.
- In the case of unsupervised learning, a column of type `Vector` (either dense or sparse) to represent the features.
- In the case of graph analytics, you will want a DataFrame of vertices and a DataFrame of edges.

The best way to do this is through transformers. Transformers are function that accepts a DataFrame as an argument and returns a modified DataFrame as a response. These tools are well documented in Spark's ML Guide and the list of transformers continues to grow. This chapter will focus on what transformers are relevant for particular use cases rather than attempting to enumerate every possible transformer.

> **note**
>
> Spark provides a number of transformers under the `org.apache.spark.ml.feature` package. The corresponding package in Python is `pyspark.ml.feature`. The most up to date list can be found on the Spark documentation site. *http://spark.apache.org/docs/latest/ml-features.html*

Before we proceed, we're going to read in several different datasets. Each of

these have different properties that we will want to manipulate in this chapter.

```
%scala

val sales = spark.read.format("csv")
  .option("header", "true")
  .option("inferSchema", "true")
  .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")
  .coalesce(5)
  .where("Description IS NOT NULL")

val fakeIntDF = spark.read.parquet("/mnt/defg/simple-ml-intege
var simpleDF = spark.read.json("/mnt/defg/simple-ml")
val scaleDF = spark.read.parquet("/mnt/defg/simple-ml-scaling"

%python

sales = spark.read.format("csv")\
  .option("header", "true")\
  .option("inferSchema", "true")\
  .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")\
  .coalesce(5)\
  .where("Description IS NOT NULL")


fakeIntDF = spark.read.parquet("/mnt/defg/simple-ml-integers")
simpleDF = spark.read.json("/mnt/defg/simple-ml")
scaleDF = spark.read.parquet("/mnt/defg/simple-ml-scaling")

sales.cache()
```

warning

It is important to note that we filtered out null values above. MLlib does not play nicely with null values at this point in time. This is a frequent cause for problems and errors and a great first step when you are debugging.

Properties of Transformers

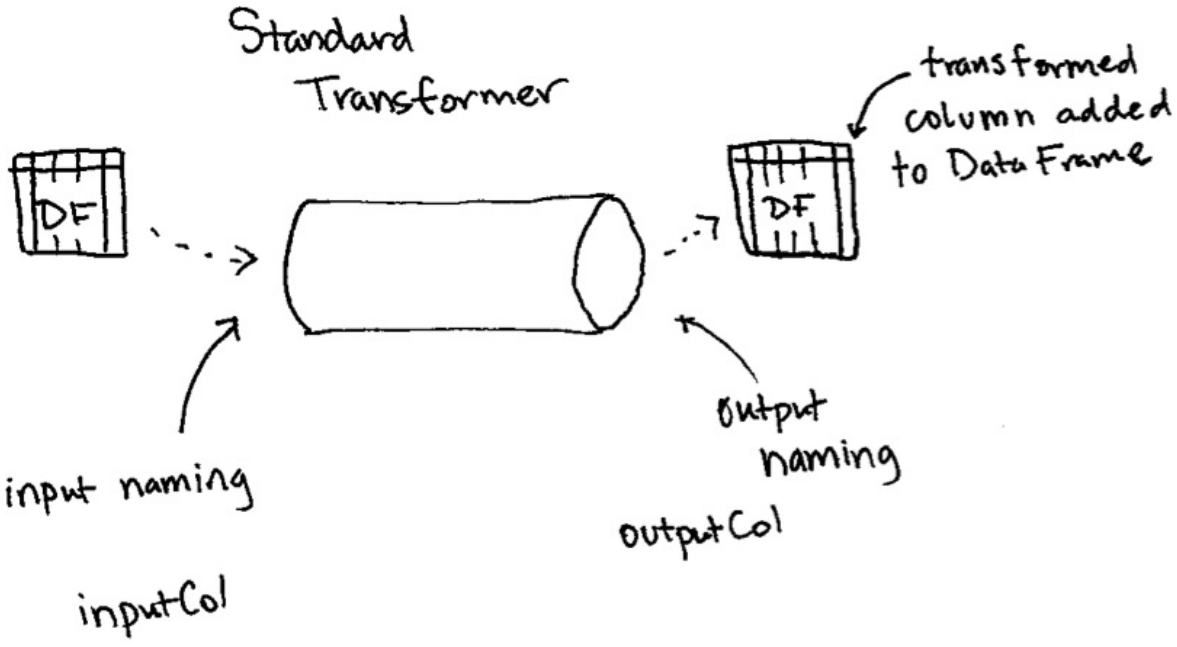
All transformers require you to specify, at a minimum the `inputCol` and the `outputCol`, obviously representing the column name of the input and output. You set these with the `setInputCol` and `setOutputCol`. At times there are defaults (you can find these in the documentation) but it is a best practice to manually specify them yourself for clarity. In addition to input and outpul columns, all transformers have different parameters that you can tune, whenever we mention a parameter in this chapter you must set it with `set<PARAMETER_NAME>`.

note

Spark MLlib stores metadata about the columns that it uses as an attribute on the column itself. This allows it to properly store (and annotate) that a column of doubles may actually represent a series of categorical variables which should not just blindly be used as numerical values. As demonstrated later on this chapter under the “Working with Categorical Variables Section”, this is why it’s important to index variables (and potentially one hot encode them) before inputting them into your model. One catch is that this will not show up when you print the schema of a column.

Different Transformer Types

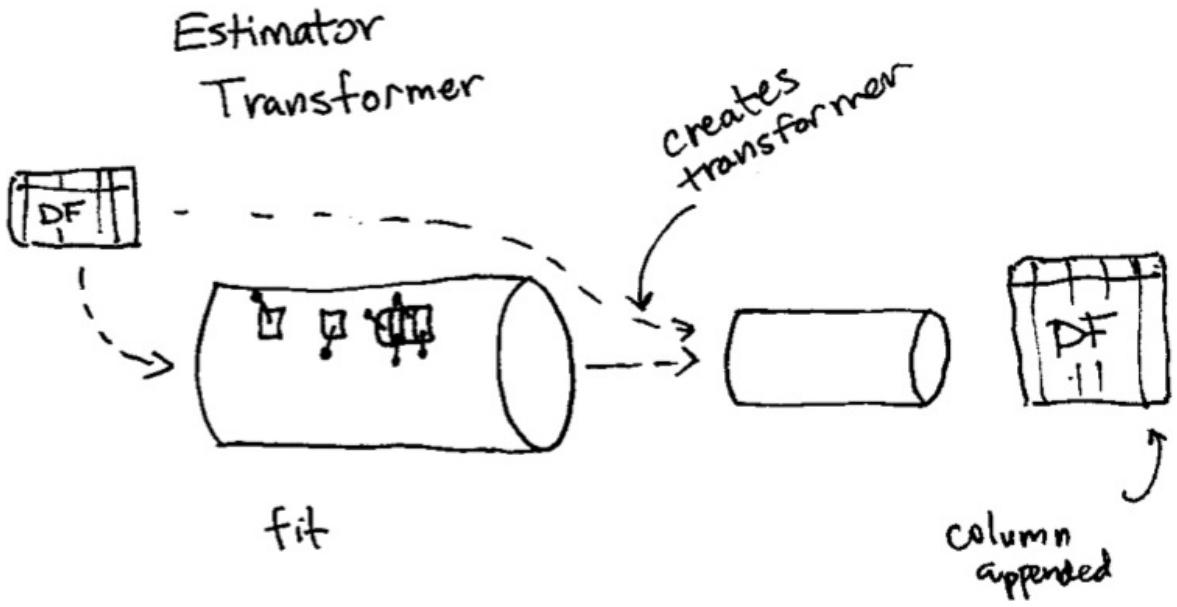
In the previous chapter we mentioned the simplified concept of "transformers" however there are actually two different kinds of tranformers. The "standard" transformer only includes a "transform" method, this is because it will not change based on the input data.



An example of this is the `Tokenizer` transformer. It has nothing to "learn" from out data.

```
import org.apache.spark.ml.feature.Tokenizer

val tkn = new Tokenizer().setInputCol("Description")
tkn.transform(sales).show()
```

The other kind of transformer is actually an *estimator*. This just means that it needs to be fit prior to being used as a transformer because it must tune itself according to the input data set. While technically incorrect, it can be helpful to think about this as simply generating a transformer at runtime based on the input data.



An example of this is the `StandardScaler` that must modify itself according to the numbers in the relevant column in order to scale the data appropriately.

```
import org.apache.spark.ml.feature.StandardScaler

val ss = new StandardScaler().setInputCol("features")
ss.fit(scaleDF).transform(scaleDF).show(false)
```

High Level Transformers

In general, you should try to use the highest level transformers that you can, this will minimize the risk of error and help you focus on the business problem instead of the smaller details of implementation. While this is not always possible, it's a good goal.

RFormula

You likely noticed in the previous chapter that the `RFormula` is the easiest transformer to use when you have "conventionally" formatted data. Spark borrows this transformer from the R language and makes it simple to declaratively specify a set of transformations for your data. What we mean by this is that values are either numerical or categorical and you do not need to extract values from the strings or manipulate them in anyway. This will automatically handle categorical inputs (specified as strings) by one hot encoding them. Numeric columns will be cast to `Double` but will *not* be one hot encoded. If the label column is of type string, it will be first transformed to double with `StringIndexer`.

> **warning**
>
> This has some strong implications. If you have numerically valued categorical variables, they will *only* be cast to `Double`, implicitly specifying an order. It is important to ensure that the input types correspond to the expected conversion. For instance, if you have categorical variables, they should be `String`. You can also manually index columns, see "Working with Categorical Variables" in this chapter.

`RFormula` also uses default columns of label and features respectively. This makes it very easy to pass it immediately into models which will require those exact column names by default.

```
%scala

import org.apache.spark.ml.feature.RFormula

val supervised = new RFormula()
  .setFormula("lab ~ . + color:value1 + color:value2")
supervised.fit(simpleDF).transform(simpleDF).show()

%python

from pyspark.ml.feature import RFormula
```

```
supervised = RFormula()\
  .setFormula("lab ~ . + color:value1 + color:value2")
supervised.fit(simpleDF).transform(simpleDF).show()
```

SQLTransformers

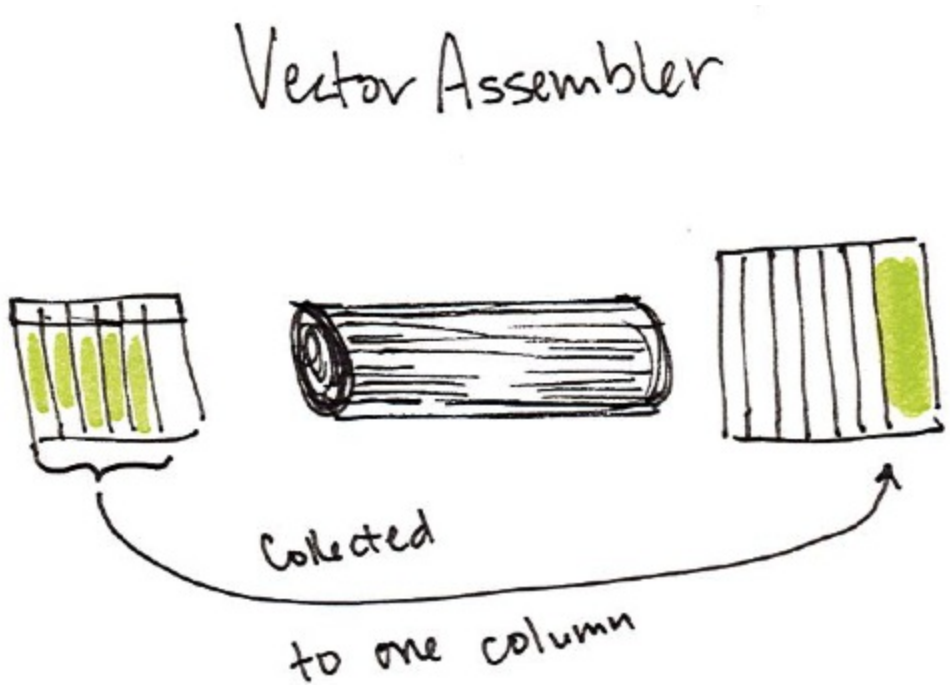
The `SQLTransformer` allows you to codify the SQL manipulations that you make as a ML transformation. Any SELECT statement is a valid transformation, the only thing that you need to change is that instead of using the table name, you should just use the keyword `__THIS__`. You might want to use this if you want to formally codify some DataFrame manipulation as a preprocessing step. One thing to note as well is that the output of this transformation will be appended as a column to the output DataFrame.

```
%scala

import org.apache.spark.ml.feature.SQLTransformer

val basicTransformation = new SQLTransformer()
  .setStatement("""
    SELECT sum(Quantity), count(*), CustomerID
    FROM __THIS__
    GROUP BY CustomerID
  """)

basicTransformation.transform(sales).show()

%python

from pyspark.ml.feature import SQLTransformer

basicTransformation = SQLTransformer()\
  .setStatement("""
    SELECT sum(Quantity), count(*), CustomerID
    FROM __THIS__
    GROUP BY CustomerID
  """)

basicTransformation.transform(sales).show()
```

For extensive samples of these transformations see Part II of the book.

VectorAssembler

The `VectorAssembler` is the tool that you'll use in every single pipeline that you generate. It helps gather all your features into one big vector that you can then pass into an estimator. It's used typically in the last step of a machine learning pipeline and takes as input a number of columns of `Double` or `Vector`.




```
import org.apache.spark.ml.feature.VectorAssembler

val va = new VectorAssembler()
  .setInputCols(Array("int1", "int2", "int3"))
va.transform(fakeIntDF).show()

%python

from pyspark.ml.feature import VectorAssembler

va = VectorAssembler().setInputCols(["int1", "int2", "int3"])
va.transform(fakeIntDF).show()
```

Text Data Transformers

Text is always a tricky input because it often requires lots of manipulation to conform to some input data that a machine learning model will be able to use effectively. There's generally two kinds of formats that you'll deal with, freeform text and text categorical variables. This section of the chapter primarily focuses on text while later on in this chapter we discuss categorical variables.

