INF 553: Foundations and Applications of Data Mining (Summer 2020)

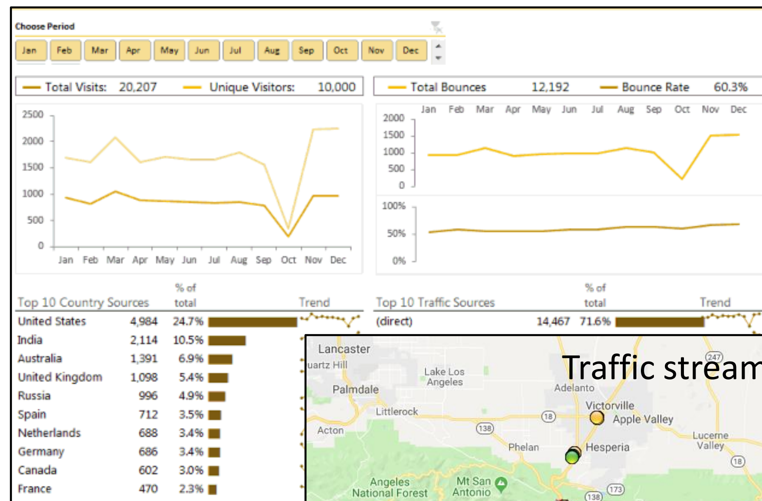
Introduction to Spark and Scala

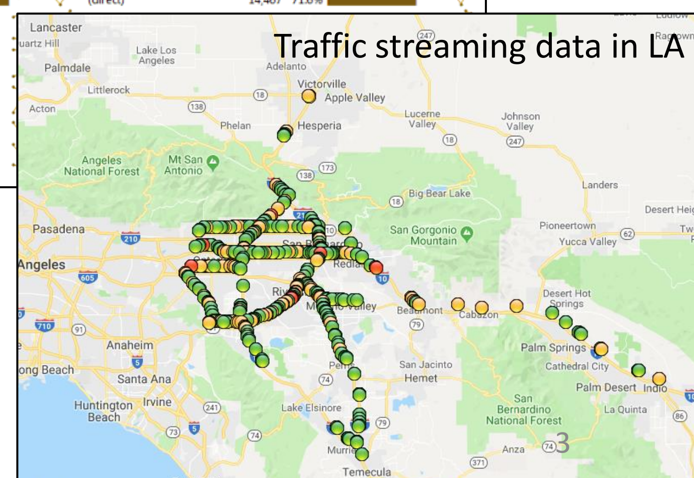
Thanks for source slide and material to: Weiwei Duan and Dr. Heather Miller
https://www.coursera.org/learn/scala-spark-big-data/home/welcome

What is Spark?

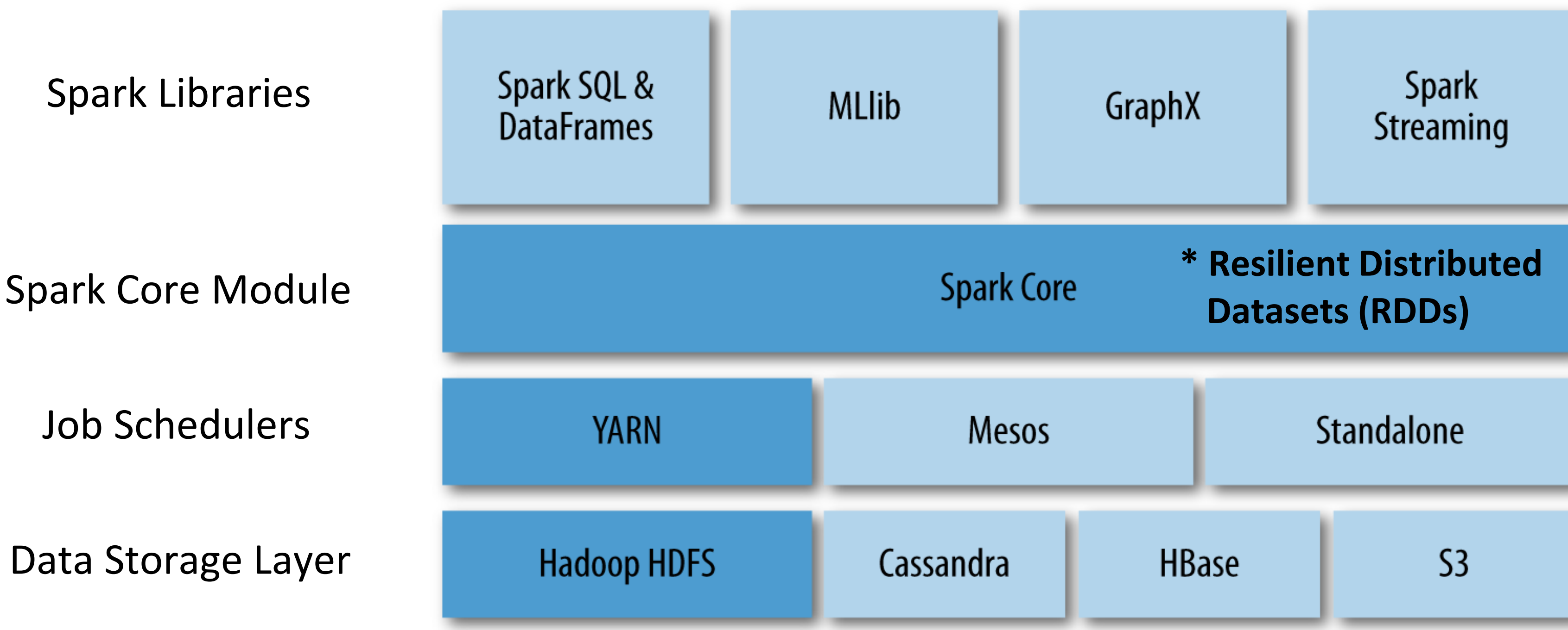
- **Apache Spark** is a unified analytics engine for large-scale data processing

