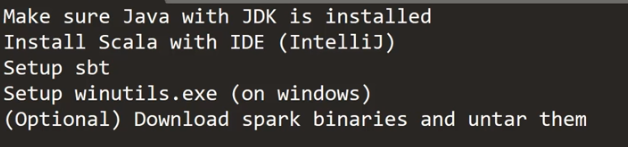
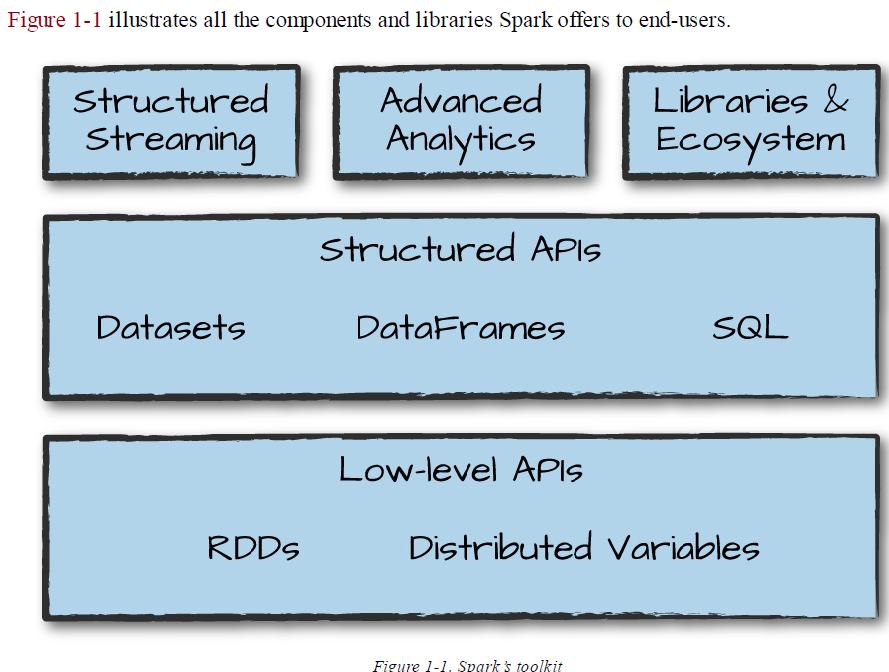
**Spark 2**

**Steps to set up spark locally:**

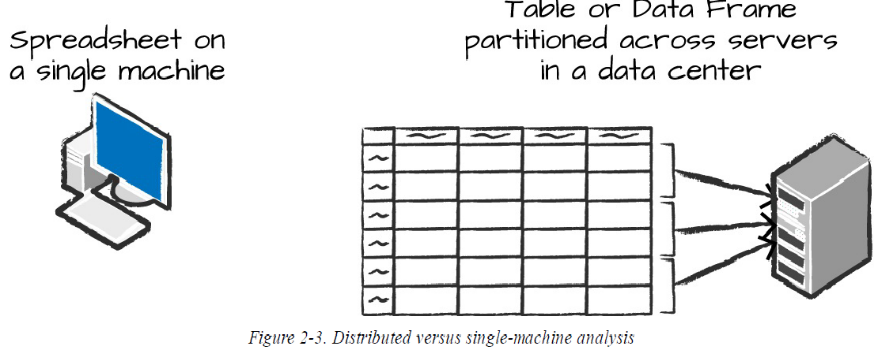


**What components are present in spark-tool kit?**



**What is a dataframe?**

A DataFrame is the most common Structured API and simply represents a table of data with rows and columns. The list that defines the columns and the types within those columns is called the schema. You can think of a DataFrame as a spreadsheet with named columns. Figure 2-3 illustrates the fundamental difference: a spreadsheet sits on one computer in one specific location, whereas 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. Spark has several core abstractions: Datasets, DataFrames, SQL Tables, and Resilient Distributed Datasets (RDDs). These different abstractions all represent distributed collections of data. The easiest and most efficient are DataFrames, which are available in all languages.



**Why data is partitioned?**

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 your cluster. A DataFrame’s partitions represent how the data is physically distributed across the cluster of machines during execution. If you have one partition, Spark will have a parallelism of only one, even if you have thousands of executors. If you have many partitions but only one executor, Spark will still have a parallelism of only one because there is only one computation resource. An important thing to note is that with DataFrames you do not (for the most part) manipulate partitions manually or individually. You simply specify high-level transformations of data in the physical partitions, and Spark determines how this work will actually execute on the cluster.