Tokenizing Text

Tokenization is the process of converting free form text into a list of "tokens" or individual words. The easiest way to do this is through the `Tokenizer`. This transformer will take a string of words, separated by white space, and convert them into an array of words. For example, in our dataset we might want to convert the Description field into a list of tokens.

```
import org.apache.spark.ml.feature.Tokenizer

val tkn = new Tokenizer()
  .setInputCol("Description")
  .setOutputCol("DescriptionOut")

val tokenized = tkn.transform(sales)
tokenized.show()

%python

from pyspark.ml.feature import Tokenizer

tkn = Tokenizer()\
  .setInputCol("Description")\
  .setOutputCol("DescriptionOut")

tokenized = tkn.transform(sales)
tokenized.show()
```

We can also create a tokenizer that is not just based off of white space but a regular expression with the `RegexTokenizer`. The format of the regular expression should conform to the Java Regular Expression Syntax.

```
%scala

import org.apache.spark.ml.feature.RegexTokenizer

val rt = new RegexTokenizer()
  .setInputCol("Description")
  .setOutputCol("DescriptionOut")
  .setPattern(" ") // starting simple
  .setToLowercase(true)
```

```
rt.transform(sales).show()

%python

from pyspark.ml.feature import RegexTokenizer

rt = RegexTokenizer()\
  .setInputCol("Description")\
  .setOutputCol("DescriptionOut")\
  .setPattern(" ")\
  .setToLowercase(True)

rt.transform(sales).show()
```

You can also have this match words (as opposed to splitting on a given value) by setting the `gaps` parameter to false.

Removing Common Words

A common task after tokenization is the filtering of common words or *stop words*. These words are not relevant for a particular analysis and should therefore be removed from our lists of words. Common stop words in English include “the”, “and”, “but” and other common words. Spark contains a list of default stop words which you can see by calling the method below. THis can be made case insensitive if necessary. Support languages for stopwords are: “danish”, “dutch”, “english”, “finnish”, “french”, “german”, “hungarian”, “italian”, “norwegian”, “portuguese”, “russian”, “spanish”, “swedish”, and “turkish” as of Spark 2.2.

```
%scala

import org.apache.spark.ml.feature.StopWordsRemover

val englishStopWords = StopWordsRemover
  .loadDefaultStopWords("english")
val stops = new StopWordsRemover()
  .setStopWords(englishStopWords)
  .setInputCol("DescriptionOut")

stops.transform(tokenized).show()

%python

from pyspark.ml.feature import StopWordsRemover

englishStopWords = StopWordsRemover\
  .loadDefaultStopWords("english")
stops = StopWordsRemover()\
  .setStopWords(englishStopWords)\
  .setInputCol("DescriptionOut")

stops.transform(tokenized).show()
```

Creating Word Combinations

Tokenizing our strings and filtering stop words leaves us with a clean set of words to use as features. Often time it is of interest to look at combinations of words, usually by looking at co-located words. Word combinations are technically referred to as *n-grams*. N-grams are sequences of words of length N. N-grams of length one are called unigrams, length two are bigrams, length three are trigrams. Anything above those are just four-gram, five-gram, etc. Order matters with N-grams, so a converting three words into bigrams would contain two bigrams. For example, the bigrams of "Bill Spark Matei" would be "Bill Spark", "Spark Matei".

We can see this below. The use case for ngrams is to look at what words commonly co-occur and potentially learn some machine learning algorithm based on those inputs.

```
import org.apache.spark.ml.feature.NGram

val unigram = new NGram()
  .setInputCol("DescriptionOut")
  .setN(1)

val bigram = new NGram()
  .setInputCol("DescriptionOut")
  .setN(2)

unigram.transform(tokenized).show()
bigram.transform(tokenized).show()
```

Converting Words into Numbers

Once we created word features, it's time to start counting instances of words and word combinations. The simplest way is just to include binary counts of the existence of a word in a given document (in our case, a row). However we can also count those up (`CountVectorizer`) as well as reweigh them according to the prevalence of a given word in all the documents `TF-IDF`.

A `CountVectorizer` operates on our tokenized data and does two things.

1. During the `fit` process it gathers information about the *vocabulary* in this dataset. For instance for our current data, it would look at all the tokens in each DescriptionOut column and then call that the vocabulary.

2. It then counts the occurrences of a given word in each row of the DataFrame column during the `transform` process and outputs a vector with the terms that occur in that row.

Conceptually this tranformer treats every row as a *document* and every word as a *term* and the total collection of all terms as the *vocabulary*. These are all tunable parameters, meaning we can set the minimum term frequency (`minTF`) for it to be included in the vocabulary (effectively removing rare words from the vocabulary), minimum number of documents a term must appear in (`minDF`) before being included in the vocabulary (another way to remove rare words from the vocabulary), and finally the total maximum vocabulary size (`vocabSize`). Lastly, by default the count vectorizer will output the counts of a term in a document. We can use `setBinary(true)` to have it output simple word existence instead.

```
%scala

import org.apache.spark.ml.feature.CountVectorizer

val cv = new CountVectorizer()
  .setInputCol("DescriptionOut")
  .setOutputCol("countVec")
  .setVocabSize(500)
  .setMinTF(1)
```

```
  .setMinDF(2)

val fittedCV = cv.fit(tokenized)
fittedCV.transform(tokenized).show()

%python

from pyspark.ml.feature import CountVectorizer

cv = CountVectorizer()\
  .setInputCol("DescriptionOut")\
  .setOutputCol("countVec")\
  .setVocabSize(500)\
  .setMinTF(1)\
  .setMinDF(2)

fittedCV = cv.fit(tokenized)
fittedCV.transform(tokenized).show()
```

TF-IDF

Another way to approach the problem in a bit more sophisticated way than simple counting is to use TF-IDF or term frequency-inverse document frequency. The complete explanation of TF-IDF beyond the scope of this book but in simplest terms it finds words that are most representative of certain rows by finding out how often those words are used and weighing a given term according to the number of documents those terms show up in. A more complete explanation can be found *http://billchambers.me/tutorials/2014/12/21/tf-idf-explained-in-python.html*. In practice, TF-IDF helps find documents that share similar topics. Let's see a worked example.

```
%scala

val tfIdfIn = tokenized
  .where("array_contains(DescriptionOut, 'red')")
  .select("DescriptionOut")
  .limit(10)
tfIdfIn.show(false)

%python

tfIdfIn = tokenized\
```

```
  .where("array_contains(DescriptionOut, 'red')")\
  .select("DescriptionOut")\
  .limit(10)
tfIdfIn.show(10, False)
```

```
+----------------------------------------+
|DescriptionOut                          |
+----------------------------------------+
|[gingham, heart, , doorstop, red]       |
...
|[red, retrospot, oven, glove]           |
|[red, retrospot, plate]                 |
+----------------------------------------+
```

We can see some overlapping words in these documents so those won't be perfect identifiers for individual documents but do identify that "topic" of sort across those documents. Now let's input that into TF-IDF. First we perform a hashing of each word then we perform the IDF weighting of the vocabulary.

```
%scala

import org.apache.spark.ml.feature.{HashingTF, IDF}

val tf = new HashingTF()
  .setInputCol("DescriptionOut")
  .setOutputCol("TFOut")
  .setNumFeatures(10000)

val idf = new IDF()
  .setInputCol("TFOut")
  .setOutputCol("IDFOut")
  .setMinDocFreq(2)

%python

from pyspark.ml.feature import HashingTF, IDF

tf = HashingTF()\
  .setInputCol("DescriptionOut")\
  .setOutputCol("TFOut")\
  .setNumFeatures(10000)

idf = IDF()\
  .setInputCol("TFOut")\
  .setOutputCol("IDFOut")\
  .setMinDocFreq(2)
```

```
%scala

idf.fit(tf.transform(tfIdfIn))
  .transform(tf.transform(tfIdfIn))
  .show(false)

%python

idf.fit(tf.transform(tfIdfIn))\
  .transform(tf.transform(tfIdfIn))\
  .show(10, False)
```

While the output is too large to include here what you will notice is that a certain value is assigned to "red" and that value appears in every document. You will then notice that this term is weighted extremely low because it appears in every document. The output format is a `Vector` that we can subsequently input into a machine learning model in a form like:

```
(10000,[2591,4291,4456],[1.0116009116784799,0.0,0.0])
```

This vector is composed of three different values, the total vocabulary size, the hash of every word appearing in the document, and the weighting of each of those terms.

Advanced Techniques

The last text manipulation tool we have at our disposal is Word2vec. Word2vec is a sophisticated neural network style natural language processing tool. Word2vec uses a technique called "skip-grams" to convert a sentence of words into an embedded vector representation. It does this by building a vocabulary, then for every sentence, removes a token and trains the model to predict the missing token in the "n-gram" representation. With the sentence, "the Queen of England" it might be trained to try to predict the missing token "Queen" in "the of England". Word2vec works best with continuous, free form text in the form of tokens, so we won't expect great results from our description field which does not include freeform text. Spark's Word2vec implementation includes a variety of tuning parameters that can be found on the documentation.

Working with Continuous Features

Continuous features are just values on the number line, from positive infinity to negative infinity. There are two transformers for continuous features. First you can convert continuous features into categorical features via a process called bucketing or you can scale and normalize your features according to several different requirements. These transformers will *only* work on `Double` types, so make sure that you've turned any other numerical values to `Double`.

```
%scala

val contDF = spark.range(500)
  .selectExpr("cast(id as double)")

%python

contDF = spark.range(500)\
  .selectExpr("cast(id as double)")
```

Bucketing

The most straightforward approach to bucketing or binning is the `Bucketizer`. This will split a given continuous feature into the buckets of your designation. You specify how buckets should be created via an array or list of `Double` values. This method is confusing because we specify bucket borders via the `splits` method, however these are not actually splits. They are actually bucket borders.

For example setting splits to `5.0, 10.0, 250.0` on our `contDF` because we don't cover all possible ranges input ranges. To specify your bucket points, the values you pass into `splits` must satisfy three requirements.

- The minimum value in your splits array must be less than the minimum value in your DataFrame.
- The maximum value in your splits array must be greater than the maximum value in your DataFrame.
- You need to specify at a minimum three values in the splits array, which creates two buckets.

To cover all possible ranges, Another split option could be `scala.Double.NegativeInfinity` and `scala.Double.PositiveInfinity` to cover all possible ranges outside of the inner splits. Or in python `float("inf"), float("-inf").`

In order to handle `null` or `NaN` values, we must specify the `handleInvalid` parameter to a certain value. We can either keep those values (`keep`), error on null `error`, or `skip` those rows.

```
%scala

import org.apache.spark.ml.feature.Bucketizer

val bucketBorders = Array(-1.0, 5.0, 10.0, 250.0, 600.0)
```

```
val bucketer = new Bucketizer()
  .setSplits(bucketBorders)
  .setInputCol("id")

bucketer.transform(contDF).show()

%python

from pyspark.ml.feature import Bucketizer

bucketBorders = [-1.0, 5.0, 10.0, 250.0, 600.0]

bucketer = Bucketizer()\
  .setSplits(bucketBorders)\
  .setInputCol("id")

bucketer.transform(contDF).show()
```

As opposed to splitting based on hardcoded values, another option is to split based on percentiles in our data. This is done with the `QuantileDiscretizer` which will bucket the values in the a number of user-specified buckets with the splits being determined by approximate quantiles values. You can control how finely the buckets should be split by setting the relative error for the approximate quantiles calculation using `setRelativeError`.

```
%scala

import org.apache.spark.ml.feature.QuantileDiscretizer

val bucketer = new QuantileDiscretizer()
  .setNumBuckets(5)
  .setInputCol("id")

val fittedBucketer = bucketer.fit(contDF)
fittedBucketer.transform(contDF).show()

%python

from pyspark.ml.feature import QuantileDiscretizer

bucketer = QuantileDiscretizer()\
  .setNumBuckets(5)\
  .setInputCol("id")

fittedBucketer = bucketer.fit(contDF)
fittedBucketer.transform(contDF).show()
```

Advanced Bucketing Techniques

There are other bucketing techniques like locality sensitive hashing. Conceptually these are no different from the above (in that they create buckets out of discrete variables) but do some according to different algorithms. Please see the documentation for more information on these techniques.

Scaling and Normalization

Bucketing is straightforward for creating groups out of continuous variables. The other frequent task is to scale and normalize continuous data such that large values do not overly emphasize one feature simply because their scale is different. This is a well studied process and the transformers available are routinely found in other machine learning libraries. Each of these transformers operate on a column of type `Vector` and for every row (of type `Vector`) in that column it will apply the normalization component wise to the values in the vector. It effectively treats every value in the vector as its own column.

Normalizer

Probably the simplest technique is that of the normalizer. This normalizes a an input vector to have unit norm to the user-supplied p-norm. For example we can get the taxicab norm with p = 1, Euclidean norm with p= 2, and so on.

```
%scala
import org.apache.spark.ml.feature.Normalizer

val taxicab = new Normalizer()
  .setP(1)
  .setInputCol("features")

taxicab.transform(scaleDF).show(false)

%python

from pyspark.ml.feature import Normalizer

taxicab = Normalizer()\
  .setP(1)\
  .setInputCol("features")

taxicab.transform(scaleDF).show()
```

StandardScaler

The `StandardScaler` standardizes a set of feature to have zero mean and unit standard deviation. the flag `withStd` will scale the data to unit standard deviation while the flag `withMean` (false by default) will center the data prior to scaling it.

