The Data Scientist's Guide to

databricks

Preface

Apache Spark has seen immense growth over the past several years. The size and scale of Spark Summit 2017 is a true reflection of innovation after innovation that has made itself into the Apache Spark project. Databricks is proud to share excerpts from the upcoming book, *Spark: The Definitive Guide.* Enjoy this free preview copy, courtesy of Databricks.

A Gentle Introduction to Spark

This chapter will present a gentle introduction to Spark - we will walk through the core architecture of a cluster, Spark Application, and Spark's Structured APIs using DataFrames and SQL. Along the way we will touch on Spark's core terminology and concepts so that you are empowered start using Spark right away. Let's get started with some basic background terminology and concepts.

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. However, as many users likely experience at some point, there are some things that your computer is not powerful enough to perform. One particularly challenging area is data processing. Single machines do not 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 allowing us to use all the cumulative resources as if they were one. 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 execution of tasks on data across a cluster of computers.

The cluster of machines that Spark will leverage to execute tasks will be managed by a cluster manager like Spark's Standalone cluster manager, YARN, or Mesos. We then submit Spark Applications to these cluster managers which will grant resources to our application so that we can complete our work.

Spark Applications

Spark Applications consist of a *driver* process and a set of executor processes. The driver process runs your `main()` function, sits on a node in the cluster, and is responsible for three things: maintaining information about the Spark Application; responding to a user's program or input; and analyzing, distributing, and scheduling work across the executors (defined momentarily). 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.

The *executors* are responsible for actually executing the work that the driver assigns them. This means, each executor is responsible for only two things: executing code assigned to it by the driver and reporting the state of the computation, on that executor, back to the driver node.

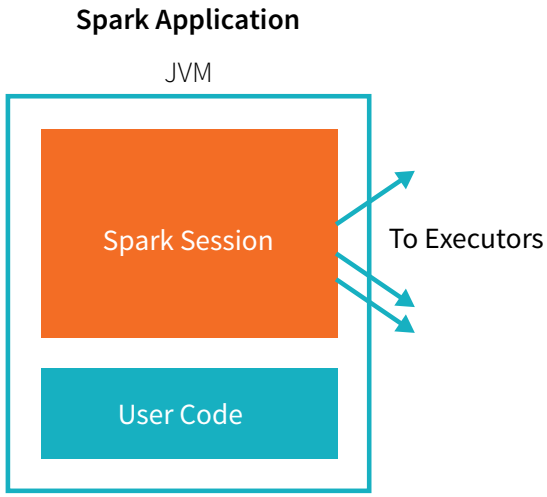


Figure 1:

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 Applications running on a cluster at the same time. We will talk more in depth about cluster managers in Part IV: Production Applications of this book.

In the previous illustration we see on the left, our driver and on the right the four executors on the right. In this diagram, we removed the concept of cluster nodes. The user can specify how many executors should fall on each node through configurations.

note

Spark, in addition to its cluster mode, also has a *local mode*. The driver and executors are simply processes, this means that they can live on a single machine or multiple machines. In local mode, these run (as threads) on your individual computer instead of a cluster. We wrote this book with local mode in mind, so everything should be runnable on a single machine.

As a short review of Spark Applications, the key points to understand at this point 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.

Now while our executors, for the most part, will always be running Spark code. Our driver can be "driven" from a number of different languages through Spark's Language APIs.

Spark's Language APIs

Spark's language APIs allow you to run Spark code from other langauges. For the most part, Spark presents some core "concepts" in every language and these concepts are translated into Spark code that runs on the cluster of machines. If you use the Structured APIs (Part II of this book), you can expect all languages to have the same performance characteristics.

note

This is a bit more nuanced than we are letting on at this point but for now, it's true "enough". We cover this extensively in first chapters of Part II of this book.

Scala

Spark is primarily written in Scala, making it Spark's "default" language. This book will include Scala code examples wherever relevant.

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.

Python

Python supports nearly all constructs that Scala supports. This book will include Python code examples whenever we include Scala code examples and a Python API exists.

SQL

Spark supports ANSI SQL 2003 standard. This makes it easy for analysts and non-programmers to leverage the big data powers of Spark. This book will include SQL code examples wherever relevant

R

Spark has two libraries, one as a part of Spark core (SparkR) and another as a R community driven package (sparklyr). We will cover these two different integrations in Part VII: Ecosystem.

Here's a simple illustration of this relationship.

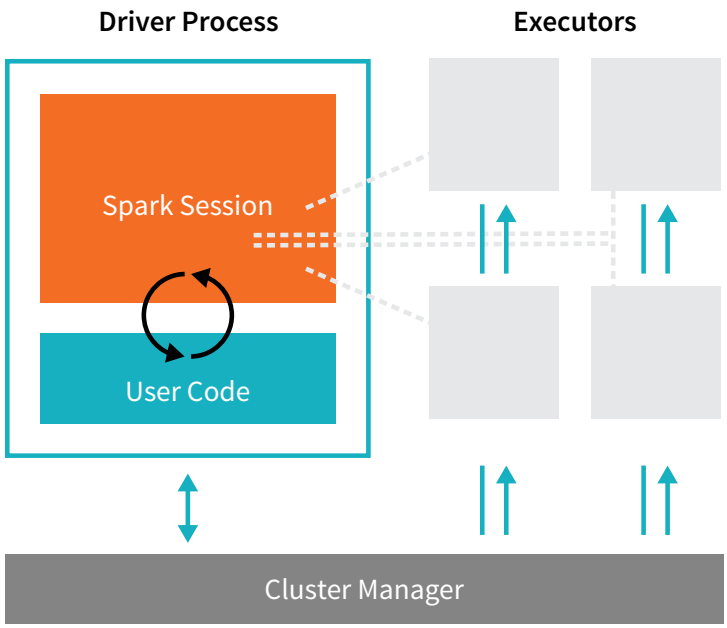


Figure 2:

Each language API will maintain the same core concepts that we described above. There is a SparkSession available to the user, the SparkSession will be the entrance point to running Spark code. When using Spark from a Python or R, the user never writes explicit JVM instructions, but instead writes Python and R code that Spark will translate into code that Spark can then run on the executor JVMs.

Spark's APIs

While Spark is available from a variety of languages, what Spark makes available in those languages is worth mentioning. Spark has two fundamental sets of APIs: the low level "Unstructured" APIs and the higher level Structured APIs. We discuss both in this book but these introductory chapters will focus primarily on the higher level APIs.

Starting Spark

Thus far we covered the basic concepts of Spark Applications. This has all been conceptual in nature. When we actually go about writing our Spark Application, we are going to need a way to send user commands and data to the Spark Application. We do that with a SparkSession.

NOTE

To do this we will start Spark's local mode, just like we did in the previous chapter. This means running `./bin/spark-shell` *to access the Scala console to start an interactive session. You can also start Python console with* `./bin/pyspark`*. This starts an interactive Spark Application. There is also a process for submitting standalone applications to Spark called* `spark-submit` *where you can submit a precompiled application to Spark. We'll show you how to do that in the next chapter.*

When we start Spark in this interactive mode, we implicitly create a SparkSession which manages the Spark Application. When we start it through a job submission, we must go about creating it or accessing it.

The SparkSession

As discussed in the beginning of this chapter, we control our Spark Application through a driver process. This driver process manifests itself to the user as something called the SparkSession. The *SparkSession* instance is the way Spark exeutes user-defined manipulations across the cluster. In Scala and Python the variable is available as `spark` when you start up the console. Let's go ahead and look at the `SparkSession` in both Scala and/or Python.

```
spark
```

In Scala, you should see something like:

```
res0: org.apache.spark.sql.SparkSession = org.apache.spark.sql.SparkSession@27159a24
```

In Python you'll see something like:

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

Let's now perform the simple task of 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*. When run on a cluster, each part of this range of numbers exists on a different executor. This is a Spark DataFrame.

DataFrames

A *DataFrame* is the most common Structured API and simply represents a table of data with rows and columns. The list of columns and the types in those columns the *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 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.

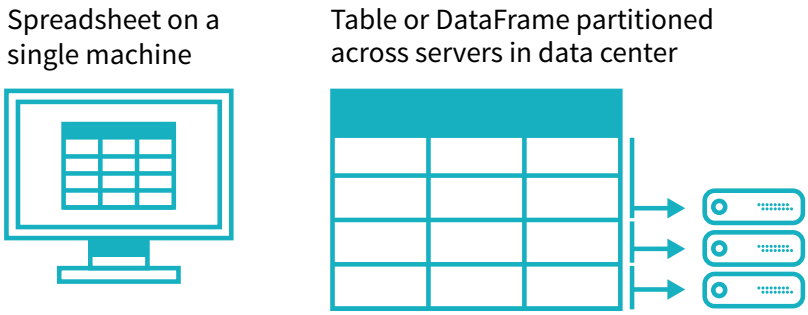


Figure 3:

The DataFrame concept is not unique to Spark. R and Python both have similar concepts. 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 at the end of Part II and RDDs in Part III of this book. The following concepts apply to all of the core abstractions.

Partitions

In order to allow every executor to perform work in parallel, 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's partitions represent how the data is physically distributed across your cluster of machines during execution. If you have one partition, Spark will only have a parallelism of one even if you have thousands of executors. If you have many partitions, but only one executor Spark will still only have a parallelism of one because there is only one computation resource.

An important thing to note, is that with DataFrames, we do not (for the most part) manipulate partitions individually. We simply specify high level transformations of data in the physical partitions and Spark determines how this work will actually execute on the cluster. Lower level APIs do exist (via the RDD interface) and we cover those in Part III of this book.

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*.

Let's perform a simple transformation to find all even numbers in our currentDataFrame.

```
%scala

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


%python

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

You will notice that these return no output, that's because we only specified an abstract transformation and Spark will not act on transformations until we call an action, discussed shortly. Transformations are the core of how you will be expressing your business logic using Spark. There are two types of transformations, those that specify narrow dependencies and those that specify wide dependencies.

Transformations consisting of *narrow dependencies* are those where each input partition will contribute to only one output partition. In the preceding code snippet, our `where` statement specifies a narrow dependency, where only one partition contributes to at most one output partition.

Narrow Transformations
1 to 1

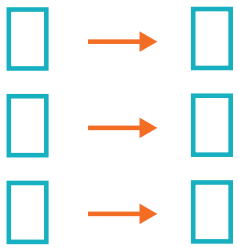


Figure 4:

A *wide dependency* (or wide transformation) style transformation will have input partitions contributing to many output partitions. You will often hear this referred to as a *shuffle* where Spark will exchange partitions across the cluster. With narrow transformations, Spark will automatically perform an operation called pipelining on narrow dependencies, this means that if we specify multiple filters on DataFrames they'll all be performed in-memory. The same cannot be said for shuffles. When we perform a shuffle, Spark will write the results to disk. You'll see lots of talks about shuffle optimization across the web because it's an important topic but for now all you need to understand are that there are two kinds of transformations.

Wide Transformations (shuffles)
1 to 1

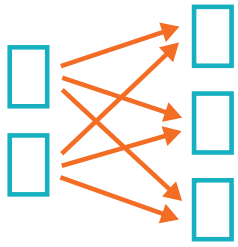


Figure 5:

We now see how transformations are simply ways of specifying different series of data manipulation. This leads us to a topic called lazy evaluation.

Lazy Evaluation

Lazy evaulation means that Spark will wait until the very last moment to execute the graph of computation instructions. In Spark, instead of modifying the data immediately when we express some operation, we build up a *plan* of transformations that we would like to apply to our source data. Spark, by waiting until the last minute to execute the code, will compile this plan from your raw, DataFrame transformations, to an efficient physical plan that will run as efficiently as possible across the cluster. This provides immense benefits to the end user because Spark can optimize the entire data flow from end to end. An example of this is something called "predicate pushdown" on DataFrames. If we build a large Spark job but specify a filter at the end that only requires us to fetch one row from our source data, the most efficient way to execute this is to access the single record that we need. Spark will actually optimize this for us by pushing the filter down automatically.

Actions

Transformations allow us to build up our logical transformation plan. 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.

```
divisBy2.count()
```

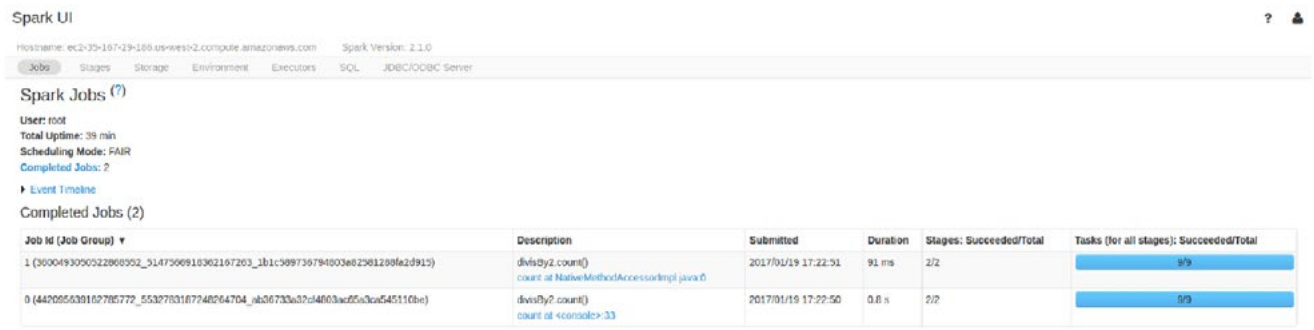
We now see a result! There are 500 number divisible by two from o to 999 (big surprise!). Now `count` is not the only action. There are three kinds of actions:

- 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.

In specifying our action, we started a Spark job that runs our filter transformation (a narrow transformation), then an aggregation (a wide transformation) that performs the counts on a per partition basis, then a collect will brings our result to a native object in the respective language. We can see all of this by inspecting the Spark UI, a tool included in Spark that allows us to monitor the Spark jobs running on a cluster.

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 two stages and nine tasks were executed.

This chapter avoids the details of Spark jobs and the Spark UI, we cover the Spark UI in detail in Part IV: Production Applications. At this point you should understand that a Spark job represents a set of transformations triggered by an individual action and we can monitor that from the Spark UI.

An End to End Example

In the previous example, we created a DataFrame of a range of numbers; not exactly groundbreaking big data. In this section we will reinforce everything we learned previously in this chapter with a worked example and explaining step by step what is happening under the hood. We'll be using some flight data available here from the United States Bureau of Transportation statistics.

Inside of the CSV folder linked above, you'll see that we have a number of files. You will also notice a number of other folders with different file formats that we will discuss in Part II: Reading and Writing data. We will focus on the CSV files.

Each file has a number of rows inside of it. Now these files are CSV files, meaning that they're a semi-structured data format with a row in the file representing a row in our future DataFrame.

```
$ head /mnt/defg/flight-data/csv/2015-summary.csv

DEST_COUNTRY_NAME,ORIGIN_COUNTRY_NAME,count
United States,Romania,15
United States,Croatia,1
United States,Ireland,344
```

Spark includes the ability to read and write from a large number of data sources. In order to read this data in, we will use a DataFrameReader that is associated with our SparkSession. In doing so, we will specify the file format as well as any options we want to specify. In our case, we want to do something called schema inference, we want Spark to take a best guess at what the schema of our DataFrame should be. The reason for this is that CSV files are not completely structured data formats. We also want to specify that the first row is the header in the file, we'll specify that as an option too.

To get this information Spark will read in a little bit of the data and then attempt to parse the types in those rows according to the types available in Spark. You'll see that this works just fine. We also have the option of strictly specifying a schema when we read in data (which we recommend in production scenarios).

```
%scala

val flightData2015 = spark

   .read
   .option("inferSchema", "true")
   .option("header", "true")
   .csv("/mnt/defg/flight-data/csv/2015-summary.csv")


%python

flightData2015 = spark\

   .read\
   .option("inferSchema", "true")\
   .option("header", "true")\
   .csv("/mnt/defg/flight-data/csv/2015-summary.csv")
```

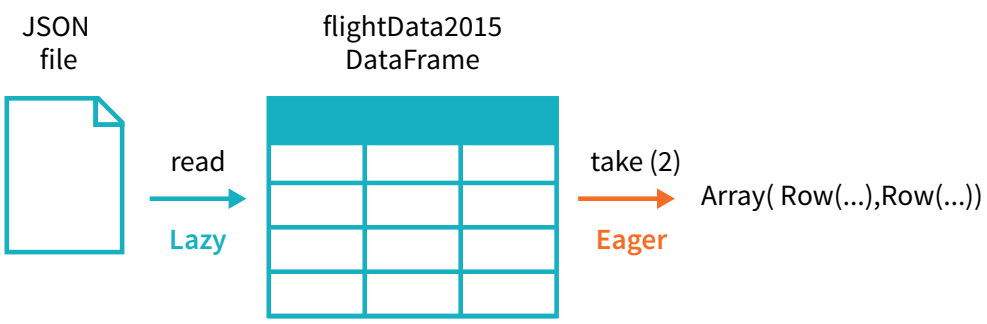


Figure 6:

Each of these DataFrames (in Scala and Python) each have a set of columns with an unspecified number of rows. The reason the number of rows is "unspecified" is because reading data is a transformation, and is therefore a lazy operation. Spark only peeked at the data to try to guess what types each column should be.

If we perform the `take` action on the DataFrame, we will be able to see the same results that we saw before when we used the command line.