**What are transformations?**

In Spark, the core data structures are immutable, meaning they cannot be changed after they’re created. This might seem like a strange concept at first: if you cannot change it, how are you supposed to use it? To “change” a DataFrame, you need to instruct Spark how you would like to modify it to do what you want. These instructions are called transformations. Let’s perform a simple transformation to find all even numbers in our current DataFrame:

// in Scala

val myRange = spark.range(1000).toDF(“number”)

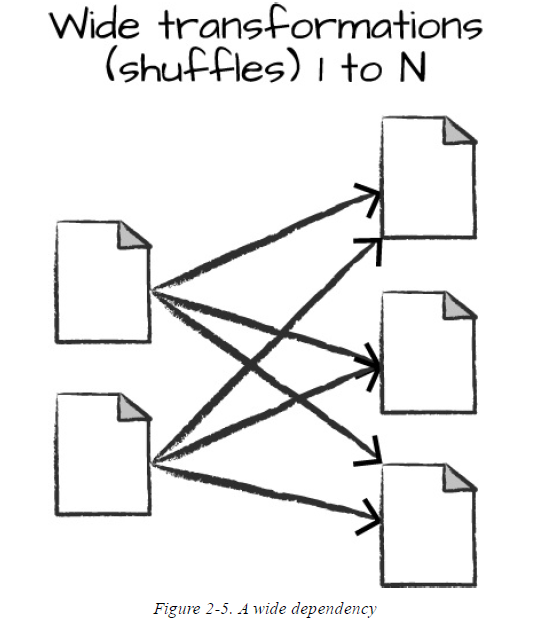
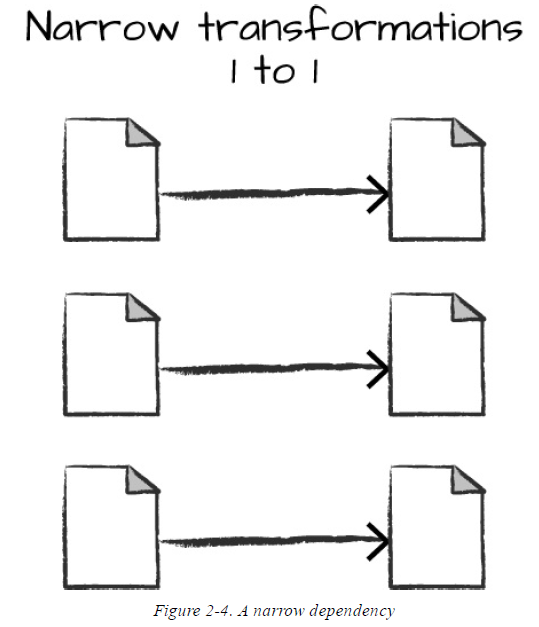
val divisBy2 = myRange.where("number % 2 = 0")

# in Python

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

Notice that these return no output. This is because we specified only an abstract transformation, and Spark will not act on transformations until we call an action (we discuss this shortly). Transformations are the core of how you express 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 (we’ll call them narrow transformations) are those for which each input partition will contribute to only one output partition. In the preceding code snippet, the where statement specifies a narrow dependency, where only one partition contributes to at most one output partition, as you can see in Figure 2-4.



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 whereby Spark will exchange partitions across the cluster. With narrow transformations, Spark will automatically perform an operation called pipelining, meaning 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 writes the results to disk. Wide transformations are illustrated in Figure 2-5.

**What is 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 you express some operation, you build up a plan of transformations that you would like to apply to your source data. By waiting until the last minute to execute the code, Spark compiles this plan from your raw DataFrame transformations to a streamlined physical plan that will run as efficiently as possible across the cluster. This provides immense benefits 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.

**What are actions in Spark?**

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()