> **warning**
>
> this centering can be very expensive on sparse vectors, so be careful before centering your data.

```
import org.apache.spark.ml.feature.StandardScaler

val sScaler = new StandardScaler()
  .setInputCol("features")

sScaler.fit(scaleDF).transform(scaleDF).show(false)
```

MinMaxScaler

The MinMaxScaler will scale the values in a vector (component wise) to the proportional values on a Scale from the min value to the max value. The min is 0 and the max is 1 by default, however we can change this as seen in the following example.

```
import org.apache.spark.ml.feature.MinMaxScaler

val minMax = new MinMaxScaler()
  .setMin(5)
  .setMax(10)
  .setInputCol("features")

val fittedminMax = minMax.fit(scaleDF)
fittedminMax.transform(scaleDF).show(false)

%python

from pyspark.ml.feature import MinMaxScaler
```

```
minMax = MinMaxScaler()\
  .setMin(5)\
  .setMax(10)\
  .setInputCol("features")

fittedminMax = minMax.fit(scaleDF)
fittedminMax.transform(scaleDF).show()
```

MaxAbsScaler

The max absolutely scales the data by dividing each value (component wise) by the maximum absolute value in each feature. It does not shift or center data.

```
import org.apache.spark.ml.feature.MaxAbsScaler

val maScaler = new MaxAbsScaler()
  .setInputCol("features")

val fittedmaScaler = maScaler.fit(scaleDF)

fittedmaScaler.transform(scaleDF).show(false)
```

ElementwiseProduct

This just performs component wise multiplication of a user specified vector and each vector in each row or your data. For example given the vector below and the row “1, 0.1, -1” the output will be “10, 1.5, -20”. Naturally the dimensions of the scaling vector must match the dimensions of the vector inside the relevant column.

```
%scala

import org.apache.spark.ml.feature.ElementwiseProduct
import org.apache.spark.ml.linalg.Vectors

val scaleUpVec = Vectors.dense(10.0, 15.0, 20.0)
val scalingUp = new ElementwiseProduct()
  .setScalingVec(scaleUpVec)
  .setInputCol("features")

scalingUp.transform(scaleDF).show()
```

```
%python

from pyspark.ml.feature import ElementwiseProduct
from pyspark.ml.linalg import Vectors

scaleUpVec = Vectors.dense(10.0, 15.0, 20.0)
scalingUp = ElementwiseProduct()\
  .setScalingVec(scaleUpVec)\
  .setInputCol("features")

scalingUp.transform(scaleDF).show()
```

Working with Categorical Features

The most common task with categorical features is indexing. This converts a categorical variable in a column to a numerical one that you can plug into Spark's machine learning algorithms. While this is conceptually simple, there are some catches that are important to keep in mind so that Spark can do this in a stable and repeatable manner.

What might come as a surprise is that you *should* use indexing with *every categorical variable* in your DataFrame. This is because it will ensure that all values not just the correct type but that the largest value in the output will represent the number of groups that you have (as opposed to just encoding business logic). This can also be helpful in order to maintain consistency as your business logic and representation may evolve and groups change.

StringIndexer

The simplest way to index is via the `StringIndexer`. Spark's `StringIndexer` creates metadata attached to the DataFrame that specify what inputs correspond to what outputs. This allows us later to get inputs back from their respective output values.

```
%scala

import org.apache.spark.ml.feature.StringIndexer

val labelIndexer = new StringIndexer()
  .setInputCol("lab")
  .setOutputCol("labelInd")

val idxRes = labelIndexer.fit(simpleDF).transform(simpleDF)
idxRes.show()

%python

from pyspark.ml.feature import StringIndexer

labelIndexer = StringIndexer()\
  .setInputCol("lab")\
  .setOutputCol("labelInd")

idxRes = labelIndexer.fit(simpleDF).transform(simpleDF)
idxRes.show()
```

As mentioned, we can apply `StringIndexer` to columns that are not strings.

```
%scala

val valIndexer = new StringIndexer()
  .setInputCol("value1")
  .setOutputCol("valueInd")

valIndexer.fit(simpleDF).transform(simpleDF).show()

%python

valIndexer = StringIndexer()\
  .setInputCol("value1")\
```

```
  .setOutputCol("valueInd")

valIndexer.fit(simpleDF).transform(simpleDF).show()
```

Keep in mind that the `StringIndexer` is a transformer that must be fit on the input data. This means that it must see all inputs to create a respective output. If you train a `StringIndexer` on inputs “a”, “b”, and “c” then go to use it against input “d”, it will throw an error by default. There is another option which is to skip the entire row if it has not seen that label before. We can set this before or after training. More options may be added to this in the future but as of Spark 2.2, you can only skip or error on invalid inputs.

```
valIndexer.setHandleInvalid("skip")
valIndexer.fit(simpleDF).setHandleInvalid("skip")
```

Converting Indexed Values Back to Text

When inspecting your machine learning results, you're likely going to want to map back to the original values. We can do this with IndexToString. You'll notice that we do not have to input our value to string key, Spark's MLlib maintains this metadata for you. You can optionally specify the outputs.

```
%scala

import org.apache.spark.ml.feature.IndexToString

val labelReverse = new IndexToString()
  .setInputCol("labelInd")

labelReverse.transform(idxRes).show()

%python

from pyspark.ml.feature import IndexToString

labelReverse = IndexToString()\
  .setInputCol("labelInd")

labelReverse.transform(idxRes).show()
```

Indexing in Vectors

`VectorIndexer` is a helpful tool for working with categorical variables that are already found inside of vectors in your dataset. It can automatically decide which features are categorical and then convert those categorical features into 0-based category indices for each categorical feature. For example, in the DataFrame below the first column in our Vector is a categorical variable with two different categories. By setting `maxCategories` to 2 we instruct the VectorIndexer that any column in our vector with less than two distinct values should be treated as categorical.

```
%scala

import org.apache.spark.ml.feature.VectorIndexer
import org.apache.spark.ml.linalg.Vectors

val idxIn = spark.createDataFrame(Seq(
  (Vectors.dense(1, 2, 3),1),
  (Vectors.dense(2, 5, 6),2),
  (Vectors.dense(1, 8, 9),3)
)).toDF("features", "label")

val indxr = new VectorIndexer()
  .setInputCol("features")
  .setOutputCol("idxed")
  .setMaxCategories(2)

indxr.fit(idxIn).transform(idxIn).show

%python

from pyspark.ml.feature import VectorIndexer
from pyspark.ml.linalg import Vectors

idxIn = spark.createDataFrame([
  (Vectors.dense(1, 2, 3),1),
  (Vectors.dense(2, 5, 6),2),
  (Vectors.dense(1, 8, 9),3)
]).toDF("features", "label")

indxr = VectorIndexer()\
  .setInputCol("features")\
```

```
  .setOutputCol("idxed")\
  .setMaxCategories(2)

indxr.fit(idxIn).transform(idxIn).show
```

One Hot Encoding

Now indexing categorical values gets our data into the correct data type however, it does not always represent our data in the correct format. When we index our “color” column you’ll notice that implicitly some colors will receive a higher number than others (in my case blue is 1 and green is 2).

```
%scala

val labelIndexer = new StringIndexer()
  .setInputCol("color")
  .setOutputCol("colorInd")

val colorLab = labelIndexer.fit(simpleDF).transform(simpleDF)

%python

labelIndexer = StringIndexer()\
  .setInputCol("color")\
  .setOutputCol("colorInd")

colorLab = labelIndexer.fit(simpleDF).transform(simpleDF)
```

Some algorithms will treat this as “green” being greater than “blue” - which does not make sense. To avoid this we use a `OneHotEncoder` which will convert each distinct value as a boolean flag (1 or 0) as a component in a vector. We can see this when we encode the color value that these are no longer ordered but a categorical representation in our vector.

```
%scala

import org.apache.spark.ml.feature.OneHotEncoder

val ohe = new OneHotEncoder()
  .setInputCol("colorInd")
ohe.transform(colorLab).show()

%python

from pyspark.ml.feature import OneHotEncoder

ohe = OneHotEncoder()\
```

```
  .setInputCol("colorInd")
ohe.transform(colorLab).show()
```

Feature Generation

While nearly every transformer in ML manipulates the feature space in some way, the following algorithms and tools are automated means of either expanding the input feature vectors or reducing them to ones that are more important.

PCA

PCA or Principal Components Analysis performs a decomposition of the input matrix (your features) into its component parts. This can help you reduce the number of features you have to the principal components (or the features that truly matter), just as the name suggests. Using this tool is straightforward, you simply specify the number of components, `k`, you would like.

```
%scala

import org.apache.spark.ml.feature.PCA

val pca = new PCA()
  .setInputCol("features")
  .setK(2)

pca.fit(scaleDF).transform(scaleDF).show(false)

%python

from pyspark.ml.feature import PCA

pca = PCA()\
  .setInputCol("features")\
  .setK(2)

pca.fit(scaleDF).transform(scaleDF).show()
```

Interaction

Often you might have some domain knowledge about specific variables in your dataset. For example, you might know that some interaction between the two is an important variable to include in a down stream estimator. The `Interaction` feature transformer allows you to create this manually. It just multiplies the two features together. This is currently only available in Scala and mostly used internally by the `RFormula`. We recommend users to just use `RFormula` from any language instead of manually creating interactions.

PolynomialExpansion

Polynomial expansion is used to generate interaction variables of all of the inputs. It's effectively taking every value in your feature vector, multiplying it by every other value, and then storing each of those results as features. In Spark, we can control the degree polynomial when we create the polynomial expansion.

> **warning**
>
> This can have a significant effect on your feature space and so it should be used with caution.

```
%scala

import org.apache.spark.ml.feature.PolynomialExpansion

val pe = new PolynomialExpansion()
  .setInputCol("features")
  .setDegree(2)

pe.transform(scaleDF).show(false)

%python

from pyspark.ml.feature import PolynomialExpansion

pe = PolynomialExpansion()\
  .setInputCol("features")\
  .setDegree(2)

pe.transform(scaleDF).show()
```

Feature Selection

ChisqSelector

In simplest terms, the Chi-Square Selector is a tool for performing feature selection of categorical data. It is often used to reduce the dimensionality of text data (in the form of frequencies or counts) to better aid the usage of these features in classification. Since this method is based on the Chi-Square test, there are several different ways that we can pick the "best" features. The methods are "numTopFeatures" which is ordered by p-value, "percentile" which takes a proportion of the input features (instead of just the top N features), "fpr" which sets a cut off p-value.

We will demonstrate this with the output of the `CountVectorizer` created previous in this chapter.

```
%scala

import org.apache.spark.ml.feature.ChiSqSelector

val prechi = fittedCV.transform(tokenized)
  .where("CustomerId IS NOT NULL")

val chisq = new ChiSqSelector()
  .setFeaturesCol("countVec")
  .setLabelCol("CustomerID")
  .setNumTopFeatures(2)

chisq.fit(prechi).transform(prechi).show()

%python

from pyspark.ml.feature import ChiSqSelector

prechi = fittedCV.transform(tokenized)\
  .where("CustomerId IS NOT NULL")

chisq = ChiSqSelector()\
  .setFeaturesCol("countVec")\
  .setLabelCol("CustomerID")\
  .setNumTopFeatures(2)

chisq.fit(prechi).transform(prechi).show()
```

Persisting Transformers

Once you've used an estimator, it can be helpful to write it to disk and simply load it when necessary. We saw this in the previous chapter were we persisted an entire pipeline. To persist a transformer we use the `write` method on the fitted transformer (or the standard transformer) and specify the location.

```
val fittedPCA = pca.fit(scaleDF)

fittedPCA.write.overwrite().save("/tmp/fittedPCA")
```

TODO: not sure why this isn't working right now…

```
val loadedPCA = PCA.load("/tmp/fittedPCA")
loadedPCA.transform(scaleDF).sow()
```

Writing a Custom Transformer

Writing a custom transformer can be valuable when you would like to encode some of your own business logic as something that other folks in your organization can use. In general you should try to use the built-in modules (e.g., `SQLTransformer`) as much as possible because they are optimized to run efficiently, however sometimes we do not have that luxury. Let's create a simple tokenizer to demonstrate.

```
import org.apache.spark.ml.UnaryTransformer
import org.apache.spark.ml.util.{DefaultParamsReadable, Default
import org.apache.spark.sql.types.{ArrayType, StringType, Data
import org.apache.spark.ml.param.{IntParam, ParamValidators}

class MyTokenizer(override val uid: String)
  extends UnaryTransformer[String, Seq[String], MyTokenizer] w

  def this() = this(Identifiable.randomUID("myTokenizer"))

  val maxWords: IntParam = new IntParam(this, "maxWords", "The
  ParamValidators.gtEq(0))

  def setMaxWords(value: Int): this.type = set(maxWords, value)

  def getMaxWords: Integer = $(maxWords)

  override protected def createTransformFunc: String => Seq[St
    inputString.split("\\s").take($(maxWords))
  }

  override protected def validateInputType(inputType: DataType)
    require(inputType == StringType, s"Bad input type: $inputTy
  }

  override protected def outputDataType: DataType = new ArrayTy
}

// this will allow you to read it back in by using this object.
object MyTokenizer extends DefaultParamsReadable[MyTokenizer]

val myT = new MyTokenizer()
  .setInputCol("someCol")
```

```
  .setMaxWords(2)

display(myT.transform(Seq("hello world. This text won't show.")

myT.write.overwrite().save("/tmp/something")
```

It is also possible to write a custom `Estimator` where you must customize the transformation based on the actual input data.

Chapter 17. Classification

Classification is the task of predicting a label, category, class or qualitative variable given some input features. The simplest case is *binary classification*, where there are only two labels that you hope to predict. A typical example is fraud analytics, a given transaction can be fraudalent or not; or email spam, a given email can be spam or not spam. Beyond binary classification lies *multiclass classification* where one label is chosen from more than two distinct labels that can be produced. A typical example would be Facebook predicting the people in a given photo or a meterologist predicting the weather (rainy, sunny, cloudy, etc.). Finally, there is *multilabel classification* where a given input can produce multiple labels. For example you might want to predict weight and height from some lifestyle observations like athletic activities.

Like our other advanced analytics chapters, this one cannot teach you the mathematical underpinnings of every model. See chapter four in ISL and ESL for a review of classification.

Now that we agree on what types of classification there are, you should think about what task you are looking to solve. Spark has good support for both binary and multiclass classification with the models. As of Spark 2.2, nearly all classification methods support multiclass classification except for Gradient Boosted Trees, which only support binary classification. However, Spark does not support making multilabel predictions natively. In orer to train a multilabel model, you must train one model per label and and combine them manually. Once manually constructed, there are built in tools that support measuring these kinds of models that we cover at the end of the chapter.

One thing that can be limiting when you go to choose your model is the scalability of that model. For the most part, Spark has great support for large scale machine learning, with that being said, here's a simple scorecard for understanding which model might be best for your task. Naturally these will depend on your configuration, machine size, and more but they're a good heuristic.

Model	Features Count	Training Examples	Output Classes
Logistic Regression	1 to 10 million	no limit	Features x Classes < 10 million
Decision Trees	1,000s	no limit	Features x Classes < 10,000s
Random Forest	10,000s	no limit	Features x Classes < 100,000s
Gradient Boosted Trees	1,000s	no limit	Features x Classes < 10,000s
Multilayer Perceptron	depends	no limit	depends

We can see that nearly all these models scale quite well and there is ongoing work to scale them even further. The reason *no limit* is in place for the number of training examples is because these are trained using methods like stochastic gradient descent and L-BFGS which are optimized for large data. Diving into the details of these two methods is far beyond the scope of this book but you can rest easy in knowing that these models will scale. Some of this scalability will depend on how large of a cluster you have, naturally there are tradeoffs but from a theoretical standpoint, these algorithms can scale significantly.

