Beginning Spark

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Conventions in the slides

The following typographical conventions are used in this material:

Italic
Indicates new terms, URLs, email addresses, filenames, and file extensions.

`Constant width`
Used for program listings, as well as within paragraphs to refer to program elements such as variable or function names, databases, data types, environment variables, statements, and keywords.

`Constant width bold` Shows commands or other text that should be typed literally by the user.

`Constant width italic`
Shows text that should be replaced with user-supplied values or by values determined by context.

Shell Conventions

All shells (bash, zsh, Windows Shell) are represented as `%`

```
% calendar
```

All Spark shells are represented as `scala>`

```
scala> spark.range(1,100)
```

Spark Intro

Spark Intro

- Big data processing framework
- Variety of packages built upon Spark engine
- Contains two API
  - Unstructured API
    - Lower Level
    - RDD
    - Accumulators
    - Broadcast Variables
  - Structured API
    - Higher Level
    - Optimized
    - DataFrames
    - Datasets
    - Spark SQL

Spark Architecture

- The reason for existence is that one computer is too slow for processing data
- A cluster can provide faster processing in parallel.
- Spark is separated by:
  - A `driver` process
  - An `executor` process

The Driver

- The driver node for your application
- Maintains information about the application
- Responds to external programs
- Analyzes work across executors
- Distributes work across executors
- Schedules work across executors

The Executor

- Executes code assigned to it by the driver
- Reports the state of the computation back to the driver

Two APIs

- Structured (Dataframes, Datasets, SparkSQL)
    - Structured in table formats like Databases, Spreadsheets
- Unstructured (Resilient Distributed Datasets)
    - Functional Programming with Java objects and Scala case classes

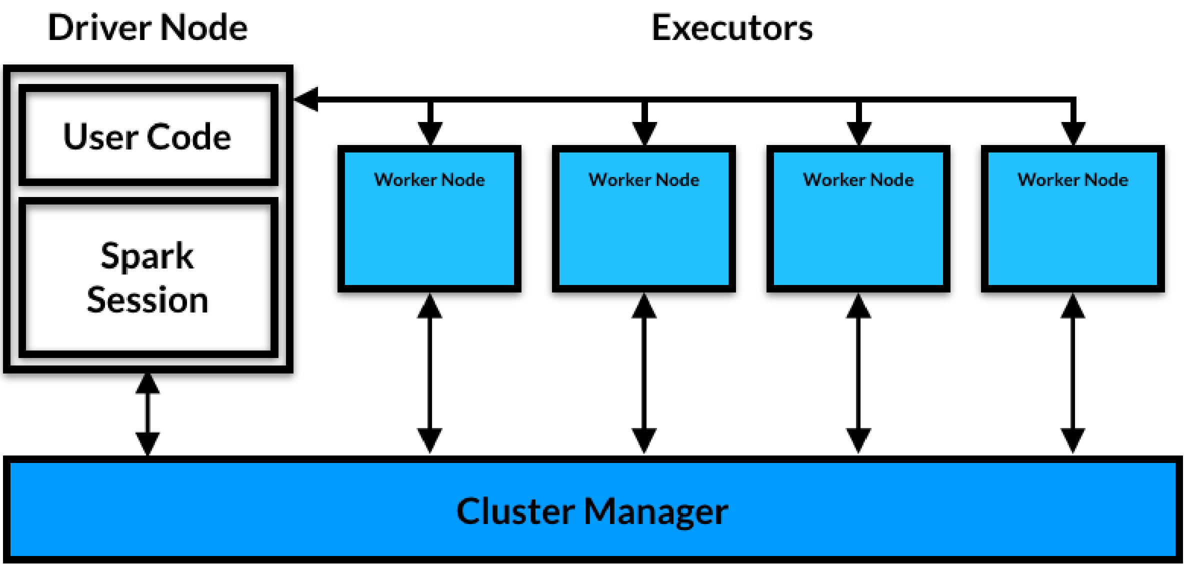
Spark Extras

- Mlib Machine Learning with Spark
- GraphX for Graph Processing
- SparkR for working with Clusters using R

Cluster Manager

- Controls the Physical Machines
- Allocates resources to Spark applications
- Cluster Managers can either be:
    - Sparks in-house cluster manager
    - YARN
    - Mesos
- Known as Cluster Mode

Spark Architecture



Local Mode

- Instead of remote machines this will run on your internal box
- Easy for testing, in house demonstrations

Languages

- Scala (Spark's default language)
- Python (Does everything that Scala does)
- Java
- SQL (Spark SQL is compliant SQL to interact with querying data)
- R/Spark R

Setup

Setup

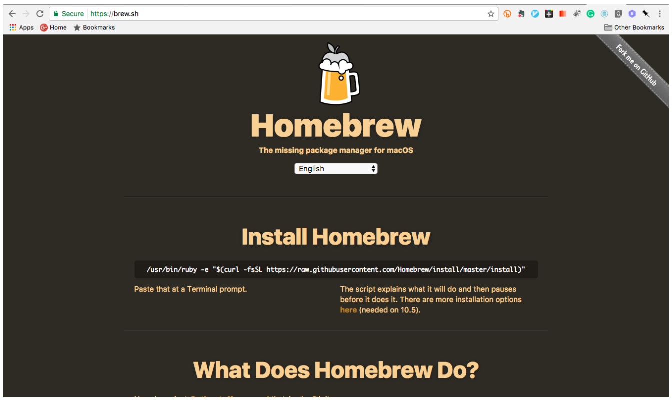
Before we begin it is assumed that all of you have the following tools installed:

- JDK 1.8 (latest java is 1.8.0_144)
- Scala 2.12.3
- SBT 1.0.2
- Spark 2.2.0
- `winutils` (Windows Only)

To verify that all your tools work as expected

```
% javac -version
javac 1.8.0_144

% scala -version
Scala code runner version 2.12.3 -- Copyright 2002-2017, LAMP/EPFL

% java -version
java version "1.8.0_144"
Java(TM) SE Runtime Environment (build 1.8.0_1.8.0_144-b17)
Java HotSpot(TM) 64-Bit Server VM (build 25.65-b01, mixed mode)

% sbt sbtVersion
[info] Set current project to scala (in build file:/<folder_location>)
[info] 1.0.2

% spark-submit -version

Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 2.2.0
      /_/

Using Scala version 2.12.3, Java HotSpot(TM) 64-Bit Server VM, 1.8.0_144
Branch
Compiled by user jenkins on 2017-04-25T23:51:10Z
Revision
Url
Type --help for more information.
```

Installing Java, Scala, Spark, SBT on a Mac Automatically with Brew



If you have a mac and brew installed, you can run the following ***and be done!***:

```
% brew update
% brew cask install java
% brew install scala
% brew install sbt
% brew install apache-spark
```

This will require an install of Homebrew. Visit https://brew.sh/ for details of installation if you want to use brew.

Depending on your company's software and security constraints, you may not be able to use brew

If you don't have Java 8 installed

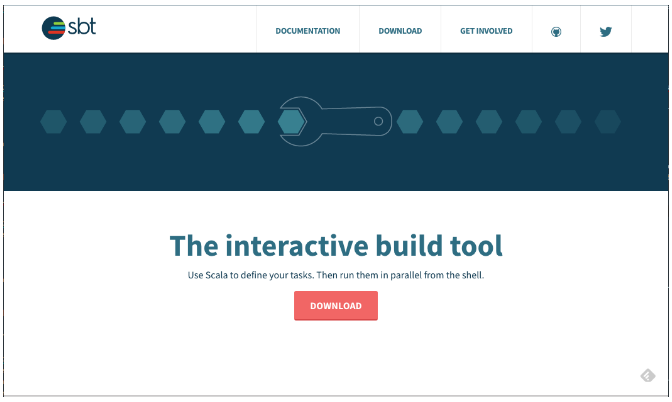
- Visit: http://www.oracle.com/technetwork/java/javase/downloads/index-jsp-138363.html
- Select: *Accept License Agreement*
- Download the appropriate Java version based on your architecture.