```
flightData2015.take(3)

Array([United States,Romania,15], [United States,Croatia...
```

Let's specify some more transformations! Now we will sort our data according to the count column which is an integer type.

> *note*
>
> *Remember, the `sort` does not modify the DataFrame. We use the sort is a transformation that returns a new DataFrame by transforming the previous DataFrame. Let's illustrate what's happening when we call `take` on that resulting DataFrame.*

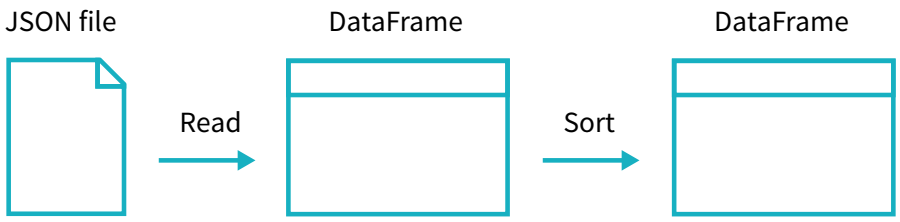


Figure 7:

Nothing will happen to the data when we call this sort because it's just a transformation. However, we can see that Spark is building up a plan for how it will execute this across the cluster by looking at the `explain` plan. We can call explain on any DataFrame object to see the DataFrame's lineage (or how Spark will execute this query).

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

Congratulations, you've just read your first explain plan! Explain plans are a bit arcane, but with a bit of practice it becomes second nature. Explain plans can be read from top to bottom, the top being the end result and the bottom being the source(s) of data. In our case, just take a look at the first keywords. You will see "sort", "exchange", and "FileScan". That's because the sort of our data is actually a wide dependency because rows will have to be compared with one another. Don't worry too much about understanding everything about explain plans, they can just be helpful tools for debugging and improving your knowledge as you progress with Spark.

Now, just like we did before, we can specify an action in order to kick off this plan. However before doing that, we're going to set a configuration. By default, when we perform a shuffle Spark will output two hundred shuffle partitions. We will set this value to five in order to reduce the number of the output partitions from the shuffle from two hundred to five.

```
spark.conf.set("spark.sql.shuffle.partitions", "5")

flightData2015.sort("count").take(2)

... Array([United States,Singapore,1], [Moldova,United States,1])
```

This operation is illustrated in the following image. You'll notice that in addition to the logical transformations, we include the physical partition count as well.

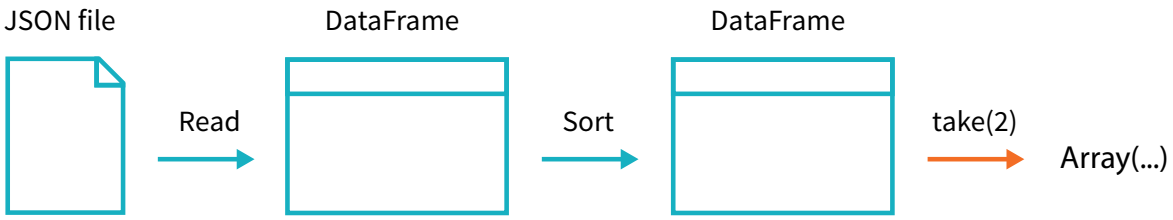


Figure 8:

The logical plan of transformations that we build up defines a lineage for the DataFrame so that at any given point in time Spark knows how to recompute any partition by performing all of the operations it had before on the same input data. This sits at the heart of Spark's programming model, functional programming where the same inputs always result in the same outputs when the transformations on that data stay constant.

We do not manipulate the physical data, but rather configure physical execution characteristics through things like the shuffle partitions parameter we set above. We got five output partitions because that's what we changed the shuffle partition value to. You can change this to help control the physical execution characteristics of your Spark

jobs. Go ahead and experiment with different values and see the number of partitions yourself. In experimenting with different values, you should see drastically different run times. Remeber that you can monitor the job progress by navigating to the Spark UI on port 4040 to see the physical and logical execution characteristics of our jobs.

DataFrames and SQL

We worked through a simple example in the previous example, let's now work through a more complex example and follow along in both DataFrames and SQL. For your purposes, DataFrames and SQL, in Spark, are the exact same thing. You can express your business logic in either language and Spark will compile that logic down to an underlying plan (that we see in the explain plan) before actually executing your code. 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.

```
%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()
```

```
== Physical Plan ==
*HashAggregate(keys=[DEST_COUNTRY_NAME#182], functions=[count(1)])
+- Exchange hashpartitioning(DEST_COUNTRY_NAME#182, 5)
   +- *HashAggregate(keys=[DEST_COUNTRY_NAME#182], functions=[partial_count(1)])
      +- *FileScan csv [DEST_COUNTRY_NAME#182] ...
== Physical Plan ==
*HashAggregate(keys=[DEST_COUNTRY_NAME#182], functions=[count(1)])
+- Exchange hashpartitioning(DEST_COUNTRY_NAME#182, 5)
   +- *HashAggregate(keys=[DEST_COUNTRY_NAME#182], functions=[partial_count(1)])
      +- *FileScan csv [DEST_COUNTRY_NAME#182] ...
```

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 statistics from our data. One thing to understand is that DataFrames (and SQL) in Spark already have a huge number of manipulations available. There are hundreds of functions that you can leverage and import to help you resolve your big data problems faster. We will use 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.

```
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)
```

Great, that's a simple example. Let's perform something a bit more complicated and find out the top five destination countries in the data? 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. You can see this in the explain plan on those DataFrames. 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 llustration is as good of a starting point as any. This execution plan is a *directed acyclic graph (DAG)* of transformations, each resulting in a new immutable DataFrame, on which we call an action to generate a result.

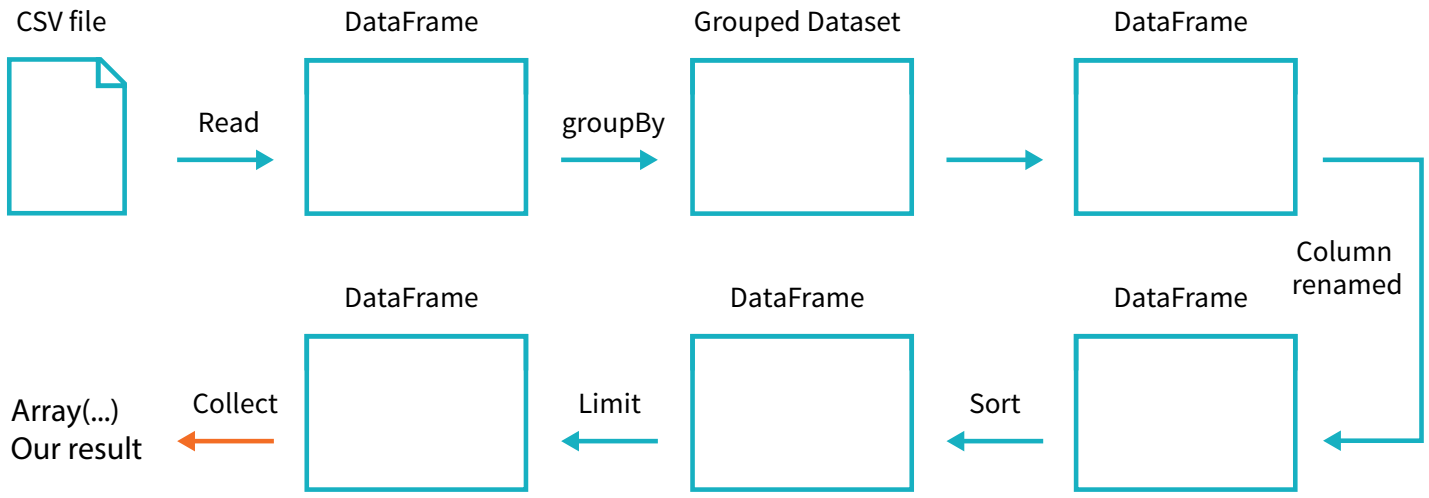


Figure 9:

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 the 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 basically specified that we're going to be grouping by a key (or set of keys) and that now we're going to perform an aggregation over each one of those keys.

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.

Penultimately, we'll specify a limit. This just specifies that we only want five values. This is just like a filter except that it filters by position 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.

```
%scala

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


%python

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#16194L DESC], output=[DEST_
COUNTRY_NAME#7323,...
```

```
+- *HashAggregate(keys=[DEST_COUNTRY_NAME#7323], functions=[sum(count#7325L)])
  +- Exchange hashpartitioning(DEST_COUNTRY_NAME#7323, 5)
     +- *HashAggregate(keys=[DEST_COUNTRY_NAME#7323], functions=[partial
sum(count#7325L)])
        +- InMemoryTableScan [DEST_COUNTRY_NAME#7323, count#7325L]
           +- InMemoryRelation [DEST_COUNTRY_NAME#7323, ORIGIN_COUNTRY_NAME#7324,
count#7325L]...
              +- *Scan csv [DEST_COUNTRY_NAME#7578,ORIGIN_COUNTRY_
NAME#7579,count#7580L]...
```

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.

Naturally, we don't always have to collect the data. We can also write it out to any data source that Spark supports. For instance, let's say that we wanted to store the information in a database like PostgreSQL or write them out to another file.

A Tour of Spark's Toolset

In the previous chapter we introduced Spark's core concepts, like transformations and actions, in the context of Spark's Structured APIs. These simple conceptual building blocks are the foundation of Apache Spark's vast ecosystem of tools and libraries. Spark is composed of the simple primitives, the lower level APIs and the Structured APIs, then a series of "standard libraries" included in Spark.

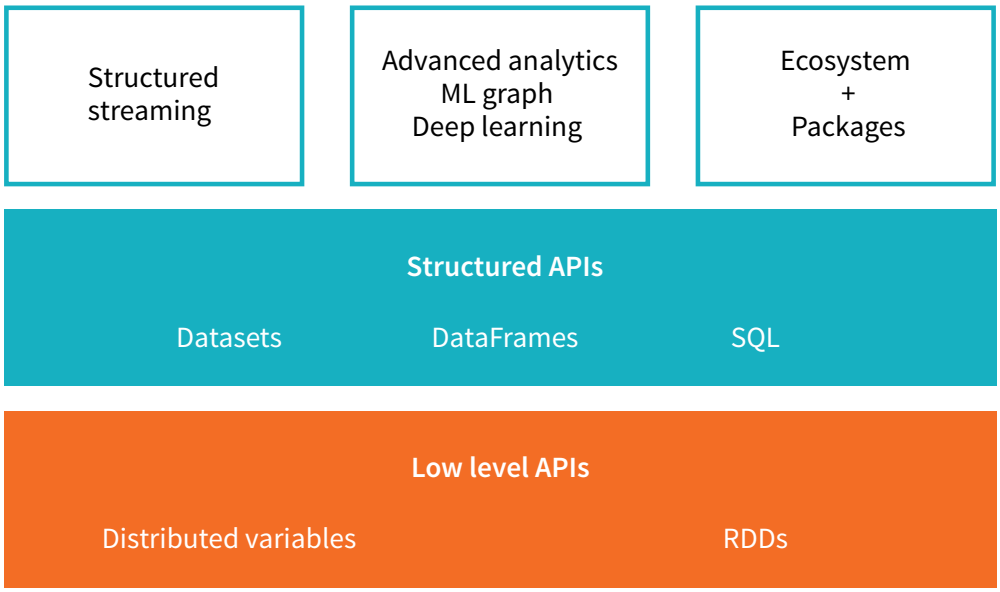


Figure 1:

Developers use these tools for a variety of different tasks, from graph analysis and machine learning to streaming and integrations with a host of libraries and databases. This chapter will present a whirlwind tour of much of what Spark has to offer. Each section in this chapter are elaborated upon by other parts of this book, this chapter is simply here to show you what's possible.

This chapter will cover:

- Production applications with spark-submit,
- Datasets: structured and type safe APIs,
- Structured Streaming,
- Machine learning and advanced analytics,

- Spark's lower level APIs,
- SparkR,
- Spark's package ecosystem.

The entire book covers these topics in depth, the goal of this chapter is simply to provide a whirlwind tour of Spark. Once you've gotten the tour, you'll be able to jump to many different parts of the book to find answers to your questions about particular topics. This chapter aims for breadth, instead of depth. Let's get started!

Production Applications

Spark makes it easy to make simple to reason about and simple to evolve big data programs. Spark also makes it easy to turn in your interactive exploration into production applications with a tool called `spark-submit` that is included in the core of Spark. spark-submit does one thing, it allows you to submit your applications to a currently managed cluster to run. When you submit this, the application will run until the application exists or errors. You can do this with all of Spark's support cluster managers including Standalone, Mesos, and YARN.

In the process of doing so, you have a number of knobs that you can turn and control to specify the resources this application has as well, how it should be run, and the parameters for your specific application.

You can write these production applications in any of Spark's supported languages and then submit those applications for execution. The simplest example is one that you can do on your local machine by running the following command line snippet on your local machine in the directory into which you downloaded Spark.

```
./bin/spark-submit \
  --class org.apache.spark.examples.SparkPi \
  --master local \
  ./examples/jars/spark-examples_2.11-2.2.0.jar 10
```

What this will do is calculate the digits of pi to a certain level of estimation. What we've done here is specified that we want to run it on our local machine, specified which class and which jar we would like to run as well as any command line arguments to that particular class.

We can do this in Python with the following command line arguments.

```
./bin/spark-submit \
  --master local \
  ./examples/src/main/python/pi.py 10
```

By swapping out the path to the file and the cluster configurations, we can write and run production applications. Now Spark provides a lot more than just DataFrames that we can run as production applications. The rest of this chapter will walk through several different APIs that we can leverage to run all sorts of production applications.

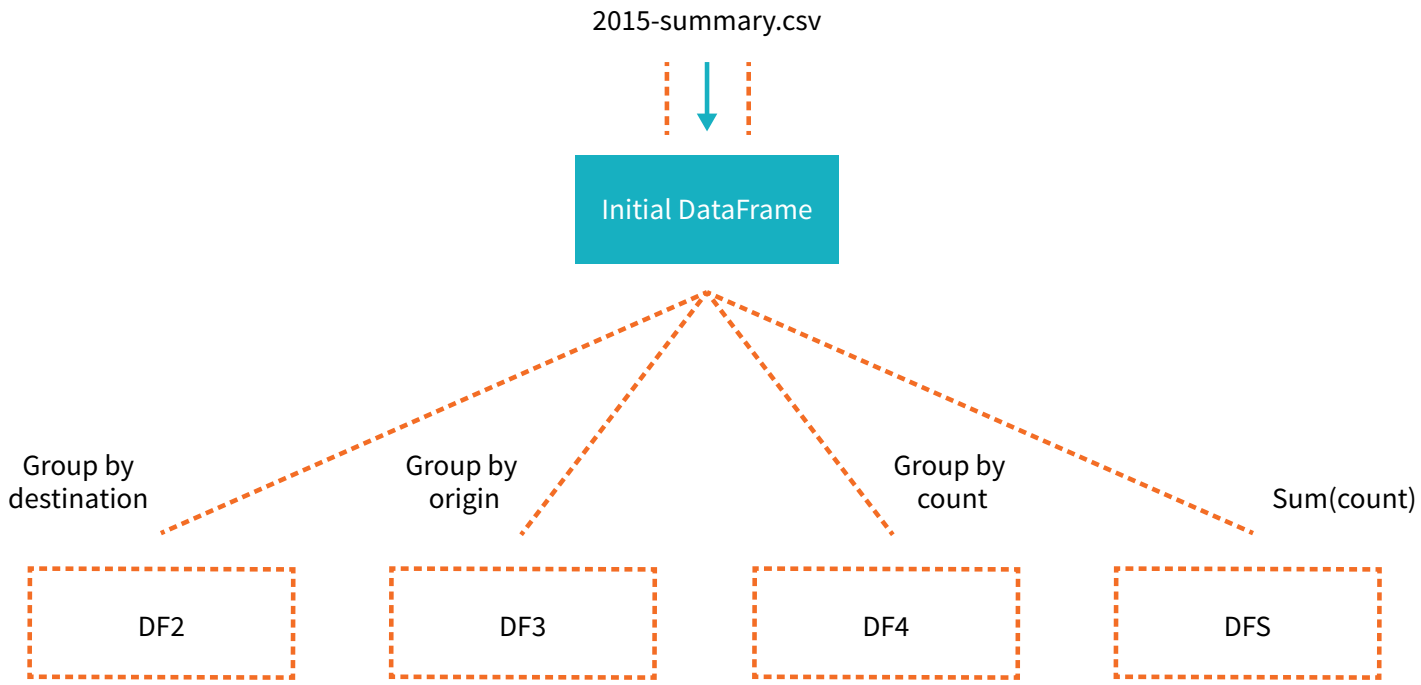


Figure 2:

Datasets: Type-Safe Structured APIs

The next topic we'll cover is a type-safe version of Spark's structured API for Java and Scala, called *Datasets*. This API is not available in Python and R, because those are dynamically typed languages, but it is a powerful tool for writing large applications in Scala and Java.

Recall that DataFrames, which we saw earlier, are a distributed collection of objects of type Row, which can hold various types of tabular data. The Dataset API allows users to assign a Java class to the records inside a DataFrame, and manipulate it as a collection of typed objects, similar to a Java `ArrayList` or Scala `Seq`. The APIs available on Datasets are *type-safe*, meaning that you cannot accidentally view the objects in a Dataset as being of another class than the class you put in initially. This makes Datasets especially attractive for writing large applications where multiple software engineers must interact through well-defined interfaces.

The Dataset class is parametrized with the type of object contained inside: `Dataset<T>` in Java and `Dataset[T]` in Scala. As of Spark 2.0, the types `T` supported are all classes following the JavaBean pattern in Java, and `case classes` in Scala. These types are restricted because Spark needs to be able to automatically analyze the type `T` and create an appropriate schema for the tabular data inside your Dataset.

The awesome thing about Datasets is that we can use them only when we need or want to. For instance, in the following example I'll define my own object and manipulate it via arbitrary map and filter functions. Once we've performed our manipulations, Spark can automatically turn it back into a DataFrame and we can manipulate it further using the hundreds of functions that Spark includes. This makes it easy to drop down to lower level, type secure coding when necessary, and move higher up to SQL for more rapid analysis. We cover this material extensively in the next part of this book, but here is a small example showing how we can use both type-safe functions and DataFrame-like SQL expressions to quickly write business logic.