For each type of model, we will include several details:

1. A simple explanation of the model,
2. model hyperparameters,

3. training parameters,
4. and prediction parameters.

You can set the hyperparameters and training parameters as parameters in a `ParamGrid` as we saw in the Advanced Analytics and Machine Learning overview.

```
%scala

val bInput = spark.read.load("/mnt/defg/binary-classification")
  .selectExpr("features", "cast(label as double) as label")

%python

bInput = spark.read.load("/mnt/defg/binary-classification")\
  .selectExpr("features", "cast(label as double) as label")
```

Logistic Regression

Logistic regression is a popular method for predicting a binary outcome via a linear combination of the inputs and and randomized noise in the form of a logistic random variable. This is a great starting place for any classification task because it's simple to reason about and interpret.

See ISL 4.3 and ESL 4.4 for more information.

Model Hyperparameters

- `family`: “multinomial” (multiple labels) or “binary” (two labels).
- `elasticNetParam`: This parameters specifies how you would like to mix L1 and L2 regularization.
- `fitIntercept`: Boolean, whether or not to fit the intercept.
- `regParam`: Determines how the inputs should be regularized before being passed in the model.
- `standardization`: Boolean, whether or not to standardize the inputs before passing them into the model.

Training Parameters

- `maxIter`: Total number of interations before stopping.
- `tol`: convergence tolerance for the algorithm.
- `weightCol`: the name of the weight column to weigh certain rows more than others.

Prediction Parameters

- `threshold`: probability threshold for binary prediction. This determines the minimum probability for a given class to be predicted.
- `thresholds`: probability threshold for multinomial prediction. This determines the minimum probability for a given class to be predicted.

Example

```
%scala

import org.apache.spark.ml.classification.LogisticRegression

val lr = new LogisticRegression()
var lrModel = lr.fit(bInput)

%python

from pyspark.ml.classification import LogisticRegression

lr = LogisticRegression()
lrModel = lr.fit(bInput)
```

Once the model is trained you can get some information about the model by taking a look at the coefficients and the intercept. This will naturally vary from model to model based on the parameters of the model itself.

```
lrModel.coefficients

lrModel.intercept
```

note

For a multinomial model use `lrModel.coefficientMatrix` and `lrModel.interceptVector` respectively. These will return `Matrix` and `Vector` types representing the values or each of the given classes.

Model Summary

Once you train your logistic regression model, you can view some useful summarization techniques just like you might find in R. This is currently only available for binary logistic regression, multiclass summaries will likely be added in the future. Using the binary summary, we can get all sorts of information about the model itself including the area under the ROC curve, the f measure by threshold, the precision, the recall, the recall by thresholds and the roc curve itself.

```
%scala

import org.apache.spark.ml.classification.BinaryLogisticRegress

val summary = lrModel.summary
val bSummary = summary
  .asInstanceOf[BinaryLogisticRegressionSummary]

bSummary.areaUnderROC
bSummary.roc
bSummary.pr.show()

%python

summary = lrModel.summary
summary.areaUnderROC
summary.roc
summary.pr.show()
```

The speed at which the model descends to the final solution is shown in the objective history.

```
summary.objectiveHistory
```

Decision Trees

Decision trees are one of the more friendly and interpretable models for performing classification. This model is a great starting plass for any classification task because it is extremely simple to reason about. Rather than trying to train coeffiecients in order to model a function, this simply creates a big giant tree to predict the output. This supports multiclass classification and provides outputs as predictions and probabilities in two different columns.

See ISL 8.1 and ESL 9.2 for more information.

Model Hyperparameters

- `impurity`: To determine splits, the model need a metric to calculate information gain. This can either be “entropy” or “gini”.
- `maxBins`: Determines the total number of bins that can be used for discretizing continuous features and for choosing how to split on features at each node.
- `maxDepth`: Determines how deep the total tree can be.
- `minInfoGain`: determines the minimum information gain that can be used for a split. A higher value can prevent overfitting.
- `minInstancePerNode`: determines the minimum number of instances that need to be in a node. A higher value can prevent overfitting.

Training Parameters

- `checkpointInterval`: determines how often that the model will get checkpointed, a value of 10 means it will get checkpointed every 10 iterations. For more information on checkpointing see the optimization and debugging part of this book.

Prediction Parameters

- `thresholds`: probability threshold for multinomial prediction.

Example

```
%scala

import org.apache.spark.ml.classification.DecisionTreeClassifie

val dt = new DecisionTreeClassifier()
val dtModel = dt.fit(bInput)

%python

from pyspark.ml.classification import DecisionTreeClassifier

dt = DecisionTreeClassifier()
dtModel = dt.fit(bInput)
```

Random Forest and Gradient Boosted Trees

These methods are logical extensions of the decision tree. Rather than training one tree on all of the data, you train multiple trees on varying subsets of the data (typically called weak learners). Random Forests and Gradient Boosted trees are two distinct ways of approaching this problem. In random forests, many de-correlated trees are trained and then averaged. With gradient boosted trees, each tree makes a weighted prediction (such that some trees have more predictive power for some classes over others). They have largely the same parameters and their differences are noted below. GBT's currently only support binary labels.

> **note**
>
> There exist other libraries, namely XGBoost, which are very popular tools for learning tree based models. XGBoost provides an integration with Spark where Spark can be used for training models. These, again, should be considered complementary. They may have better performance in some instances and not in others. Read about XGBoost here: *https://xgboost.readthedocs.io/en/latest/*

See ISL 8.2 and ESL 10.1 for more information.

Model Hyperparameters

- `impurity`: To determine splits, the model need a metric to calculate information gain. This can either be “entropy” or “gini”.
- `maxBins`: Determines the total number of bins that can be used for discretizing continuous features and for choosing how to split on features at each node.
- `maxDepth`: Determines how deep the total tree can be.
- `minInfoGain`: determines the minimum information gain that can be used for a split. A higher value can prevent overfitting.
- `minInstancePerNode`: determines the minimum number of instances that need to be in a node. A higher value can prevent overfitting.
- `subsamplingRate`: the franction of the training data that should be used for learning each decision tree. This varies how much information each tree should be trained on.

Random Forest Only

- `featureSubsetStrategy`: determines how many features should be considered for splits. This can be a variety of different values including “auto”, “all”, “sqrt”, “log2”, and “n” where n is in the range (0, 1.0], use n * number of features. When n is in the range (1, number of features), use n features.
- `numTrees`: the total number of trees to train.

GBT Only

- `lossType`: loss function for gradient boosted trees to minimize. This is how it determines tree success.

- `maxIter`: Maximum number of iterations that should be performed.
- `stepSize`: The learning rate for the algorithm.

Training Parameters

- `checkpointInterval`: determines how often that the model will get checkpointed, a value of 10 means it will get checkpointed every 10 iterations. For more information on checkpointing see the optimization and debugging part of this book.

Prediction Parameters

Random Forest Only

- `thresholds`: probability threshold for multinomial prediction.

Example

```
%scala

import org.apache.spark.ml.classification.RandomForestClassifie

val model = new RandomForestClassifier()
val trainedModel = dt.fit(bInput)

%scala

import org.apache.spark.ml.classification.GBTClassifier

val model = new GBTClassifier()
val trainedModel = dt.fit(bInput)

%python

from pyspark.ml.classification import RandomForestClassifier

model = RandomForestClassifier()
trainedModel = dt.fit(bInput)

%python

from pyspark.ml.classification import GBTClassifier

model = GBTClassifier()
trainedModel = dt.fit(bInput)
```

Multilayer Perceptrons

The multilayer perceptron in Spark is feedforward neural network with multiple layers of fully connected nodes. The hidden nodes use the sigmoid activation function with some weight and bias applied and the output layer uses softmax regression. Spark trains the network with backpropagation and logistic loss as the loss function. The number of inputs must be equal in size to the first layer while the number of outputs should be equal to the last layer.

As you may have noticed at the beginning of this chapter. The scalability of this model depends significantly on a number of factors. These are a function of the number of inputs, the number of layers, and the number of outputs. Larger networks will have much more scalability issues.

See DLB chapter 6 for more information.

Model Hyperparameters

- `layers`: An array that specifies the size of each layer in the network.

Training Parameters

- `maxIter`: the limit on the number of iterations over the dataset.
- `stepSize`: the learning rate or how much the the model should descend based off a training example.
- `tol`: determines the convergence tolerance for training.

Example

```
%scala

import org.apache.spark.ml.classification.MultilayerPerceptron(

val model = new MultilayerPerceptronClassifier()
val trainedModel = dt.fit(bInput)

%python

from pyspark.ml.classification import MultilayerPerceptronClass

model = MultilayerPerceptronClassifier()
trainedModel = dt.fit(bInput)
```

Naive Bayes

Naive Bayes is primarily used in text or document classification tasks although it can be used as a general classifier as well. There are two different model types: either a *multivariate bernoulli model*, where indicator variables represent the existence of a term in a document; or the *multinomial model*, where the total count of terms is used.

See ISL 4.4 and ESL 6.6 for more information.

Model Hyperparameters

- `modelType`: either “bernoulli” or “multinomial”.
- `weightCol`: an optional column that represents manual weighting of documents.

Training Parameters

- `smoothing`: This determines the amount of regularization that should take place.

Prediction Parameters

- `thresholds`: probability threshold for multinomial prediction.

Example.

```
%scala

import org.apache.spark.ml.classification.NaiveBayes

val model = new NaiveBayes()
val trainedModel = dt.fit(bInput)

%python

from pyspark.ml.classification import NaiveBayes

model = NaiveBayes()
trainedModel = dt.fit(bInput)
```

Evaluators

Evaluators, as we saw, allow us to perform an automated grid search that optimizes for a given metric. In classification there are two evaluators. In general, they expect two columns a prediction and a true label. For binary classification we use the `BinaryClassificationEvaluator`. This supports optimizing for two different metrics “areaUnderROC” and areaUnderPR”. For multiclass classification we use `MulticlassClassificationEvaluator`. This supports optimizing for “f1”, “weightedPrecision”, “weightedRecall”, and “accuracy”. See the Advanced Analytics and Machine Learning capter for how to use than evaluator.

```
%scala

import org.apache.spark.ml.evaluation.BinaryClassificationEvalu
import org.apache.spark.ml.evaluation.MulticlassClassificationE

%python

from pyspark.ml.evaluation import BinaryClassificationEvaluato
from pyspark.ml.evaluation import MulticlassClassificationEvalu
```

Metrics

Metrics are a way of seeing how your model performs according to a variety of different success criteria. Rather than just optimizing for one metric (as an evaluator does), this allows you to see a variety of different criteria. Unfortunately, metrics have not been ported over to Spark's ML package from the underlying RDD framework. Therefore at the time of this writing you still have to create an RDD to use these. In the future, this functionality will be ported to DataFrames and the below may no longer be the best way to see metrics (although you will still be able to use these APIs).

There are three different classification metrics we can use:

- Binary Classification Metrics
- Multiclass Classification Metrics
- Multilabel Classification Metrics

All of these different measure follow the same approximate style, we'll compare generated outputs with true values and it will calculate all of the relevant metrics for us. After which we can query the object for the values for each of the metrics.

```
%scala

import org.apache.spark.mllib.evaluation.BinaryClassificationMe
val out = lrModel.transform(bInput)
  .select("prediction", "label")
  .rdd
  .map(x => (x(0).asInstanceOf[Double], x(1).asInstanceOf[Doubl

val metrics = new BinaryClassificationMetrics(out)

%python

from pyspark.mllib.evaluation import BinaryClassificationMetric

out = lrModel.transform(bInput)\
```

```
  .select("prediction", "label")\
  .rdd\
  .map(lambda x: (float(x[0]), float(x[1])))

metrics = BinaryClassificationMetrics(out)

metrics.pr.toDF().show()
metrics.areaUnderROC
```

There are more metrics available and being released, please refer to the documentation for the latest methods.
http://spark.apache.org/docs/latest/mllib-evaluation-metrics.html

Chapter 18. Regression

Regression is the task of predicting quantitative values from a given set of features. This obviously differs from classification where the outputs are qualitative. A typical example might be predicting the value of a stock after a set amount of time or the temperature on a given day. This is a more difficult task that classification because there are infinite possible outputs.

Like our other advanced analytics chapters, this one cannot teach you the mathematical underpinnings of every model. See chapter three in ISL and ESL for a review of regression.

Now that we reviewed regression, it's time to review the model scalability of each model. For the most part this should seem similar to the classification chapter, as there is significant overlap between the available models. This is as of Spark 2.2.

Model	Number Features	Training Examples
Linear Regression	1 to 10 million	no limit
Generalized Linear Regression	4096	no limit
Isotonic Regression	NA	millions
Decision Trees	1000s	no limit
Random Forest	10000s	no limit
Gradient Boosted Trees	1000s	no limit

Survival Regression	1 to 10 million	no limit

We can see that these methods also scale quite well.

Now let's go over the models themselves, again we will include the following details for each model.

1. A simple explanation of the model,
2. model hyperparameters,
3. training parameters,
4. and prediction parameters.

You can set the hyperparameters and training parameters as parameters in a `ParamGrid` as we saw in the Advanced Analytics and Machine Learning overview.

```
%scala

val df = spark.read.load("/mnt/defg/regression")

%python

df = spark.read.load("/mnt/defg/regression")
```

Linear Regression

Linear regression assumes that the regression function to produce your output is a linear combination of the input variables with gaussian noise. Spark implements the elastic net regularization version of this model. This allows you to mix L1 and L2 regularization. A value of `0` sets the model to regularize via lasso regularization(L1) while a value of `1` sets the model to regularize via ridge regression(L2). This shares largely the same hyperparameters and training parameters that we saw for logistic regression so they have are not included in this chapter.

See ISL 3.2 and ESL 3.2 for more information.