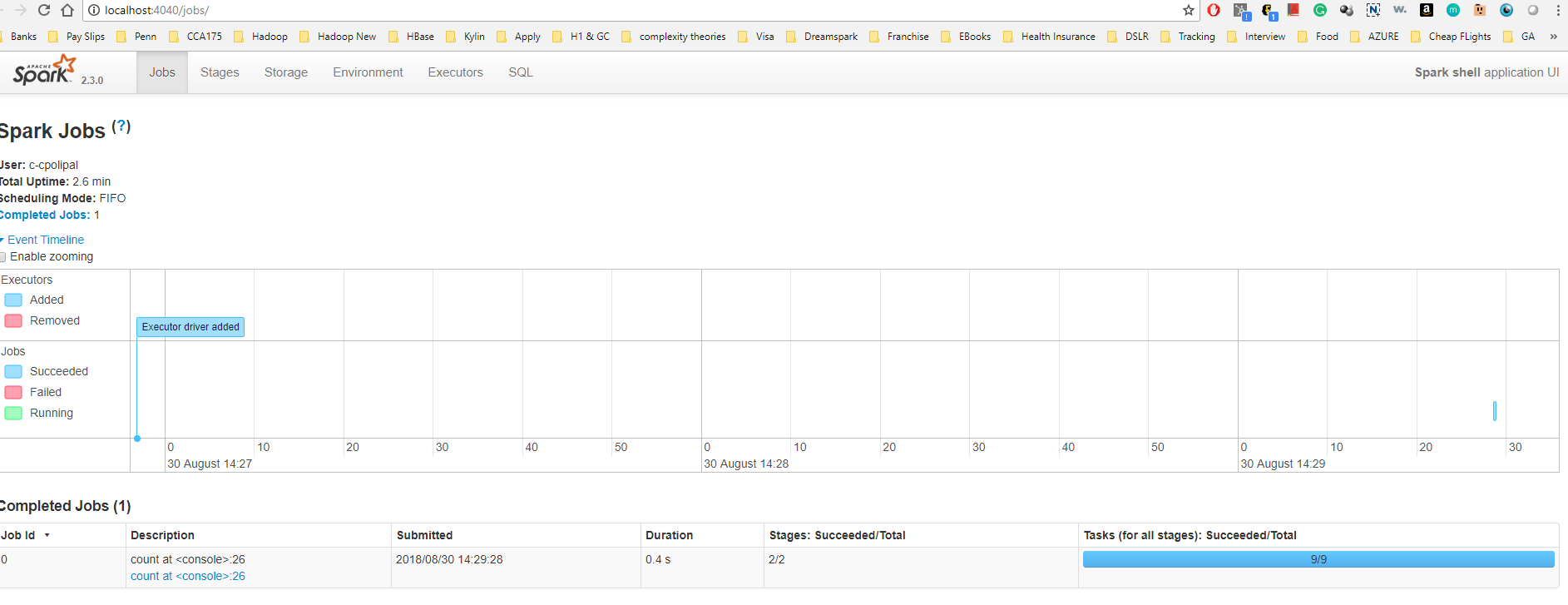
The output of the preceding code should be 500. Of course, count is not the only action. There are three kinds of actions:

* Actions to view data in the console
* Actions to collect data to native objects in the respective language
* Actions to write to output data sources

In specifying this 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, and then a collect, which brings our result to a native object in the respective language. You can see all of this by inspecting the Spark UI, a tool included in Spark with which you can monitor the Spark jobs running on a cluster.

**What is Spark UI?**

You can monitor the progress of a job through the Spark web UI. The Spark UI is available on port 4040 of the driver node. If you are running in local mode, this will be http://localhost:4040. The Spark UI displays information on the state of your Spark jobs, its environment, and cluster state. It’s very useful, especially for tuning and debugging. Figure 2-6 shows an example UI for a Spark job where two stages containing nine tasks were executed.



At this point, all you need to understand is that a Spark job represents a set of transformations triggered by an individual action, and you can monitor that job from the Spark UI.

**What is schema inference?**

Spark includes the ability to read and write from a large number of data sources. To read this data, 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, which means that we want Spark to take a best guess at what the schema of our DataFrame should be.

#Examples from Definitive guide

val flightData = spark.read.

option("inferSchema","true").option("header","true").csv("/user/chaitanyapolipalli/flight-data/csv/2010-summary.csv")

#Sorting

val flightDataSort = flightData.sort("count").show //ascending order

val

flightDataSortDesc = flightData.sort($"count".desc).show //descending order

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

#Registering data frame as table or view

flightData.createOrReplaceTempView("flight\_data")

val sqlWay = spark.sql("select DEST\_COUNTRY\_NAME, count(1) from flight\_data group by DEST\_COUNTRY\_NAME")

val dfWay = flightData.groupBy("DEST\_COUNTRY\_NAME").count()

sqlWay.explain & dfWay.explain should give you similar physical plan

#Using max function

spark.sql("select max(count) from flight\_data").take(1)

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

#Find the top five destination countries in the data

spark.sql("select DEST\_COUNTRY\_NAME, sum(count) as destination\_total from flight\_data group by DEST\_COUNTRY\_NAME order by destination\_total desc limit 5").show

flightData.groupBy("DEST\_COUNTRY\_NAME").sum("count").withColumnRenamed("sum(count)","destination\_total").sort($"destination\_total".desc).limit(5).show

or

flightData.groupBy("DEST\_COUNTRY\_NAME").sum("count").withColumnRenamed("sum(count)","destination\_total").sort(desc("destination\_total")).limit(5).show

**What are type safe structured api’s?**

Type-safe version of Spark’s structured API called Datasets, for writing statically typed code in Java and Scala. The Dataset API is not available in Python and R, because those languages are dynamically typed.

Recall that DataFrames, which we saw in the previous chapter, are a distributed collection of objects of type Row that can hold various types of tabular data. The Dataset API gives users the ability to assign a Java/Scala class to the records within 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, with which multiple software engineers must interact through well-defined interfaces.