```
%scala

// A Scala case class (similar to a struct) that will automatically
// be mapped into a structured data table in Spark
case class Flight(DEST_COUNTRY_NAME: String, ORIGIN_COUNTRY_NAME: String, count:
BigInt)

val flightsDF = spark.read.parquet("/mnt/defg/flight-data/parquet/2010-summary.
parquet/")
val flights = flightsDF.as[Flight]
```

One final advantage is that when you call `collect` or `take` on a Dataset, we're going to collect to objects of the proper type in your Dataset, not DataFrame Rows. This makes it easy to get type safety and safely perform manipulation in a distributed and a local manner without code changes.

```
%scala

flights
 .filter(flight_row => flight_row.ORIGIN_COUNTRY_NAME != "Canada")
 .take(5)
```

Structured Streaming

SStructured Streaming is a high-level API for stream processing that became production-ready in Spark 2.2. Structured Streaming allows you to take the same operations that you perform in batch mode using Spark's structured APIs, and run them in a streaming fashion. This can reduce latency and allow for incremental processing. The best thing about Structured Streaming is that it allows you to rapidly and quickly get value out of streaming systems with virtually no code changes. It also makes it easy to reason about because you can write your batch job as a way to prototype it and then you can convert it to streaming job. The way all of this works is by incrementally processing that data.

Let's walk through a simple example of how easy it is to get started with Structured Streaming. For this we will use a retail dataset. One that has specific dates and times for us to be able to use. We will use the "by-day" set of files where one file represents one day of data.

We put it in this format to simulate data being produced in a consistent and regular manner by a different process. Now this is retail data so imagine that these are being produced by retail stores and sent to a location where they will be read by our Structured Streaming job.

It's also worth sharing a sample of the data so you can reference what the data looks like.

```
InvoiceNo,StockCode,Description,Quantity,InvoiceDate,UnitPrice,CustomerID,Country
536365,85123A,WHITE HANGING HEART T-LIGHT HOLDER,6,2010-12-01
08:26:00,2.55,17850.0,United Kingdom
536365,71053,WHITE METAL LANTERN,6,2010-12-01 08:26:00,3.39,17850.0,United Kingdom
536365,84406B,CREAM CUPID HEARTS COAT HANGER,8,2010-12-01
08:26:00,2.75,17850.0,United Kingdom
```

Now in order to ground this, let's first analyze the data as a static dataset and create a DataFrame to do so. We'll also create a schema from this static dataset. There are ways of using schema inference with streaming that we will touch on in the Part V of this book.

```
%scala

val staticDataFrame = spark.read.format("csv")
   .option("header", "true")
   .option("inferSchema", "true")
   .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")
```

```
staticDataFrame.createOrReplaceTempView("retail_data")
val staticSchema = staticDataFrame.schema
```

```
%python

staticDataFrame = spark.read.format("csv")\
   .option("header", "true")\
   .option("inferSchema", "true")\
   .load("dbfs:/mnt/defg/retail-data/by-day/*.csv")

staticDataFrame.createOrReplaceTempView("retail_data")
staticSchema = staticDataFrame.schema
```

Now since we're working with time series data it's worth mentioning how we might go along grouping and aggregating our data. In this example we'll take a look at the largest sale hours where a given customer (identified by `CustomerId`) makes a large purchase. For example, let's add a total cost column and see on what days a customer spent the most.

The window function will include all data from each day in the aggregation. It's simply a window over the time series column in our data. This is a helpful tool for manipulating date and timestamps because we can specify our requirements in a more human form (via intervals) and Spark will group all of them together for us.

```
%scala

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

staticDataFrame
   .selectExpr(
   "CustomerId",
   "(UnitPrice * Quantity) as total_cost",
   "InvoiceDate")
   .groupBy(
   col("CustomerId"), window(col("InvoiceDate"), "1 day"))
   .sum("total_cost")
   .orderBy(desc("sum(total_cost)"))
   .take(5)
```

```
%python

from pyspark.sql.functions import window, column, desc, col

staticDataFrame\
   .selectExpr(
   "CustomerId",
   "(UnitPrice * Quantity) as total_cost" ,
   "InvoiceDate" )\
   .groupBy(
   col("CustomerId"), window(col("InvoiceDate"), "1 day"))\
   .sum("total_cost")\
   .orderBy(desc("sum(total_cost)"))\
   .take(5)
```

It's worth mentioning that we can also run this as SQL code, just as we saw in the previous chapter.

Here's a sample of the output that you'll see.

```
+----------+--------------------+------------------+
|CustomerId|              window|   sum(total_cost)|
+----------+--------------------+------------------+
|   17450.0|[2011-09-20 00:00...|          71601.44|
|      null|[2011-11-14 00:00...|          55316.08|
|      null|[2011-11-07 00:00...|          42939.17|
|      null|[2011-03-29 00:00...| 33521.39999999998|
|      null|[2011-12-08 00:00...|31975.590000000007|
+----------+--------------------+------------------+
```

That's the static DataFrame version, there shouldn't be any big surprises in there if you're familiar with the syntax. Now we've seen how that works, let's take a look at the streaming code! You'll notice that very little actually changes about our code. The biggest change is that we used `readStream` instead of `read`, additionally you'll notice `maxFilesPerTrigger` option which simply specifies the number of files we should read in at once. This is to make our demonstration more "streaming" and in a production scenario this would be omitted.

Now since you're likely running this in local mode, it's a good practice to set the number of shuffle partitions to something that's going to be a better fit for local mode. This configuration simple specifies the number of partitions that should be created after a shuffle, by default the value is two hundred but since there aren't many executors

on this machine it's worth reducing this to five. We did this same operation in the previous chapter, so if you don't remember why this is important feel free to flip back to the previous chapter to review.

```
val streamingDataFrame = spark.readStream
   .schema(staticSchema)
   .option("maxFilesPerTrigger", 1)
   .format("csv")
   .option("header", "true")
   .load("d/mnt/defg/retail-data/by-day/*.csv")
```

```
%python

streamingDataFrame = spark.readStream\
   .schema(staticSchema)\
   .option("maxFilesPerTrigger", 1)\
   .format("csv")\
   .option("header", "true")\
   .load("/mnt/defg/retail-data/by-day/*.csv")
```

Now we can see the DataFrame is streaming.

```
streamingDataFrame.isStreaming // returns true
```

Let's set up the same business logic as the previous DataFrame manipulation, we'll perform a summation in the process.

```
%scala

val purchaseByCustomerPerHour = streamingDataFrame
   .selectExpr(
   "CustomerId",
   "(UnitPrice * Quantity) as total_cost",
   "InvoiceDate")
   .groupBy(
   $"CustomerId", window($"InvoiceDate", "1 day"))
   .sum("total_cost")
```

```
%python

purchaseByCustomerPerHour = streamingDataFrame\
   .selectExpr(
   "CustomerId",
   "(UnitPrice * Quantity) as total_cost" ,
   "InvoiceDate" )\
   .groupBy(
   col("CustomerId"), window(col("InvoiceDate"), "1 day"))\
   .sum("total_cost")
```

This is still a lazy operation, so we will need to call a streaming action to start the execution of this data flow.

NOTE

Before kicking off the stream, we will set a small optimization that will allow this to run better on a single machine. This simply limits the number of output partitions after a shuffle, a concept we discussed in the last chapter. We discuss this in Part VI of the book.

```
spark.conf.set("spark.sql.shuffle.partitions", "5")
```

Streaming actions are a bit different from our conventional static action because we're going to be populating data somewhere instead of just calling something like count (which doesn't make any sense on a stream anyways). The action we will use will out to an in-memory table that we will update after each *trigger.* In this case, each trigger is based on an individual file (the read option that we set). Spark will mutate the data in the in-memory table such that we will always have the highest value as specified in our aggregation above.

```
%scala

purchaseByCustomerPerHour.writeStream
   .format("memory") // memory = store in-memory table
   .queryName("customer_purchases") // counts = name of the in-memory table
   .outputMode("complete") // complete = all the counts should be in the table
   .start()
```

```
%python

purchaseByCustomerPerHour.writeStream\
   .format("memory")\
   .queryName("customer_purchases")\
   .outputMode("complete")\
   .start()
```

Once we start the stream, we can run queries against the stream to debug what our result will look like if we were to write this out to a production sink.

```
%scala

spark.sql("""
   SELECT *
   FROM customer_purchases
   ORDER BY `sum(total_cost)` DESC
   """)
   .take(5)


%python

spark.sql("""
   SELECT *
   FROM customer_purchases
   ORDER BY `sum(total_cost)` DESC
   """)\
   .take(5)
```

You'll notice that as we read in more data - the composition of our table changes! With each file the results may or may not be changing based on the data. Naturally since we're grouping customers we hope to see an increase in the top customer purchase amounts over time (and do for a period of time!). Another option you can use is to just simply write the results out to the console.

```
purchaseByCustomerPerHour.writeStream
  .format("console")
  .queryName("customer_purchases_2")
  .outputMode("complete")
  .start()
```

Neither of these streaming methods should be used in production but they do make for convenient demonstration of Structured Streaming's power. Notice how this window is built on event time as well, not the time at which the data Spark processes the data. This was one of the shortcoming of Spark Streaming that Structured Streaming as resolved. We cover Structured Streaming in depth in Part V of this book.

Machine Learning and Advanced Analytics

Another popular aspect of Spark is its ability to perform large scale machine learning with a built-in library of machine learning algorithms called MLlib. MLlib allows for preprocessing, munging, training of models, and making predictions at scale on data. You can even use models trained in MLlib to make predictions in Strucutred Streaming. Spark provides a sophisticated machine learning API for performing a variety of machine learning tasks, from classification to regression and clustering. To demonstrate this functionality, we will perform some basic clustering on our data using a common algorithm called K-Means.

BOX What is K-Means? K-means is a clustering algorithm where "K" centers are randomly assigned within the data. The points closest to that point are then "assigned" to a particular cluster. Then a new center for this cluster is computed (called a centroid). We then label the points closest to that centroid, to the centroid's class, and shift the centroid to the new center of that cluster of points. We repeat this process for a finite set of iterations or until convergence (where our centroid and clusters stop changing.

Spark includes a number of preprocessing methods out of the box. To demonstrate these methods, we will start with some raw data, build up transformations before getting the data into the right format at which point we can actually train our model and then serve predictions.

```
staticDataFrame.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)
```

Machine learning algorithms in MLlib, for the most part, require data to be represented as numerical values. Our current data is represented by a variety of different types including timestamps, integers, and strings. Therefore we need to transform this data into some numerical representation. In this instance, we will use several DataFrame transformations to manipulate our date data.

```
%scala

import org.apache.spark.sql.functions.date_format

val preppedDataFrame = staticDataFrame
   .na.fill(0)
   .withColumn("day_of_week", date_format($"InvoiceDate", "EEEE"))
   .coalesce(5)


%python

from pyspark.sql.functions import date_format, col

preppedDataFrame = staticDataFrame\
   .na.fill(0)\
   .withColumn("day_of_week", date_format(col("InvoiceDate"), "EEEE"))\
   .coalesce(5)
```

Now we are also going to need to split our data into training and test sets. In this instance we are going to do this manually by the data that a certain purchase occurred however we could also leverage MLlib's transformation APIs to create a training and test set via train validation splits or cross validation. These topics are covered extensively in Part VI of this book.

```
%scala

val trainDataFrame = preppedDataFrame
   .where("InvoiceDate < '2011-07-01'")
val testDataFrame = preppedDataFrame
   .where("InvoiceDate >= '2011-07-01'")


%python

trainDataFrame = preppedDataFrame\
.where("InvoiceDate < '2011-07-01'")
   testDataFrame = preppedDataFrame\
   .where("InvoiceDate >= '2011-07-01'")
```

Now that we prepared our data, let's split it into a training and test set. Since this is a time-series set of data, we will split by an arbitrary date in the dataset. While this may not be the optimal split for our training and test, for the intents and purposes of this example it will work just fine. We'll see that this splits our dataset roughly in half.

```
trainDataFrame.count()

testDataFrame.count()
```

Now these transformations are DataFrame transformations, covered extensively in part two of this book. Spark's MLlib also provides a number of transformations that allow us to automate some of our general transformations. One such transformer is a `StringIndexer`.

```
%scala

import org.apache.spark.ml.feature.StringIndexer

val indexer = new StringIndexer()
   .setInputCol("day_of_week")
   .setOutputCol("day_of_week_index")
```

```
%python

from pyspark.ml.feature import StringIndexer

indexer = StringIndexer()\
.setInputCol("day_of_week")\
.setOutputCol("day_of_week_index")
```

This will turn our days of weeks into corresponding numerical values. For example, Spark may represent Saturday as 6 and Monday as 1. However with this numbering scheme, we are implicitly stating that Saturday is greater than Monday (by pure numerical values). This is obviously incorrect. Therefore we need to use a `OneHotEncoder` to encode each of these values as their own column. These boolean flags state whether that day of week is the relevant day of the week.

```
%scala

import org.apache.spark.ml.feature.OneHotEncoder

val encoder = new OneHotEncoder()
   .setInputCol("day_of_week_index")
   .setOutputCol("day_of_week_encoded")


%python

from pyspark.ml.feature import OneHotEncoder

encoder = OneHotEncoder()\
   .setInputCol("day_of_week_index")\
   .setOutputCol("day_of_week_encoded")
```

Each of these will result in a set of columns that we will "assemble" into a vector. All machine learning algorithms in Spark take as input a `Vector` type, which must be a set of numerical values.

```
%scala

import org.apache.spark.ml.feature.VectorAssembler
```

```
val vectorAssembler = new VectorAssembler()
  .setInputCols(Array("UnitPrice", "Quantity", "day_of_week_encoded"))
  .setOutputCol("features")
```

```
%python
from pyspark.ml.feature import VectorAssembler
vectorAssembler = VectorAssembler()\
  .setInputCols(["UnitPrice", "Quantity", "day_of_week_encoded"])\
  .setOutputCol("features")
```

We can see that we have 3 key features, the price, the quantity, and the day of week. Now we'll set this up into a pipeline so any future data we need to transform can go through the exact same process.

```
%scala
import org.apache.spark.ml.Pipeline
val transformationPipeline = new Pipeline()
   .setStages(Array(indexer, encoder, vectorAssembler))
```

```
%python
from pyspark.ml import Pipeline
transformationPipeline = Pipeline()\
   .setStages([indexer, encoder, vectorAssembler])
```

Now preparing for training is a two step process. We first need to fit our transformers to this dataset. We cover this in depth, but basically our `StringIndexer` needs to know how many unique values there are to be index. Once those exist, encoding is easy but Spark must look at all the distinct values in the column to be indexed in order to store those values later on.

```
%scala
val fittedPipeline = transformationPipeline.fit(trainDataFrame)
%python
fittedPipeline = transformationPipeline.fit(trainDataFrame)
```

Once we fit the training data, we are now create to take that fitted pipeline and use it to transform all of our data in a consistent and repeatable way.