Linux ARM 32 Hard Float ABI	Linux ARM 64 Hard Float ABI
Linux x86	Linux x86
Linux x64	Linux x64
Mac OS X	Solaris SPARC 64-bit
Solaris SPARC 64-bit	Solaris x64
Solaris x64	Windows x86

If you do not have Scala installed

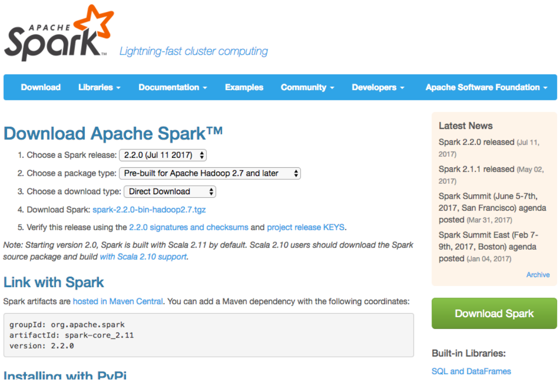
- Visit http://scala-lang.org
- Click the *Download* Button
- Download the appropriate binary for your system:
  - Mac and Linux will load a *.tgz* file
  - Windows will download an *.msi* executable
- For Mac and Linux you can expand with `tar -xvfz scala-2.12.3.tgz`

If you do not have SBT installed



- Visit http://scala-sbt.org
- Click the *Download* Button
- Download the appropriate binary for your system:
  - Mac and Linux will load a *.tgz*, or a *.zip* file
  - Windows will download an *.msi* executable
- For Mac and Linux you can expand with `tar -xvfz scala-2.12.3.tgz`

If you do not have Spark installed



- Visit https://spark.apache.org/downloads.html
- Click the spark-2.2.0-bin-hadoop2.8.1.tgz link to download
- For Mac and Linux, you can expand with `tar -xvfz spark-2.2.0-bin-hadoop2.8.1.tgz` to folder of your choosing
- For Windows, you will need a utility like WinZip to extract a tar.gz file to a folder of your choosing

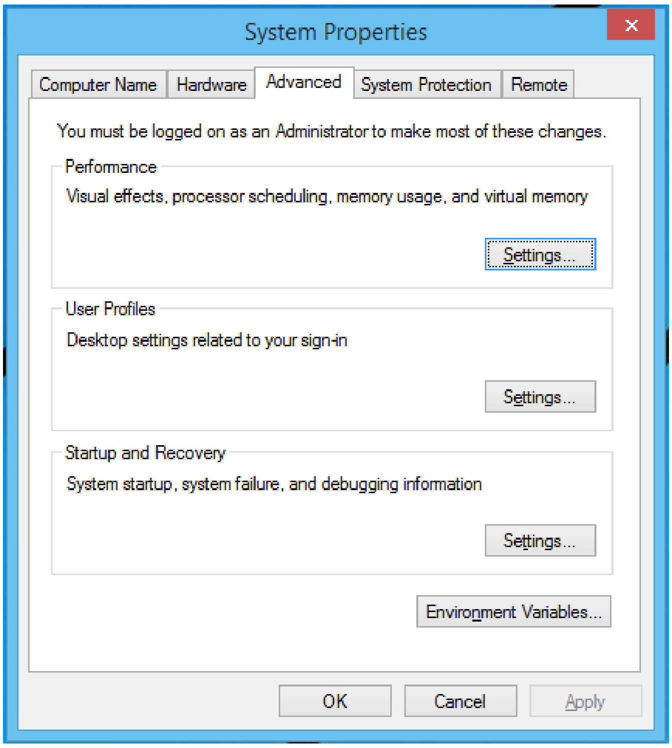
Windows Users Only: Download `winutils`

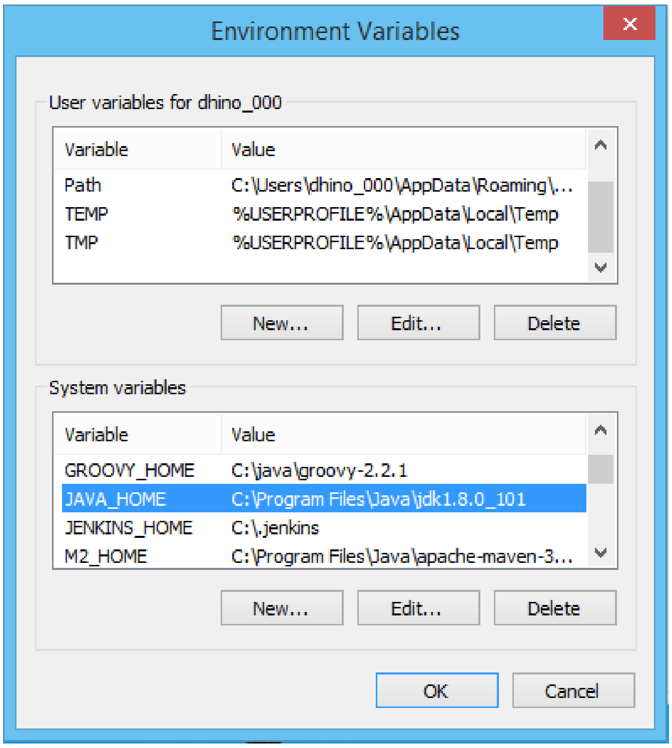
- Download *winutils.exe* from https://github.com/steveloughran/winutils/tree/master/hadoop-2.7.1/bin
- Place *winutils.exe* in a folder named *hadoop* anywhere you would like *C:\Program File\hadoop* or *C:\hadoop*.
- Note the location, since this will be your `HADOOP_HOME`

More about the installation at this link: https://hernandezpaul.wordpress.com/2016/01/24/apache-spark-installation-on-windows-10/

Windows Users Only: Setting up the Windows Environment Variables for Java

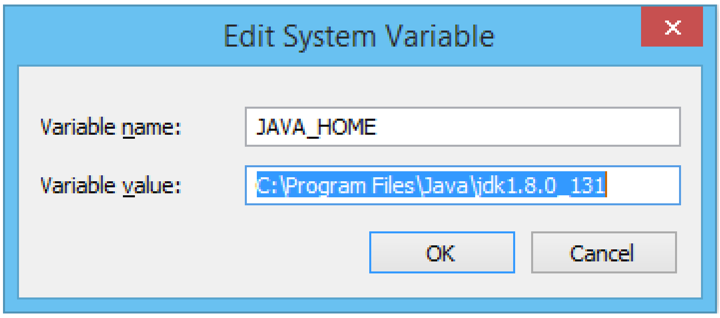
- Go to your *Environment Variables*, typically done by typing the Windows key(⊞) and type `env`





Windows Users Only: Setting up `JAVA_HOME`

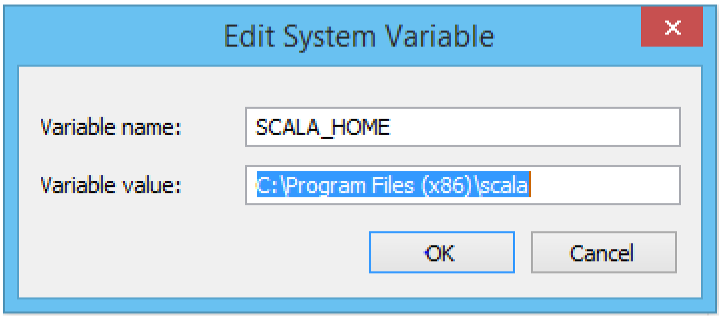
- Edit `JAVA_HOME` in the System Environment Variable window with the location of your JDK



Using `jdk1.8.0_131` in the image. Your version may vary.

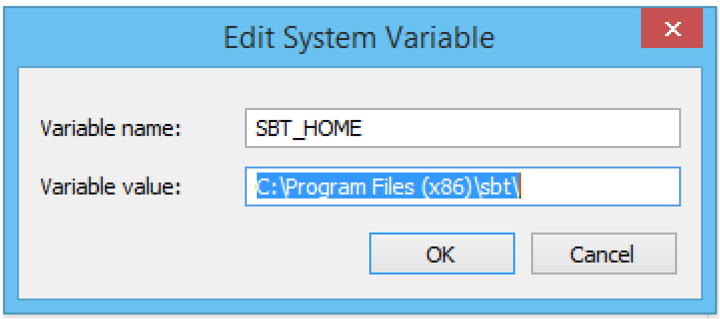
Windows Users Only (Optional): Setting up `SCALA_HOME`

- This setting is not necessary with Scala on Windows since the .msi file installs everything required
- If you do have problems where a tool is unable to locate Scala, set up an environment variable `SCALA_HOME`



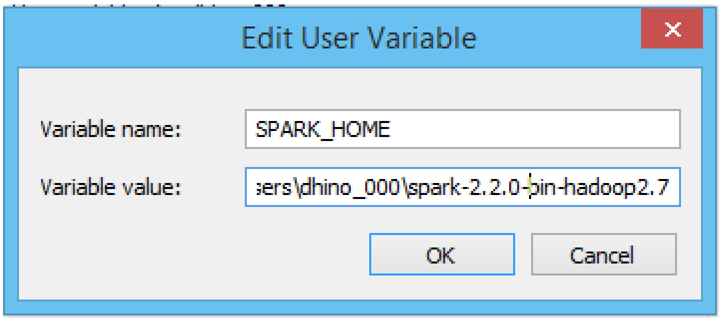
Windows Users Only: Setting up `SBT_HOME`

- This setting is not necessary since SBT on Windows since the .msi file installs everything required
- If you do have problems where a tool is unable to locate SBT, set up an environment variable `SBT_HOME`



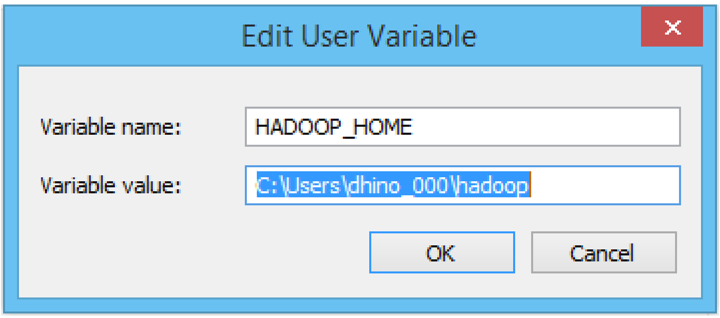
Windows Users Only: Setting up SPARK_HOME