The Dataset class is parameterized with the type of object contained inside: Dataset<T> in Java and Dataset[T] in Scala. For example, a Dataset[Person] will be guaranteed to contain objects of class Person. As of Spark 2.0, the supported types are 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 within your Dataset.

Eg:

#Case Class Example

case class Flight(DEST\_COUNTRY\_NAME: String,ORIGIN\_COUNTRY\_NAME: String,count: BigInt)

val flightsDF =

spark.read.parquet("/user/chaitanyapolipalli/flight-data/parquet/2010-summary.parquet/")

val flights = flightsDF.as[Flight]

flights.filter

(x =>

x.ORIGIN\_COUNTRY\_NAME != "Canada").map(x => x).take(5).foreach(println)

**What are Lower-Level API’s in Spark?**

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. 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 than DataFrames because they reveal physical execution characteristics (like partitions) to end users. One thing that you might use RDDs for is to parallelize raw data that you have stored in memory on the driver machine.

**What are Structured API?**

The Structured APIs are a tool for manipulating all sorts of data, from unstructured log files to semi-structured CSV files and highly structured Parquet files. These APIs refer to three core types of distributed collection APIs:

1. Datasets
2. DataFrames
3. SQL tables and views

**What is a Schema?**

A schema defines the column names and types of a DataFrame. You can define schemas manually or read a schema from a data source (often called schema on read). Schemas consist of types, meaning that you need a way of specifying what lies where.

**Difference between DataFrames and DataSets?**

In essence, within the Structured APIs, there are two more APIs, the “untyped” DataFrames and the “typed” Datasets. To say that DataFrames are untyped is aslightly inaccurate; they have types, but Spark maintains them completely and only checks whether those types line up to those specified in the schema at runtime. Datasets, on the other hand, check whether types conform to the specification at compile time. Datasets are only available to Java Virtual Machine (JVM)–based languages (Scala and Java) and we specify types with case classes or Java beans.

For the most part, you’re likely to work with DataFrames. To Spark (in Scala), DataFrames are simply Datasets of Type Row. The “Row” type is Spark’s internal representation of its optimized inmemory format for computation. This format makes for highly specialized and efficient computation because rather than using JVM types, which can cause high garbage-collection and object instantiation costs, Spark can operate on its own internal format without incurring any of those costs. To Spark (in Python or R), there is no such thing as a Dataset: everything is a DataFrame and therefore we always operate on that optimized format.

**Overview of structured API execution:**

This section will demonstrate how this code is actually executed across a cluster. This will help you understand (and potentially debug) the process of writing and executing code on clusters, so let’s walk through the execution of a single structured API query from user code to executed code. Here’s an overview of the steps:

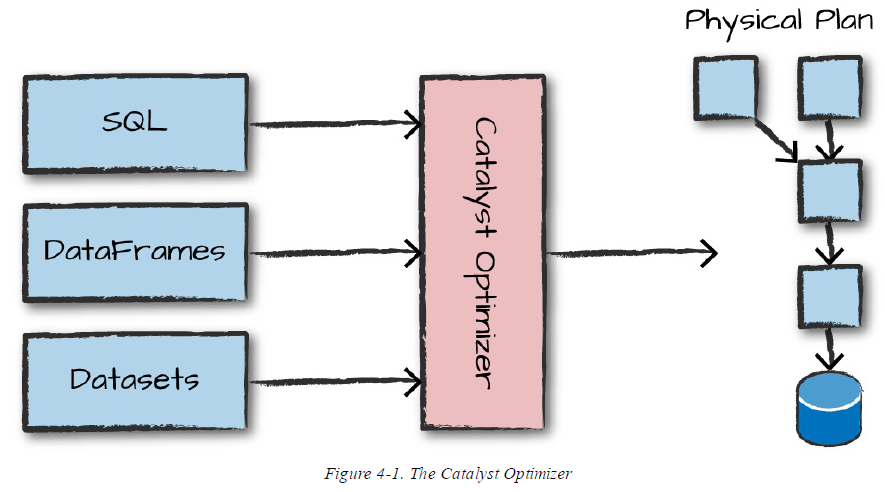
1. Write DataFrame/Dataset/SQL Code.