```
%scala
val transformedTraining = fittedPipeline.transform(trainDataFrame)
%python
transformedTraining = fittedPipeline.transform(trainDataFrame)
```

At this point, it's worth mentioning that we could have included our model training in our pipeline. We chose not to in order to demonstrate a use case for caching the data. At this point, we're going to perform some hyperparameter tuning on the model, since we do not want to repeat the exact same transformations over and over again, we'll leverage an optimization we discuss in Part IV of this book, caching. This will put a copy of this intermediately transformed dataset into memory, allowing us to repeatedly access it at much lower cost than running the entire pipeline again. If you're curious to see how much of a difference this makes, skip this line and run the training without caching the data. Then try it after caching, you'll see the results are significant.

```
transformedTraining.cache()
```

Now we have a training set, now it's time to train the model. First we'll import the relevant model that we'd like to use and instantiate it.

```
%scala
import org.apache.spark.ml.clustering.KMeans
```

```
val kmeans = new KMeans()
   .setK(20)
   .setSeed(1L)
```

```
%python

from pyspark.ml.clustering import KMeans

kmeans = KMeans()\
   .setK(20)\
   .setSeed(1L)
```

In Spark, training machine learning models is a two phase process. First we initialize an untrained model, then we train it. There are always two types for every algorithm in MLlib's DataFrame API. They following the naming pattern of `Algorithm`, for the untrained version, and `AlgorithmModel` for the trained version. In our case, this is `KMeans` and then `KMeansModel`.

Algorithms and models in MLlib's DataFrame API share roughly the same interface that we saw above with our preprocessing transformers like the `StringIndexer`. This should come as no surprise because it makes training an entire pipeline (which includes the model) simple. In our case we want to do things a bit more step by step, so we chose to not do this at this point.

```
%scala

val kmModel = kmeans.fit(transformedTraining)

%python

kmModel = kmeans.fit(transformedTraining)
```

We can see the resulting cost at this point. Which is quite high, that's likely because we didn't necessary scale our data or transform.

```
kmModel.computeCost(transformedTraining)

%scala

val transformedTest = fittedPipeline.transform(testDataFrame)
```

```
%python

transformedTest = fittedPipeline.transform(testDataFrame)

kmModel.computeCost(transformedTest)
```

Naturally we could continue to improve this model, layering more preprocessing as well as performing hyperparameter tuning to ensure that we're getting a good model. We leave that discussion for Part VI of this book.

Lower Level APIs

Spark includes a number of lower level primitives to allow for arbitrary Java and Python object manipulation via Resilient Distributed Datasets (RDDs). Virtually everything in Spark is built on top of RDDs. As we will cover in the next chapter, DataFrame operations are built on top of RDDs and compile down to these lower level tools for convenient and extremely efficient distributed execution. There are some things that you might use RDDs for, especially when you're reading or manipulating raw data, but for the most part you should stick to the Structured APIs. RDDs are lower level that DataFrames because they reveal physical execution characteristics (like partitions) to end users.

One thing you might use RDDs for is to parallelize raw data you have stored in memory on the driver machine. For instance let's parallelize some simple numbers and create a DataFrame after we do so. We can then convert that to a DataFrame to use it with other DataFrames.

```
%scala

spark.sparkContext.parallelize(Seq(1, 2, 3)).toDF()


%python

from pyspark.sql import Row

spark.sparkContext.parallelize([Row(1), Row(2), Row(3)]).toDF()
```

RDDs are available in Scala as well as Python. However, they're not equivalent. This differs from the DataFrame API (where the execution characteristics are the same) due to some underlying implementation details. We cover lower level APIs, including RDDs in Part IV of this book. As end users, you shouldn't need to use RDDs much in order to perform many tasks unless you're maintaining older Spark code. There are basically no instances in modern Spark where you should be using RDDs instead of the structured APIs beyond manipulating some very raw unprocessed and unstructured data.

SparkR

SparkR is a tool for running R on Spark. It follows the same principles as all of Spark's other language bindings. To use SparkR, we simply import it into our environment and run our code. It's all very similar to the Python API except that it follows R's syntax instead of Python. For the most part, almost everything available in Python is available in SparkR.

```
%r

library(SparkR)

sparkDF <- read.df("/mnt/defg/flight-data/csv/2015-summary.csv",
         source = "csv", header="true", inferSchema = "true")

take(sparkDF, 5)


%r

collect(orderBy(sparkDF, "count"), 20)
```

R users can also leverage other R libraries like the pipe operator in magrittr in order to make Spark transformations a bit more R like. This can make it easy to use with other libraries like ggplot for more sophisticated plotting.

```
%r

library(magrittr)