- Set up an environment variable `SPARK_HOME` and setting it to the unpackaged spark folder from your download.
- **Do not include bin**
- **Do not use the `%USERPROFILE%` variable as it may cause side effects**



Windows Users Only: Setting up HADOOP_HOME

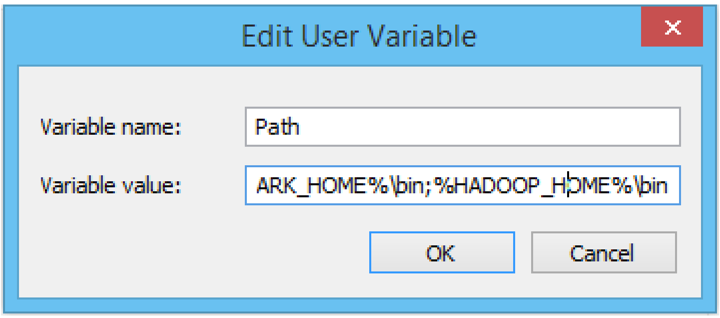
- Set up an environment variable `HADOOP_HOME` and setting it where you created your hadoop directory
- **Do not include bin**
- **Do not use the `%USERPROFILE%` variable as it may cause side effects**



Windows Users Only: Setting up PATH

- Once you establish `JAVA_HOME`, possibly `SCALA_HOME`, `SPARK_HOME`, `HADOOP_HOME`, ***append*** to the `PATH` setting the following:

```
;%JAVA_HOME%\bin;%SCALA_HOME%\bin;%SPARK_HOME%\bin;%HADOOP_HOME%\bin
```

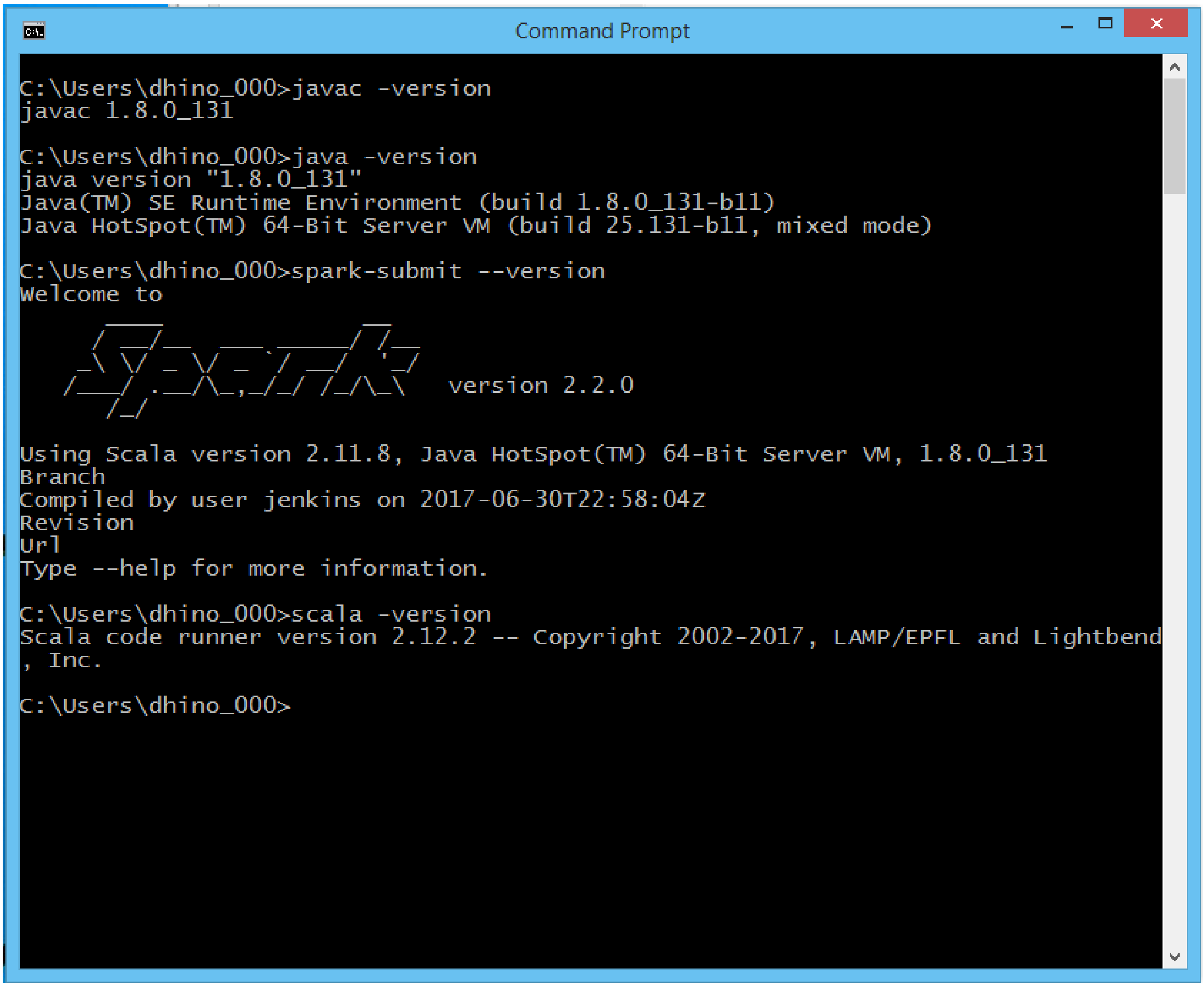


Windows Users Only: Permissions for the folder `C:\tmp\hive`

- Unfortunately, there will be issues with Windows users when the run `spark-shell`
- Attempt to run `spark-shell`
- Notice if you receive an error stating that there is not enough permission on `/tmp/hive`
- Use `winutils` to change the permission to `C:\tmp\hive` by using the command

```
winutils.exe chmod 777 \tmp\hive
```

Windows Users Only: Restart All Command Prompts And Try Again



Changes won't take effect until you open a new command prompt!

Mac Users Only: Editing your *.bash_profile* or *.zshrc*

- If you are using the Bash shell, edit the your *.bash_profile* in your home directory using your favorite editor
- If you are using the Zsh shell, edit the your *.zshrc* in your home directory using your favorite editor

For example, if using nano

```
% nano ~/.bash_profile
```

Replace *nano* with your favorite editor *vim*, *emacs*, *atom*, etc.

- Make sure the following contents are in your *.bash_profile*

- If you already have a `PATH`, append the new values to the end.

```
export SPARK_HOME= <location_of_spark>
export SCALA_HOME= <location_of_scala>
export SBT_HOME= <location_of_sbt>
export JAVA_HOME=$(/usr/libexec/java_home)
export PATH=$PATH:$JAVA_HOME/bin:$SCALA_HOME/bin:$SBT_HOME
/bin:$SPARK_HOME/bin
```

If you used `brew`, many of these application will not require their `PATH` setup.

You can locate where `scala` and `spark` is by either doing

```
% which scala
% whereis scala
% which spark
% whereis spark
```

When done open a new terminal or if already on an open terminal type:

- For bash: **`source .bash_profile`**
- For zsh: **`source .zshrc`**

Linux Users Only: Editing your *.bash_profile* or *.zshrc*

- If you are using the Bash shell, edit the your *.bash_profile* in your home directory using your favorite editor
- If you are using the Zsh shell, edit the your *.zshrc* in your home directory using your favorite editor

For example, if using `nano`

```
% nano ~/.bash_profile
```

Replace *nano* with your favorite editor *vim*, *emacs*, *atom*, etc.

- Make sure the following contents are in your *.bash_profile*
- If you already have a `PATH`, append the new values to the end.

```
export SPARK_HOME= <location_of_spark>
export SCALA_HOME= <location_of_scala>
export SBT_HOME= <location_of_sbt>
export JAVA_HOME= <location_of_jdk>
export PATH=$PATH:$JAVA_HOME/bin:$SCALA_HOME/bin:$SBT_HOME
/bin:$SPARK_HOME/bin
```

When done open a new terminal or if already on an open terminal type:

- For bash: `source .bash_profile`
- For zsh: `source .zshrc`

Overview of Abstractions

The following are the main abstractions of Spark

- DataFrames
- Datasets
- SQL Tables
- Resilient Distributed Datasets

DataFrames

- Are the most efficient
- Are available in all languages
- A table with data rows and columns
- Analogous to a spreadsheet or table
- **Distributed and spans over multiple machines!**
- Easiest to use, particularly for non-functional programmers

Partitions

- For management, Spark breaks up data into chunks
- A Partition is a collection of *rows* that sit on *one machine* in a cluster
- Therefore a DataFrame contains 0 or more partitions
- DataFrame is the interface to all the computations and data stored on remote machines
- In local mode they are laid across a single instance

Partition parallelism

- Partitions are operated on in parallel
- Unless they undergo a process called *shuffling*

Transformations

- All data structures are *immutable*
- Any change receives a copy
- Therefore, any change will be done via a transformation
- Should be very familiar if you do functional programming like Scala
- Transformation of a `DataFrame` returns a `DataFrame`