2. If valid code, Spark converts this to a Logical Plan.

3. Spark transforms this Logical Plan to a Physical Plan, checking for optimizations along the way.

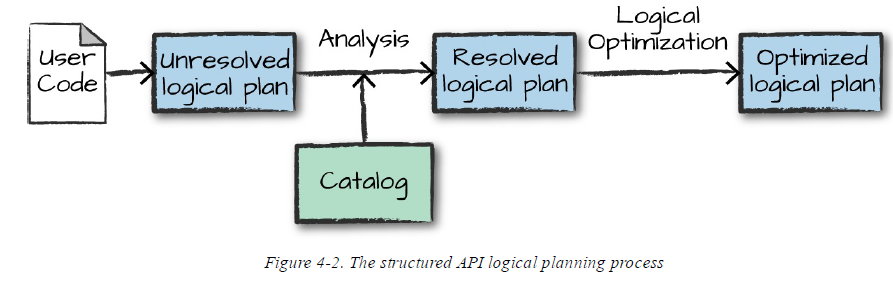
4. Spark then executes this Physical Plan (RDD manipulations) on the cluster.

To execute code, we must write code. This code is then submitted to Spark either through the console or via a submitted job. This code then passes through the Catalyst Optimizer, which decides how the code should be executed and lays out a plan for doing so before, finally, the code is run and the result is returned to the user. Figure 4-1 shows the process.



**Logical Planning**

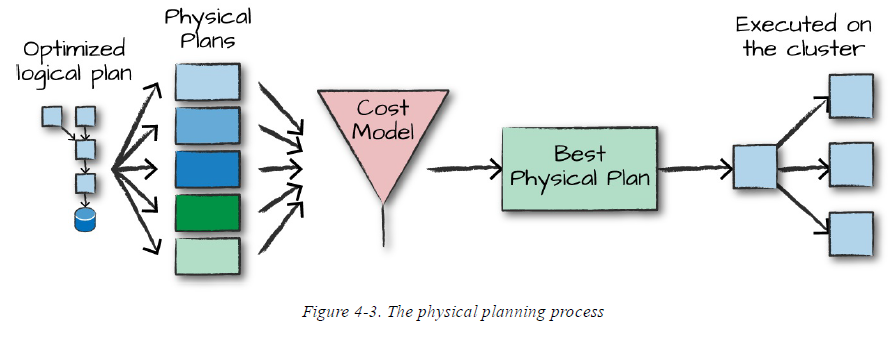
The first phase of execution is meant to take user code and convert it into a logical plan. Figure 4-2 illustrates this process.



This logical plan only represents a set of abstract transformations that do not refer to executors or drivers, it’s purely to convert the user’s set of expressions into the most optimized version. It does this by converting user code into an unresolved logical plan. This plan is unresolved because although your code might be valid, the tables or columns that it refers to might or might not exist. Spark uses the catalog, a repository of all table and DataFrame information, to resolve columns and tables in the analyzer. The analyzer might reject the unresolved logical plan if the required table or column name does not exist in the catalog. If the analyzer can resolve it, the result is passed through the Catalyst Optimizer, a collection of rules that attempt to optimize the logical plan by pushing down predicates or selections. Packages can extend the Catalyst to include their own rules for domainspecific optimizations.

**Physical Planning:**

After successfully creating an optimized logical plan, Spark then begins the physical planning process. The physical plan, often called a Spark plan, specifies how the logical plan will execute on the cluster by generating different physical execution strategies and comparing them through a cost model, as depicted in Figure 4-3. An example of the cost comparison might be choosing how to perform a given join by looking at the physical attributes of a given table (how big the table is or how big its partitions are).



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

**Execution:**

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

**What is catalog in spark?**

Spark uses the catalog, a repository of all table and DataFrame information, to resolve columns and tables in the analyzer. The analyzer might reject the unresolved logical plan if the required table or column name does not exist in the catalog. If the analyzer can resolve it, the result is passed through the Catalyst Optimizer, a collection of rules that attempt to optimize the logical plan by pushing down predicates or selections.

**What is Schema in spark?**

Any DataFrame consists of a series of records (like rows in a table), that are of type Row, and a number of columns (like columns in a spreadsheet) that represent a computation expression that can be performed on each individual record in the Dataset. Schemas define the name as well as the type of data in each column. A schema is a StructType made up of a number of fields, StructFields, that have a name, type, a Boolean flag which specifies whether that column can contain missing or null values, and, finally, users can optionally specify associated metadata with that column. The metadata is a way of storing information about this column (Spark uses this in its machine learning library). Schemas can contain other StructTypes (Spark’s complex types). We will see this in Chapter 6 when we discuss working with complex types. If the types in the data (at runtime) do not match the schema, Spark will throw an error. The example that follows shows how to create and enforce a specific schema on a DataFrame.

Eg:

df.printSchema()

or

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

or

val myManualSchema = StructType(Array

(StructField

("DEST\_COUNTRY\_NAME", StringType, true),StructField("ORIGIN\_COUNTRY\_NAME", StringType, true),StructField("count", LongType,false,Metadata.fromJson("{\"hello\":\"world\"}"))

))

val df =

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

**What is partitioning?**

Partitioning of the DataFrame defines the layout of the DataFrame or Dataset’s physical distribution across the cluster. The partitioning scheme defines how that is allocated. You can set this to be based on values in a certain column or nondeterministically.