- Application areas
  - Interactive Data Query
  - Real-time Data Analysis
  - Streaming Data Processing





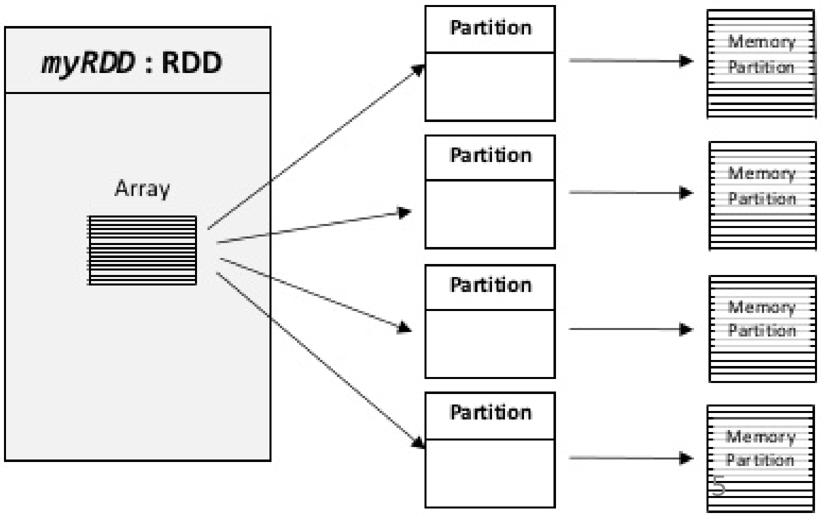
Spark Stack


Spark Libraries
Spark SQL & DataFrames
MLlib
GraphX
Spark Streaming
Spark Core Module
Spark Core
* Resilient Distributed Datasets (RDDs)
Job Schedulers
YARN
Mesos
Standalone
Data Storage Layer
Hadoop HDFS
Cassandra
HBase
S3

Resilient Distributed Datasets (RDDs)

- An RDD is an **immutable**, **in-memory collection** of objects
- Each RDD can be split into multiple partitions, which in turn are computed on different nodes of the cluster

- RDDs seem a lot like Scala collections
  - RDD[T] and List[T]



Resilient Distributed Datasets (RDDs)

- Resilient
- Distributed
- In-Memory
- Immutable
- Lazy Evaluated
- Cacheable
- Parallel
- Partitioned
- Location-Stickiness

How to create an RDD

- RDDs can be created in two ways:
  - Creating from a SparkContext object
    - ParallelizedCollections
    - External datasets
  - Transforming from an existing RDD

RDD Creation – SparkContext Object

- Creating from a **SparkContext** object
  - Can be thought as your handle to the Spark cluster
  - Represents the connection to a Spark cluster

```
conf = SparkConf().setAppName(appName).setMaster(master)
sc = SparkContext(conf=conf)
```

RDD Creation – SparkContext Object

- Creating from a **SparkContext** object
  - **parallelize**: convert a local Scala collection to an RDD

```
val aList: List[String] = List("you", "jump", "I", "jump", "")
// Create an RDD from a list
val wordsRDD = sc.parallelize(aList) // RDD[String]
```

RDD Creation – SparkContext Object

- Creating from a **SparkContext** object
  - **parallelize**: convert a local Scala collection to an RDD

```scala
val aList: List[String] = List("you", "jump", "I", "jump", "")
// Create an RDD from a list
val wordsRDD = sc.parallelize(aList) // RDD[String]
```

  - **textFile**: read a file from HDFS or local file system

```scala
val textRDD = sc.textFile("./text.txt")
```

RDD Creation – Transforming existing RDD

- Transforming from an existing RDD
  - E.g., calling a *map operation* on an existing RDD, it will return a new RDD

```
// call a map operation on wordsRDD
val lengthRDD = wordsRDD.map(_.length) // RDD[Int]
```

RDD Operations

- Transformations
  - E.g., map, filter, ...

```scala
// call a map operation on wordsRDD
val lengthRDD = wordsRDD.map(_.length) // RDD[Int]
```

- Actions
  - E.g., collect, reduce ...

```scala
val wordsColl = wordsRDD.collect() // RDD -> Collection
print(wordsColl.toList) // List("you", "jump", "I", "jump", "")
```

Transformations VS Actions

- Transformations
  - Return new RDDs as results
  - They are **lazy**, the result RDD is not immediately computed
- Actions
  - Compute a result based on an RDD, and returned
  - They are **eager**, the result is immediately computed

Transformations VS Actions

- Transformations
  - Return new RDDs as results
  - They are **lazy**, the result RDD is not immediately computed

```
// call a map operation on wordsRDD
val lengthRDD = wordsRDD.map(_.length) // RDD[Int]
```

- Actions
  - Compute a result based on an RDD, and returned
  - They are **eager**, the result is immediately computed

```
val wordsColl = wordsRDD.collect() // RDD -> Collection
print(wordsColl.toList) // List("you", "jump", "I", "jump", "")
```