Lazy Evaluation

- All changes do not run right away
- Transformations to DataFrames are calculated and evaluated only when needed
- Before execution a *plan* is automatically created before evaluation

Actions

- To trigger the series of transformation we would need an *action* or *terminal operation*
- There are three kinds of actions:
  - View data in the console
  - Collect data
  - Output data to a file system or database
- Many terminal operations include:
  - `reduce`
  - `collect`
  - `count`

Running the Spark Shell

- You can run the Spark Shell using `spark-shell`
- The spark shell provides access to a *SparkSession*
- *SparkSession*
  - Starting point to the execution of Spark
  - Can be retrieved by calling `spark` in the SparkShell

Lab: Starting up the Spark Shell

Step 1: Invoke the spark-shell for Scala:

```
% spark-shell
```

Step 2: Verify that you get the `SparkSession` by calling `spark` in the Spark shell:

```
> spark
```

Step 3: Where you would get something like the following:

```
res1: org.apache.spark.sql.SparkSession =
org.apache.spark.sql.SparkSession@2a8081f5
```

Lab: Creating our first job

Step 1: Create some data with `spark.range` from 1 to 100 and process it with map with finally return a `DataFrame`

```
val dataFrame = spark.range(1, 100)
                     .toDF("mappedRange")
```

The above example creates data in a raw form and then puts it into a `DataFrame`

Lab: Evaluating a series of Data using Spark:

Step 1: Open up the spark shell.

Step 2: Enter the following which will create a range from 1 to 100, map, then filter, and then create a `DataFrame`

```
> val df = spark.range(1,100).map(x => x + 10).filter(x => x % 2 !=
0).toDF("numbers")

df: org.apache.spark.sql.DataFrame = [numbers: bigint]
```

Step 3: Next run `count` and this will evaluate the `count`. You may also see some extra process by doing so.

```
> df.count
res1: Long = 50
```

Lab: `show()` the data

`show()` will show the `DataFrame` by default of the first 20 rows

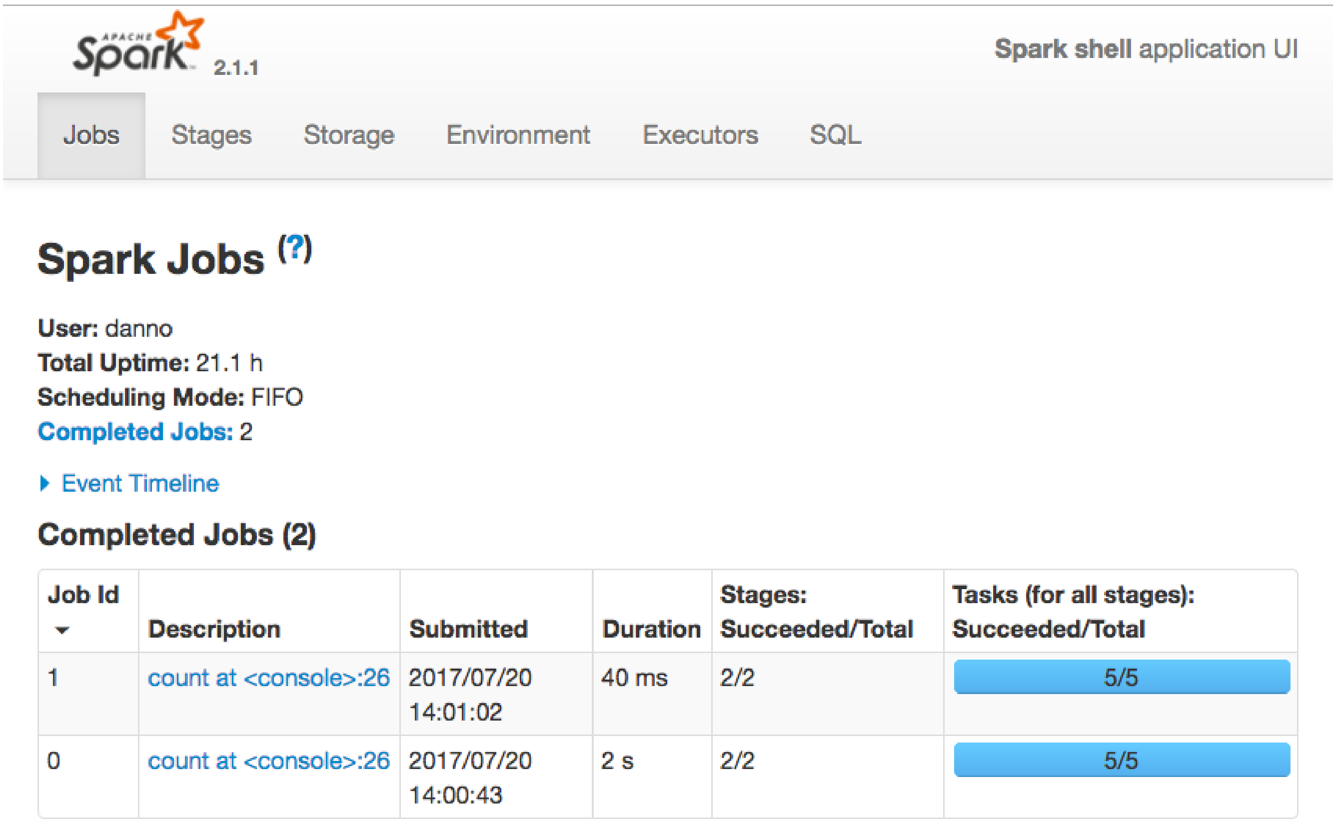
Step 1: Next `show()` the data to see what is left

```
> df.show()
```

Spark UI

- At anytime, you can go to the Spark UI for a local node setup by going to http://localhost:4040
- The Spark UI contains information about Spark:
  - Environment
  - Jobs
  - Cluster Configuration and Performance
  - Storage

Spark UI Example



Lab: Stock Data From a CSV

To start things in Spark, let's start with some CSV data. Spark can use various forms of data

Step 1: Download data from https://raw.githubusercontent.com/dhinojosa/spark-training/master/goog.csv

Step 2: In the Spark Console, run the following, remember to use your own location of the file to look for the data

```
scala> val googleHistoryCSV = spark.read.csv("<downloads>/goog.csv")

googleHistoryCSV: org.apache.spark.sql.DataFrame = [_c0: string, _c1:
string ... 4 more fields]
```

Step 3: Take the first five elements of the data

```
scala> googleHistoryCSV.take(5)

res10: Array[org.apache.spark.sql.Row] =
Array([Date,Open,High,Low,Close,Volume], [19-Jun-
17,967.84,973.04,964.03,970.89,1224540], [18-Jul-
17,953.00,968.04,950.60,965.40,1153964], [17-Jun-
17,957.00,960.74,949.24,953.42,1165537], [14-Jul-
17,952.00,956.91,948.00,955.99,1053774])
```

`take` is a terminator operation

Lab: Getting rid of the Data cruft

- Given the previous run, we see that Spark had accumulated the header row
- We also saw with the response that the data found was awkward: `[_c0: string, _c1: string … 4 more fields]`
- We can clean both situations up by adding to options to our call
  - `option("inferSchema", "true")` - determine the schema automatically
  - `option("header", "true")` - the first row of data is the header

Step 1: Reread the the csv with a header and assuming a schema

```
scala> val googleHistoryCSV = spark.read
                               .option("inferSchema", "true")
                               .option("header", "true")
                               .csv("<downloads>/goog.csv")
```

Step 2: Next use `show()` to view the output of running the `csv`

Plans

- Before any execution, a plan is always made
- The plan can views the previous analysis on the last `DataFrame`
- Shows the last transformation step

Lab: Running the plan

Step 1: Given the `googleHistoryCSV` that has already been calculated, use to sort the high values and take the top 5

```
> val sortedGoogleHistoryCSV = googleHistoryCSV.sort("high")
```

Step 2: To view the plan, run `explain()`

```
> sortedGoogleHistoryCSV.explain()
```

```
== Physical Plan ==
*Sort [high#15 ASC NULLS FIRST], true, 0
+- Exchange rangepartitioning(high#15 ASC NULLS FIRST, 200)
   +- *FileScan csv [Date#13,Open#14,High#15,Low#16,Close#17,Volume#18]
Batched: false, Format: CSV, Location: InMemoryFileIndex
[file:/Users/danno/Development/goog.csv], PartitionFilters: [],
PushedFilters: [], ReadSchema: struct<Date:string,Open:double,High
:double,Low:double,Close:double,Volume:int>
```

Spark makes a plan before invocation to get the processing path

Lab: Stock Data From JSON

Step 1: Download data from https://raw.githubusercontent.com/dhinojosa/spark-training/master/goog.json

Step 2: In the Spark Console, run the following, remember to use your own location of the file to look for the data

```
scala> val googleHistoryJSON = spark.read.json("<downloads>/goog.json")
```