Example

```
import org.apache.spark.ml.regression.LinearRegression

val lr = new LinearRegression()
  .setMaxIter(10)
  .setRegParam(0.3)
  .setElasticNetParam(0.8)

val lrModel = lr.fit(df)

%python

from pyspark.ml.regression import LinearRegression

lr = LinearRegression()\
  .setMaxIter(10)\
  .setRegParam(0.3)\
  .setElasticNetParam(0.8)

lrModel = lr.fit(df)
```

Training Summary

Similar to logistic regression, we get detailed training information back from our model.

```
%scala

val summary = lrModel.summary
summary.residuals.show()

summary.totalIterations

summary.objectiveHistory

summary.rootMeanSquaredError

summary.r2
```

Some of these summary values may not show up if you use L1 regulariation or many features.

```
%python

summary = lrModel.summary
summary.residuals.show()

summary.totalIterations
summary.objectiveHistory
summary.rootMeanSquaredError
summary.r2
```

Generalized Linear Regression

In addition to the “standard” linear regression. Spark also includes an interface for performing more general cases of linear regression. These allow you to set the expected noise distribution to a variey of families including gaussian (linear regression), binomial (logistic regression), poisson (poisson regression), and gamma (gamma regression). The generalized models also support the specification of a link function which specifies the relationship between the linear predictor and the mean of the distribution function. The available link functions depend on the family specified and new ones continue to be added so they are not enumerated here.

See ISL 3.2 and ESL 3.2 for more information.

warning

A fundamental limitation as of Spark 2.2 is that generalized linear regression only accepts a maximum of 4096 features for inputs. This will likely change for later versions of Spark so be sure to refer to the documentation in the future.

Model Hyperparameters

- `family`: defines the family for the error distribution.
- `fitIntercept`: a boolean value determining whether or not you should fit the intercept.
- `link`: defines the link function name. See the documentation for the complete list.
- `regParam`: regularization parameter.
- `solver`: the solver algorithm to be used for optimization.

Training Parameters

- `tol`: This is the convergence tolerance for each iteration.
- `weightCol`: this selects a certain column to weigh certain examples more than others.

Prediction Parameters

- `linkPredictionCol`: The output of our link function for that given prediction.

Example

```
%scala

import org.apache.spark.ml.regression.GeneralizedLinearRegressi

val glr = new GeneralizedLinearRegression()
  .setFamily("gaussian")
  .setLink("identity")
  .setMaxIter(10)
  .setRegParam(0.3)
  .setLinkPredictionCol("linkOut")

val glrModel = glr.fit(df)

%python

from pyspark.ml.regression import GeneralizedLinearRegression

glr = GeneralizedLinearRegression()\
  .setFamily("gaussian")\
  .setLink("identity")\
  .setMaxIter(10)\
  .setRegParam(0.3)\
  .setLinkPredictionCol("linkOut")

glrModel = glr.fit(df)
```

Training Summary

Generalized linear regression also provides an extensive training summary. This includes:

- Coefficient Standard Errors
- T Values
- P Values
- Dispersion
- Null Deviance
- Residual Degree Of Freedom Null
- Deviance
- Residual Degree Of Freedom
- AIC
- Deviance Residuals

```
%scala

val summary = glrModel.summary

%python

glrModel.summary
```

Decision Trees

Decision trees are one of the more friendly and interpretable models that we saw for classification and the same applies for regression. Rather than trying to train coeffiecients in order to model a function, we simply creates a big giant tree to predict the output. Like with classification, this model provides outputs as predictions and probabilities (in two different columns.) Decision tree regression has the same model hyperparameters and training parameters as the `DecisionTreeClassifier` that we saw in the previous chapter except that the only supported impurity measure is variance for the regressor. To use the `DecisionTreeRegressor` you simply import it and run it just like you would the classifier.

```
import org.apache.spark.ml.regression.DecisionTreeRegressor
```

```
%python

from pyspark.ml.regression.DecisionTreeRegressor
```

Random Forest and Gradient-boosted Trees

Both of these methods, rather than just training one decision tree, train an ensemble of trees. In random forests, many de-correlated trees are trained and then averaged. With gradient boosted trees, each tree makes a weighted prediction (such that some trees have more predictive power for some classes over others). Random Forest and Gradient-boosted tree regression has the same model hyperparameters and training parameters as the corresponding classification models except for the purity measure (as is the case with `DecisionTreeRegressor`). The proper imports can be found below.

```
%scala

import org.apache.spark.ml.regression.RandomForestRegressor
import org.apache.spark.ml.regression.GBTRegressor

%python

from pyspark.ml.regression import RandomForestRegressor
from pyspark.ml.regression import GBTRegressor
```

Survival Regression

Statisticians use survival analysis to analyze the survival rate of individuals, typically in controlled experiments. Spark implements the accelerated failure time model which, rather that describing the actual survival time, models the log of the survival time. Spark does not implement the more well known Cox Proportional Hazard's model because of it's non-parametric requirements. The core difference between these two is covered in this paper. *http://www.biostat.harvard.edu/robins/publications/structura_accelerated_*

The requirement for input is quite similar to other regressions, we will tune coefficients according to feature values. However there is one departure and that is the introduction of a censor variable. An individual test subject *censors* during a scientific study when they either drop out of a study and therefore their end state at the end of the experiment is unknown. This is important because we cannot assume an outcome for someone that censors halfway through a study.

Model Hyperparameters

- `fitIntecept`: whether or not to fit the intercept.

Training Parameters

- `censorCol`: column containing censoring of individuals.
- `tol`: Convergence tolerance.
- `maxIter`: the maximum number of iterations over the data.

Prediction Parameters

- `quantilesCol`: The output column for the quantiles.
- `quantileProbabilities`: Because this method estimates a distribution, as opposed to point values, we specify the quantile probabilities that we would like to get values for as parameters to the model.

Example

```
%scala

import org.apache.spark.ml.regression.AFTSurvivalRegression

val AFT = new AFTSurvivalRegression()
  .setFeaturesCol("features")
  .setCensorCol("censor")
  .setQuantileProbabilities(Array(0.5, 0.5))

%python

from pyspark.ml.regression import AFTSurvivalRegression

AFT = AFTSurvivalRegression()\
  .setFeaturesCol("features")\
  .setCensorCol("censor")\
  .setQuantileProbabilities([0.5, 0.5])
```

Isotonic Regression

Isotonic regression is a non-parametric regression that makes no assumptions about the input data but does require that the data be always positively increasing and negatively decreasing but never varying between the two. Isotonic regression is commonly used in conjunction with a classifier in order to

```
%scala

import org.apache.spark.ml.regression.IsotonicRegression

val ir = new IsotonicRegression().setIsotonic(true)
val model = ir.fit(df)

println(s"Boundaries in increasing order: ${model.boundaries}\n
println(s"Predictions associated with the boundaries: ${model.p

%python

from pyspark.ml.regression import IsotonicRegression

ir = IsotonicRegression().setIsotonic(True)
model = ir.fit(df)

model.boundaries
model.predictions
```

Evaluators

The regression evaluator is similar to the evaluator that we saw in previous chapters. We build the evaluator, pick an output metric, and fit our model according to that metric in a given pipeline. The evaluator for regression, as you may have guessed is the `RegressionEvaluator`.

```
%scala

import org.apache.spark.ml.evaluation.RegressionEvaluator

%python

from pyspark.ml.evaluation import RegressionEvaluator
```

Metrics

Evaluators provide us a way to evaluate and fit a model according to one specific metric, as we saw with classification. There are also a number of regression metrics that we can use and see as well. Once we train a model, we can see how it performs according to our training, validation, and test sets according to a number of metrics, not just one evaluation metric.

```
%scala

import org.apache.spark.mllib.evaluation.RegressionMetrics
val out = lrModel.transform(df)
  .select("prediction", "label")
  .rdd
  .map(x => (x(0).asInstanceOf[Double], x(1).asInstanceOf[Doubl

val metrics = new RegressionMetrics(out)

// Squared error
println(s"MSE = ${metrics.meanSquaredError}")
println(s"RMSE = ${metrics.rootMeanSquaredError}")

// R-squared
println(s"R-squared = ${metrics.r2}")

// Mean absolute error
println(s"MAE = ${metrics.meanAbsoluteError}")

// Explained variance
println(s"Explained variance = ${metrics.explainedVariance}")

%python

from pyspark.mllib.evaluation import RegressionMetrics

out = lrModel.transform(df)\
  .select("prediction", "label")\
  .rdd\
  .map(lambda x: (float(x[0]), float(x[1])))

metrics = RegressionMetrics(out)

%python
```

```
metrics.meanSquaredError
```

Chapter 19. Recommendation

Recommendation is, thus far, one of the best use cases for big data. At their core, recommendation algorithms are powerful tools to connect users with content. Amazon uses recommendation algorithms to recommend items to purchase, Google websites to visit, and Netflix movies to watch. There are many use cases for recommendation algorithms and in the big data space, Spark is the tool of choice used across a variety of companies in production. In fact, Netflix uses Spark as one of the core engines for making recommendations. To learn more about this use case you can see the talk by DB Tsai, a Spark Committer from Netflix at Spark Summit - *https://spark-summit.org/east-2017/events/netflixs-recommendation-ml-pipeline-using-apache-spark/*

Currently in Spark, there is one recommendation workhorse algorithm, Alternating Least Squares (ALS). This algorithm leverages a technique called collaborative filtering where large amounts of data are collected on user activity or ratings and that information is used to fill in recommendations for others users that may share similar historical behavior or ratings. Spark's RDD API also includes a lower level matrix factorization method that will not be covered in this book.

Alternating Least Squares

ALS is the workhorse algorithm that achieves the above goal or recommending things to similar users by finding the latent factors that describe the users and the movies and alternating between predicting one, given the inputs of the other. Therefore this method requires three inputs. A user column, an item column (like a movie), and a rating column (which either is a implicit behavior or explicit rating). It should be noted that user and item columns must be integers as opposed to `Double` as we have seen elsewhere in MLlib.

ALS in Spark can scale extremely well too. In general, you can scale this to millions of users, millions of items, and billions of ratings.

Model Hyperparameters

- `alpha`: sets the baseline confidence for preference when training on implicit feedback.
- `rank`: determines the number of latent factors that the algorithm should use.
- `regParam`: determines the regularization of the inputs.
- `implicitPrefs`: states whether or not users made *implicit* or passive endorsement (say by clicks) or whether those were *explicit* or active endorsements (say via a rating.)
- `nonnegative`: states whether or not predicted ratings can be negative or not. If this is true, they will be set to zero.

Training Parameters

A good rule of thump is to shoot for approximately one to five million ratings per block. If you have less than that, more blocks will not improve the algorithm's performance.

- `numUserBlocks`: This determines the physical partitioning of the users in order to help parallelize computation.
- `numItemBlocks`: This determines the physical partitioning of the items in order to help parallelize computation.
- `maxIter`: The total number of iterations that should be performed.
- `checkpointInterval`: How often Spark should checkpoint the model at that current state in time in order to be able to recover from failures.

```
%scala

import org.apache.spark.ml.recommendation.ALS

val ratings = spark.read.textFile("/mnt/defg/sample_movielens_r
  .selectExpr("split(value , '::') as col")
  .selectExpr(
    "cast(col[0] as int) as userId",
    "cast(col[1] as int) as movieId",
    "cast(col[1] as float) as rating",
    "cast(col[1] as long) as timestamp")

val Array(training, test) = ratings.randomSplit(Array(0.8, 0.2)

val als = new ALS()
  .setMaxIter(5)
  .setRegParam(0.01)
  .setUserCol("userId")
  .setItemCol("movieId")
  .setRatingCol("rating")
val alsModel = als.fit(training)

val predictions = alsModel.transform(test)
```

```
%python

from pyspark.ml.recommendation import ALS
from pyspark.sql import Row

ratings = spark.read.text("/mnt/defg/sample_movielens_ratings.t
  .rdd.toDF()\
  .selectExpr("split(value , '::') as col")\
  .selectExpr(
    "cast(col[0] as int) as userId",
    "cast(col[1] as int) as movieId",
    "cast(col[1] as float) as rating",
    "cast(col[1] as long) as timestamp")

training, test = ratings.randomSplit([0.8, 0.2])

als = ALS()\
  .setMaxIter(5)\
  .setRegParam(0.01)\
  .setUserCol("userId")\
  .setItemCol("movieId")\
  .setRatingCol("rating")
alsModel = als.fit(training)

predictions = alsModel.transform(test)
```

Evaluators

The proper way to evaulate ALS in the context of Spark is actually the same as the `RegressionEvaluator` that we saw in the previous chapter. Just like with a conventional regression, we are trying to predict a real value. In the ALS case this is a rating or preference level. See the previous chapter for more information on evaluating regression.

```
%scala

import org.apache.spark.ml.evaluation.RegressionEvaluator

val evaluator = new RegressionEvaluator()
  .setMetricName("rmse")
  .setLabelCol("rating")
  .setPredictionCol("prediction")
val rmse = evaluator.evaluate(predictions)
println(s"Root-mean-square error = $rmse")

%python

from pyspark.ml.evaluation import RegressionEvaluator

evaluator = RegressionEvaluator()\
  .setMetricName("rmse")\
  .setLabelCol("rating")\
  .setPredictionCol("prediction")

rmse = evaluator.evaluate(predictions)
```

Metrics

There are two metrics for recommendation. The first is regression and the second is ranking.