Common Transformations

map

map[T](f: A=>B): RDD[T]
Apply function to each element in the RDD and return an RDD of the result.

flatmap

flatmap[T](f: A=>B): RDD[T]
Apply function to each element in the RDD and return an RDD of the result, but output is flattened.

filter

filter[T](pred: A=>Boolean): RDD[T]
Apply predicate function, pred, to each element in the RDD and return an RDD of elements that passed the condition.

distinct

distinct():RDD[T]
Return an RDD with duplicates removed

Common Transformations

flatmap **flatmap[T](f: A=>B): RDD[T]**

Apply function to each element in the RDD and return an RDD of the result, but output is flattened.

```
val text: List[String] = List("you and me", "jump and run", "I love you", "jump forward", "")
val textRDD = sc.parallelize(text)

val splitText = textRDD.flatMap(phase => phase.split(" ")) // Flatten the output

val splitTextColl = splitText.collect()
splitTextColl.foreach(println) // "you", "me", "jump", "and", "run", "I", "love", "you", "jump", "forward"
```

Common Transformations

distinct **distinct():RDD[T]**

Return an RDD with duplicates removed

```
val text: List[String] = List("you and me", "jump and run", "I love you", "jump forward", "")
val textRDD = sc.parallelize(text)

val splitText = textRDD.flatMap(phase => phase.split(" ")) // Flatten the output
val textDist = splitText.distinct() // Get the distinct words

val textDistColl = textDist.collect()
textDistColl.foreach(println) // "me", "I", "love", "run", "forward", "jump", "you", "and"
```

Common Actions

collect	**collect: Array[T]** Return all elements from RDD.
count	**count(): Long** Return the number of elements in the RDD.
take	**take(num: Int): Array[T]** Return the first num elements of the RDD.
reduce	**reduce(op: (A, A) => A): A** Combine the elements in the RDD together using op function and return result.
foreach	**foreach(f: A => Unit): Unit** Apply function to each element in the RDD, and return Unit.

Common Actions

count **count(): Long**

Return the number of elements in the RDD.

```
val text: List[String] = List("you and me", "jump and run", "I love you", "jump forward", "")
val textRDD = sc.parallelize(text)

val splitText = textRDD.flatMap(phase => phase.split(" ")) // Flatten the output
val textDist = splitText.distinct() // Get the distinct words
val counts = textDist.count() // return 8
```

Example

- Consider the following example:

```
val aList: List[String] = List("you", "jump", "I", "jump", "")
// Create an RDD from a list
val wordsRDD = sc.parallelize(aList) // RDD[String]

// call a map operation on wordsRDD
val lengthRDD = wordsRDD.map(_.length) // RDD[Int]
```

What has happened on the cluster at this point?

Example (Cont.)

- Consider the following example:

```
val aList: List[String] = List("you", "jump", "I", "jump", "")
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```

What has happened on the cluster at this point?

Nothing. Execution of map (a transformation) is deferred.

Example (Cont.)

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```

What has happened on the cluster at this point?
Nothing. Execution of *map* (a transformation) is deferred.

How to ensure this computation is done on the cluster?

Example (Cont.)

- Consider the following example:

```
val aList: List[String] = List("you", "jump", "I", "jump", "")
// Create an RDD from a list
val wordsRDD = sc.parallelize(aList) // RDD[String]

// call a map operation on wordsRDD
val lengthRDD = wordsRDD.map(_.length) // RDD[Int]
val totalChars = lengthRDD.reduce(_+_) // 12
```

add an action, *reduce*

Spark starts the execution when an action is called

Return the total number of characters in the entire RDD of strings

Benefits of Laziness

- Another example:

```
val logs: RDD[String] = ...
val logsWithErrors = logs.filter(_.contain("ERROR")).take(10)
```

Benefits of Laziness

- Another example:

```
val logs: RDD[String] = ...
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- The execution of *filter* is deferred until the *take* action happens
  - Spark will not compute intermediate RDDs. As soon as 10 elements of the filtered RDD have been computed, *logsWithErrors* is done.

Benefits of Laziness

- Another example:

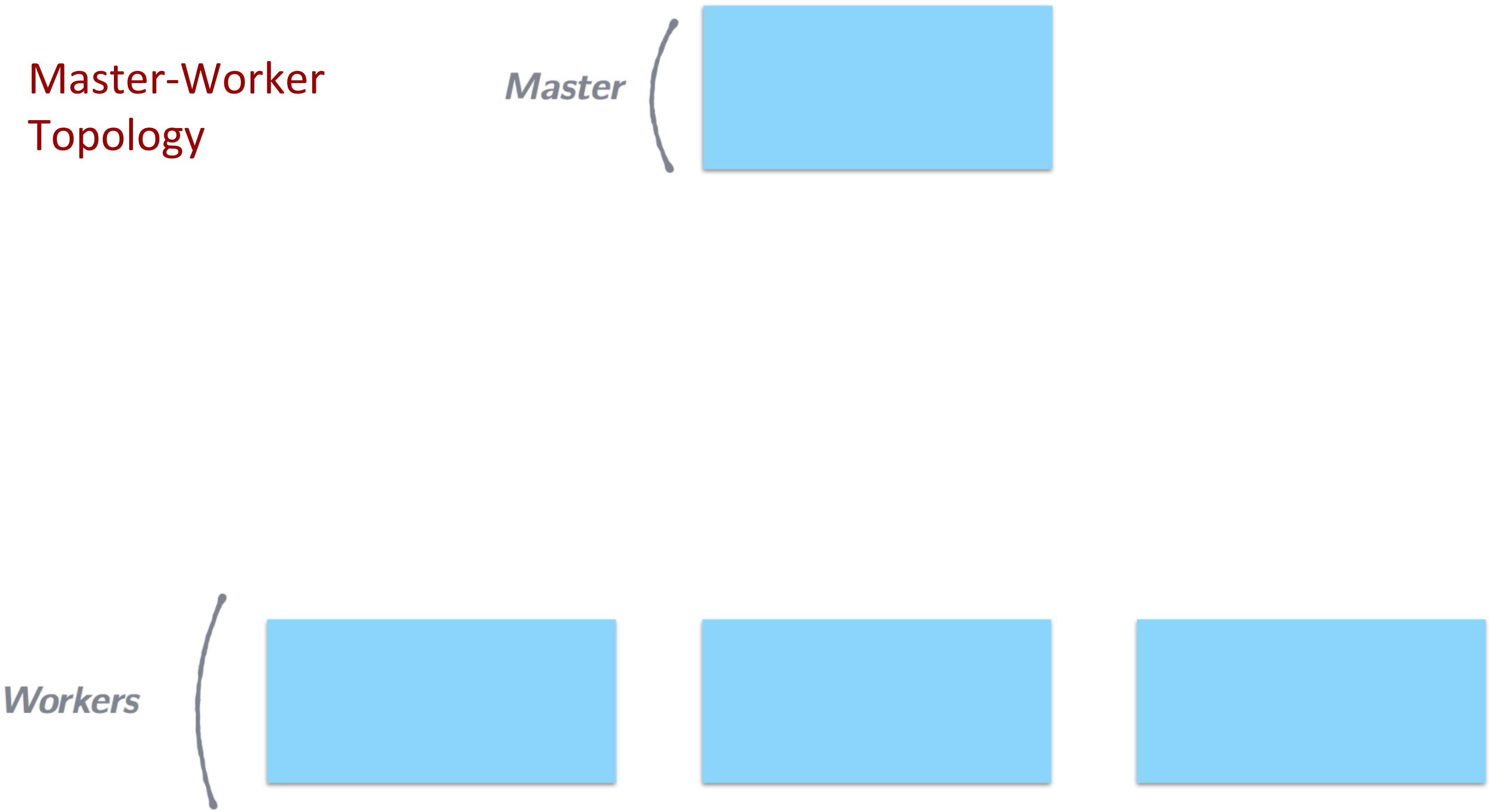
```
val logs: RDD[String] = ...
val logsWithErrors = logs.filter(_.contain("ERROR")).take(10)
```

- The execution of *filter* is deferred until the *take* action happens
  - Spark will not compute intermediate RDDs. As soon as 10 elements of the filtered RDD have been computed, *logsWithErrors* is done

- Spark leverages this by analyzing and optimizing the chain of operations before executing it
  - Spark saves time and space to compute elements of the unused result of the *filter operation*