Step 3: Take the first five elements of the data

```
scala> googleHistoryJSON.take(5)

res10: Array[org.apache.spark.sql.Row] =
Array([Date,Open,High,Low,Close,Volume], [19-Jun-
17,967.84,973.04,964.03,970.89,1224540], [18-Jul-
17,953.00,968.04,950.60,965.40,1153964], [17-Jun-
17,957.00,960.74,949.24,953.42,1165537], [14-Jul-
17,952.00,956.91,948.00,955.99,1053774])
```

Schemas

- So far schemas have been assumed by the structure of our tables
- We can view the schemas of each of these `DataFrame` by calling `schema`
- A schema is a `StructType` made up of a number of fields called `StructFields`
- A `StructField` has:
    - A name,
    - A type
    - A boolean that specifies whether the column is nullable
- A schema can also contain other `StructType` (Spark's complex types).
- Can also be overridden by your own custom schema

Lab: View the Schemas

```
googleHistoryCSV.schema
googleHistoryJSON.schema
```

SparkSQL

- SparkSQL allows you to query data as if it was a SQL database
- A registration of the `DataFrame` is done using `createOrReplaceTempView`
- There is no performance loss from doing a query

Lab: SparkSQL

Step 1: In the spark-shell establish a temp view

```
googleHistoryCSV.createOrReplaceTempView("google_stocks")
```

Step 2: In the spark-shell run a sql command

```
val badDays = spark.sql("SELECT Date, Open, Close FROM google_stocks
WHERE Close < Open SORT BY Date DESC")
badDays.show()
```

Step 3: In the spark-shell explain what happened

```
googleHistoryCSV.explain()
```

Lab: Create an Equivalent Explanation

Step 1: In the spark shell create the following command that runs our equivalent

```
val badDays2 = googleHistoryCSV.select(col("Date"), col("Open"), col
("Close")).filter(col("Open") > col("Close")).orderBy(desc("Date"))
```

Step 2: Verify the output, by using `show()`

Step 3: Verify the steps taken on `badDays2.explain()` and they should look somewhat similar to `badDays` from the previous slide

Rows and Columns

- Dataframes are described as rows and columns
- Rows and columns are established as objects in Spark

Columns

- Embodied in the API as a `Column` type

Rows

- Embodied in the API as a `Row` type

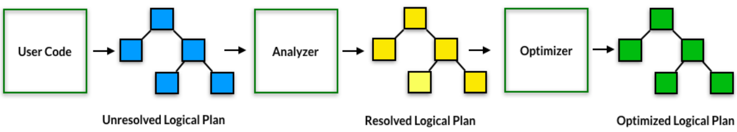
Plans

Understanding Plans

The ordering of how Spark operates is as follows:

- Write DataFrame/Dataset/SQL Code
- If valid code, Spark converts this to a Logical Plan
- Spark transforms this Logical Plan to a Physical Plan
- Spark then executes this Physical Plan on the cluster

Plans Diagram



- Unresolved Logical Plan - Taking the code and and creating a plan without consideration to actual table data
- Resolved Logical Plan - Takes the unresolved logical plan, and the *catalog* of actual data and analyzes it into a *resolved logical plan*
- Optimized Logical Plan - After it is resolved, it uses an optimizer to determine the best course to aggregate and operate on the data

Physical Planning

- After optimization of the plan, comes the physical planning
- This is called the *Spark Plan*
- Specifies how and where the Optimized Logical Plan will run by analyzing:
  - Costs
  - Best Physical Plan
- Becomes a series of RDD (Resilient Distributed Datasets) and Transformations

Lab: Explain all the plans

Step 1: Using spark-shell, call `explain(true)` to explain `badDays`

Step 2: View the analysis which should look like the following

```
scala> badDays.explain(true)
== Parsed Logical Plan ==
'Sort ['Date DESC NULLS LAST], false
+- 'Project ['Date, 'Open, 'Close]
   +- 'Filter ('Close < 'Open)
      +- 'UnresolvedRelation <code>google_stocks</code>

== Analyzed Logical Plan ==
Date: string, Open: double, Close: double
Sort [Date#21 DESC NULLS LAST], false
+- Project [Date#21, Open#22, Close#25]
   +- Filter (Close#25 < Open#22)
      +- SubqueryAlias google_stocks
         +- Relation[Date#21,Open#22,High#23,Low#24,Close#25,Volume#26]
csv

== Optimized Logical Plan ==
Sort [Date#21 DESC NULLS LAST], false
+- Project [Date#21, Open#22, Close#25]
   +- Filter ((isnotnull(Close#25) && isnotnull(Open#22)) && (Close#25 <
Open#22))
      +- Relation[Date#21,Open#22,High#23,Low#24,Close#25,Volume#26] csv

== Physical Plan ==
*Sort [Date#21 DESC NULLS LAST], false, 0
+- *Project [Date#21, Open#22, Close#25]
   +- *Filter ((isnotnull(Close#25) && isnotnull(Open#22)) && (Close#25
< Open#22))
      +- *FileScan csv [Date#21,Open#22,Close#25] Batched: false,
Format: CSV, Location:
InMemoryFileIndex[file:/Users/danno/Downloads/goog.csv],
PartitionFilters: [], PushedFilters: [IsNotNull(Close),
IsNotNull(Open)], ReadSchema:
struct<Date:string,Open:double,Close:double>
```

Step 3: Notice the differences between each of the plans

Value Types

- Again, all of Spark is based on types
- To work with types in Scala, you must import `import org.apache.spark.sql.types._`
- To work with types in Java, you must import `import org.apache.spark.sql.types.DataTypes`

Lab: Scala Value Types

Step 1: Start up the spark-shell

Step 2: Import `import org.apache.spark.sql.types._`

```
import org.apache.spark.sql.types._
```

Step 3: Create a `ByteType`

```
val b = ByteType()
```

Scala Table of Types

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

DataFrames

- Table of data with rows and columns
- The list of columns and the types are called *schemas*
- **Important** A spark data frame can span multiple machines.
- The distribution for `DataFrame` on multiple machines is for performance
- The *partitioning scheme* is how the data is broken and can either be by:
  - column
  - non-deterministically

`DataFrame` is Transformable

- Due to the `DataFrame` not actually holding data they are transformable
- You can:
  - Remove columns
  - Turn a column to a row
  - Turn a row into a column
  - Add columns
  - Add rows
  - Sort by columns
  - Sort by rows

Schemas

- Schemas have by default are assumed by the structure of our tables
- We can view the schemas of each of these `DataFrame` by calling `schema`
- A schema is a `StructType` made up of a number of fields called `StructFields`
- A `StructField` has:
  - A name,
  - A type
  - A boolean that specifies whether the column is nullable
- A schema can also contain other `StructType` (Spark complex types).
- Can also be overridden by your own custom schema which is preferred for production

View the Schema of a `DataFrame`

A schema for a `DataFrame` can viewed with:

```
df.printSchema()
```

Customizing A Schema

- import the types that you are requiring for Spark
- `import org.apache.spark.sql.types.{StructField, StructType, StringType, LongType}`
- Include them when calling `read` to get specific types

Lab: Override our read with our own customized schema

Step 1: In the `spark-shell`, copy the following, and paste it into the spark-shell using `:paste` mode

```
val mySchema = new StructType(Array(
   new StructField("VOLUME", LongType, false),
   new StructField("HIGH", DoubleType, false),
   new StructField("LOW", DoubleType, false),
   new StructField("DATE", StringType, false),
   new StructField("CLOSE", DoubleType, false),
   new StructField("OPEN", DoubleType, false)))
```

Step 2: In the `spark-shell`, read in the csv once more only this time, using our custom schema

```
val googleHistoryCSV = spark.read.schema(mySchema).csv
("/Users/danno/Downloads/goog.json")
```

Step 3: Analyze the schema using `printSchema` and the `schema` method on the `DataFrame`

```
googleHistoryCSV.printSchema
```

```
googleHistoryCSV.schema
```

Columns

- Embodied in the API as a `Column` type
- Can be obtained by either `col` or `column` function residing in `org.apache.spark.sql.functions`
- **IMPORTANT** We can program what we want and those columns don't really need to exist

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

col("someColumnName")
column("someColumnName")
$"someColumnName"
'someColumnName
```

Columns direct from `DataFrame`

- Columns can also be called upon from the `DataFrame` directly

```
dataFrame.col("count")
```

Access all the columns from a `DataFrame`

- All the columns can be accessed from a `DataFrame` using `columns`

```
df.columns
```

Access all the columns from a `googleHistoryCSV`

Step 1: In spark-shell, determine all the column names that are currently in `googleHistoryCSV`

```
> googleHistoryCSV.columns
```

- All the columns can be accessed from a `DataFrame` using `columns`

```
df.columns
```

Expressions

- Transformations on one or more values of records on a `DataFrame`
- Is a function that can be imported `import org.apache.spark.sql.functions.expr`

Obtaining a single column

- There is more than one way to get a column, and you can use an expression

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

expr("someColumn")
```

Making complex expressions

- Expressions are dynamic, and you can do varying things
- For example: `expr(col("High") + 5 < col("Low") - 2)`
- This creates directed acyclic graph
- You can also place the entire expression into a String
- `expr("HIGH + 5 < LOW - 2")`
- This creates the foundation as to why SparkSQL works

Lab: Find all the rows using expressions

Step 1: In the spark-shell and given `googleHistoryCSV` already established enter the following:

```
val badDays3 = googleHistoryCSV.where(expr("CLOSE < OPEN"))
```