Regression Metrics

Again, as we saw in the previous chapter, we can recycle the regression metrics for ALS. This is because we can effectively see how close the prediction is to the actual rating and train our model that way.

```
import org.apache.spark.mllib.evaluation.{
  RankingMetrics,
  RegressionMetrics}

val regComparison = predictions.select("rating", "prediction")
  .rdd
  .map(x => (
    x(0).asInstanceOf[Float].toDouble,
    x(1).asInstanceOf[Float].toDouble))

val metrics = new RegressionMetrics(regComparison)

%python

from pyspark.mllib.evaluation import RegressionMetrics

regComparison = predictions.select("rating", "prediction")\
  .rdd\
  .map(lambda x: (float(x(0)), float(x(1))))

metrics = RegressionMetrics(regComparison)
```

Ranking Metrics

There is also another way of measuring how well a recommendation algorithm performs. A `RankingMetric` allows us to compare our recommendations with an actual set of rating by a given user. This does not focus on the value of the rank but rather whether or not our algorithm recommends an already ranked item again to a user. To prepare our predictions for this requires several steps. First we need to collect a set of all ranked movies for a given user.

```
%scala

import org.apache.spark.mllib.evaluation.{RankingMetrics, Regre
import org.apache.spark.sql.functions.{col, expr}

val perUserActual = predictions
  .where("rating > 2.5")
  .groupBy("userId")
  .agg(expr("collect_set(movieId) as movies"))

%python

from pyspark.mllib.evaluation import RankingMetrics, Regressior
from pyspark.sql.functions import col, expr

perUserActual = predictions\
  .where("rating > 2.5")\
  .groupBy("userId")\
  .agg(expr("collect_set(movieId) as movies"))
```

Now we have a truth set of previously ranked movies on a per user basis. Now we can get our top ten recommendations per user in order to see how well our algorithm reveals user preference to previously ranked movies. This should be high if it's a good algorithm.

```
%scala

val perUserPredictions = predictions
  .orderBy(col("userId"), col("prediction").desc)
  .groupBy("userId")
  .agg(expr("collect_list(movieId) as movies"))
```

```
%python

perUserPredictions = predictions\
  .orderBy(col("userId"), expr("prediction DESC"))\
  .groupBy("userId")\
  .agg(expr("collect_list(movieId) as movies"))
```

Now that we gathered these two indepedently, we can compare the ordered list of predictions to our truth set of ranked items.

```
val perUserActualvPred = perUserActual.join(perUserPredictions,
  .map(row => (
    row(1).asInstanceOf[Seq[Integer]].toArray,
    row(2).asInstanceOf[Seq[Integer]].toArray.take(15)
  ))

val ranks = new RankingMetrics(perUserActualvPred.rdd)

%python

perUserActualvPred = perUserActual.join(perUserPredictions, ["u
  .map(lambda row: (row[1], row[2][:15]))

ranks = RankingMetrics(perUserActualvPred)
```

Now we can see the metrics from that ranking. For instance we can see how precise our algorithm is with the mean average precision. We can also get the precision at certain ranking points, for instance to see where the majority of the positive recommendations fall.

```
%scala

ranks.meanAveragePrecision
ranks.precisionAt(5)

%python

ranks.meanAveragePrecision
ranks.precisionAt(2)
```

Chapter 20. Clustering

In addition to supervised learning, Spark includes a number of tools for performing unsupervised learning and in particular, clustering. The clustering methods in MLlib are not cutting edge but they are fundamental approaches found in industry. As things like deep learning in Spark mature, we are sure that more unsupervised models will pop up in Spark's MLlib.

Cluster is a bit different form supervised learning because it is not as straightforward to recommend scaling parameters. For instance, when clustering in high dimensional spaces, you are quite likely to overfit. Therefore in the following table we include both computational limits as well as a set of statistical recommendations. These are purely rules of thumb and should be helpful guides, not necessary strict requirements.

Model	Statistical Recommendation	Computation Limits	Training Examples
K-means	50 to 100 maximum	Features x clusters < 10 million	no limit
Bisecting K-means	50 to 100 maximum	Features x clusters < 10 million	no limit
GMM	50 to 100 maximum	Features x clusters < 10 million	no limit

Let's read in our data for clustering.

```
%scala

val df = spark.read.load("/mnt/defg/clustering")
val sales = spark.read.format("csv")
```

```
  .option("header", "true")
  .option("inferSchema", "true")
  .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")
  .coalesce(5)
  .where("Description IS NOT NULL")

%python

df = spark.read.load("/mnt/defg/clustering")
sales = spark.read.format("csv")\
  .option("header", "true")\
  .option("inferSchema", "true")\
  .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")\
  .coalesce(5)\
  .where("Description IS NOT NULL")
```

K-means

K-means is an extremely common algorithm for performing bottom up clustering. The user sets the number of clusters and the algorithm iteratively groups the data according to their distance from a cluster center. This process is reapeated for a number of iterations.

Model Hyperparameters

- `k`: the number of clusters to find in the data.

Training Parameters

- `maxIter`: the number of iterations.
- `tol`: the convergence tolerance threshold

```
%scala

import org.apache.spark.ml.clustering.KMeans

val km = new KMeans().setK(2)
val kmModel = km.fit(df)

%python

from pyspark.ml.clustering import KMeans

km = KMeans().setK(2)
kmModel = km.fit(df)
```

K-means Summary

K-means includes a summary class that we can use to evaluate our model. This includes information about the clusters created as well as their relative sizes (number of examples).

```
%scala

val summary = kmModel.summary

%python

summary = kmModel.summary

summary.cluster.show()
summary.clusterSizes
```

Bisecting K-means

Bisecting K-means is (obviously) similar to K-means. The core difference is that instead of clustering things together it starts by creating groups and then continually splitting those based on cluster cetners.

Model Hyperparameters

- `k`: the number of clusters to find in the data.

Training Parameters

- `maxIter`: the number of iterations.

```
import org.apache.spark.ml.clustering.BisectingKMeans

val bkm = new BisectingKMeans().setK(2)
val bkmModel = bkm.fit(df)

%python

from pyspark.ml.clustering import BisectingKMeans

bkm = BisectingKMeans().setK(2)
bkmModel = bkm.fit(df)
```

Bisecting K-means Summary

Bisecting K-means includes a summary class that we can use to evaluate our model. This includes information about the clusters created as well as their relative sizes (number of examples).

```
%scala

val summary = bkmModel.summary

%python

summary = bkmModel.summary

summary.cluster.show()
summary.clusterSizes
```

Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is hierarchical clustering model typically used to perform topic modelling on text documents. LDA tries to extact high level topics from a series of documents and keywords associated with those topics. There are two implementations that you can use (the optimizer choices). In general online LDA will work better when there are more examples and the expectation maximization optimizer will work better when there is a larger input vocabulary. This method is also capable of scaling to hundreds or thousands of topics.

Model Hyperparameters

- `docConcentration`: The prior placed on documents' distribution over topics.
- `k`: the total number of topics to find.
- `optimizer`: This determines whether to use EM or online training optimization to determine the LDA model.
- `topicConcentration`: The prior placed on topics' distribution over terms

Training Parameters

- `checkpointInterval`: determines how often that the model will get checkpointed, a value of 10 means it will get checkpointed every 10 iterations.

- `maxIter`: the number of iterations.

Prediction Parameters

- `topicDistributionCol`: The column that has the output of the topic mixture distribution for each document.

```
%scala

import org.apache.spark.ml.feature.{Tokenizer, CountVectorizer}

val tkn = new Tokenizer()
  .setInputCol("Description")
  .setOutputCol("DescriptionOut")

val tokenized = tkn.transform(sales)

val cv = new CountVectorizer()
  .setInputCol("DescriptionOut")
  .setOutputCol("features")
  .setVocabSize(500)
  .setMinTF(0)
  .setMinDF(0)
  .setBinary(true)

val prepped = cv.fit(tokenized).transform(tokenized)

%python

from pyspark.ml.feature import Tokenizer, CountVectorizer

tkn = Tokenizer()\
  .setInputCol("Description")\
  .setOutputCol("DescriptionOut")

tokenized = tkn.transform(sales)

cv = CountVectorizer()\
  .setInputCol("DescriptionOut")\
  .setOutputCol("features")\
  .setVocabSize(500)\
  .setMinTF(0)\
  .setMinDF(0)\
  .setBinary(True)

prepped = cv.fit(tokenized).transform(tokenized)
```

```
import org.apache.spark.ml.clustering.LDA

val lda = new LDA().setK(10).setMaxIter(10)
val model = lda.fit(prepped)

%python

from pyspark.ml.clustering import LDA

lda = LDA().setK(10).setMaxIter(10)
model = lda.fit(prepped)

model.logLikelihood(df)
model.logPerplexity(df)
model.describeTopics(3).show()
```

Gaussian Mixture Models

Gaussian mixture model are a somewhat top down clustering algorithm with an assumption that there are `k` clusters that produce data based upon drawing from a gaussian distribution. Each gassian cluster can be of arbitrary size with its own mean and standard deviation.

Model Hyperparameters

- `k`: the number of clusters to find in the data.

Training Parameters

- `maxIter`: the number of iterations.
- `tol`: the convergence tolerance threshold

```
%scala

import org.apache.spark.ml.clustering.GaussianMixture

val gmm = new GaussianMixture().setK(2)
val model = gmm.fit(df)

for (i <- 0 until model.getK) {
  println(s"Gaussian $i:\nweight=${model.weights(i)}\n" +
      s"mu=${model.gaussians(i).mean}\nsigma=\n${model.gaussian
}

%python

from pyspark.ml.clustering import GaussianMixture

gmm = GaussianMixture().setK(2)
model = gmm.fit(df)

for x in model.getK:
  print x
```

Gaussian Mixture Model Summary

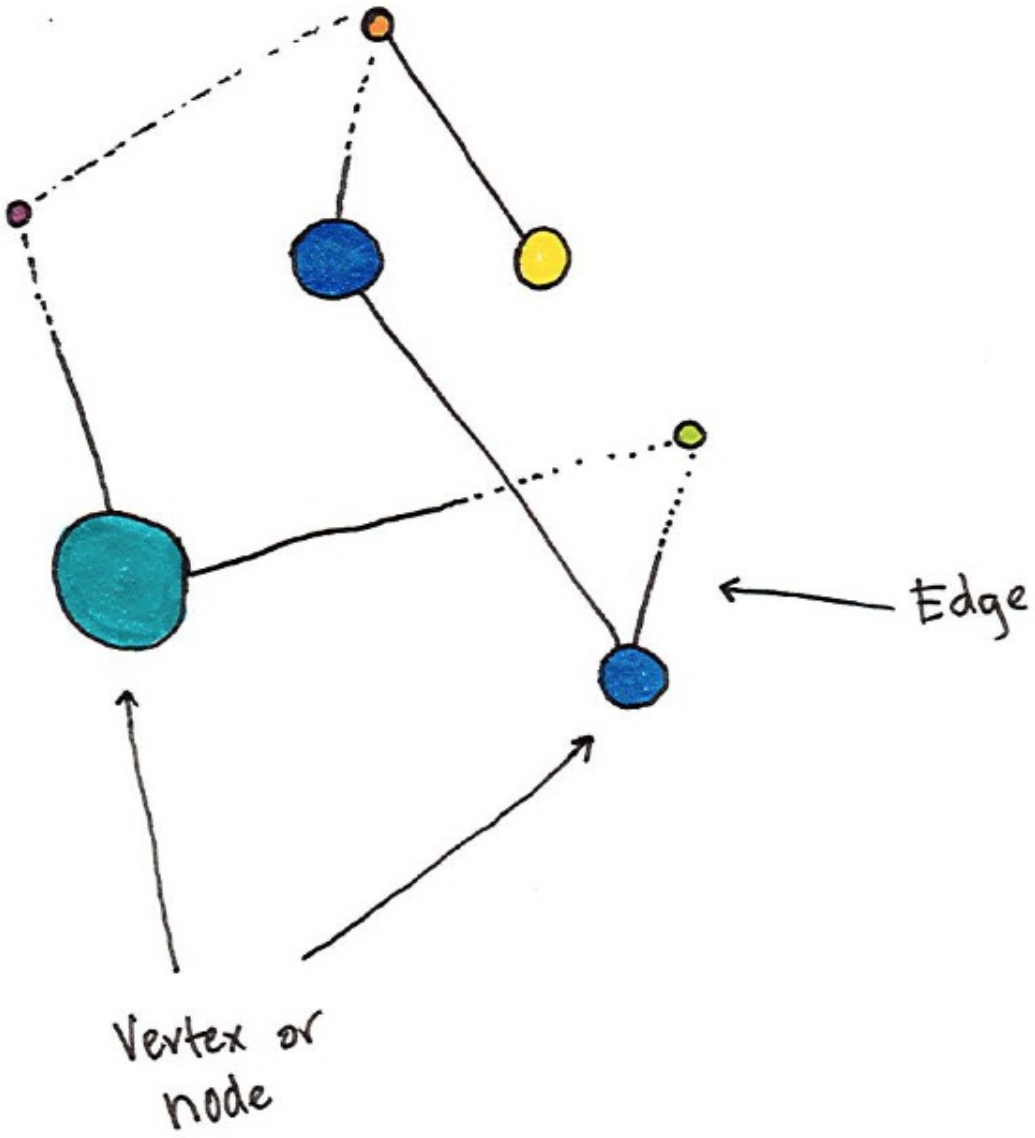
Gaussian mixture models include a summary class that we can use to evaluate our model. This includes information about the clusters created as well as their relative sizes (number of examples). It also includes information like the probability of each cluster.

soft versions of cluster assignments.

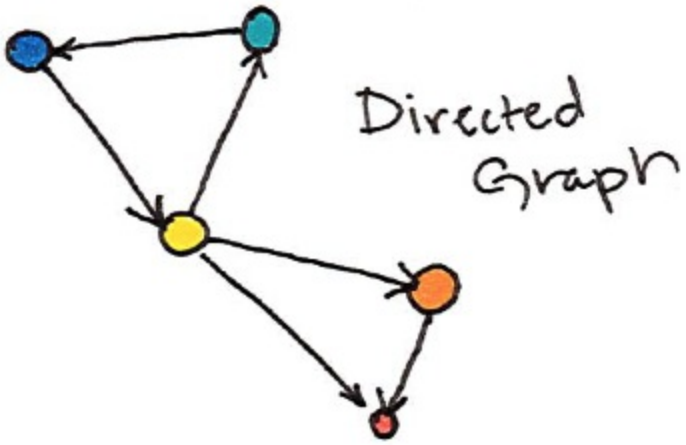
```
%scala

val summary = model.summary

%python

summary = model.summary

summary.cluster.show()
summary.clusterSizes
summary.probability.show()
```

Chapter 21. Graph Analysis

Graphs are an intuitive and natural way of describing relationships between objects. In the context of graphs, *nodes* or *vertices* are the units while *edges* define the relationships between those nodes. The process of *graph analysis* is the process of analyzing these relationships. An example analysis might be your friend group, in the context of graph analysis each *vertex* or *node* would represent a person and each *edge* would represent a relationship.



You can see the above image is a representation of a *directed* graph where the edges are directional. There are also *undirected* graphs in which there is no start and beginning for given edges.



Using our example, the length of the edge might represent the intimacy between different friends; acquaintances would have long edges between them while married individuals would have extremely short edges. We could infer this by looking at communication frequency between nodes and weighting the edges accordingly. Graph are a natural way of describing relationships and many different problem sets and Spark provides several ways of working in this analytics paradigm. Some business use cases could be detecting credit card fraud, importance of papers in bibliographic networks [which papers are most referenced], and ranking web pages as Google famously used the PageRank algorithm to do.