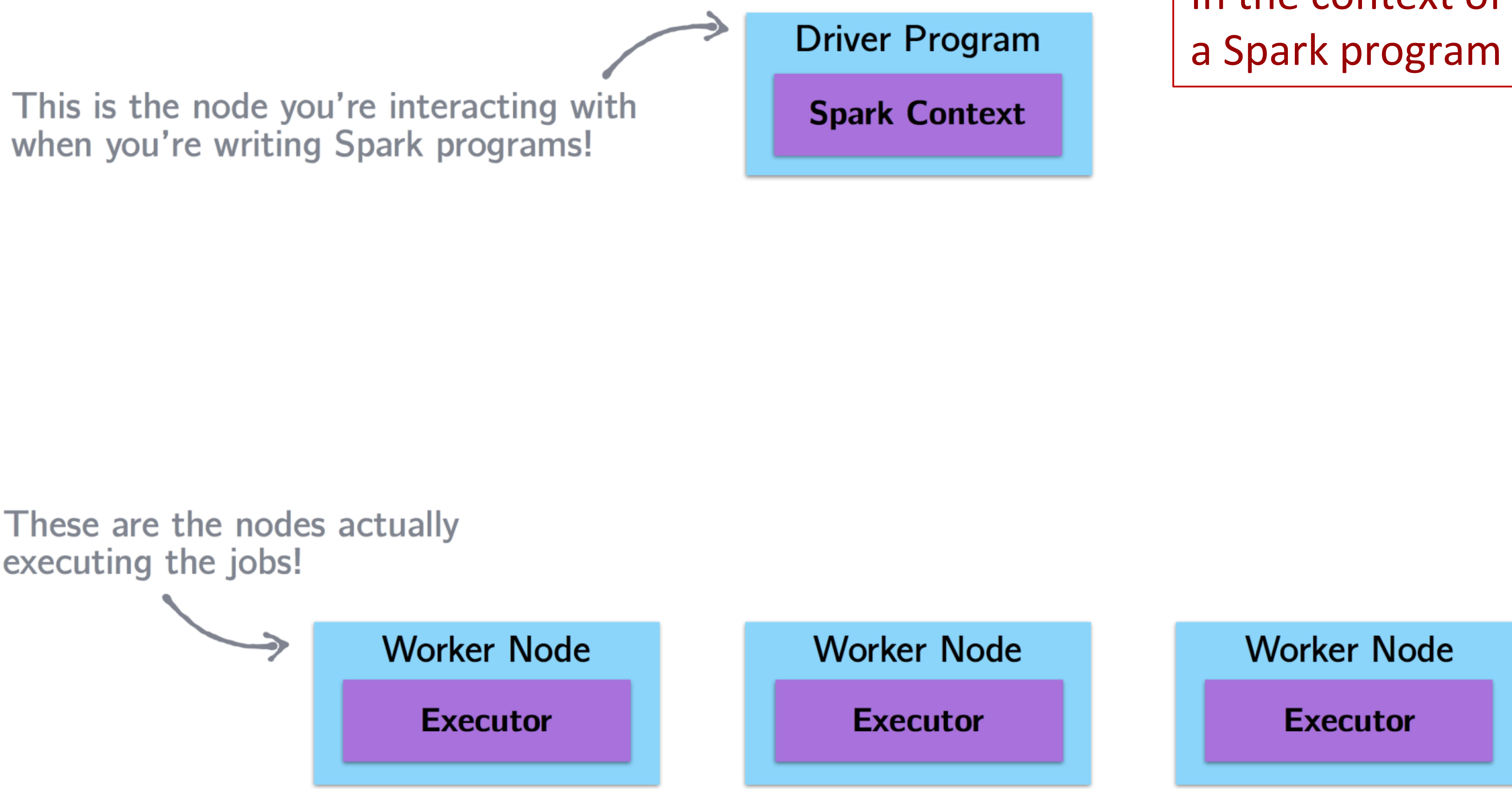
How Spark jobs are Executed

Master-Worker Topology

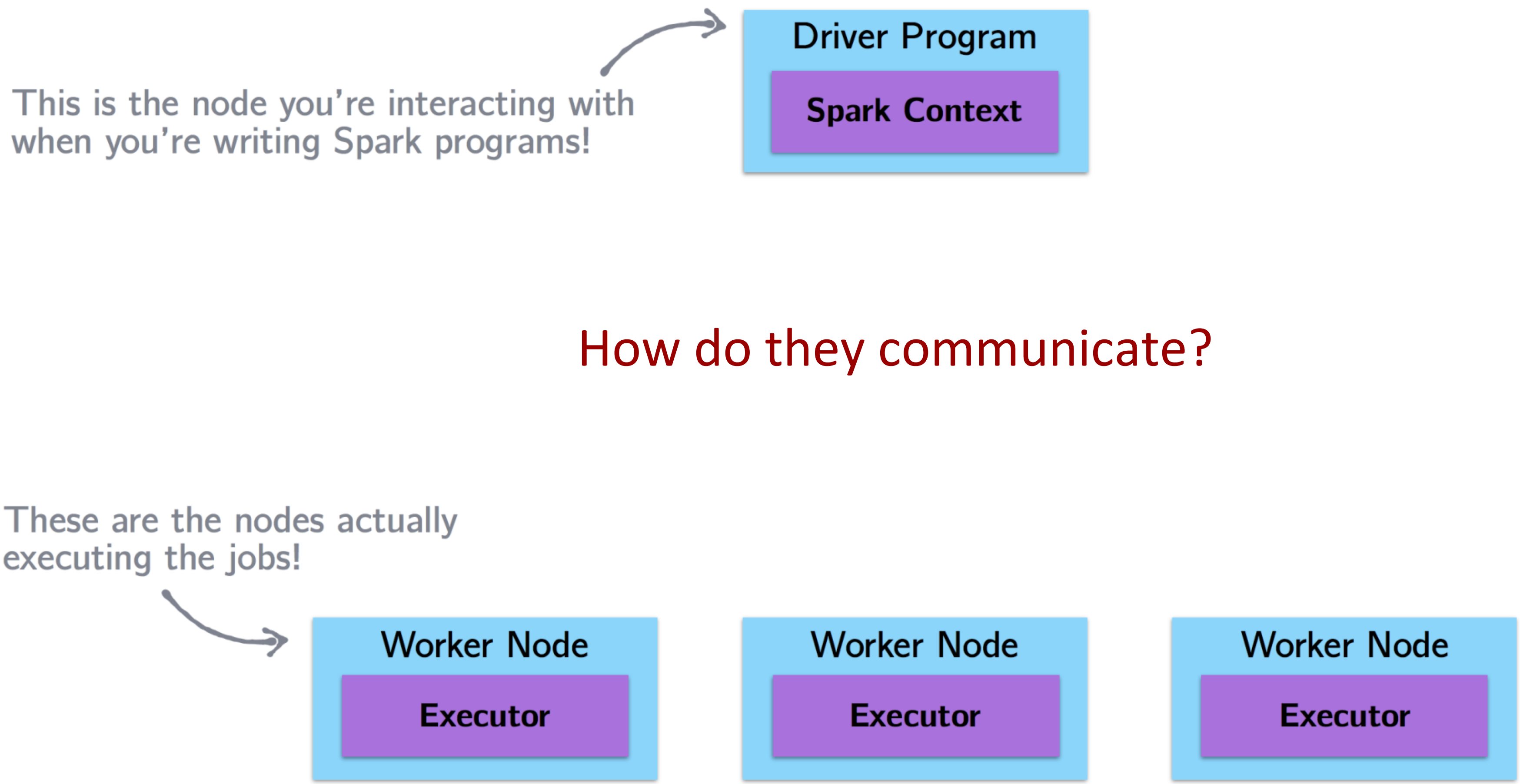


How Spark jobs are Executed

In the context of a Spark program