Step 2: `show` the results of `badDays3`

```
badDays3.show
```

Rows

- Embodied in the API as a `Row` type
- You can add a row after the fact to a `DataFrame`

```
val newRow = Row("24-Jul-17", 967.84, 967.84, 960.33, 961.08, 1493955)
```

Getting the first row from a `DataFrame`

- You can get the first row of a `DataFrame` by calling `first` or `head`

```
df.first
df.head
```

`parallelize`

- When creating `DataFrames` on the fly we can use `parallelize`
- `parallelize`:
    - Takes a `Seq` with `Row`
    - Returns an RDD (Resilient Distributed Dataset) which is a lower level API for data manipulation

Lab: Create your own DataFrame using and `Row`

Step 1: In spark-shell, copy and paste the following imports:

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

Step 2: Create a schema

```
val employeeSchema = new StructType(Array(
  new StructField("firstName", StringType, false),
  new StructField("middleName", StringType, true),
  new StructField("lastName", StringType, false),
  new StructField("salaryPerYear", IntegerType, false)
))
```

Step 3: Create some rows in a `Seq`

```
val employees = Seq(Row("Abe", null, "Lincoln", 40000),
                    Row("Martin", "Luther", "King", 80000),
                    Row("Ben", null , "Franklin", 82000),
                    Row("Toni", null , "Morrisson", 82000))
```

Step 4: Create a `DataFrame` using an alternate means using `spark.createDataFrame` and verify using `show`

```
val employeeDF = spark.createDataFrame(employees, employeeSchema)
employeeDF.show
```

Creating a `DataFrame` on the cheap using `toDF`

- You can create a `DataFrame` on the spot using `toDF` from a `Seq`
- Doesn't work well with `null`
- Uses `implicit` in Scala to create the `DataFrame`

```scala
val afcNorth = Seq(("Bengals", "Cincinnati", "Paul Brown Stadium"),
                   ("Steelers", "Pittsburgh", "Heinz Field"),
                   ("Browns", "Cleveland", "FirstEnergy Field"),
                   ("Ravens", "Baltimore", "M&T Bank Stadium"))
val afcNorthDataFrame = afcNorth.toDF("NAME", "CITY", "STADIUM")
afcNorthDataFrame.show
```

Sample Data

All example in this chapter use the `googleHistoryCSV` which we will rename for all example with `dataFrame` which was derived from:

```
val mySchema = new StructType(Array(
   new StructField("DATE", StringType, false),
   new StructField("OPEN", DoubleType, false),
   new StructField("HIGH", DoubleType, false),
   new StructField("LOW", DoubleType, false),
   new StructField("CLOSE", DoubleType, false),
   new StructField("VOLUME", LongType, false)))

val dataFrame = spark.read.schema(mySchema).option("header", true).csv
("/Users/danno/Downloads/goog.csv")

dataFrame.createOrReplaceTempView("google_data")
```

Sample Data Results

```
scala> dataFrame.show
+---------+------+------+------+------+-------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|
+---------+------+------+------+------+-------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|
|17-Jul-17| 957.0|960.74|949.24|953.42|1165537|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|
|12-Jul-17|938.68| 946.3|934.47|943.83|1532144|
|11-Jul-17|929.54|931.43| 922.0|930.09|1113235|
|10-Jul-17|921.77|930.38|919.59| 928.8|1192825|
| 7-Jul-17|908.85|921.54|908.85|918.59|1637785|
| 6-Jul-17|904.12|914.94| 899.7|906.69|1424503|
| 5-Jul-17|901.76|914.51| 898.5|911.71|1813884|
| 3-Jul-17|912.18|913.94|894.79| 898.7|1710373|
|30-Jun-17|926.05|926.05|908.31|908.73|2090226|
|29-Jun-17|929.92|931.26|910.62|917.79|3299176|
|28-Jun-17| 929.0|942.75| 916.0|940.49|2721406|
|27-Jun-17|942.46|948.29|926.85|927.33|2579930|
|26-Jun-17| 969.9|973.31|950.79|952.27|1598355|
|23-Jun-17|956.83| 966.0| 954.2|965.59|1527856|
|22-Jun-17| 958.7|960.72|954.55|957.09| 941958|
|21-Jun-17|953.64| 960.1|950.76|959.45|1202233|
+---------+------+------+------+------+-------+
only showing top 20 rows
```

Labs all the way!

- Feel free to try out none, some, or all of the following to get a feel for what they do.
- Experiment using spark-shell

`select`

- `select` allows us to manipulate `DataFrame` to another `DataFrame`
- Easiest to pass the columns you wish to transform or use

```
scala> dataFrame.select("DATE").show(5)
+---------+
|     DATE|
+---------+
|19-Jul-17|
|18-Jul-17|
|17-Jul-17|
|14-Jul-17|
|13-Jul-17|
-----------
```

Spark SQL Equivalent:

```
scala> spark.sql("SELECT DATE FROM google_data").show(5)
```

`select` multiple columns

- `select` can do multiple columns

```
scala> dataFrame.select("DATE", "VOLUME").show(5)
+---------+-------+
|     DATE| VOLUME|
+---------+-------+
|19-Jul-17|1224540|
|18-Jul-17|1153964|
|17-Jul-17|1165537|
|14-Jul-17|1053774|
|13-Jul-17|1294687|
+---------+-------+
only showing top 5 rows
```

Spark SQL Equivalent:

```
scala> spark.sql("SELECT DATE, VOLUME FROM google_data").show(5)
```

`select` Column Alternatives

All variants for selecting a column

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

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

`selectExpr`

- Combines both `select` and `expr`
- Accepts a list of String as expressions
- No need to include `expr`

```
scala> dataFrame.selectExpr("DATE as TRADEDATE", "DATE").show(5)
+---------+---------+
|TRADEDATE|     DATE|
+---------+---------+
|19-Jul-17|19-Jul-17|
|18-Jul-17|18-Jul-17|
|17-Jul-17|17-Jul-17|
|14-Jul-17|14-Jul-17|
|13-Jul-17|13-Jul-17|
+---------+---------+
only showing top 5 rows
```

Showing all the columns using `*` in `selectExpr`

- A `*` can be used to show all the columns in a `selectExpr`

```
scala> dataFrame.selectExpr("*", "DATE as TRADEDATE").show(5)
+---------+------+------+------+------+-------+---------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|TRADEDATE|
+---------+------+------+------+------+-------+---------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|19-Jul-17|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|18-Jul-17|
|17-Jul-17| 957.0|960.74|949.24|953.42|1165537|17-Jul-17|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|14-Jul-17|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|13-Jul-17|
+---------+------+------+------+------+-------+---------+
only showing top 5 rows
```

Spark SQL Equivalent:

```
scala> spark.sql("SELECT *, DATE as TRADEDATE FROM google_data").show(5)
```

Literals

- Literals are explicit values made to be included in a `DataFrame`
- This will inevitably be created into your preferred languages type

```
scala> dataFrame.select(expr("*"), lit(30).as("CONSTANT")).show(5)
+---------+------+------+------+------+-------+--------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|CONSTANT|
+---------+------+------+------+------+-------+--------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|      30|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|      30|
|17-Jul-17| 957.0|960.74|949.24|953.42|1165537|      30|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|      30|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|      30|
+---------+------+------+------+------+-------+--------+
only showing top 5 rows
```

For Spark SQL, there is no `lit` function, just express the value

Spark SQL Equivalent:

```
scala> spark.sql("SELECT *, 30 as CONSTANT FROM google_data").show(5)
```

Adding a column

- An alternative way to add a column is with `withColumn`
- Adds a column or replacing the existing column that has the same name.

- `withColumn` takes a name, and a column definition or function

```
scala> dataFrame.withColumn("CONSTANT", lit(30)).show(5)
+---------+------+------+------+------+-------+--------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|CONSTANT|
+---------+------+------+------+------+-------+--------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|      30|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|      30|
|17-Jul-17| 957.0|960.74|949.24|953.42|1165537|      30|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|      30|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|      30|
+---------+------+------+------+------+-------+--------+
only showing top 5 rows
```

Renaming Columns with `withColumnRenamed`

- A column can also be renamed with `withColumnRenamed`
- `withColumnRenamed` takes the old column name first, then the new name

```
scala> dataFrame.withColumnRenamed("DATE", "TRADEDATE").show(5)
+---------+------+------+------+------+-------+
|TRADEDATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|
+---------+------+------+------+------+-------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|
|17-Jul-17| 957.0|960.74|949.24|953.42|1165537|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|
+---------+------+------+------+------+-------+
only showing top 5 rows
```

Removing Columns

- Removing columns is done with `drop`
- The function can take 1 or more Strings for the column names

```
scala> dataFrame.drop("OPEN", "LOW").show(5)
+---------+------+------+-------+
|     DATE|  HIGH| CLOSE| VOLUME|
+---------+------+------+-------+
|19-Jul-17|973.04|970.89|1224540|
|18-Jul-17|968.04| 965.4|1153964|
|17-Jul-17|960.74|953.42|1165537|
|14-Jul-17|956.91|955.99|1053774|
|13-Jul-17|954.45|947.16|1294687|
+---------+------+------+-------+
only showing top 5 rows
```