When Spark first came out, in its core was a package called GraphX that provides an interface for performing graph analysis on top of RDDs. This package was not available in Python and is quite low level. GraphX still exists and companies build production products on top of it, however recently the next generation graph analytics library on Spark called GraphFrames has popped up. GraphFrames is currently available as a Spark Package, an external package that you need to load when you start up your Spark application, but will likely be merged into the core of Spark in the future. The package is available at *http://spark-packages.org/package/graphframes/graphframes* and we will cover how to install it shortly. For the the most part, there should be little difference in

performance between the two (except for a huge user experience improvement in GraphFrames). There is some overhead when using GraphFrames but for the most part it tries to call down to GraphX where appropriate.

note

How does GraphFrames compare to Graph Databases? There are many graph databases on the market and some of them are quite popular. Like most of Spark, GraphFrames is not a drop in replacement for a transactional database. It can scale to much larger workloads than many graph databases and you should use it primarily for analytics instead of a online transaction processing workloads.

The goal of this chapter is to show you how to use GraphFrames to perform graph analysis on Spark. We are going to be doing this with publicly available bike data from the Bay Area Bike Share portal.

To get setup you're going to need to point to the proper package. In order to do this from the command line you'll run.

```
./bin/spark-shell --packages graphframes:graphframes:0.3.0-spa

%scala

val bikeStations = spark.read
  .option("header","true")
  .csv("/mnt/defg/bike-data/201508_station_data.csv")
val tripData = spark.read
  .option("header","true")
  .csv("/mnt/defg/bike-data/201508_trip_data.csv")

%python

bikeStations = spark.read\
  .option("header","true")\
  .csv("/mnt/defg/bike-data/201508_station_data.csv")
tripData = spark.read\
  .option("header","true")\
  .csv("/mnt/defg/bike-data/201508_trip_data.csv")
```

Building A Graph

The first step is to build the graph, to do this we need to define the vertices and edges. In our case we're creating a *directed graph*. This graph will point from the source to the location. In the context of this bike trip data, this will point from a trip's starting location to a trip's ending location.To define the graph, we use the naming conventions presented in the GraphFrames library. In the vertices table we define our identifier as `id` and in the edges table we label the source id as `src` and the destination id as `dst`.

```
val stationVertices = bikeStations
  .withColumnRenamed("name", "id")
  .distinct()

val tripEdges = tripData
  .withColumnRenamed("Start Station", "src")
  .withColumnRenamed("End Station", "dst")

%python

stationVertices = bikeStations\
  .withColumnRenamed("name", "id")\
  .distinct()

tripEdges = tripData\
  .withColumnRenamed("Start Station", "src")\
  .withColumnRenamed("End Station", "dst")
```

This allows us to build out graph out of the DataFrames we have so far. We will also leverage caching because we'll be accessing this data frequently in the following queries.

```
%scala

import org.graphframes.GraphFrame
val stationGraph = GraphFrame(stationVertices, tripEdges)

tripEdges.cache()
stationVertices.cache()

%python
```

```
from graphframes import GraphFrame
stationGraph = GraphFrame(stationVertices, tripEdges)

tripEdges.cache()
stationVertices.cache()
```

Now we can see the basic statistics about data (and query our original DataFrame to ensure that we see the expected results).

```
stationGraph.vertices.count
stationGraph.edges.count
tripData.count
```

This returns the following results.

```
Total Number of Stations: 70
Total Number of Trips in Graph: 354152
Total Number of Trips in Original Data: 354152
```

Querying the Graph

The most basic way of interacting with the graph is simply querying it, performing things like counting trips and filtering by given destinations. GraphFrames provides simple access to both vertices and edges.

```
%scala

import org.apache.spark.sql.functions.desc

stationGraph
  .edges
  .groupBy("src", "dst")
  .count()
  .orderBy(desc("count"))
  .show(10)

%python

from pyspark.sql.functions import desc

stationGraph\
  .edges\
  .groupBy("src", "dst")\
  .count()\
  .orderBy(desc("count"))\
  .show(10)
```

We can also filter by any valid DataFrame expression. In this instance I want to look at one specific station and the count of trips in and out of that station.

```
%scala

stationGraph
  .edges
  .where("src = 'Townsend at 7th' OR dst = 'Townsend at 7th'")
  .groupBy("src", "dst")
  .count()
  .orderBy(desc("count"))
  .show(10)

%python
```

```
stationGraph\
  .edges\
  .where("src = 'Townsend at 7th' OR dst = 'Townsend at 7th'")\
  .groupBy("src", "dst")\
  .count()\
  .orderBy(desc("count"))\
  .show(10)
```

Subgraphs

Subgraphs are just smaller graphs within the larger one. We saw above how we can query a given set of edges and vertices. We can use this in order to create subgraphs.

```
%scala

val townAnd7thEdges = stationGraph
  .edges
  .where("src = 'Townsend at 7th' OR dst = 'Townsend at 7th'")

val subgraph = GraphFrame(stationGraph.vertices, townAnd7thEdge

%python

townAnd7thEdges = stationGraph\
  .edges\
  .where("src = 'Townsend at 7th' OR dst = 'Townsend at 7th'")

subgraph = GraphFrame(stationGraph.vertices, townAnd7thEdges)
```

We can then apply the following algorithms to either the original or the subgraph.

Graph Algorithms

A graph is just a logical representation of data. Graph theory provides numerous algorithms for describing data in this format and GraphFrames allows us to leverage many algorithms out of the box. Development continues as new algorithms are added to GraphFrames so this list is likely to continue to grow.

PageRank

Arguably one of the most prolific graph algorithms is PageRank *https://en.wikipedia.org/wiki/PageRank*. Larry Page, founder of Google, created PageRank as a research project for how to rank webpages. Unfortunately an in depth explanation of how PageRank works is outside the scope of this book, however to quote Wikipedia the high level explanation is as follows.

> PageRank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other websites.

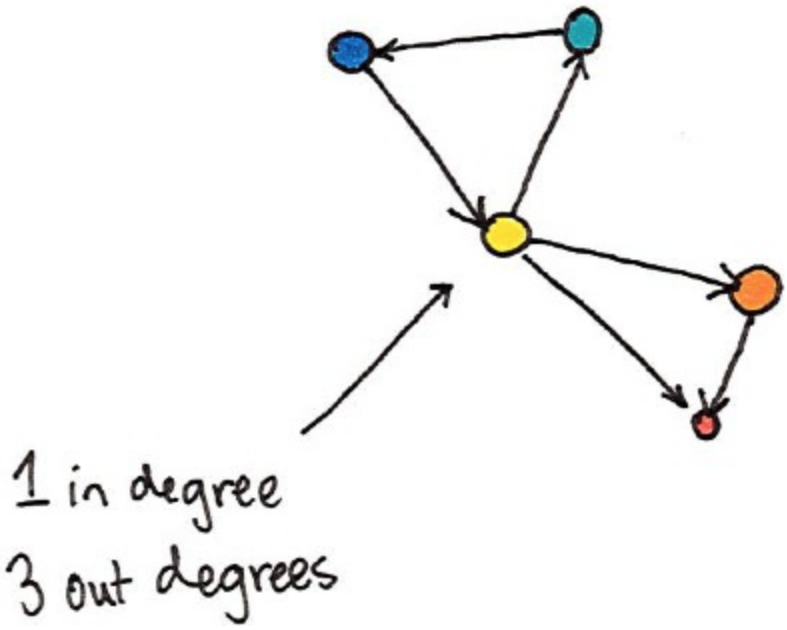
However PageRank generalizes quite well outside of the web domain. We can apply this right to our own data and get a sense for important bike stations.

```
%scala

val ranks = stationGraph.pageRank
  .resetProbability(0.15)
  .maxIter(10)
  .run()

ranks.vertices
  .orderBy(desc("pagerank"))
  .select("id", "pagerank")
  .show(10)

%python

ranks = stationGraph.pageRank(resetProbability=0.15, maxIter=1(

ranks.vertices\
  .orderBy(desc("pagerank"))\
  .select("id", "pagerank")\
  .show(10)

+--------------------+------------------+
|                  id|          pagerank|
+--------------------+------------------+
```

```
|San Jose Diridon ...| 3.211176118037002|
...
|Embarcadero at Sa...|1.2343689576475716|
+--------------------+------------------+
```

Interestingly, we see that Caltrain stations rank quite highly. This makes sense because these are natural connection points where a lot of bike trips might end up. Either as commuters move from home to the Caltrain station for their commute or from the Caltrain station to home.

In and Out Degrees



Our graph is a directed graph. This is due to the bike trips being directional, starting in one location and ending in another. One common task is to count the number of trips into or out of a given station. We counted trips previously, in this case we want to count trips into and out of a given station. We measure these with in and out degrees respectively. GraphFrames provides a simple way to query this information.

```
%scala

val inDeg = stationGraph.inDegrees
inDeg.orderBy(desc("inDegree")).show(5, false)

%python

inDeg = stationGraph.inDegrees
inDeg.orderBy(desc("inDegree")).show(5, False)
```

We can query the out degrees in the same fashion.

```
val outDeg = stationGraph.outDegrees
outDeg.orderBy(desc("outDegree")).show(5, false)
```

```
%python

outDeg = stationGraph.outDegrees
outDeg.orderBy(desc("outDegree")).show(5, False)
```

The ratio of these two values is an interesting metric to look at. A higher ratio value will tell us where a large number of trips end (but rarely begin) while a lower value tells us where trips often begin (but infrequently end).

```
%scala

val degreeRatio = inDeg.join(outDeg, Seq("id"))
  .selectExpr("id", "double(inDegree)/double(outDegree) as degr

degreeRatio
  .orderBy(desc("degreeRatio"))
  .show(10, false)

degreeRatio
  .orderBy("degreeRatio")
  .show(10, false)

%python

degreeRatio = inDeg.join(outDeg, "id")\
  .selectExpr("id", "double(inDegree)/double(outDegree) as degr

degreeRatio\
  .orderBy(desc("degreeRatio"))\
  .show(10, False)

degreeRatio\
  .orderBy("degreeRatio")\
  .show(10, False)
```

Breadth-first Search

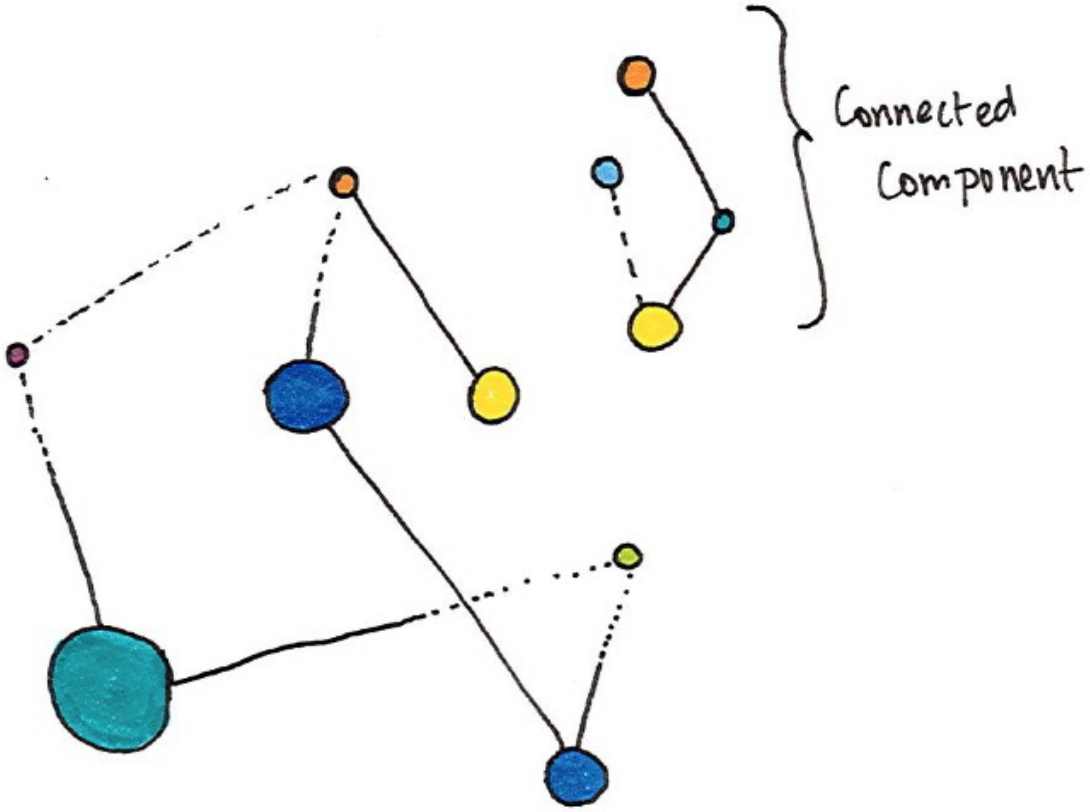
Breadth-first Search will search our graph for how to connect two given nodes based on the edges in the graph. In our context, we might want to do this to find the shortest paths to different stations.

```
%scala

val bfsResult = stationGraph.bfs
  .fromExpr("id = 'Townsend at 7th'")
  .toExpr("id = 'Redwood City Medical Center'")
  .maxPathLength(4)
  .run()

%python

bfsResult = stationGraph.bfs(
  fromExpr="id = 'Townsend at 7th'",
  toExpr="id = 'Redwood City Medical Center'",
  maxPathLength=4)

bfsResult.show(10)
```

This command will take some time to run if you're running on your local machine and actually won't find a result. This is because these two stations are so distant from one another that it would not be feasible to ride a bike from one station to another, at least not by combining four different edges (the `maxPathLength`). We can also specify an `edgeFilter` to filter out certain edges that do not meet a certain requirement like trips during non-business hours.