sparkDF %>%
    orderBy(desc(sparkDF$count)) %>%
    groupBy("ORIGIN_COUNTRY_NAME") %>%
    count() %>%
    limit(10) %>%
    collect()
```

We cover SparkR more in the Ecosystem Part of this book along with short discussion of PySpark specifics (PySpark is covered heavily through this book), and the new sparklyr package.

Spark's Ecosystem and Packages

One of the best parts about Spark is the ecosystem of packages and tools that the community has created. Some of these tools even move into the core Spark project as they mature and become widely used. The list of packages is rather large at over 300 at the time of this writing and more are added frequently. The largest index of Spark Packages can be found at https://spark-packages.org/, where any user can publish to this package repository. There are also various other projects and packages that can be found through the web, for example on GitHub.

Advanced Analytics and Machine Learning

This part of the book will dive deeper into some of the more cutting edge, machine learning use cases available in Spark. Beyond large scale SQL analysis and Streaming, Spark also provides support for large scale machine learning and graph analysis. These are apart of a set of workloads that we frequently call “advanced analytics”. This part of the book will cover the different parts of Spark your organization can leverage for advanced analytics including:

- Preprocessing your data (cleaning data and feature engineering)
- Supervised Learning
- Unsupervised Learning
- Recommendation Engines
- Graph Analysis
- Deep Learning

This particular chapter, will cover a basic primer on advanced analytics, some example use cases, and a basic advanced analytics workflow. After which we’ll cover the previous bullets and teaching you how you can apply them.

WARNING

This book is not intended to teach you everything you need to know about machine learning. We won’t go into strict mathematical definitions and formulations - not for lack of importance but simply because it’s too much information to include. This part of the book is *not* an algorithm guide that will teach you the mathematical underpinnings of every available Spark algorithm nor the in depth implementation strategies of every algorithm. This will be a user guide for what you’re going to need to know and do to use Spark’s advanced analytics capabilities successfully.

A short primer on Advanced Analytics

Before covering the topics in detail, let's define advanced analytics more formally and provide a simple crash course in machine learning.

Gartner defines advanced analytics as follows in their IT Glossary:

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.

predict

模拟

emotion

In other words, advanced analytics is a grab bag of techniques solving the core problem of deriving insights and making predictions or recommendations based on data. The best ontology for machine learning is structured based on the task that you would like to perform. The most common tasks are the following:

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1. Supervised learning including classification and regression.
2. Recommendation engines to recommend different products based on behavior or preferences.
3. Unsupervised Learning including clustering, anomaly detection, and topic modeling.
4. Graph analysis tasks like discovering and understanding relationship structures in the graph.

Before talking about Spark, let's review each of these fundamental tasks along with some common use cases before introducing Spark's functionality in this problem area. The challenge here is that this information can be quite challenging. While we will certainly trying to make this introduction as gentle as possible, some times you may need to reference more examples or other explanations in order to understand the material. O'Reilly also has a number of books on the folling subjects that serve as excellent references for more detailed material. For the purposes of this book, we will reference three books throughout the following chapters because they are available for free on the web (at the linked websites). They are a great resource for those 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. We will refer to this book as "ISL".
- Elements of Statistical Learning by Trevor Hastie, Robert Tibshirani, and Jerome Friedman. We will refer to this book as "ESL".
- Deep Learning by Ian Goodfellow, Yoshua Bengio, and Aaron Courville. We will refer to this book as "DLB".

Supervised Learning

Supervised learning is probably the type of machine learning that you are most familiar with. The goal is simple; using historical data that already has labels (often called the dependent variable), teach an algorithm to predict the value of that label. If the algorithm predicts it wrong, we adjust the algorithm (not the training data) and try again on the next row of the data. Then, after training that algorithm, use it to make predictions on future data that it has never seen before. There's a number of different things that we're going to have to do around this, like measuring success of trained models before using them in the field, but the fundamental principle is simple. Train on historical data, ensure that it generalizes to data we didn't train on, then make predictions with that algorithm.

We can further organize supervised learning based on the type of variable we're hoping to predict.

Classification

A common task for supervised learning is classification. Classification is the act training algorithm to predict a dependent variable that is *categorical* (and belongs to a discrete, finite set of values). The most common case is *binary classification*, where there are only two groups to choose from. The cononical example is that of email spam. we may have a number of historical emails that have been organized into two groups: spam or not spam. Using this historical data, we will train an algorithm to analyze the words in, and any number of properties of, the historical emails and make a prediction as to its category. One we are satisfied with its performance, we will use that algorithm to make predictions on future emails that the algorithm has never seen before.

Another example of classification is rather than just predicting whether or not an email is spam or not, we might want to try and categorize that email further. For example, we may have four different categories of email: shopping, personal, work related, and other and the accompany historical data organized into these categories. We could train an algorithm to predict the category of an email based on the contents of the email (and who its coming from), then apply this trained algorithm to new data that it has never seen. If we've done things correctly, it could help organize someones inbox into those different groups. This task is commonly referred to as multiclass classification.

Use Cases

There are a number of use cases for classification. Some other examples are:

- Predicting heart disease - A doctor or hospital might have a historical dataset of behavioral and physiological attributes of a set of patients. They could then train an algorithm on this historical data (and evaluate its success and ethical implications before applying it) and then leverage that to predict whether or not a patient has significant heart disease or not. This could be an example of binary classification (healthy heart, unhealthy heart) or multiclass classification (healthly heart, somewhat healthy heart, unhealthy heart).

- Classifying images - There are a number of applications from companies like Apple, Google, or Facebook that will predict who is in a given picture by running a classification algorithm on faces that they find in an image that has been trained on historical images of people in your past photos. A common use case might be to classify images or label the objects in images.
- Predicting customer churn - A more business applied use case might be predicting customer churn. You can do this by training a binary classifier on past customers that have churned (and not churned) and using those to try and predict whether or not current customers will churn or not.
- Buy or won't buy - A company may want to predict whether an individual on their website will purchase a given product or not. They might use the information about the user's browsing habits in order to drive this prediction.

There are many of different use cases for classification and this is just a small sample. The key requirement is that you have sufficient data to train your algorithm on and that you have proper evaluation criteria. We will discuss these in the classification chapter itself.

Regression

In classification, we saw that there are only a discrete set of values that our dependent variable can be. In regression, we try to predict a continuous variable (a real number) instead. In simplest terms, rather than predicting a category, we want to predice a value on a number line. This is a harder task that binary or multiclass classification because our result can assume any number of values - not just those from a discrete set. The rest is largely the same process (and hence why they're both a part of supervised learning), we will train on historical data to predict on data that we have never seen.

Use Cases

- Predicting sales - A store may want to predict total product sales on a given data using the historical sales data that they have. The are a number of potential input variables, but a simple example might be using the last week's sales data to predict the next day's data.
- Predicting height - Based on properties of an individual's parents, we might want to predict the high of their son or daughter.
- Precting the number of viewers of a show - A company like Netflix might try to predict how many of their subscribers will watch a particular show in order to judge the overall value of predicting a particular show based on historical viewership numbers of other shows.

Regression, as we mentioned, is a bit more complicated that classification but quite powerful as well. We'll cover more details in the chapter on regression.

Recommendation

The task of recommendation is one of the most intuitive. By studying people's explicit preferences (through ratings) or implicit ones (through observed behavior) you can make recommendations on what one user may like by drawing similarities between the user and other users. Based on this result, we can make a recommendation to another user based on this information. The is a common use case for Spark and well suited to big data.

Use cases

Recommendation algorithms have a number of applications in the real world. One of the reasons for this is that building a set historical set of behavioral observations is quite simple. Additionally, serving a trained algorithm is also quite easy for reasons we will discuss later on in this part of the book.

- Movie Recommendations - Netflix uses Spark, although not necessarily this specific implementation, to make large scale movie recommendations to their users. They do this by studying what movies users watch and do not watch when they login to the application. In addition, they likely take into consideration how similar a given user's ratings are to other users watch as another way to recommend movies.
- Product Recommendations - Amazon uses product recommendations in order to increase sales. For instance, based on the items in our shopping cart, Amazon may recommend other items that were added to similar shopping carts in the past. Another way of performing this task is through a task called collaborative filtering where item similarities are computed from people's viewing behavior.

We'll discuss recommendation further in the chapter on recommendation.

Unsupervised Learning

Unsupervised learning is the act of trying to find patterns or discover the underlying structure in a given set of data. This differs from supervised learning because there is no dependent variable that we train our algorithm one. This makes it one of the more difficult advanced analytics tasks because it can be quite difficult to measure success.

Use Cases

As we mentioned above, the goal of unsupervised learning differs from our other tasks because there isn't always a simple measure of success that you can leverage to call your analysis a succes. More often than not, you might run an unsupervised learning algorithm not to make predictions, but to discover underlying patterns in your data and better understand the different properties that define groups in your data.

- Topic modeling - Given a set of documents, we might analyze the different words in these documents to see if there is some underlying relation between these documents. Taking the structure of this book as an example, by running a topic modeling algorithm on the chapters, we might find that the streaming chapters differ from the machine learning chapters because there are words that are unique to these two different parts of the book.

- Anomaly Detection - Given some standard event type often occuring over time, we might want to report when a non-standard type of event occurs. An example 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.
细分
- User segmentation - Given a set of user behaviors, we might want to better understand what attributes certain users share with other users. For instance, a gaming company might cluster their users based on properties like number of hours played in each given game. The algorithm might reveal that players of game a often play game b as well. Doing so might motivate formalizing this into a recommendation system to provide payers with recommendatiosn for other games.

As with the other tasks, we will discuss this in the unsupervised learning chapter.

Graph Analysis

While less common than the above tasks, graph analysis is something that we are seeing more and more in advanced analytics use cases. Graph analysis can provide alternative approaches to the aforementioned tasks. By all means this does not invalidate or obviate the above approaches, consider it as an alternative or different way of framing the problem. Fundamentally, Graph analysis is the study of relationships where we specify *vertices* which are objects and *edges* which represent relationships between those objects. By looking at the properties of vertices and edges, we can better study the connections and similarities of different vertices and edges.

Use cases

Since graphs are all about relationships, there are a number of different use cases for graph analysis.

- Fraud Prediction - Capital One uses Spark's graph analytics capabilities to better understand fraud networks. This includes connecting different using different fraudulent phone numbers, addresses, or other information and leveraging that new information in order to discover new fraudulent information (or suspicious information) to try and combat fraud ahead of time.
- Anomaly Detection - By looking at how networks of individuals connect with one another, outliers and anomalies can be flagged for manual analysis. For instance, if typically in our data a given vertex has ten edges associated with it and a vertex only has one edge, that might be worth investigating as something strange that should be studied.
- Classification - Given some facts about certain vertices in the network, you can classify other vertices according to their connection to that original node. For instance, if a certain individual is labelled as an influencer in a social network, we could classify other individuals with similar network structures as influencers.
- Recommendation - Google's original web recommendation algorithm, PageRank, is a graph algorithm that analyzes web sites relationships in order to provide rank the importance of web pages. As an example, if a web page has a lot of links to it is ranked as more important that one with no links to it.

We'll discuss some examples of graph analysis in the upcoming chapters.

The Advanced Analytics Process

We just took a quick review of different advanced analytics applications and use cases, from recommendation to regression. However, this is only a small sliver of the actual advanced analytics process. As you will likely discover, choosing a task or algorithm is often the easy part. The primary challenge is everything around the particular algorithm. This section of the chapter will provide structure to the overall anaytics process and the steps we are going to have to take to not just perform one of the above tasks, but actually evaulate success objectively in order to understand whether or not we should or should not use the algorithm we trained in production.

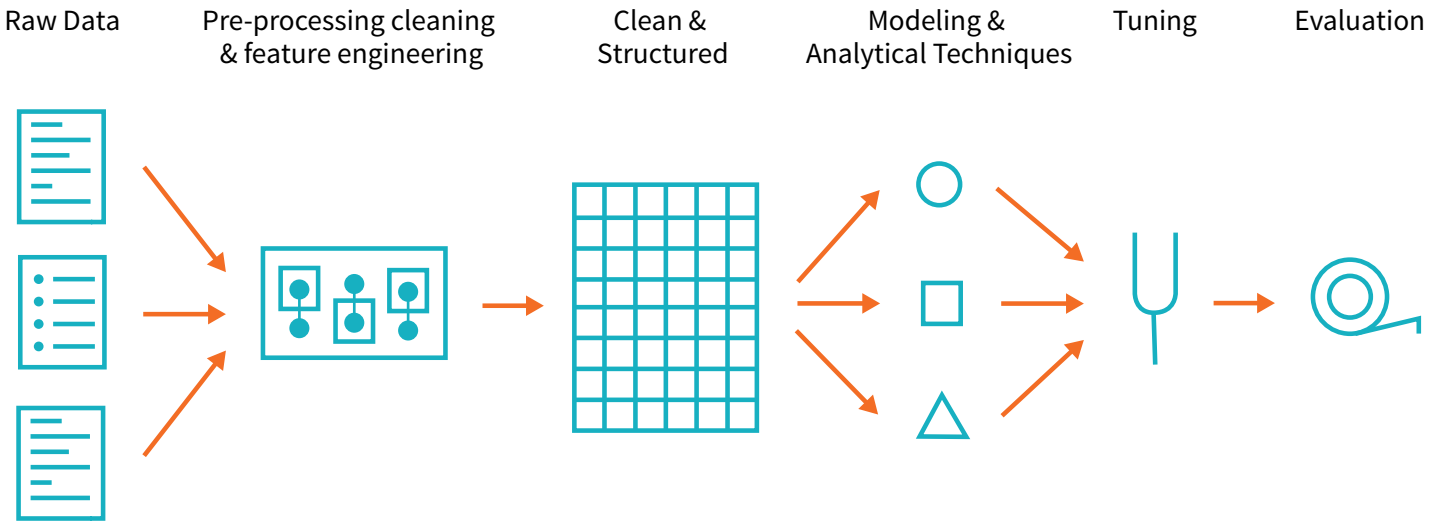


Figure 1:

The overall process follows some variation of the following process:

- Gathering and collecting the relevant data for your task.
- Cleaning and inspecting the data to better understand it.
- Performing feature engineering to allow the algorithm to leverage more information.
- Using a portion of this data as a training set to train one or more algorithms to generate some candidate models.
- Evaluating and comparing models against your success criteria by objectively measuring results on a subset of the same data (that was not used for training). This allows you to better understand how your model may perform in the wild.
- Leveraging the insights from the above process and/or using the model to make predictions, recommndations, detect anomalies or solve more general business challenges.

As we mentioned, is this going to be the same for every advanced analytics task ever? No, absolutely not. However, it

does serve as a general framework for what you're going to need to do in order to take an advanced analytics use case and get value out of it. Just as we did with the various advanced analytics tasks earlier in the chapter, let's break down each of these steps in the process to better understand each step's overall objective.

Data Collection

Naturally it's hard to create a training set without first collecting data. Typically this means at least gathering the datasets that you'll want to leverage to train your algorithm. Spark is, somewhat obviously, an excellent tool for this because of its ability to speak to a variety of data sources and work with data big and small

Data Cleaning

After you've gather the proper data, you're going to need to clean it and inspect it and perform something along the lines of exploratory data analysis or EDA. EDA is a suitable technique for this stage of the process as you seek to better understand your data and EDA has an emphasis on using visual methods in order to better understand distributions, correlations, and other details in your data. During this process you may notice that you need to remove some values that may have been misrecorded upstream or that other values may be missing. Whatever the case, it's always good have a good understanding and what is in your data to avoid mistakes down the road. The multitude of Spark functions in the Structured APIs will provide a simple way to clean your data.

Feature Engineering

Now that we have a clean dataset, it's time to augment it (if necessary) by potentially normalizing data, add variables to represent the interactions of other variables , manipulating categorical variables and converting them to the proper format to be input into our machine learning model. In MLlib, Spark's machine learning library, all variables will have to be input as doubles (regardless of what they actually represent). This means that you're likely going to have to do something like one-hot encode categorical variables and other indexing style techniques. We're going to cover the process of feature engineering in great depth in the next chapter but for the most part, Spark provides the essentials that you'll leverage to manipulate your data using a variety of machine learning specific statistical techniques.

Training Models

NOTE

The following two steps (training models, model tuning and evaluation) are not relevant to all use cases. This is a general workflow that can potentially vary significantly based on the end objective you would like to achieve.

At this point in the process we have a dataset that we are ready to train our model on. Now we've used this terminology several times, so let's be a bit more precise. To train a model means that we will give the model a set

of data and the machine learning model will attempt to perform the task that we specified above. In doing so, the parameters inside of the model will change according to the loss function in order to try and perform better at the given task. For instance, if we hope to classify spam emails, our algorithm will likely find that certain words are better predictors of spam than other words. These will receive higher influence in our model than words that have little relevance. The output of this algorithm and data is what we call a model. A model is a tuned version of an algorithm that is simplified version of the world that we can leverage for insights or prediction. We then can give our model new information and it will manipulate that data accordingly. In the case of the classification example, we now have a model of what characteristics are associated with a spam email and if we give our model a new email, it will output its prediction about whether or not the email is spam or not.

However, training an algorithm isn't the objective - we want to leverage our model to produce insights. Therefore we must answer the question, how do we know our model is any good at what it's supposed to do? That's where model tuning and evaluation come in.

Model Tuning and Evaluation

You likely noticed in our list above that we mentioned that we usually split our data into multiple portions and use only one for training. The reason that we create a *training set* and don't just train on the entire dataset is so that we can use the other parts to either tune our model or evaluate it against other models. The reason for this is simple. When we build a model, we want that model to generalize to new data or data that it hasn't seen before. The portion of our cleaned data that we will use to test the effectiveness of our data is what we call a test set. Think of it just like an exam that you take in school. The objective is to see if your model understands something fundamental about this data process or whether or not it just noticed the things particular to only the training set. In the process of training models, we also might take another subset of data and treat that as a miniature test set (called a validation set) in order to try out different *hyperparameters* or parameters that can affect other parameters - in essense, variations of the model.

To continue with the classification example we referenced previously. We have three sets of data, we have a training set for training models, we have a validation set for testing different variations of the models that we're training, and finally we have a test set that we will use for the final evaluation of our different model variations to see which one performed the best.

Leveraging the model and/or insights

Now we finally get to use our model! This might be to simply better understand customers or perform user segmentation or predict spam emails. Whatever the case is, this should always be the end objective! Try to solve a problem and better understand your data!

This quick workflow overview is just an example workflow and doesn't encompass all use cases or potential workflows. There are also *a lot* of details that can have tremendous impact on your results so if this refresher felt a bit foreign to you but you'd like to learn more there are a multitude of resources across the web that can teach you more.

Spark's Advanced Analytics Toolkit

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

- gathering and cleaning data,
- feature engineering and feature selection,
- training and tuning large scale supervised and unsupervised machine learning models,
- and using those models in production.

MLlib helps with all three steps of the process although it really shines in steps one and two for reasons that we will touch on shortly.

WARNING

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. The RDD API is the lower level interface that that is in maintenance mode (meaning it will only receive bug fixes, not new features) at the time of this writing. It has also been covered fairly extensively in other books and is therefore omitted from this text.

When and why should you use MLlib (vs scikit learn vs tensorflow vs foo 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? 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, these single machine tools do reach limits either in terms of the size of data you would like to train on or the processing time. The fact that they hit a limit in terms of scale makes them *complementary* tools, not competitive ones. When you do hit those scalability issues, take advantage of Spark's abilities.

There are two key use cases where you want to leverage Spark's ability to scale. Firstly, you want to leverage Spark for preprocessing and feature generation to reduce the amount of time it might take to produce training and test sets

from a large amount of data. You then might leverage single machine learning algorithms to train on those given data sets. Secondly, 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.

WARNING

An important caveat to the previous paragraphs is that while training and data preparation are made simple, there are still some complexities that you will need to keep in mind. For example, if you train a recommender system on a Spark cluster, the resulting model will 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 "structural" types: transformers, estimators, evaluator and pipelines. By structural, we mean that they'll define the overall architectural choices that you'll be making. The following illustration is an example of the overall workflow.

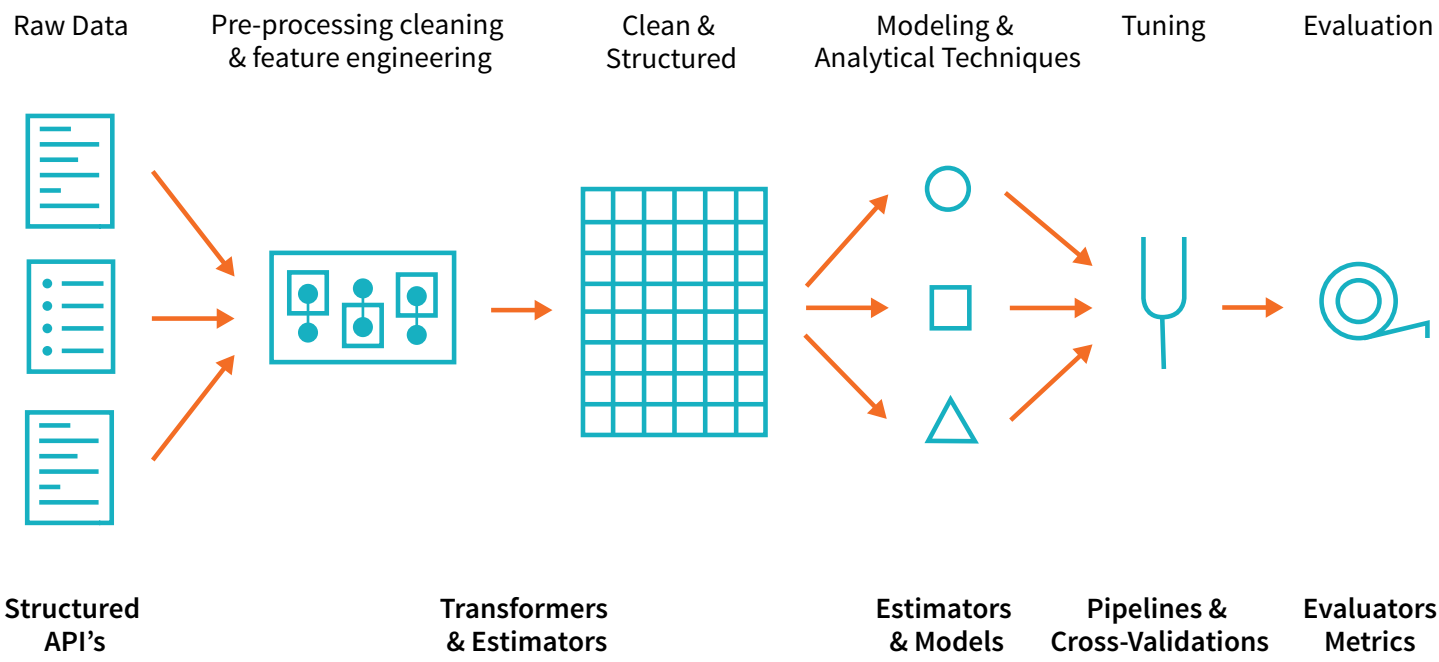


Figure 2:

Transformers are functions that convert raw data in some way. This might be to create a new interaction variable (from two other variables), normalize a column, or simply turn it into a Double to be input into a model. An example of a transformer is one converts string categorical variables into numerical values that can be used in MLlib. Transformers are primarily used in preprocessing or feature generation.

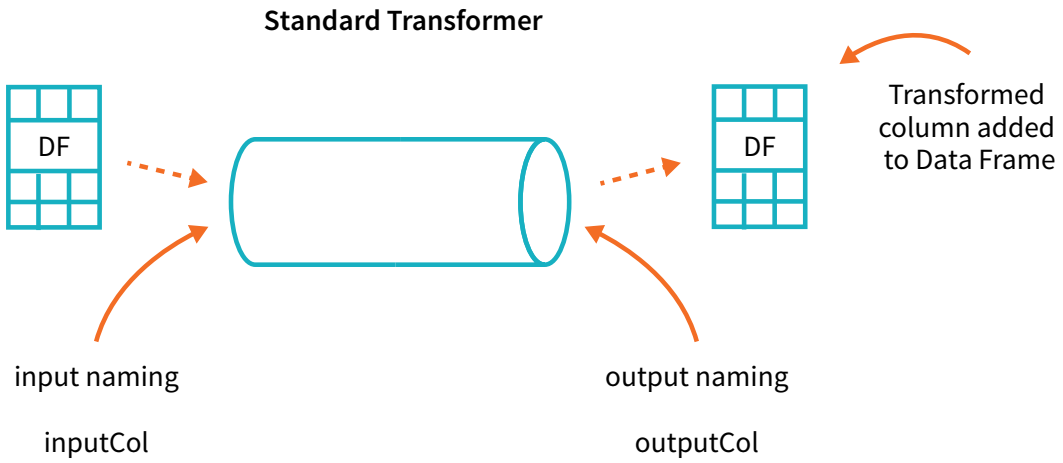


Figure 3:

Estimators are one of two kinds of things. Firstly, estimators can be a kind of transformer that is initialized with data. An example would be converting a column into a percentile representation of our column - in order to do this we need to initialize it based on the values in that column. Lastly, estimators are Spark's name for the actual models that we will be training and turning into models so that we can use them to make predictions. Lastly, 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.

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 `Doubles`. 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 that we have described some of the core pieces which we are going to come across, let's create a simple pipeline to demonstrate each of the component parts. We'll use a small synthetic dataset that will help illustrate our point. Let's read the data in and see a sample before talking about it further.

```
%scala

var df = spark.read.json("/mnt/defg/simple-ml")
df.orderBy("value2").show()

%python

df = spark.read.json("/mnt/defg/simple-ml")
df.orderBy("value2").show()
```

```
+-----+----+------+------------------+
|color| lab|value1|            value2|
+-----+----+------+------------------+
|green|good|     1|14.386294994851129|
|green| bad|    16|14.386294994851129|
| blue| bad|     8|14.386294994851129|
...
|  red| bad|    16|14.386294994851129|
|green|good|    12|14.386294994851129|
+-----+----+------+------------------+
```

This dataset consists of a categorical label with two values, a categorical variable (color), and two numerical variables. While the data is synthetic, an example of when this data might be used would be to predict customer health at a company. The label represents their true current health, the color represents a rating before a phone call to determine their true health and the two values represent some sort of usage metric. You should immediately recognize that this will be a classification task where we hope to predict our binary output variable based on the inputs.

NOTE

There are some particular data foramts for supervised learning including LIBSVM. These formats have real valued labels and sparse input data. Spark can read and write for these formats quite easily. For more information on the LIBSVM format see the documentation.

```
%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

As we mentioned, transformer will help us manipulate our current columns in one way or another. These columns, in machine learning terminology, represent features (that we will input into our model) and in our particular case, a label that represents the correct output. 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. In general, transformers add new columns to DataFrames.

One requirement is that when we are using MLlib, all inputs to machine learning algorithms in Spark must consist of type `Double` (for labels) and `Vector[Double]` for features. 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 the intercept (this means that the y-intercept of the line that we will fit will be 0.);
- `-` remove a term, "- 1" means removing intercept (this means that the y-intercept of the line that we will fit will be 0. Yes, this does the same thing as the bullet above.);
- `:` interaction (multiplication for numeric values, or binarized categorical values);
- `.` all columns except the target/dependant variable.

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(formula="lab ~ . + color:value1 + color:value2")
```

At this point we have declaratively specified how we would like to change out data into what we will train our model on. The above transformation is a special kind of transformer (called an estimator) that has to be fit on the input 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.

NOTE

We're using the RFormula because it makes performing several transformations extremely easy to do. We saw in Chapter 3 another way that we can specify a similar set of transformations and in the next chapter we will see all the component parts of the RFormula when we cover the specific transformers in MLlib.

Now that we covered those details, let's continue on and prepare our DataFrame.

```
%scala
val fittedRF = supervised.fit(df)
val preparedDF = fittedRF.transform(df)
```

```
%python
```

```
fittedRF = supervised.fit(df)
preparedDF = fittedRF.transform(df)

preparedDF.show()
```

```
+-----+----+------+------------------+--------------------+-----+
|color| lab|value1|            value2|            features|label|
+-----+----+------+------------------+--------------------+-----+
|green|good|     1|14.386294994851129|(10,[1,2,3,5,8],[...|  1.0|
| blue| bad|     8|14.386294994851129|(10,[2,3,6,9],[8....|  0.0|
...
|  red| bad|     1| 38.97187133755819|(10,[0,2,3,4,7],[...|  0.0|
|  red| bad|     2|14.386294994851129|(10,[0,2,3,4,7],[...|  0.0|
+-----+----+------+------------------+--------------------+-----+
```

In the output we can see the result of our transformation, a column called features that has our previously raw 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 out model, we're know nearing the final stpes in the advanced analytics workflow we described above. We (pre)processed our data so that it's clean and tidy and added some features along the way. Now it comes time to actually train our model (or a set of models on this. In order to do this, we need to prepare a test set for evaluation.

> *TIP*
>
> *Having a good test set is probably the most important thing that you can do to ensure that you train a model that you can actually use in the real world (in a dependable way). Not creating a representative test set or using your test set for hyperparameter tuning are surefire ways to create a model that does not perform well in real world scenarios. Don't skip creating a test set, it's a requirement to know how well your model actually does! This is stressed in all of the books that we mention above so see those books for more information.*

```
%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`, a method for classification, using the default configuration or hyperparameters(for those more familiar with machine learning). 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(
  labelCol="label",
  featuresCol="features")
```

Before we actually go about training this model, it can be a best practice to inspect the parameters, this is also a great way of getting a refresher of the options available for each particular model.