Casting

- You can cast to a type by using the `cast` function
- Available in Scala and Spark SQL

Given the schema currently is all double:

```
scala> dataFrame.printSchema
root
 |-- DATE: string (nullable = true)
 |-- OPEN: double (nullable = true)
 |-- HIGH: double (nullable = true)
 |-- LOW: double (nullable = true)
 |-- CLOSE: double (nullable = true)
 |-- VOLUME: long (nullable = true)
```

We can convert say LOW to an int using `cast:

```
scala> dataFrame.withColumn("LOW", col("LOW").cast("int")).printSchema
root
 |-- DATE: string (nullable = true)
 |-- OPEN: double (nullable = true)
 |-- HIGH: double (nullable = true)
 |-- LOW: integer (nullable = true)
 |-- CLOSE: double (nullable = true)
 |-- VOLUME: long (nullable = true)
```

Spark SQL Equivalent:

```
scala> spark.sql("SELECT CAST(LOW as int) FROM google_data").printSchema
root
 |-- LOW: integer (nullable = true)
```

Filtering Rows

- Filtering is a common functional programming construct
- It "weeds out" data from a container that doesn't meet the requirements
- Comes with two forms: `where` and `filter`
    - `where` takes either a `Column` or a `String` expression
    - `filter` takes a predicate `A => Boolean`

```
scala> dataFrame.filter(col("OPEN") < col("CLOSE")).show(5)
```

```
scala> dataFrame.where("OPEN < CLOSE").show(5)
```

Both the above will return ...

```
+---------+------+------+------+------+-------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|
+---------+------+------+------+------+-------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|
|12-Jul-17|938.68| 946.3|934.47|943.83|1532144|
+---------+------+------+------+------+-------+
only showing top 5 rows
```

Spark SQL Equivalent:

```
scala> spark.sql("SELECT * from google_data WHERE CLOSE < OPEN").show(5)
```

There is no benefit to putting all filter logic in one block since Spark will inevitably calculate the best process regardless

Distinct Data

- Intuitively use `distinct` to obtain distinct data from where required

Given:

```
val countriesMedalCountSeq =
    Seq(("United States", "100m Freestyle", 1, 0, 3),
        ("Spain", "100m Butterfly", 2, 1, 1),
        ("Japan", "100m Butterfly", 0, 3, 0),
        ("Spain", "100m Freestyle", 0, 0, 3),
        ("Uruguay", "100m Breaststroke", 0, 1, 0),
        ("United States", "100m Breaststroke", 2, 2, 0))
val countriesMedalCountDF = countriesMedalCountSeq
                                .toDF("Country", "Event", "Gold",
                                      "Silver", "Bronze")
```

You can retreive the distinct data by doing the following:

```
scala> countriesMedalCountDF.selectExpr("Country").distinct.show
+--------------+
|       Country|
+--------------+
| United States|
|         Spain|
|       Uruguay|
|         Japan|
---------------
```

Spark SQL Equivalent:

```
scala> spark.sql("SELECT DISTINCT(Country) from country_medal_count"
).show
```

Appending Rows to Existing Data

- Data can be appended from one DataFrame into another using 'union'
- This is one the great features of Spark, two `DataFrame` can come from two different data sources
- Consider multiple datasource with similar data where you want to structure the data in the same way

Starting with Two Datasources

Consider one DataSource:

```
val countriesMedalCountDF =
    Seq(("United States", "100m Freestyle", 1, 0, 3),
        ("Spain", "100m Butterfly", 2, 1, 1),
        ("Japan", "100m Butterfly", 0, 3, 0),
        ("Spain", "100m Freestyle", 0, 0, 3),
        ("Uruguay", "100m Breaststroke", 0, 1, 0),
        ("United States", "100m Breaststroke", 2, 2, 0))
           .toDF("Country", "Event", "Gold", "Silver", "Bronze")
```

And another that is somewhat different that came from a different source:

```
val countriesMedalCountDF2 =
    Seq(("United States", "100m Freestyle", 1, 0, 3),
        ("Spain", "100m Backstroke", 2, 1, 1),
        ("Spain", "200m Breaststroke", 1, 0, 0),
        ("Spain", "500m Freestyle", 3, 0, 0),
        ("Spain", "1000m Freestyle", 2, 1, 0),
        ("United States", "100m Breaststroke", 2, 2, 0))
           .toDF("Country", "Event", "Gold", "Silver", "Bronze")
```

You also notice that the second you only need `Spain`. You can merge the following:

Using `union` to bring them together

```
scala> countriesMedalCountDF.union(countriesMedalCountDF2.where("country
== 'Spain'")).show(20)
+-------------+-----------------+----+------+------+
|      Country|            Event|Gold|Silver|Bronze|
+-------------+-----------------+----+------+------+
|United States|   100m Freestyle|   1|     0|     3|
|        Spain|   100m Butterfly|   2|     1|     1|
|        Japan|   100m Butterfly|   0|     3|     0|
|        Spain|   100m Freestyle|   0|     0|     3|
|      Uruguay|100m Breaststroke|   0|     1|     0|
|United States|100m Breaststroke|   2|     2|     0|
|        Spain|  100m Backstroke|   2|     1|     1|
|        Spain|200m Breaststroke|   1|     0|     0|
|        Spain|   500m Freestyle|   3|     0|     0|
|        Spain|  1000m Freestyle|   2|     1|     0|
+-------------+-----------------+----+------+------+
```

Sorting

- Sorting is done with `sort` or `orderBy`
- `sort` can either take a list of expressions or `String` that represents the `Column`

- `orderBy` is an alias so that you can express yourself differently
- The default is to sort in ascending order

```
dataFrame.sort("VOLUME").show(5)
dataFrame.orderBy("VOLUME", "HIGH").show(5)
dataFrame.orderBy(col("VOLUME"), col("HIGH")).show(5)
```

```
scala> dataFrame.orderBy("VOLUME", "HIGH").show(5)
+---------+------+------+------+------+------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE|VOLUME|
+---------+------+------+------+------+------+
|25-Nov-16|764.26| 765.0|760.52|761.68|587421|
|23-Dec-16| 790.9|792.74|787.28|789.91|623944|
|18-Aug-16|780.01|782.86| 777.0| 777.5|719429|
|12-Aug-16| 781.5| 783.4| 780.4|783.22|740498|
|29-Dec-16|783.33|785.93|778.92|782.79|744272|
+---------+------+------+------+------+------+
only showing top 5 rows
```

Sorting using functions `asc` and `desc`

- Both `asc` and `desc` are methods that accept a `String` and return `Column`
- Therefore can be used for sorting as a `Column`

```
scala> dataFrame.selectExpr("*").orderBy(desc("VOLUME")).show(5)
+---------+------+------+------+------+-------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|
+---------+------+------+------+------+-------+
|10-Nov-16|791.17|791.17|752.18|762.56|4745183|
|28-Oct-16|808.35|815.49|793.59|795.37|4269902|
|29-Jul-16|772.71|778.55|766.77|768.79|3841482|
|12-Jun-17|939.56|949.36|915.23| 942.9|3763529|
|14-Nov-16| 755.6|757.85|727.54|736.08|3654385|
+---------+------+------+------+------+-------+
only showing top 5 rows
```

Getting the `limit` of the results

- The difference between this function and `head` is that `head` is an action
- `limit` on the other hand is lazy and returns a new `Dataset`.

```
scala> dataFrame.selectExpr("*").limit(5).show(5)
+---------+------+------+------+------+-------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|
+---------+------+------+------+------+-------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|
|17-Jul-17| 957.0|960.74|949.24|953.42|1165537|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|
+---------+------+------+------+------+-------+
```

Repartition

- Just like indexing in RDBS, it would be a good idea in time to repartition often used columns into their own partitions
- This is done for performance and minimizing network traffic
- `repartition` can be set with either:
  - The number of partitions
  - The `Column`
  - Both

```
scala> val largeRange = spark.range(1, 1000000).toDF
largeRange: org.apache.spark.sql.DataFrame = [id: bigint]

scala> largeRange.rdd.getNumPartitions
res145: Int = 4
```

Repartitioning to 10 partitions

```
scala> val largeRangeDistributed = largeRange.repartition(10)
largeRangeDistributed: org.apache.spark.sql.Dataset
[org.apache.spark.sql.Row] = [id: bigint]

scala> largeRangeDistributed.rdd.getNumPartitions
res146: Int = 10
```

Coalesce

- To `coalesce` will also rearrange to a number of partitions
- It will make an attempt to bring down the number of columns where possible
- In the following example, the number of columns will likely be brought down to 4.

```
scala> val largeRange = spark.range(1, 1000000).toDF
largeRange: org.apache.spark.sql.DataFrame = [id: bigint]

scala> val coalescedRange = largeRange.repartition(10).coalesce(5)
coalescedRange: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] =
[id: bigint]

scala> coalescedRange.rdd.getNumPartitions
res148: Int = 4
```