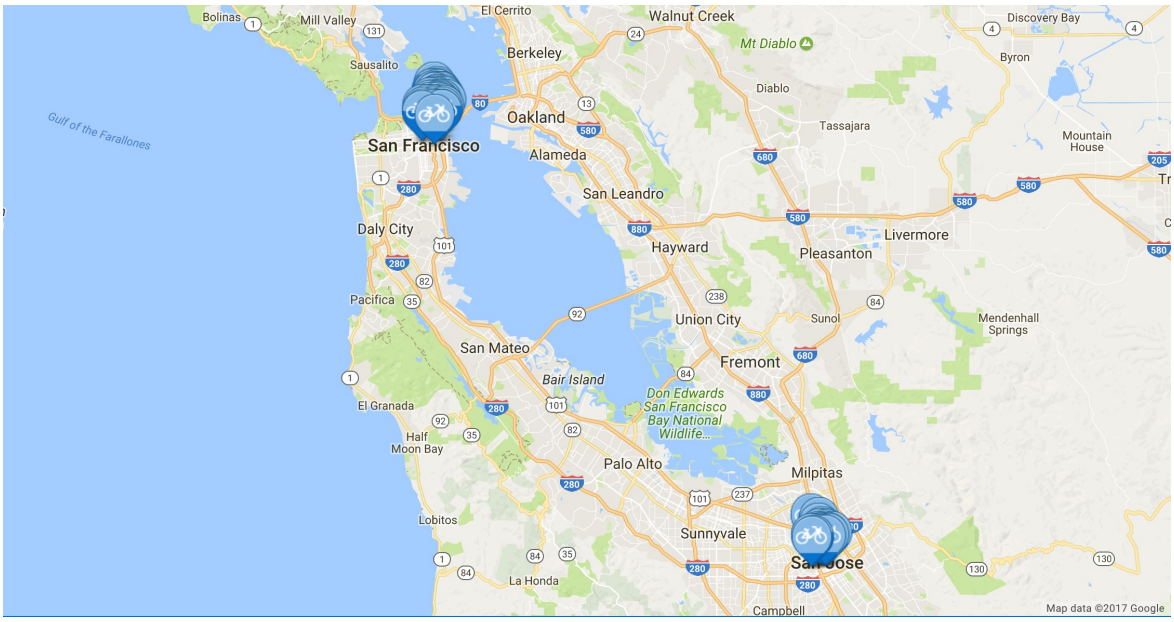
Connected Components

A connected component simply defines a graph that has connections to itself but does not connect to the greater graph. As illustrated in the following image.



Connected components do not directly relate to our current problem because we have a directed graph, however we can still run the algorithm which just assumes that there are is no directionality associated with our edges. In fact if

we look at the bike share map, we assume that we would get two distinct connected components.



In order to run this algorithm you will need to set a checkpoint directory which will store the state of the job at every iteration. This allows you to continue where you left off if for some reason the job crashes.

```
%scala

spark.sparkContext.setCheckpointDir("/tmp/checkpoints")

%python

spark.sparkContext.setCheckpointDir("/tmp/checkpoints")

%scala

cc = stationGraph.connectedComponents.run()

%python

cc = stationGraph.connectedComponents()
```

Interesting, we actually get three distinct connected components. Why we get this might be an opportunity for further analysis but we can assume that someone might be taking a bike in a car or something similar.

Strongly Connected Components

However GraphFrames also include another version of the algorithm that does relate to directed graphs called strongly connected components. This does the same approximate task as finding connected components but takes directionality into account. A strongly connected component effectively has one way into a subgraph and no way out.

TODO: (Should this get an image too?)

```
%scala

val scc = stationGraph
  .stronglyConnectedComponents
  .maxIter(3)
  .run()

%python

scc = stationGraph.stronglyConnectedComponents(maxIter=3)

scc.groupBy("component").count().show()
```

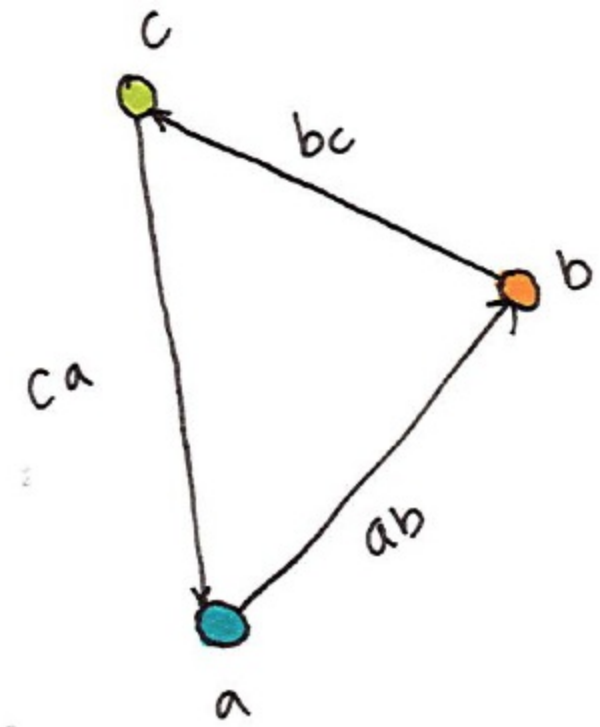
Motif Finding

Motifs are a way of expresssing structural patterns in a graph. When we specify a motif, we are querying for patterns in the data instead of actual data. Our current dataset does not suit this sort of querying because our graph consists of individual trips, not repeated interactions of certain individuals or identifiers. In GraphFrames, we specify our query in a Domain-Specific Language. We specify combinations of vertices and edges. For example, if we want to specify a given vertex to another vertex we would specify `(a)-[ab]->(b)`. The letters inside of parenthesis or brackets do not signify values but signify what the columns should be named in the resulting DataFrame. We can omit the names (e.g., `(a)-[]->()`) if we do not intend to query the resulting values.

Let's perform a query. In plain english, let's find all the round trip rides with two stations in between. We express this with the following motif using the `find` method to query our GraphFrame for that pattern.

```
%scala

val motifs = stationGraph
  .find("(a)-[ab]->(b); (b)-[bc]->(c); (c)-[ca]->(a)")

%python

motifs = stationGraph\
  .find("(a)-[ab]->(b); (b)-[bc]->(c); (c)-[ca]->(a)")
```

Here's a visual representation of this query.



The resulting DataFrame contains nested fields for vertices `a`, `b`, and `c` as well as the respective edges. Now we can query this data as if it were a DataFrame. Now we can query that to answer a specific question. Given a certain bike what is the shortest round trip time where that bike is taken from one station (a), ridden to another, dropped off(b), ridden to another, dropped off(c), and then ridden back to the original station (a). This is just going to be a lot of filtering, as we can see below.

```
%scala

import org.apache.spark.sql.functions.expr

motifs
// first simplify dates for comparisons
  .selectExpr("*", """
  cast(unix_timestamp(ab.`Start Date`, 'MM/dd/yyyy HH:mm')
    as timestamp) as abStart
  """,
  """
  cast(unix_timestamp(bc.`Start Date`, 'MM/dd/yyyy HH:mm')
    as timestamp) as bcStart
  """,
  """
```

```
  cast(unix_timestamp(ca.`Start Date`, 'MM/dd/yyyy HH:mm')
    as timestamp) as caStart
  """)
// ensure the same bike
  .where("ca.`Bike #` = bc.`Bike #`")
  .where("ab.`Bike #` = bc.`Bike #`")
// ensure different stations
  .where("a.id != b.id")
  .where("b.id != c.id")
// start times are correct
  .where("abStart < bcStart")
  .where("bcStart < caStart")
// order them all
  .orderBy(expr("cast(caStart as long) - cast(abStart as long)'
  .selectExpr("a.id", "b.id", "c.id",
    "ab.`Start Date`", "ca.`End Date`")
  .limit(1)
  .show(false)

%python

motifs
# first simplify dates for comparisons
  .selectExpr("*", """
  cast(unix_timestamp(ab.`Start Date`, 'MM/dd/yyyy HH:mm')
    as timestamp) as abStart
  """,
  """
  cast(unix_timestamp(bc.`Start Date`, 'MM/dd/yyyy HH:mm')
    as timestamp) as bcStart
  """,
  """
  cast(unix_timestamp(ca.`Start Date`, 'MM/dd/yyyy HH:mm')
    as timestamp) as caStart
  """)
# ensure the same bike
  .where("ca.`Bike #` = bc.`Bike #`")
  .where("ab.`Bike #` = bc.`Bike #`")
# ensure different stations
  .where("a.id != b.id")
  .where("b.id != c.id")
# start times are correct
  .where("abStart < bcStart")
  .where("bcStart < caStart")
# order them all
  .orderBy(expr("cast(caStart as long) - cast(abStart as long)'
  .selectExpr("a.id", "b.id", "c.id",
    "ab.`Start Date`", "ca.`End Date`")
```

```
  .limit(1)
  .show(False)
```

We see the fastest trip is approximately 20 minutes. Pretty fast for three different people (we assume) using the same bike!

Advanced Tasks

This is just a short selection of some of the things GraphFrames allows you to achieve. Development continues as well and so you will be able to continue to find new algorithms and features being added the library. Some of these advanced features include writing your own algorithms via a message passing interface, triangle counting, converting to and from GraphX among other tasks. It is also likely that in the future this library will join GraphX in the core of Spark.

Chapter 22. Deep Learning

In order to define deep learning, we must first define neural networks. Neural networks allow computers to understand concepts by layering simple representations on top of one another. For the most part, each one of these representations, or *layers*, consist of a variety of inputs connected together that are activated when combined together, similar in concept to a neuron in the brain. Our goal is to train the network to associate certain inputs with certain outputs. *Deep learning*, or *deep neural networks*, just combine many of these layers together in various different architectures. Deep learning has gone through several periods of fading and resurgence and has only recently become popular in the past decade because of its ability to solve an incredibly diverse set of complex problems.

Spark being a robust tool for performing operations in parallel has a number of good opportunities for end users to leverage both Spark and deep learning together.

warning

if you have little experience with machine learning and deep learning, this is not the chapter for you. We recommend spending some time learning about the core methods of machine learning before embarking on using deep learning with Spark.

Ways of using Deep Learning in Spark

For the most part, when it comes to large scale machine learning, you can either parallelize the data or parallelize the model (Dean 2016). Parallelizing the data is quite trivial and Spark does quite well with this workload. A much harder problem, is in parallelizing the model because the model itself is too large to fit into memory. Both of these areas are fruitful areas of research however for the most part if you are looking to get started with machine learning on Spark it is much easier to use models that are pretrained by the massive companies with large amount of time, and money, to throw at the problem than to try and train your own.

Spark currently has native support for one deep learning algorithm, the multilayer perceptron classifier. While it does work, it is not particularly flexible or tunable according to different architectures or workloads and has not received a significant amount of innovation since it was first introduced. This chapter will not focus on packages that are necessarily core to Spark but will rather focus on the *massive* amount of innovation in libraries built on top of Spark. We will start with several theoretical approaches to deep learning on Spark, discuss those of which you are likely to succeed in using in practice today, and discuss some of the libraries that make this possible.

There are associated tradeoffs with these implementations but for the most part, Spark is not structured for model parallelization because of synchronous communication overhead and immutability. This does not mean that Spark is not used for deep learning workloads because the volume of libraries proves otherwise. Below is an incomplete list of different ways that Spark can be used in conjunction with deep learning.

note

in the following examples we use the term “small data” and “big data” to differentiate that which can fit on a single node and that which must be

distributed. To be clear this is not actuall *small* data (say 100s of rows) this is many gigabytes of data that can still fit on one machine.

1. Distributed training of many deep learning models. “Small learning, small data”.

Spark can parallelize work efficiently when there is little communication required between the nodes. This makes it an excellent tool for performing distributed training of one deep learning model per worker node that might have different architectures or initialization. There are many libraries that take advantage of Spark in this way.

1. Distributed usage of deep learning models. “Small model, big data”

As we mentioned in the previous bullet, Spark makes it extremely easy to parallelize tasks across a large number of machines. One wonderful thing about machine learning research is that many models are available to the public as pretrained deep learning models that you can use without having to perform any training yourself. These can do things like identify humans in an image or provide a translation of a Chinese character into an english word or phrase. Spark makes it easy for you to get immediate value out of these networks by applying them, at scale, to your own data.

If you are lookign to get started with Spark and deep learning, get started here!

1. Large Scale ETL and preprocessing leading to learning a deep learning model on a single node. “Small learning, big data”

This is often referred to as “learn small with big data”. Rather than trying to collect all of your data onto one node right away you can use Spark to iterate over your entire (distributed) dataset on the driver itself with the `toLocalIterator` method. You can, of course, use Spark for feature generation and simply collect the dataset to a large node as well but this does limit the total datasize that you can train on.

1. Distributed training of a large deep learning model. “Big learning, big data”

This use cases stretches Spark more than any other. As you saw throughout the book, Spark has its own notions of how to schedule transformations and communication across a cluster. The efficiency of Spark's ability to perform large scale data manipulation with little overhead, at times, conflicts with the type of system that a can efficiently train a single, massive deep learning model. This is a fruitful area of research and some of the below projects attempt to bring this functionality to Spark.

Deep Learning Projects on Spark

There exist a number of projects that attempt to bring deep learning to Spark in the aforementioned ways. This part of the chapter will focus on sharing some of the more well known projects and some code samples. As mentioned, this is a fruitful area of research and it is likely that the state of the art will progress by the time this book is published and in your hand. Visit the Spark documentation site for the latest news. The projects are listed in alphabetical order.

- BigDL

BigDL (pronounced big deal) is a distributed deep learning framework for Spark. It aims to support the training of large models as wekk as the loading and usage of pre-trained models into Spark.

https://github.com/intel-analytics/BigDL

- CaffeOnSpark

Caffe is a popular deep learning framework focused on image processing. CaffeOnSpark is an open source package for using Caffe on top of Spark that includes model training, testing, and feature extraction.

https://github.com/yahoo/CaffeOnSpark

- DeepDist

DeepDist accelerates the training by distributing stochastic gradient descent for data stored in Spark.

https://github.com/dirkneumann/deepdist/

- Deeplearning4J

Deeplearning4j is an open-source, distributed deep-learning preojct in Java

and Scala which provides both single node and distributed training options.

https://deeplearning4j.org/spark

- TensorFlowOnSpark

TensorFlow is a popular open source deep learning framework and aims to make TensorFlow easier to operate in a distributed setting.

https://github.com/yahoo/TensorFlowOnSpark

- TensorFrames

TensorFrames lets you manipulate Spark DataFrames with TensorFlow Programs. It supports Python and Scala interfaces and focuses on providing a simple interface to use single node deep learning models at scale as well as distributed hyperparameter tuning of single node models.

https://github.com/databricks/tensorframes

Here's a simple project scorecard of the various deep learning projects.

	Deep Learning Framework	**Focus**
BigDL	BigDL	big model training, ETL
CaffeOnSpark	Caffe	small model training, ETL
DeepLearning4J	DeepLearning4J	big/small model training, ETL
DeepDist	DeepDist	big model training
TensorFlowOnSpark	TensorFlow	small model training, ETL

TensorFrames	TensorFlow	Spark integration, small model training, ETL

A Simple Example with TensorFrames

TODO: This example will be coming but we are waiting for Spark 2.2 to officially come out in order to upgrade the package.