```
%scala

println(lr.explainParams())


%python

print lr.explainParams()
```

Here's the output of calling the above explain command.

```
aggregationDepth: suggested depth for treeAggregate (>= 2) (default: 2)
elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha = 0,
the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty (default: 0.0)
family: The name of family which is a description of the label distribution to
be used in the model. Supported options: auto, binomial, multinomial. (default:
auto) featuresCol: features column name (default: features, current: features)
fitIntercept: whether to fit an intercept term (default: true) labelCol: label
column name (default: label, current: label) lowerBoundsOnCoefficients: The lower
bounds on coefficients if fitting under bound constrained optimization. (undefined)
lowerBoundsOnIntercepts: The lower bounds on intercepts if fitting under bound
constrained optimization. (undefined) maxIter: maximum number of iterations (>=
0) (default: 100) predictionCol: prediction column name (default: prediction)
probabilityCol: Column name for predicted class conditional probabilities. Note:
Not all models output well-calibrated probability estimates! These probabilities
should be treated as confidences, not precise probabilities (default: probability)
rawPredictionCol: raw prediction (a.k.a. confidence) column name (default:
rawPrediction) regParam: regularization parameter (>= 0) (default: 0.0)
standardization: whether to standardize the training features before fitting the
model (default: true) threshold: threshold in binary classification prediction, in
range [0, 1] (default: 0.5) thresholds: Thresholds in multi-class classification
to adjust the probability of predicting each class. Array must have length
equal to the number of classes, with values > 0 excepting that at most one
value may be 0. The class with largest value p/t is predicted, where p is the
original probability of that class and t is the class's threshold (undefined)
tol: the convergence tolerance for iterative algorithms (>= 0) (default: 1.0E-6)
upperBoundsOnCoefficients: The upper bounds on coefficients if fitting under bound
constrained optimization. (undefined) upperBoundsOnIntercepts: The upper bounds on
```

```
intercepts if fitting under bound constrained optimization. (undefined) weightCol: weight column name. If this is not set or empty, we treat all instance weights as 1.0 (undefined)?
```

Once we instantiate the model, we can train it. This is done with the `fit` method which returns a `LogisticRegressionModel`.

```
%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()


+-----+----------+
|label|prediction|
+-----+----------+
|  0.0|       0.0|
|  0.0|       0.0|
...
|  0.0|       0.0|
|  0.0|       0.0|
+-----+----------+
```

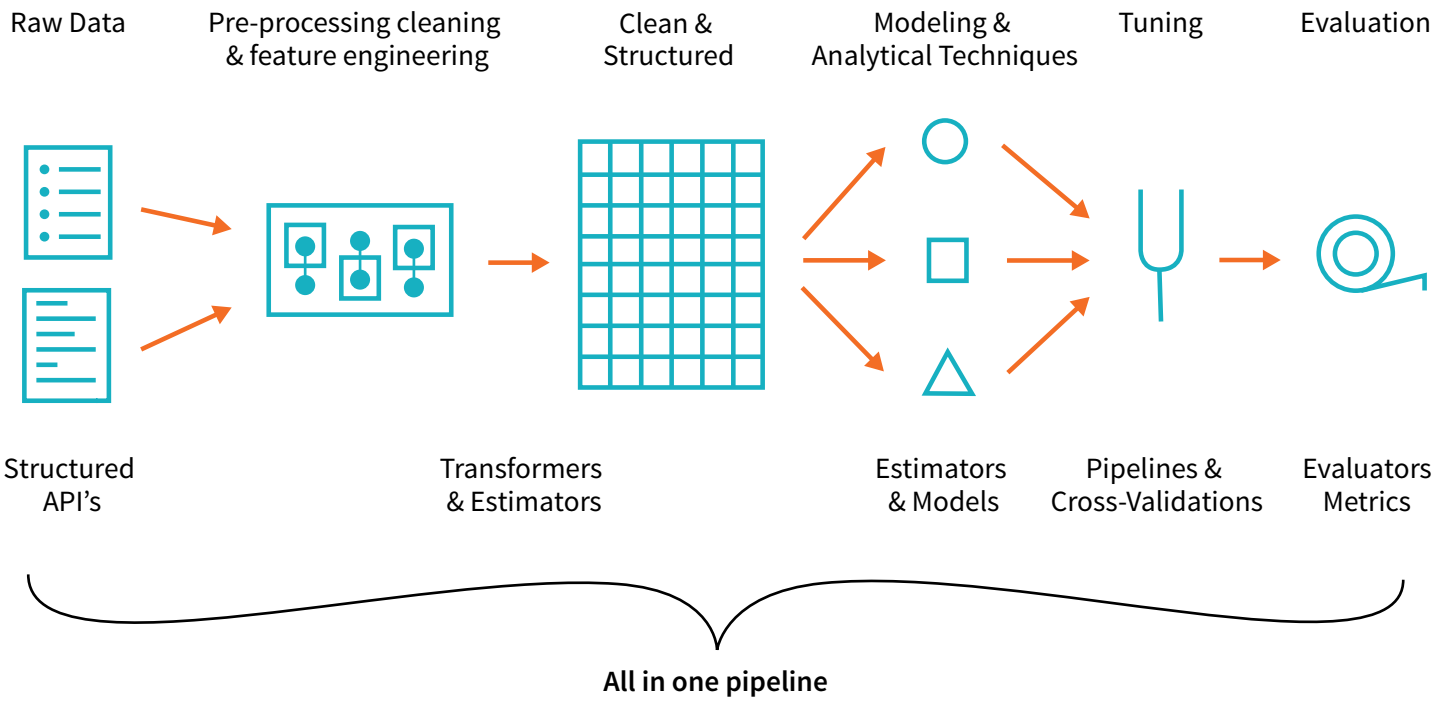
Our next step would be to manually evaluate this model and calculate performance metrics like the true positive rate, false negative rate, etc. We might then turn around and try a different set of parameters to see if those perform better. This process, while useful, is actually quite tedious and well 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.

box: *What are hyperparameters?*

Hyperparameters are initialization configurations for model. They are parameters that influence other parameters. Logistic regression is a simple model that doesn't have that many hyperparameters (we'll cover the details in a couple of chapters). However, we could choose to look at different interaction variables in our RFormula. In doing so, we'd effectively be tuning hyperparameters that affect the preprocessing of the data. Pipelines, as you will see momentarily, allow us to configure the entire data manipulation process from raw data to the model in different ways - allowing us to tune the hyperparameters to the best ones that we try.

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. While we don't want to go into too much detail in this chapter we explain the elastic net parameter as well as the regularization options in the Classification Chapter.

With the grid built it is now time to specify our evaluation. There are evaluators for classification and regression, which we cover in subsequent chapters. 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 a very common measure of classification performance that we cover in the classification chapter.

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.BinaryClassificationEvaluator
```

```
val evaluator = new BinaryClassificationEvaluator()
  .setMetricName("areaUnderROC")
  .setRawPredictionCol("prediction")
  .setLabelCol("label")
```

```
%python

from pyspark.ml.evaluation import BinaryClassificationEvaluator

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 k 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)) // 0.9166666666666667
```

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.LogisticRegressionModel

val trainedPipeline = tvsFitted.bestModel.asInstanceOf[PipelineModel]
```

```
val TrainedLR = trainedPipeline.stages(1)
  .asInstanceOf[LogisticRegressionModel]

val summaryLR = TrainedLR.summary

SummaryLR.objectiveHistory
```

The objective history shows how our algorithm performed over each training iteration. This can be helpful because we can note the progress our algorithm is making towards the best model. Large jumps are typically expected at the beginning, but over time the values should become smaller and smaller, with only small amounts of variation between the values.

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 illustrates common workflows.

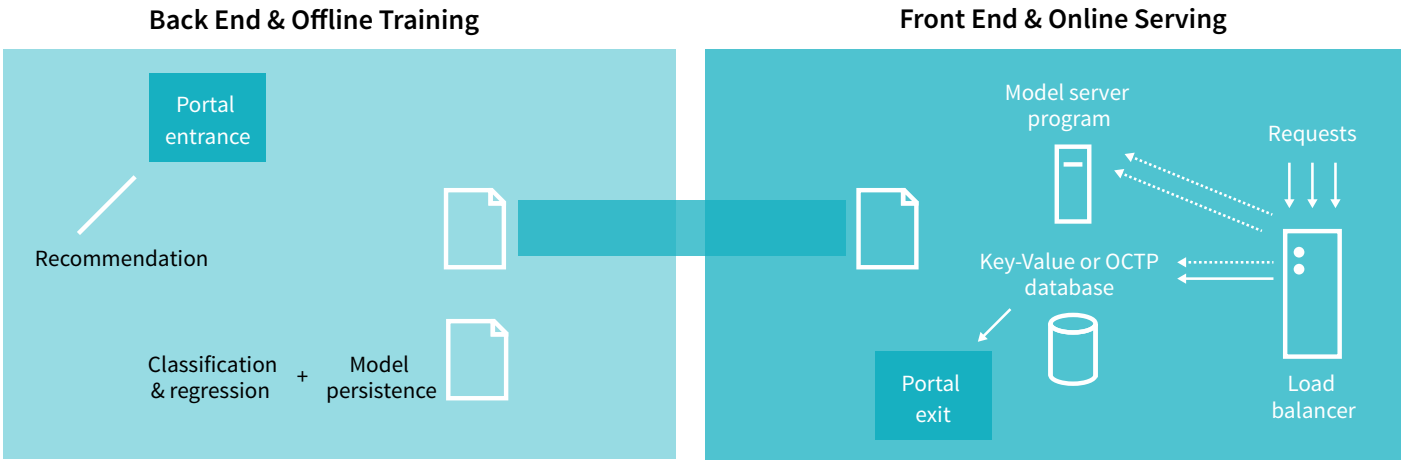


Figure 5:

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 in front of multiple model replicas and build out some REST API integration yourself. 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.

NOTE

These are specific to Spark and don't apply to many single machine frameworks that don't have the ability to train on really large data, but can serve responses more quickly than Spark can.

While these are some of the options, there are more potential ways of performing model deployment and management. This is a heavy area for development that is certainly likely to change and progress quickly.

Graph Analysis

The last chapter covered some conventional unsupervised techniques. This chapter is going to dive into a more specialized toolset: graph processing. 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 graph 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.

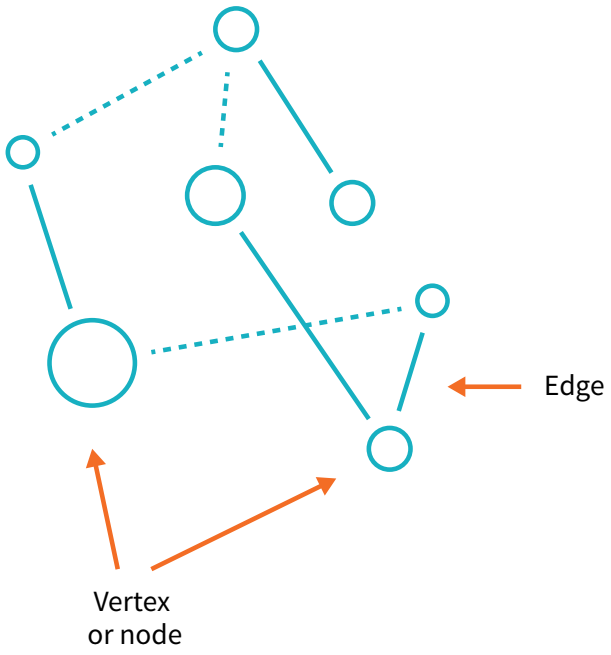


Figure 1:

You can see the image at the right 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 weight of the edge might represent the intimacy between different friends; acquaintances would have low-weight edges between them while married individuals would have edges with large weights. 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.

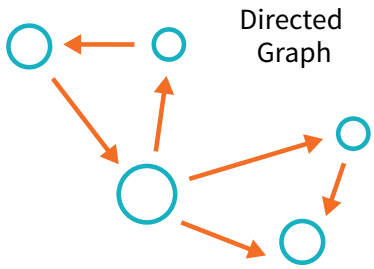


Figure 2:

When Spark first came out, Spark included a library for performing graph processing called GraphX. GraphX provides an interface for performing graph analysis on top of the RDD API. This provided a very low level interface that was extremely powerful but just like RDDs, wasn't the most powerful. GraphX is still a core part of Spark. Companies still build production applications on top of it and it still sees some minor feature development. This API is quite well documented simply because it hasn't changed much since its creation. However, some of the developers of Spark (including some of the original authors of GraphX) have recently created the next generation graph analytics library on Spark called GraphFrames. GraphFrames extends GraphX to

provide a DataFrame API as well as support for Spark's different language bindings so that users of Python can take advantage of the scalability of the tool as well.

GraphFrames is currently available as a Spark Package available here, an external package that you need to load when you start up your Spark application, but may be merged into the core of Spark in the future. 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 small overhead when using GraphFrames but for the most part it tries to call down to GraphX where appropriate and for most, the user experience gains greatly outweight this minor overhead.

> *NOTE*
>
> How does GraphFrames compare to Graph Databases? *Spark is not a database. Spark is a distributed computation engine. You can build a graph API on top of Spark but his fundamentally approaches the problem differently than a database. GraphFrames can scale to much larger workloads than many graph databases and performs well in the context of analytics but not transaction data processing and serving.*

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.

> *NOTE*
>
> *Over the course of the writing of this book. This map and data have changed dramatically (even the naming!). We include a copy of the dataset inside of the data folder of this book's repository. Be sure to use that dataset to replicate the below results and when you're feeling adventuous, expand to the whole dataset!*

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:0.5.0-spark2.1-s_2.11
```

```
%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`.

```
%scala

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)

stationGraph.cache()


%python

from graphframes import GraphFrame
stationGraph = GraphFrame(stationVertices, tripEdges)

stationGraph.cache()
```

Now we can see the basic statistics about data (and query our original DataFrame to ensure that we see the expected results).

```
%scala

println(s"Total Number of Stations: ${stationGraph.vertices.count()}")
println(s"Total Number of Trips in Graph: ${stationGraph.edges.count()}")
println(s"Total Number of Trips in Original Data: ${tripData.count()}")


%python

print "Total Number of Stations: " + str(stationGraph.vertices.count())
print "Total Number of Trips in Graph: " + str(stationGraph.edges.count())
print "Total Number of Trips in Original Data: " + str(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 as DataFrames.

```
%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)
```

```
+--------------------+--------------------+-----+
|                 src|                 dst|count|
+--------------------+--------------------+-----+
|San Francisco Cal...|     Townsend at 7th| 3748|
|Harry Bridges Pla...|Embarcadero at Sa...| 3145|
...
|     Townsend at 7th|San Francisco Cal...| 2192|
|Temporary Transba...|San Francisco Cal...| 2184|
+--------------------+--------------------+-----+
```

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)
```

```
+--------------------+--------------------+-----+
|                 src|                 dst|count|
+--------------------+--------------------+-----+
|San Francisco Cal...|     Townsend at 7th| 3748|
|     Townsend at 7th|San Francisco Cal...| 2734|
...
|   Steuart at Market|     Townsend at 7th|  746|
|     Townsend at 7th|Temporary Transba...|  740|
+--------------------+--------------------+-----+
```

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, townAnd7thEdges)


%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. 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. In this example, important bike stations will be assigned large PageRank values.

box: Graph algorithm APIs: parameters and return values *Most algorithms in GraphFrames are accessed as methods which take parameters (e.g.,* `resetProbability` *in this PageRank example). Most algorithms return either a new GraphFrame or a single DataFrame. The results of the algorithm are stored as one or more columns in the GraphFrame's vertices and/or edges or the DataFrame. For PageRank, the algorithm returns a GraphFrame, and we can extract the estimated PageRank values for each vertex from the new* `pagerank` *column.*

> *WARNING*
>
> *Depending on the resources available on your machine, this may take some time. You can always try a smaller set of data before running this to see the results. On Databricks Community Edition, this takes about twenty seconds to run although some reviewers found it to take much longer on their personal machines.*

```
%scala

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

```
val ranks = stationGraph.pageRank
  .resetProbability(0.15)
  .maxIter(10)
  .run()

ranks.vertices
  .orderBy(desc("pagerank"))
  .select("id", "pagerank")
  .show(10)
```

```
%python

from pyspark.sql.functions import desc

ranks = stationGraph.pageRank(resetProbability=0.15, maxIter=10)

ranks.vertices\
  .orderBy(desc("pagerank"))\
  .select("id", "pagerank")\
  .show(10)
```

```
+--------------------+------------------+
|                  id|          pagerank|
+--------------------+------------------+
|San Jose Diridon ...| 4.051504835989922|
|San Francisco Cal...|3.3511832964279518|
...
|     Townsend at 7th| 1.568456580534273|
|Embarcadero at Sa...|1.5414242087749768|
+--------------------+------------------+
```

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-degree and out-degree respectively.