**What are columns and expressions in Spark?**

Columns in Spark are similar to columns in a spreadsheet, R dataframe, or pandas DataFrame. You can select, manipulate, and remove columns from DataFrames and these operations are represented as expressions.

To Spark, columns are logical constructions that simply represent a value computed on a per-record basis by means of an expression. This means that to have a real value for a column, we need to have a row; and to have a row, we need to have a DataFrame. You cannot manipulate an individual column outside the context of a DataFrame; you must use Spark transformations within a DataFrame to modify the contents of a column.

**How to access columns:**

spark.read.json("/user/chaitanyapolipalli/flight-data/json/2010-summary.json").columns

res2: Array[String] = Array(DEST\_COUNTRY\_NAME, ORIGIN\_COUNTRY\_NAME, count)

**How to create dataframes on the fly?**

import org.apache.spark.sql.Row

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

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

val myRows = Seq(Row("Hello", null, 1L))

val myRDD = spark.sparkContext.parallelize(myRows)

val myDf = spark.createDataFrame(myRDD, myManualSchema)

myDf.show()

**Some useful dadtaframe methods:**

#Examples of 'select' and 'selectExpr' methods

df.select("DEST\_COUNTRY\_NAME").show(2)

You can select multiple columns by using the same style of query, just add more column name strings to your select method call:

df.select("DEST\_COUNTRY\_NAME", "ORIGIN\_COUNTRY\_NAME").show(2)

#Multiple ways of printing column

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

df.select(

df.col("DEST\_COUNTRY\_NAME"),

col("DEST\_COUNTRY\_NAME"),

column("DEST\_COUNTRY\_NAME"),

'DEST\_COUNTRY\_NAME,

$"DEST\_COUNTRY\_NAME",

expr("DEST\_COUNTRY\_NAME"))

.show(2)

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

df.select(col("DEST\_COUNTRY\_NAME"), "DEST\_COUNTRY\_NAME")

#As we’ve seen thus far, expr is the most flexible reference that we can use. It can refer to a plain column or a string manipulation of a column. To illustrate, let’s change the column name, and then change it back by using the AS keyword and then the alias method on the column:

df.select(expr("DEST\_COUNTRY\_NAME AS destination")).show(2)

#This changes the column name to “destination.” You can further manipulate the result of your expression as another expression:

df.select(expr("DEST\_COUNTRY\_NAME as destination").

alias("DEST\_COUNTRY\_NAME")).show(2)

#The preceding operation changes the column name back to its original name.Because select followed by a series of expr is such a common pattern, Spark has a shorthand for doing this efficiently: selectExpr. This is probably the most convenient interface for everyday use:

df.selectExpr

("DEST\_COUNTRY\_NAME as newColumnName", "DEST\_COUNTRY\_NAME").show(2)

#This opens up the true power of Spark. We can treat selectExpr as a simple way to build up complex expressions that create new DataFrames. In fact, we can add any valid non-aggregating SQL statement, and as long as the columns resolve, it will be valid! Here’s a simple example that adds a new column withinCountry to our DataFrame that specifies whether the destination and origin are the same:

df.selectExpr

("\*",

"(DEST\_COUNTRY\_NAME = ORIGIN\_COUNTRY\_NAME) as withinCountry").show(2)

#With select expression, we can also specify aggregations over the entire DataFrame by taking advantage of the functions that we have. These look just like what we have been showing so far:

df.selectExpr("avg(count)", "count(distinct(DEST\_COUNTRY\_NAME))").show

#Sometimes, we need to pass explicit values into Spark that are just a value (rather than a new column). This might be a constant value or something we’ll need to compare to later on.The way we do this is through literals. This is basically a translation from a given programming language’s literal value to one that Spark understands. Literals are expressions and you can use them in the same way:

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

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

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

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

df.withColumn

("withInCountry",expr("ORIGIN\_COUNTRY\_NAME == DEST\_COUNTRY\_NAME"))

#Renaming columns

df.withColumnRenamed("DEST\_COUNTRY\_NAME", "dest").columns

#Escaping column names appropriately. In Spark, we do this by using backtick(`) characters.In this example, however, we need to use backticks because we’re referencing a column in an expression:

val dfWithLongColName =

df.withColumn("This Long Column-Name",expr("ORIGIN\_COUNTRY\_NAME"))

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

#By default Spark is case insensitive; however, you can make Spark case sensitive by setting the configuration:

set spark.sql.caseSensitive true

#Removing columns

df.drop("ORIGIN\_COUNTRY\_NAME")

dfWithLongColName.drop("ORIGIN\_COUNTRY\_NAME", "DEST\_COUNTRY\_NAME")