How Spark jobs are Executed



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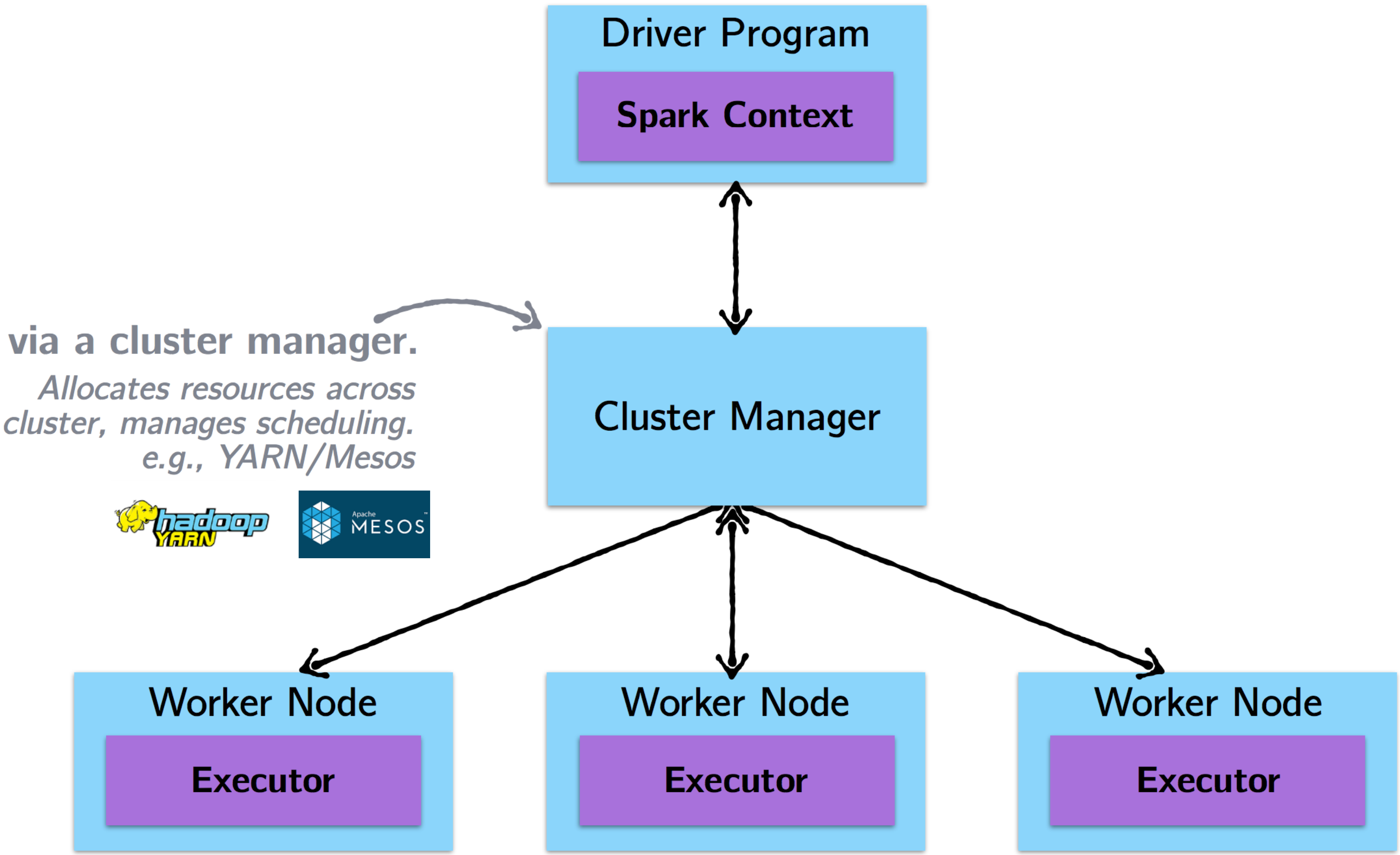
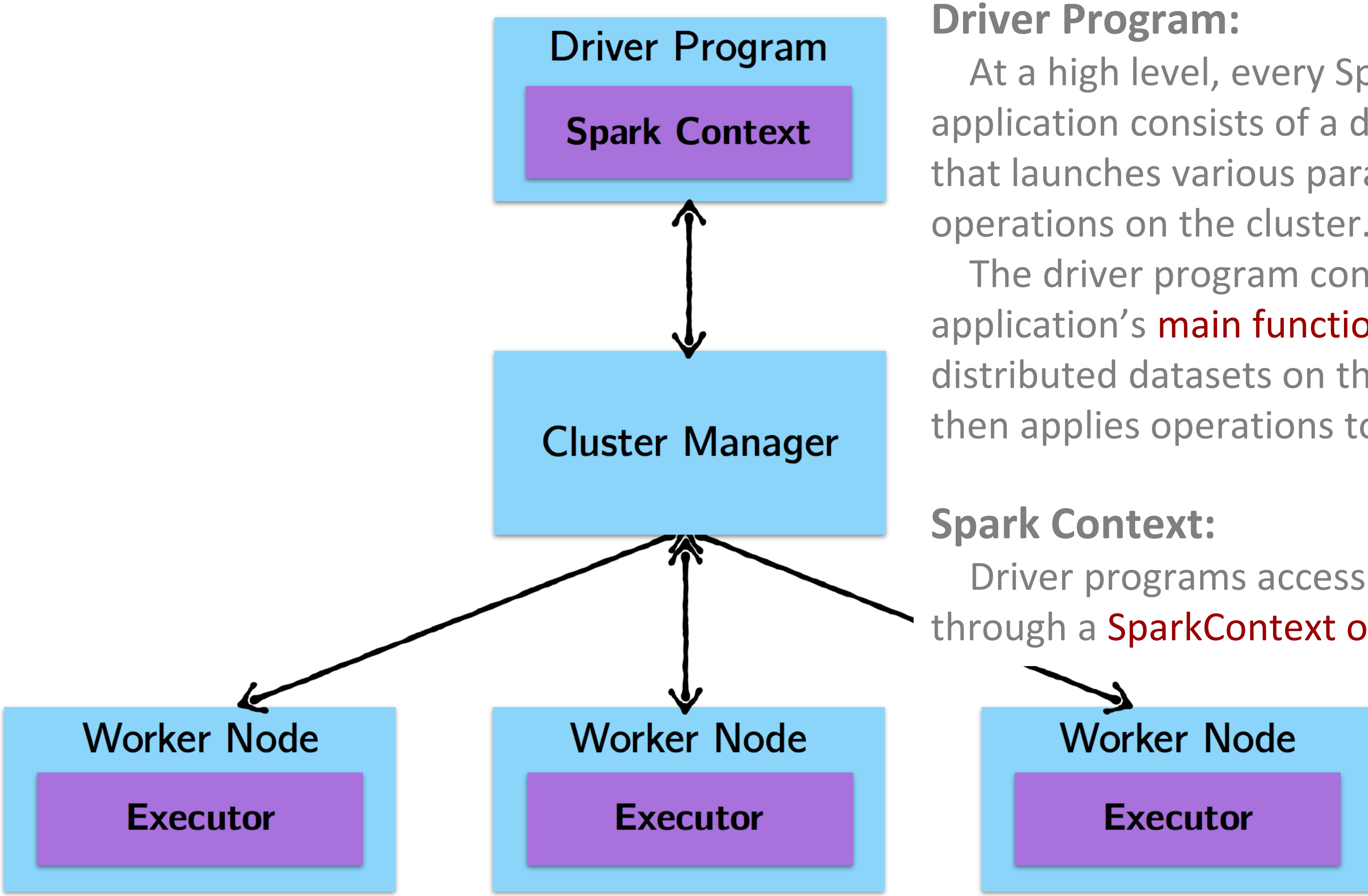