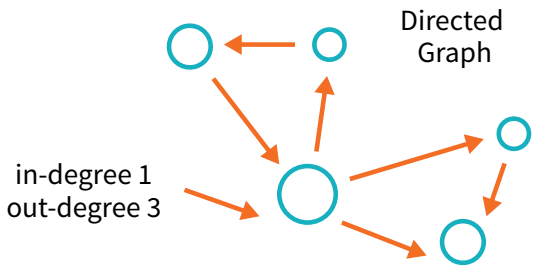


Figure 3:

This is particularly applicable in the context of social networking because certain users may have many more inbound connections (say followers) than outbound connections (people they follow). Using the following query, you can find interesting people in the social network that might have more influence than others. GraphFrames provides a simple way to query our graph for 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)
```

The result of querying for the stations sorted by the highest in-degree.

```
+----------------------------------------+--------+
|id                                      |inDegree|
+----------------------------------------+--------+
|San Francisco Caltrain (Townsend at 4th)|34810   |
|San Francisco Caltrain 2 (330 Townsend) |22523   |
|Harry Bridges Plaza (Ferry Building)    |17810   |
|2nd at Townsend                         |15463   |
|Townsend at 7th                         |15422   |
+----------------------------------------+--------+
```

We can query the out degrees in the same fashion.

```
%scala

val outDeg = stationGraph.outDegrees
outDeg.orderBy(desc("outDegree")).show(5, false)


%python

outDeg = stationGraph.outDegrees
outDeg.orderBy(desc("outDegree")).show(5, False)
```

```
+-----------------------------------------------+---------+
|id                                             |outDegree|
+-----------------------------------------------+---------+
|San Francisco Caltrain (Townsend at 4th)       |26304    |
|San Francisco Caltrain 2 (330 Townsend)        |21758    |
|Harry Bridges Plaza (Ferry Building)           |17255    |
|Temporary Transbay Terminal (Howard at Beale)  |14436    |
|Embarcadero at Sansome                         |14158    |
+-----------------------------------------------+---------+
```

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 degreeRatio")

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 degreeRatio")

degreeRatio\
  .orderBy(desc("degreeRatio"))\
  .show(10, False)

degreeRatio\
  .orderBy("degreeRatio")\
  .show(10, False)
```

Those queries result in the following data.

```
+----------------------------------------+------------------+
|id                                      |degreeRatio       |
+----------------------------------------+------------------+
|Redwood City Medical Center             |1.5333333333333334|
|San Mateo County Center                 |1.4724409448818898|
...
|Embarcadero at Vallejo                  |1.2201707365495336|
|Market at Sansome                       |1.2173913043478262|
+----------------------------------------+------------------+
```

```
+------------------------------+------------------+
|id                            |degreeRatio       |
+------------------------------+------------------+
|Grant Avenue at Columbus Avenue|0.5180520570948782|
|2nd at Folsom                 |0.5909488686085761|
...
|San Francisco City Hall       |0.7928849902534113|
|Palo Alto Caltrain Station    |0.8064516129032258|
+------------------------------+------------------+
```

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. We can specify the maximum of edges to follow with the `maxPathLength` and we can also specify an `edgeFilter` to filter out certain edges that do not meet a certain requirement like trips during non-business hours.

We'll choose two fairly close stations so that this does not run too long. However, you can do some pretty interesting graph traversals when you have some sparse graphs that have some distant connections. Feel free to play around with the stations (especially those in other cities) to see if you can get some distant stations to connect.

```
%scala

val bfsResult = stationGraph.bfs
  .fromExpr("id = 'Townsend at 7th'")
  .toExpr("id = 'Spear at Folsom'")
  .maxPathLength(2)
  .run()

bfsResult.show(10)


%python

bfsResult = stationGraph.bfs(
  fromExpr="id = 'Townsend at 7th'",
  toExpr="id = 'Spear at Folsom'",
  maxPathLength=2)
```

```
bfsResult.show(10)
```

```
+--------------------+--------------------+--------------------+
|                from|                  e0|                  to|
+--------------------+--------------------+--------------------+
|[65,Townsend at 7...|[913371,663,8/31/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[913265,658,8/31/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[911919,722,8/31/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[910777,704,8/29/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[908994,1115,8/27...|[49,Spear at Fols...|
|[65,Townsend at 7...|[906912,892,8/26/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[905201,980,8/25/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[904010,969,8/25/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[903375,850,8/24/...|[49,Spear at Fols...|
|[65,Townsend at 7...|[899944,910,8/21/...|[49,Spear at Fols...|
+--------------------+--------------------+--------------------+
```

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.

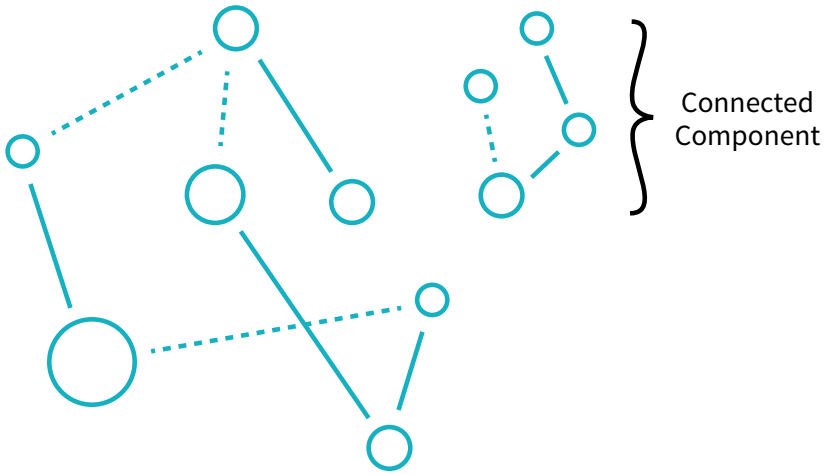
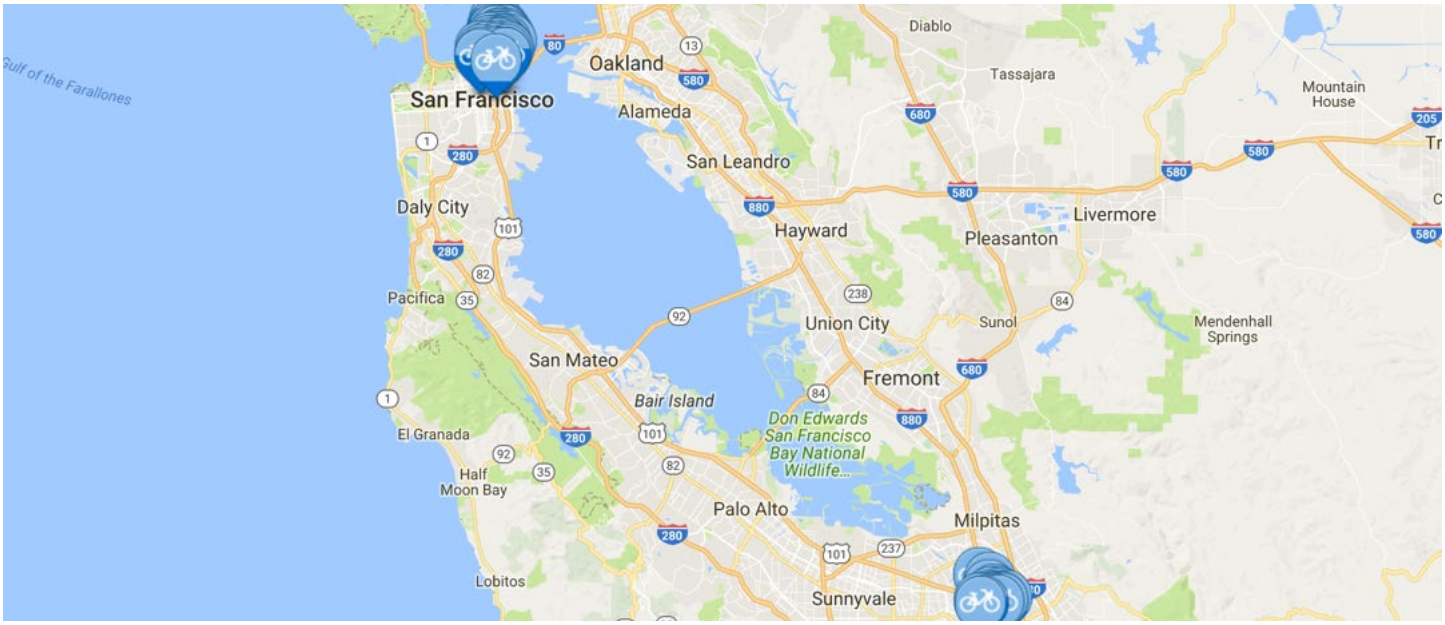


Figure 4:

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.



WARNING

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. The reason for this is that this is probably one of the most intensive algorithms so expect this to take some time to complete and potential instability. This takes approximately three minutes to run on Databricks Community Edition.

One thing you will likely have to do to run this algorithm on your local is take a sample of the data, just as we do below. This can help you get to a result without crashing the Spark application with garbage collection issues. We're also going to clear the cache in order to ensure there's enough memory to run for our computation.

```
%scala

spark.sqlContext.clearCache()
spark.sparkContext.setCheckpointDir("/tmp/checkpoints")


%python

spark.sparkContext.setCheckpointDir("/tmp/checkpoints")
```

```
%scala

val minGraph = GraphFrame(stationVertices, tripEdges.sample(false, 0.1))
val cc = minGraph.connectedComponents.run()


%python

minGraph = GraphFrame(stationVertices, tripEdges.sample(False, 0.2))
cc = minGraph.connectedComponents()
```

From this same we only get two connected components, which does seem a bit strange. Why we get this might be an opportunity for further analysis. One potential idea is that a friend of a bike renter picked up their friend in a car and drove them to a distant station, thus connecting two sets of stations that wouldn't otherwise be connected. Our sample also may not have all of the correct data or information and we'd probably need more compute resources to investigate further.

```
%scala

cc.where("component != 0").show()


%python

cc.where("component != 0").show()


+----------+--------------------+---------+-----------+---------+-------------+
|station_id|  id|     lat|   long|dockcount| landmark|installation|   component|
+----------+--------------------+---------+-----------+---------+-------------+
|  47|     Post at Kearney|37.788975|-122.403452| 19|San Francisco|
8/19/2013|317827579904|
|  46|Washington at Kea...|37.795425|-122.404767| 15|San Francisco|
8/19/2013| 17179869184|
+----------+--------------------+---------+-----------+---------+-------------+
```

Strongly Connected Components

However GraphFrames also includes 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.

WARNING

This takes about thirty seconds to run on Databricks Community Edition, it may take longer on your local machine.

```
%scala

val scc = minGraph
  .stronglyConnectedComponents
  .maxIter(3)
  .run()


%python

scc = minGraph.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 connects 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. `(a)` signifies the starting station, `[ab]` represents an edge from `(a)` to our next station `(b)`. We repeat this for stations `(b)` to `(c)` and then from `(c)` to `(a)`.

```
%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.

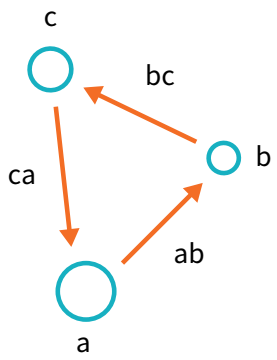


Figure 5:

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 at `(b)`, ridden to another, dropped off at `(c)`, and then ridden back to the original station, `(a)`. The following logic will parse our timestamps into Spark timestamps and then we'll do comparisons to make sure that it's the same bike, traveling from station to station, and that the start times for each trip are correct.

```
%scala

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

motifs// first simplify dates for comparisons
  .selectExpr("*", """
  to_timestamp(ab.`Start Date`, 'MM/dd/yyyy HH:mm') as abStart
  """,
  """
  to_timestamp(bc.`Start Date`, 'MM/dd/yyyy HH:mm') as bcStart
  """,
  """
  to_timestamp(ca.`Start Date`, 'MM/dd/yyyy HH:mm') as caStart
  """)
  .where("ca.`Bike #` = bc.`Bike #`") // ensure the same bike
  .where("ab.`Bike #` = bc.`Bike #`")
  .where("a.id != b.id") // ensure different stations
  .where("b.id != c.id")
  .where("abStart < bcStart") // start times are correct
  .where("bcStart < caStart")
  .orderBy(expr("cast(caStart as long) - cast(abStart as long)")) // order them
all
  .selectExpr("a.id", "b.id", "c.id",
    "ab.`Start Date`", "ca.`End Date`")
  .limit(1)
  .show(false)


%python

from pyspark.sql.functions import expr

motifs\
  .selectExpr("*", """
  to_timestamp(ab.`Start Date`, 'MM/dd/yyyy HH:mm') as abStart
  """,
  """
  to_timestamp(bc.`Start Date`, 'MM/dd/yyyy HH:mm') as bcStart
  """,
  """
  to_timestamp(ca.`Start Date`, 'MM/dd/yyyy HH:mm') as caStart
```

```
  """)\
  .where("ca.`Bike #` = bc.`Bike #`")\
  .where("ab.`Bike #` = bc.`Bike #`")\
  .where("a.id != b.id")\
  .where("b.id != c.id")\
  .where("abStart < bcStart")\
  .where("bcStart < caStart")\
  .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(1, False)
```

```
+----------------------------------------+---------------+----------------------+
|id                                      |id             |id
|Start Date     |End Date       |
+----------------------------------------+---------------+----------------------+
|San Francisco Caltrain 2 (330 Townsend)|Townsend at 7th|San Francisco Caltrain
(Townsend at 4th)|5/19/2015 16:09|5/19/2015 16:33|
+----------------------------------------+---------------+----------------------+
```

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.

Deep Learning

One of the most exciting areas of development around Spark is deep learning. Deep learning is rapidly growing into one of the most powerful techniques for solving machine learning problems, especially those involving unstructured data such as images, audio and text. This chapter will cover how Spark works in tandem with deep learning, and some of the different approaches that you can take using Spark and deep learning together.

This chapter will not focus on packages that are necessarily core to Spark but rather on the massive amount of innovation in libraries built on top of Apache Spark. Because deep learning is still a new field, many of the newest tools are implemented in external libraries. We will start with several high-level ways to use deep learning on Spark, discuss when to use each one, and discuss the libraries available for them. As usual, we will include end-to-end examples.

> *WARNING*
>
> *If you have little experience with machine learning and/or deep learning, unfortunately this chapter cannot provide a complete summary of everything you need to know. To be truly successful in this chapter you should know at least the basics of deep learning as well as the basics of Spark. With that being said, we point to an excellent resource at the beginning of this part of the book called the Deep Learning Book, by some of the most successful researchers in this area. We recommend taking some time to learn about the core machine learning methods as well as getting a basic grasp of deep learning before continuing with this chapter.*

What is deep learning?

In order to define deep learning, we must first define neural networks. A neural network is a graph of nodes that consist of a weight and an activation function. These nodes are organized into *layers* that are stacked on top of one another. Each layer is connected, either partially or completely, to the previous layer in the network. Each node activation's function will fire when sufficient inputs trigger that activation. Together, the network's layers can represent progressively more complex functions that often "learn" a hierarchy of features in the input data (e.g. edges, circles and textures for image recognition). The goal is to train the network to associate certain inputs with certain outputs by tuning the weights associated with each connection and the values of each node in the network.

Deep learning, or *deep neural networks*, just combine many of these layers together in various different architectures. Neural networks themselves have existed for decades, and have waxed and waned in terms of popularity for various machine learning problems. Recently, however, a combination of much larger datasets (e.g., the ImageNet corpus for object recognition), parallel infrastructure (clusters and GPUs), and new training algorithms have enabled training much larger neural networks that outperformed pervious approaches in many machine learning tasks. Deep neural networks have now become the standard in computer vision, speech processing, and many natural language tasks,

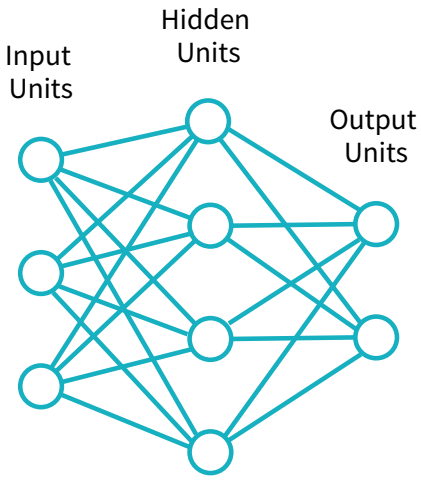


Figure 1:

where they often "learn" better features than previous hand-tuned models. They are also actively being applied in other areas of machine learning. Apache Spark's strength as a big data and parallel computing system makes it a natural framework to use with deep learning.