Collect

- `collect()` will get all the rows from the `DataFrame`
- May come at a cost depending on the size of the result
- Will return an `Array[Row]` of your data

```
scala> val collectedData = dataFrame.collect
collectedData: Array[org.apache.spark.sql.Row] = Array([19-Jul-17,967.
84,973.04,964.03,970.89,1224540], [18-Jul-17,953.0,968.04,950.6,965.4
,1153964], [17-Jul-17,957.0,960.74,949.24,953.42,1165537], [14-Jul-17
,952.0,956.91,948.0,955.99,1053774], [13-Jul-17,946.29,954.45,943.01,
947.16,1294687], [12-Jul-17,938.68,946.3,934.47,943.83,1532144], [11-Jul
-17,929.54,931.43,922.0,930.09,1113235], [10-Jul-17,921.77,930.38,919.
59,928.8,1192825], [7-Jul-17,908.85,921.54,908.85,918.59,1637785], [6
-Jul-17,904.12,914.94,899.7,906.69,1424503], [5-Jul-17,901.76,914.51,
898.5,911.71,1813884], [3-Jul-17,912.18,913.94,894.79,898.7,1710373],
[30-Jun-17,926.05,926.05,908.31,908.73,2090226], [29-Jun-17,929.92,931
.26,910.62,917.79,3299176], [28-Jun-17,929.0,942.75,916.0,940.49,
2721406], [27-Jun-17,942.46,948.29,...
```

User Defined Functions

- If you don't have enough functions to work with? Create your own!
- Start with a standard function

```
def is_odd(x:Int):Boolean = x % 2 != 0
```

- Wrap it in a `udf` (User defined function)

```
val is_odd_udf = udf(is_odd(_:Int):Boolean)
```

- Use the `udf`

```
scala> dataFrame.withColumn("IS_ODD_VOLUME", is_odd_udf('VOLUME)).show(
5)
+---------+------+------+------+------+-------+-------------+
|     DATE|  OPEN|  HIGH|   LOW| CLOSE| VOLUME|IS_ODD_VOLUME|
+---------+------+------+------+------+-------+-------------+
|19-Jul-17|967.84|973.04|964.03|970.89|1224540|        false|
|18-Jul-17| 953.0|968.04| 950.6| 965.4|1153964|        false|
|17-Jul-17| 957.0|960.74|949.24|953.42|1165537|         true|
|14-Jul-17| 952.0|956.91| 948.0|955.99|1053774|        false|
|13-Jul-17|946.29|954.45|943.01|947.16|1294687|         true|
+---------+------+------+------+------+-------+-------------+
```

Joins

- Spark can bring in separate DataFrames/Datasets and join them together
- Joins are *left* and *right*
- Matched by a *key*

Join Types

inner joins	Keep rows with keys that exist in the left and right `Dataframe`
outer joins	Keep rows with keys in either the left or right `DataFrame`
left outer joins	Keep rows with keys in the left `DataFrame`
right outer joins	Keep rows with keys in the right `DataFrame`
left semi joins	Keep the rows in the left and only left `DataFrame` where the key appears in the right `DataFrame`
left anti joins	Keep the rows in the left and only the left `DataFrame` where they does not appear in the right `DataFrame`
cross joins	Match every row in the left `DataFrame` with every row in the right `DataFrame`

Setting up the tables to join

Given the following:

```
val cities = Seq(
                  (1, "San Francisco", "CA"),
                  (2, "Dallas", "TX"),
                  (3, "Pittsburgh", "PA"),
                  (4, "Buffalo", "NY"),
                  (5, "Oklahoma City", "OK"),
                  (6, "New York City", "NY"),
                  (7, "Los Angeles", "CA"),
                  (8, "Omaha", "NE")).toDF("id", "city", "state")

val teams = Seq(
                  (1, 7, "Rams", "Football"),
                  (2, 7, "Dodgers", "Baseball"),
                  (3, 6, "Giants", "Football"),
                  (4, 1, "Giants", "Baseball"),
                  (5, 4, "Bills", "Football"),
                  (6, 3, "Pirates", "Baseball"),
                  (7, 1, "49ers", "Football"),
                  (8, 3, "Steelers", "Football")).toDF("id", "city_id",
"team", "sport_type")
```

Inner Join

Create an inner join with the following:

```
scala> val innerjoin = cities.join(teams, cities.col("id") === teams.
col("city_id"))
```

The above returns the following:

```
scala> innerjoin.show
+---+-------------+-----+---+-------+--------+----------+
| id|         city|state| id|city_id|    team|sport_type|
+---+-------------+-----+---+-------+--------+----------+
|  1|San Francisco|   CA|  7|      1|   49ers|  Football|
|  1|San Francisco|   CA|  4|      1|  Giants|  Baseball|
|  3|   Pittsburgh|   PA|  8|      3|Steelers|  Football|
|  3|   Pittsburgh|   PA|  6|      3| Pirates|  Baseball|
|  4|      Buffalo|   NY|  5|      4|   Bills|  Football|
|  6|New York City|   NY|  3|      6|  Giants|  Football|
|  7|  Los Angeles|   CA|  2|      7| Dodgers|  Baseball|
|  7|  Los Angeles|   CA|  1|      7|    Rams|  Football|
+---+-------------+-----+---+-------+--------+----------+
```

Outer Join

Create an outer join with the following:

```
scala> val outerjoin = cities.join(teams, cities.col("id") === teams.
col("city_id"), "outer")
```

The above returns the following:

```
scala> outerjoin.show
+---+-------------+-----+----+-------+--------+----------+
| id|         city|state|  id|city_id|    team|sport_type|
+---+-------------+-----+----+-------+--------+----------+
|  1|San Francisco|   CA|   4|      1|  Giants|  Baseball|
|  1|San Francisco|   CA|   7|      1|   49ers|  Football|
|  6|New York City|   NY|   3|      6|  Giants|  Football|
|  3|   Pittsburgh|   PA|   6|      3| Pirates|  Baseball|
|  3|   Pittsburgh|   PA|   8|      3|Steelers|  Football|
|  5|Oklahoma City|   OK|null|   null|    null|      null|
|  4|      Buffalo|   NY|   5|      4|   Bills|  Football|
|  8|        Omaha|   NE|null|   null|    null|      null|
|  7|  Los Angeles|   CA|   1|      7|    Rams|  Football|
|  7|  Los Angeles|   CA|   2|      7| Dodgers|  Baseball|
|  2|       Dallas|   TX|null|   null|    null|      null|
+---+-------------+-----+----+-------+--------+----------+
```

Duplicate Keys

- In the other example, keys have also been duplicated, `id` and `id`
- One `id` is for the `city`, the other is for `team`
- Use `withColumnRenamed` to establish desired field names

```
val outerjoin = cities.join(teams.withColumnRenamed("id", "team_id"),
cities.col("id") === teams.col("city_id"), "outer").withColumnRenamed
("id", "city_id").show
```

This gives the result of:

```
+-------+------------+-----+-------+-------+--------+----------+
|city_id|        city|state|team_id|city_id|    team|sport_type|
+-------+------------+-----+-------+-------+--------+----------+
|      1|San Francisco|   CA|      4|      1|  Giants|  Baseball|
|      1|San Francisco|   CA|      7|      1|   49ers|  Football|
|      6|New York City|   NY|      3|      6|  Giants|  Football|
|      3|   Pittsburgh|   PA|      6|      3| Pirates|  Baseball|
|      3|   Pittsburgh|   PA|      8|      3|Steelers|  Football|
|      5|Oklahoma City|   OK|   null|   null|    null|      null|
|      4|      Buffalo|   NY|      5|      4|   Bills|  Football|
|      8|        Omaha|   NE|   null|   null|    null|      null|
|      7|  Los Angeles|   CA|      1|      7|    Rams|  Football|
|      7|  Los Angeles|   CA|      2|      7| Dodgers|  Baseball|
|      2|       Dallas|   TX|   null|   null|    null|      null|
+-------+------------+-----+-------+-------+--------+----------+
```

Clustering

Clustering Methodology

- Clustering in Spark can be done with:
  - Standalone Mode
  - YARN
  - Mesos

Glossary

Term	Description
Application	User program built on Spark. Consists of a driver program and executors on the cluster.
Application jar	A jar containing the user’s Spark application. In some cases users will want to create an "uber jar" containing their application along with its dependencies. The user’s jar should never include Hadoop or Spark libraries, however, these will be added at runtime.
Driver program	The process running the main() function of the application and creating the SparkContext
Cluster manager	An external service for acquiring resources on the cluster (e.g. standalone manager, Mesos, YARN)
Deploy mode	Distinguishes where the driver process runs. In "cluster" mode, the framework launches the driver inside of the cluster. In "client" mode, the submitter launches the driver outside of the cluster.
Worker node	Any node that can run application code in the cluster
Executor	A process launched for an application on a worker node, that runs tasks and keeps data in memory or disk storage across them. Each application has its own executors.
Task	A unit of work that will be sent to one executor
Job	A parallel computation consisting of multiple tasks that gets spawned in response to a Spark action (e.g. save, collect); you’ll see this term used in the driver’s logs.
Stage	Each job gets divided into smaller sets of tasks called stages that depend on each other (similar to the map and reduce stages in MapReduce); you’ll see this term used in the driver’s logs.