#Changing column type

df.withColumn("count2", col("count").cast("long"))

#Filtering rows - below commands will yield same results

df.filter(col("count") < 2).show(2)

df.where("count < 2").show(2)

#Instinctually, you might want to put multiple filters into the same expression. Although this is possible,it is not always useful, because Spark automatically performs all filtering operations at the same time regardless of the filter ordering. This means that if you want to specify multiple AND filters, just chain them sequentially and let Spark handle the rest:

#In Scala, you must use the =!= operator so that you don’t just compare the unevaluated column expression to a string but instead to the evaluated one:

df.where

(col("count") < 2).where(col("ORIGIN\_COUNTRY\_NAME") =!= "Croatia").show(2)

#Getting distinct/unique rows

df.select("ORIGIN\_COUNTRY\_NAME", "DEST\_COUNTRY\_NAME").distinct().count()

df.select("ORIGIN\_COUNTRY\_NAME").distinct().count()

#To more explicitly specify sort direction, you need to use the asc and desc functions if operating on a column. These allow you to specify the order in which a given column should be sorted:

df.orderBy(expr("count desc")).show(2)

df.orderBy(desc("count"), asc("DEST\_COUNTRY\_NAME")).show(2)

**An advanced tip is to use asc\_nulls\_first, desc\_nulls\_first, asc\_nulls\_last, or desc\_nulls\_last to specify where you would like your null values to appear in an ordered DataFrame.**

#For optimization purposes, it’s sometimes advisable to sort within each partition before another set of transformations. You can use the sortWithinPartitions method to do this:

spark.read.json("/data/flight-data/json/\*-summary.json").sortWithinPartitions("count")

#Another important optimization opportunity is to partition the data according to some frequently filtered columns, which control the physical layout of data across the cluster including the partitioning scheme and the number of partitions. Repartition will incur a full shuffle of the data, regardless of whether one is necessary. **This means that you should typically only repartition when the future number of partitions is greater than your current number of partitions or when you are looking to partition by a set of columns**:

df.rdd.getNumPartitions #get number of repartitions

df.repartition(5)

#If you know that you’re going to be filtering by a certain column often, it can be worth repartitioning based on that column:

df.repartition(col("DEST\_COUNTRY\_NAME"))

#You can optionally specify the number of partitions you would like, too:

df.repartition(5, col("DEST\_COUNTRY\_NAME"))

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

df.repartition(5, col("DEST\_COUNTRY\_NAME")).coalesce(2)

**/\*Functions on Booleans\*/**

#Filtering Example

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

Eg:

val df =

spark.read.format("csv").option("inferSchema","true").option("header","true").load("/user/chaitanyapolipalli/retail-data/by-day/2010-12-01.csv")

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

or

df.where("InvoiceNo = 536365").show(false)

or

df.where

(col("InvoiceNo") === 536365).select("InvoiceNo", "Description").show(false)

#Complex filter example

val priceFilter = col("UnitPrice") > 600

val descripFilter = col("Description").contains("POSTAGE")

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

-- in SQL

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

#One “gotcha” that can come up is if you’re working with null data when creating Boolean expressions. If there is a null in your data, you’ll need to treat things a bit differently. Here’s how you can ensure that you perform a null-safe equivalence test:

df.where(col("Description").eqNullSafe("hello")).show()

**/\*Functions on Numbers\*/**

#numerical function 'pow' function example

val fabricatedQuantity = pow(col("Quantity") \* col("UnitPrice"),2) + 5

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

#The round function rounds up if you’re exactly in between two numbers. You can round down by using the bround:

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

#Another common task is to compute summary statistics for a column or set of columns. We can use the describe method to achieve exactly this. This will take all numeric columns and calculate the count, mean, standard deviation, min, and max.

df.describe().show()

#As a last note, we can also add a unique ID to each row by using the function monotonically\_increasing\_id. This function generates a unique value for each row, starting with 0:

df.select(monotonically\_increasing\_id()).show(2)

**/\*Functions on Strings\*/**

#The initcap function will capitalize every word in a given string when that word is separated from another by a space

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

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

#Another trivial task is adding or removing spaces around a string. You can do this by using lpad, ltrim, rpad and rtrim, trim:

#Note that if lpad or rpad takes a number less than the length of the string, it will always remove values from the right side of the string.

df.select(

ltrim(lit(" HELLO ")).as("ltrim"),

rtrim(lit(" HELLO ")).as("rtrim"),

trim(lit(" HELLO ")).as("trim"),

lpad(lit("HELLO"), 3, " ").as("lp"),

rpad(lit("HELLO"), 10, " ").as("rp")).show(2)

**/\*Regular Expressions\*/**

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

val regexString = simpleColors.map(\_.toUpperCase).mkString("|")