Ways of Using Deep Learning in Spark

For the most part, regardless of which application you are targeting, there are three major ways to use deep learning in Spark.

1. **Inference:** The simplest way to use deep learning is to take a pre-trained model and apply it to large datasets in parallel using Spark. For example, given an image classification model that can recognized people, trained using a standard dataset like ImageNet, one might apply it to images from a retail store to track customer flows within it. Many organizations publish large, pre-trained models on common datasets (e.g., FasterRCNN and YOLO for object detection), so you can often take a model from your favorite deep learning framework and apply it in parallel using a Spark function. In the extreme, simply calling a framework such as TensorFlow or PyTorch in a `map` function can get you distributed inference, though some of the libraries we discuss for it make further optimizations beyond that.

2. **Featurization and Transfer Learning:** The next level of complexity is to use an existing model as a *featurizer* instead of taking its final output. Many deep learning models learn useful feature representations in their lower layers as they train the network for an end-to-end task. For example, a classifier trained on the ImageNet dataset (a popular labeled dataset with thousands of object classes) will also learn low-level features present in all natural images, such as edges and textures. We can then use these features to learn models for a new problem not covered by the original dataset. For example, the ImageNet dataset does not contain any images of cancer tumors, but several research papers have used models trained on it as featurizers to produce classifiers

for these types of images. This method is called *transfer learning*, and generally involves cutting off the last few layers of a pre-trained model and retraining them with the data of interest. Transfer learning is also especially useful if you do not have a large amount of training data: training a full-blown network from scratch requires a dataset of hundreds of thousands of images, like ImageNet, to avoid overfitting, which will not be available in many business contexts. In contrast, transfer learning can work even with a few thousand images because it updates fewer parameters.

3. **Model Training:** Spark can also be used to train a new deep learning model from scratch. There are two common methods here. First, you can use a Spark cluster to parallelize the training of a *single* model over multiple servers, communicating updates between them. Alternatively, some libraries let the user train *multiple* instances of similar models in parallel to try various model architectures and hyperparameters, accelerating the model search and tuning process. In both cases, Spark's deep learning libraries make it simple to pass data from RDDs and DataFrames to deep learning algorithms. Finally, even if you do not wish to train your model in parallel, these libraries can be used to extract data from a cluster and export it to a single-machine trainign script using the native data format of frameworks like TensorFlow.

In all three cases, the deep learning code typically runs as part of a larger application that includes Extract, Transform and Load (ETL) steps to parse the input data, I/O from various sources, and potentially batch or streaming inference. For these other parts of the application, you can simply use the DataFrame, RDD and MLlib APIs described earlier in this book. One of Spark's strengths is the ease of combining these steps into a single parallel workflow.

Deep Learning Libraries

In this section of the chapter, we'll survey a few of the most popular libraries available for deep learning in Spark. We will describe the main use cases of the library and link to references or a small example when possible. This list is not meant to be exhaustive, because the field is rapidly evolving, so we encourage you to check each library's website and the Spark documentation for the latest updates. The Databricks Engineering blog at https://databricks.com/blog also regularly has articles on deep learning.

MLlib Neural Network Support

Spark's MLlib currently has native support for one deep learning algorithm, the multilayer perceptron classifier in the `ml.classification.MultilayerPerceptronClassifier` class. This class is limited to training relatively shallow networks containing fully connected layers with the sigmoid activation function, and an output layer with a softmax activation function. This class is most useful for training the last few layers of a classification model when using transfer learning on top of an existing deep learning based featurizer. For example, it can be added on top of the Deep Learning Pipelines library we describe later in this chapter to quickly perform transfer learning over Keras and TensorFlow models. However, the MultiLayerPerceptronClassifier alone is not enough to train a deep learning model from scratch on raw input data.

TensorFrames

TensorFrames is an inference and transfer learning oriented library that makes it easy to pass data between Spark DataFrames and TensorFlow. It supports Python and Scala interfaces and focuses on providing a simple but optimized interface to pass data from TensorFlow to Spark and back. In particular, using TensorFrames to apply a model over Spark DataFrames is generally more efficient than calling a Python `map` function that directly invokes the TensorFlow model, due to faster data transfer and amortization of the startup cost. TensorFrames is most useful for inference, in both streaming and batch settings, and for transfer learning, where you can apply an existing model over raw data to featurize it, then learn the last layers using a MultilayerPerceptronClassifier or even a simpler logistic regression or random forest classifier over the data.

https://github.com/databricks/tensorframes

BigDL

BigDL (pronounced “big deal”) is a distributed deep learning framework for Apache Spark primarily developed by Intel. It aims to support distributed training of large models as well as fast applications of these models using inference. One key advantage of BigDL over the other libraries described here is that it is primiarily optimzied to use CPUs instead of Graphics Processing Units (GPUs), making it efficient to run on an existing, CPU-based cluster (e.g. an Apache Hadoop deployment). BigDL provides high-level APIs to build a neural network from scratch and automatically distributes all operations by default.

https://github.com/intel-analytics/BigDL

TensorFlowOnSpark

TensorFlowOnSpark is a widely used library that can train Google TensorFlow models in a parallel fashion on Spark clusters. TensorFlow already provides support for distributed training, but it does not come with a cluster manager or a distributed I/O layer out of the box – instead, users have to manually set up a distributed TensorFlow cluster and feed data into it. TensorFlowOnSpark launches TensorFlow’s existing distributed mode inside a Spark job, and automatically feeds data from Spark RDDs or DataFrames into the TensorFlow job. If you already know how to use TensorFlow’s distributed mode, TensorFlowOnSpark makes it easy to launch your job inside a Spark cluster and pass it data processed with other Spark libraries (e.g. DataFrame transformations) from any input source that Spark supports. TensorFlowOnSpark was originally developed at Yahoo! and is also used in production at other large organizations.

https://github.com/yahoo/TensorFlowOnSpark

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 parallel model training, testing, and feature extraction. Much like TensorFlowOnSpark, it aims to run Caffe in parallel on an existing Spark cluster and easily pass data into it from Spark. CaffeOnSpark was also developed at Yahoo!

https://github.com/yahoo/CaffeOnSpark

DeepLearning4J

DeepLearning4j is an open-source, distributed deep-learning project in Java and Scala that provides both single node and distributed training options. One of its advantages over the Python-based deep learning frameworks is that it was primarily designed for the JVM, making it more convenient for groups that do not wish to add Python to their development process. It includes a wide variety of training algorithms and support for CPUs as well as GPUs.

https://deeplearning4j.org/spark

Deep Learning Pipelines

Deep Learning Pipelines is an open source package from Databricks that integrates deep learning functions into Spark's ML Pipelines API. The package calls into existing deep learning frameworks (TensorFlow and Keras at the time of writing), but focuses on two goals: (1) incorporating these into standard Spark APIs, such as ML Pipelines and Spark SQL, to make them very easy to use and (2) distributing all computation by default. For example, Deep Learning Pipelines provides a `DeepImageFeaturizer` class that acts as a Transformer in the Spark ML Pipeline API, allowing you to build a transfer learning pipeline in just a few lines of code (e.g., by adding a perceptron or logistic regression classifier on top). Likewise, the project supports parallel grid search over multiple model parameters using MLlib's grid search and cross validation API. Finally, users can export a ML model as a Spark SQL user-defined function and make it available to analysts using SQL or streaming applications. At the time of writing (summer 2017), Deep Learning Pipelines is under heavy development, so we encourage you to check its website for the latest updates.

https://github.com/databricks/spark-deep-learning

Here is a summmary table of the various deep learning libraries and the main use cases they support.

Library	Underlying DL Framework	Use Cases
BigDL	BigDL	distributed training, inference, ML Pipeline integration
CaffeOnSpark	Caffe	distributed training
DeepLearning4J	DeepLearning4J	inference, transfer learning, distributed training
Deep Learning Pipelines	TensorFlow, Keras	inference, transfer learning, multi-model training, ML Pipeline and Spark SQL integration
MLlib Perceptron	Spark	distributed training, ML Pipeline integration
TensorFlowOnSpark	TensorFlow	distributed training
TensorFrames	TensorFlow	inference, transfer learning, DataFrame integration

While there are several approaches different companies have taken to integrating Spark and deep learning libraries, the one currently aiming for the closest integration with MLlib and DataFrames is Deep Learning Pipelines. This project aims to improve Spark's support for image and tensor data (which may also be integrated into the core Spark codebase in the future), and to make all deep learning functionality available in the standard ML Pipeline API. For this reason, we'll be covering the project in a bit more detail through the rest of the chapter with simple examples of the power of the library.

A Simple Example with Deep Learning Pipelines

As we described, Deep Learning Pipelines provides high-level APIs for scalable deep learning by integrating popular deep learning frameworks with ML Pipelines and Spark SQL.

Deep Learning Pipelines builds on Spark's ML Pipelines for training, and with Spark DataFrames and SQL for deploying models. It includes high-level APIs for common aspects of deep learning so they can be done efficiently in a few lines of code:

- Working with images in Spark DataFrames;
- Applying deep learning models at scale, whether they are your own or standard popular models, to image and tensor data;
- Transfer learning using common pre-trained deep learning models;
- Exporting models as Spark SQL functions to make it simple for all kinds of users to take advantage of deep learning;
- Distributed deep learning hyperparameter tuning via ML Pipelines.
- Deep Learning Pipelines currently only offers an API in Python, which is designed to work closely with existing Python deep learning packages such as TensorFlow and Keras.

WARNING

Readers should be aware that this library, like every Spark related deep learning library, is currently under active development and may have changed since the time we wrote this chapter. Before getting started, it's worth checking on the development of these various projects in order to better understand their current status and new functionality that may have been added.

Setup

Deep Learning Pipelines is a Spark Package, so we'll load it just like we loaded GraphFrames. Deep Learning Pipelines works on Spark 2.x and the package can be found here. You're going to need to install a couple of dependencies including tensorframes, TensorFlow, keras, and h5py. Make sure that these are installed across both your driver and worker machines.

We'll use the flowers dataset from the TensorFlow retraining tutorial. Now if you're running this on a cluster of machines, you're going to need a way to put these files on a distributed file system once you download them. We include a sample of these images in the book's GitHub Repository.

Images and DataFrames

One of the historical challenges when it came to working with images in Spark is that getting them into a DataFrame was difficult and tedious. Deep Learning Pipelines includes utility functions that making loading and decoding images in a distributed fashion easy.

TODO: can you say what formats are supported or what image library this uses to load stuff?

```
%python

from sparkdl import readImages

img_dir = '/mnt/defg/deep-learning-images/'
image_df = readImages(img_dir)
```

The resulting DataFrame contains the path, and then the image along with some associated metadata.

```
%python

image_df.show()
image_df.printSchema()
```

```
+--------------------+-----+
|            filePath|image|
+--------------------+-----+
|/mnt/defg/de...     | null|
+--------------------+-----+
```

```
root
 |-- filePath: string (nullable = false)
 |-- image: struct (nullable = true)
 |    |-- mode: string (nullable = false)
 |    |-- height: integer (nullable = false)
 |    |-- width: integer (nullable = false)
 |    |-- nChannels: integer (nullable = false)
 |    |-- data: binary (nullable = false)
```

Transfer Learning

Now that we have some data, we can get started with some simple transfer learning. Remember, this means leveraging a model that someone else created and modifying it to better suit our own purposes. First we will load the data for each type of flower and create a training and a test set.

```
%python

from sparkdl import readImages
from pyspark.sql.functions import lit

tulips_df = readImages(img_dir + "/tulips").withColumn("label", lit(1))
daisy_df = readImages(img_dir + "/daisy").withColumn("label", lit(0))

tulips_train, tulips_test = tulips_df.randomSplit([0.6, 0.4])
daisy_train, daisy_test = daisy_df.randomSplit([0.6, 0.4])
```

```
train_df = tulips_train.unionAll(daisy_train)
test_df = tulips_test.unionAll(daisy_test)
```

The next step will be to leverage a transformer called the `DeepImageFeaturizer`. This will allow us to leverage a pre-trained model called Inception, a powerful neural network successfully used to identify patterns in images. The version were are using is pre-trained to work well with images. This is a part of the standard pretrained models that ship with the Keras library. However, this particular neural network is not trained to work with our particular set of images (involving flowers). Therefore we're going to use transfer learning in order to make it into something useful for our own purposes.

One thing that's quite powerful here is that we can use the same ML pipeline concepts that we saw throughout this part of the book and leverage them with Deep Learning: `DeepImageFeaturizer` is just a Spark ML transformer. Additionally, all that we've done to extend this model is add on a logistic regression model in order to facilitate the training of our end model. We could use another classifier in its place.

> *WARNING*
>
> *This next code snippet is unlikely to run successfully on small machines because of the large resource requirements when using and applying this model.*

```
%python

from pyspark.ml.classification import LogisticRegression
from pyspark.ml import Pipeline
from sparkdl import DeepImageFeaturizer

featurizer = DeepImageFeaturizer(inputCol="image", outputCol="features",
modelName="InceptionV3")
lr = LogisticRegression(maxIter=1, regParam=0.05, elasticNetParam=0.3,
labelCol="label")
p = Pipeline(stages=[featurizer, lr])

p_model = p.fit(train_df)
```

Once we trained the model, we can use the same classification evaluator that we saw several chapters ago. We can specify the metric we'd like to test and then test against that.

```
%python

from pyspark.ml.evaluation import MulticlassClassificationEvaluator

tested_df = p_model.transform(test_df)
evaluator = MulticlassClassificationEvaluator(metricName="accuracy")
print("Test set accuracy = " + str(evaluator.evaluate(tested_
df.select("prediction", "label"))))
```

With our DataFrame of examples, we can inspect the rows and images in which we made mistakes in the previous training.

```
%python

from pyspark.sql.types import DoubleType
from pyspark.sql.functions import expr

# a simple UDF to convert the value to a double
def _p1(v):
  return float(v.array[1])
p1 = udf(_p1, DoubleType())

df = tested_df.withColumn("p_1", p1(tested_df.probability))
wrong_df = df.orderBy(expr("abs(p_1 - label)"), ascending=False)
wrong_df.select("filePath", "p_1", "label").limit(10).show()
```

Applying deep learning models at scale

Spark DataFrames are a natural construct for applying deep learning models to a large-scale dataset. Deep Learning Pipelines provides a set of (Spark MLlib) Transformers for applying TensorFlow Graphs and TensorFlow-backed Keras Models at scale. In addition, popular images models can be applied out of the box, without requiring any TensorFlow or Keras code. The Transformers, backed by the Tensorframes library, efficiently handle the distribution of models and data to Spark workers.

Applying popular image models

There are many standard deep learning models for images. If the task at hand is very similar to what the models provide (e.g. object recognition with ImageNet classes), or for pure exploration, one can use the Transformer

`DeepImagePredictor` by simply specifying the model name. Deep Learning Pipelines supports a variety of standard models included in Keras, which are listed on its website.

```
%python

from sparkdl import readImages, DeepImagePredictor

image_df = readImages(img_dir)

predictor = DeepImagePredictor(inputCol="image", outputCol="predicted_labels",
modelName="InceptionV3", decodePredictions=True, topK=10)
predictions_df = predictor.transform(image_df.where("image.mode is not null"))
```

Notice that the `predicted_labels` column shows "daisy" as a high probability class for all sample flowers using this base model. However, as can be seen from the differences in the probability values, the neural network has the information to discern the two flower types. Hence our transfer learning example above was able to properly learn the differences between daisies and tulips starting from the base model.

```
df = p_model.transform(image_df)
```

Applying Custom Keras Models

Spark deep learing also allows for the application of a TensorFlow-backed Keras model in a distributed manner using Spark. To do this check the user guide on the `KerasImageFileTransformer`. The way this works by loading the keras model and then applying that model in the same DataFrame that we've seen in the previous sections.

Applying TensorFlow Models

Deep Learning Pipelines, through a deep integration with TensorFlow, can be used to create custom transformers that manipulate images using TensorFlow. For instance, you could create a transformer to change the size of an image or modify the color spectrum.

TODO: can you say which class they should use for this?

TODO: Show how to export a function as UDF and call it

The Unified Analytics Platform

The datasets used in the book are also available for you to explore:
Spark: The Definitive Guide Datasets

Try Databricks for free
databricks.com/try-databricks

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