How Spark jobs are Executed



Driver Program:

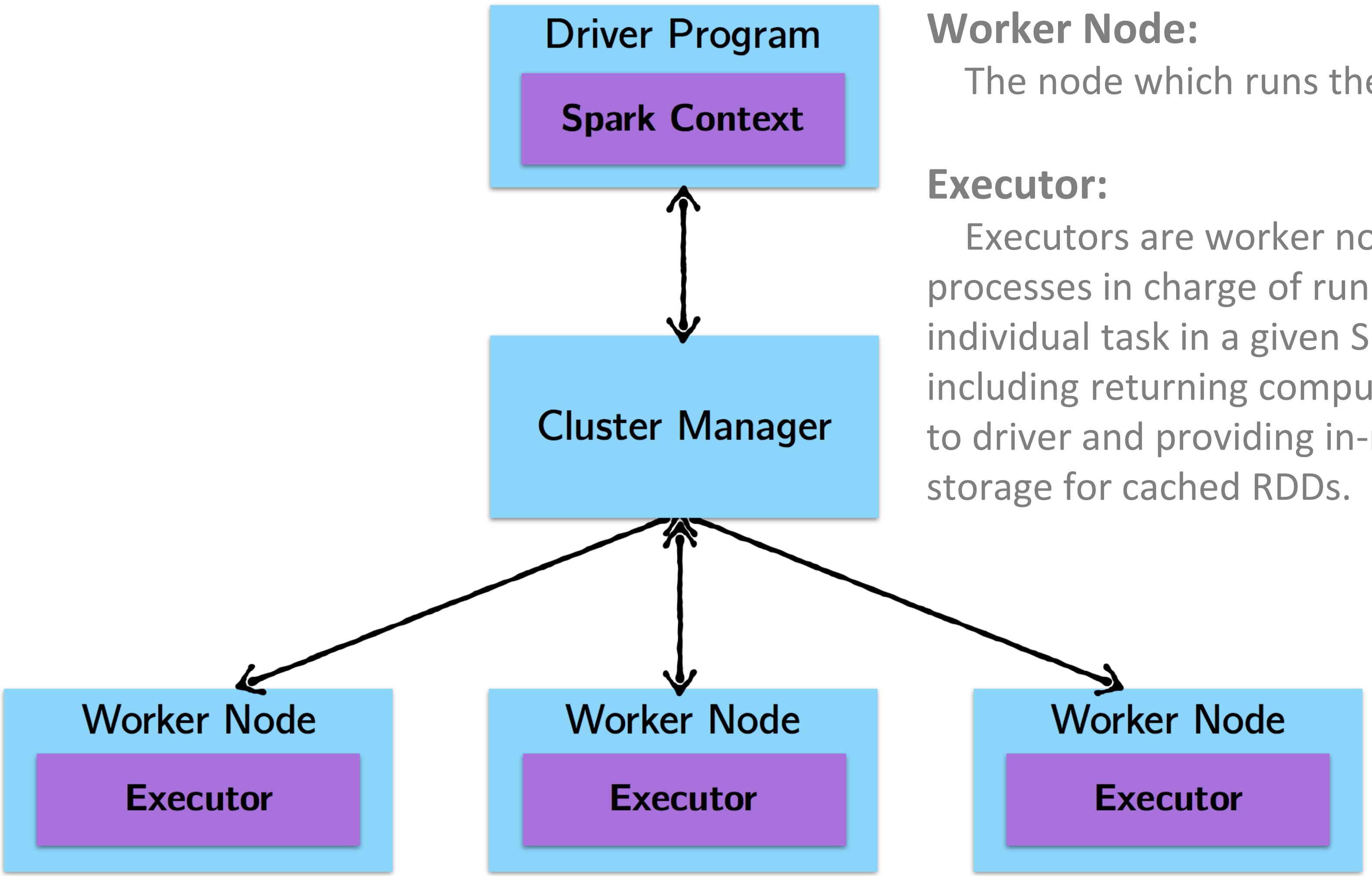
At a high level, every Spark application consists of a driver program that launches various parallel operations on the cluster.