// the | signifies `OR` in regular expression syntax

df.select(regexp\_replace(col("Description"),regexString, "COLOR").alias("color\_clean"),col("Description")).show(false)

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

df.select

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

# “regexp\_extract” example

val regexString = simpleColors.map(\_.toUpperCase).mkString("(", "|", ")")

// the | signifies OR in regular expression syntax

df.select(regexp\_extract(col("Description"),regexString, 1).alias("color\_clean"),col("Description")).show(2)

# “contains” example

val containsBlack = col("Description").contains("BLACK")

val containsWhite = col("DESCRIPTION").contains("WHITE")

df.

withColumn("hasSimpleColor", containsBlack.or(containsWhite)).

where("hasSimpleColor").select("Description").show(3, false)

**/\*Dates Examples\*/**

val

dateDF = spark.range(10).withColumn("today", current\_date()).withColumn("now", current\_timestamp())dateDF.createOrReplaceTempView("dateTable")

#add 5 days and subtract five days

dateDF.select(date\_sub(col("today"), 5), date\_add(col("today"), 5)).show()

#difference between months and days

dateDF.

withColumn("week\_ago",date\_sub(col("today"), 7)).select(datediff(col("today"), col("week\_ago"))).show()

dateDF.select(to\_date(lit("2016-01-01")).alias("start"),to\_date(lit("2017-05-22")).alias("end")).select(months\_between(col("end"), col("start"))).show()

#The to\_date function allows you to convert a string to a date, optionally with a specified format. to\_date (optionally requires a format) and to\_timestamp (always requires a format) examples

# “to\_date” example

val dateFormat = "yyyy-dd-MM"

val

cleanDateDF = spark.range(1).select(to\_date(lit("2017-12-11"), dateFormat).

alias("date"),to\_date(lit("2017-20-12"), dateFormat).alias("date2"))

cleanDateDF.createOrReplaceTempView("dateTable2")

# “to\_timestamp” example

cleanDateDF.select(to\_timestamp(col("date"), dateFormat)).show()

# "drop" function. The simplest function is drop, which removes rows that contain nulls. The default is to drop any row in which any value is null:

#Specifying "any" as an argument drops a row if any of the values are null. Using “all” drops the row only if all values are null or NaN for that row:

df.na.drop("any")

df.na.drop("all")

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

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

# "fill" example. Using the fill function, you can fill one or more columns with a set of values. This can be done by specifying a map—that is a particular value and a set of columns. For example, to fill all null values in columns of type String, you might specify the following:

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

#We could do the same for columns of type Integer by using df.na.fill(5:Integer), or for Doubles

df.na.fill(5:Double)

#To specify columns, we just pass in an array of column names like we did in the previous example:

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

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

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

df.na.fill(fillColValues)

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

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

**/\*Working with Complex Types\*/**

# "Structs" Example

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

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

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

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

complexDF.createOrReplaceTempView("complexDF")

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

complexDF.select("complex.Description")

complexDF.select(col("complex").getField("Description"))

#We can also query all values in the struct by using \*. This brings up all the columns to the top-level DataFrame:

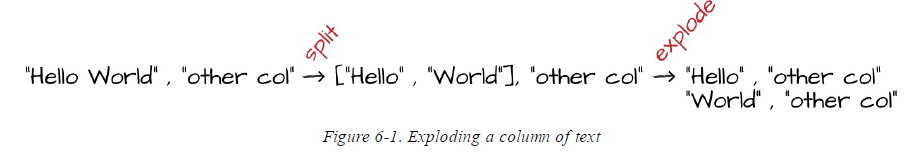
complexDF.select("complex.\*")

# "array" example. To define arrays, let’s work through a use case. With our current data, our objective is to take every single word in our Description column and convert that into a row in our DataFrame. The first task is to turn our Description column into a complex type, an array.

#We do this by using the split function and specify the delimiter:

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

# "explode" example. The explode function takes a column that consists of arrays and creates one row (with the rest of the values duplicated) per value in the array.



df.withColumn("splitted", split(col("Description"), " ")).

withColumn("exploded", explode(col("splitted"))).

select("Description", "InvoiceNo", "exploded").show(2)

# "Map" example

df.select(map(col("Description"), col("InvoiceNo")).alias("complex\_map")).show(false)

#You can also explode map types, which will turn them into columns:

df.select(map(col("Description"), col("InvoiceNo")).alias("complex\_map")).selectExpr("explode(complex\_map)").show(false)

**Difference between coalesce and repartition?**

<https://stackoverflow.com/questions/31610971/spark-repartition-vs-coalesce>

<https://hackernoon.com/managing-spark-partitions-with-coalesce-and-repartition-4050c57ad5c4>