The driver program contains your application's main function and defines distributed datasets on the cluster, then applies operations to them.

Spark Context:

Driver programs access Spark through a SparkContext object

How Spark jobs are Executed



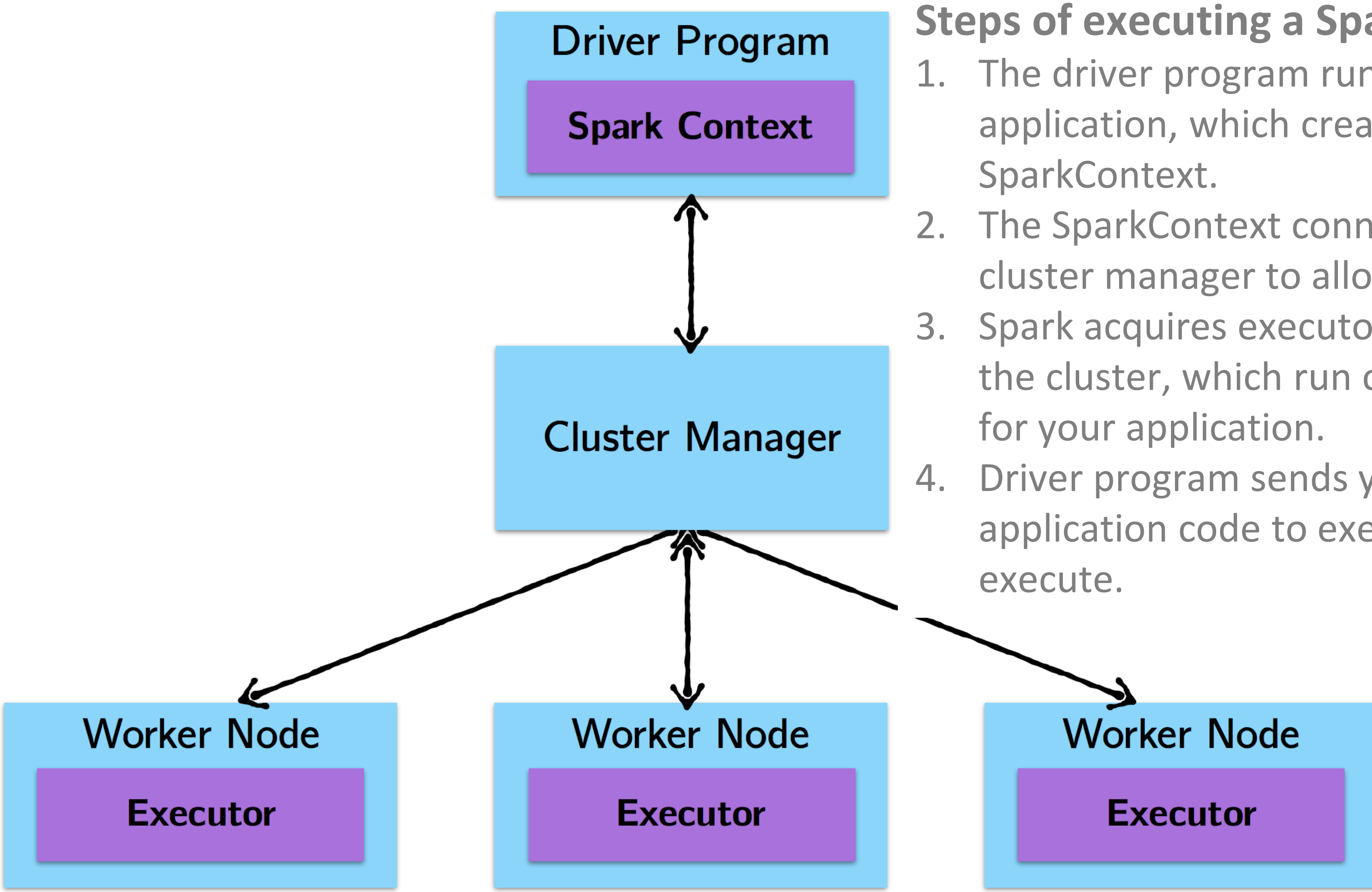
Worker Node:

The node which runs the application

Executor:

Executors are worker nodes' processes in charge of running individual task in a given Spark job, including returning computed results to driver and providing in-memory storage for cached RDDs.

How Spark jobs are Executed



Steps of executing a Spark program:

1. The driver program runs the Spark application, which creates a SparkContext.
2. The SparkContext connects to a cluster manager to allocate resources
3. Spark acquires executors on nodes in the cluster, which run computations for your application.
4. Driver program sends your application code to executors to execute.

Cluster Topology

- A simple example with *println*

```scala
case class Person(name: String, age: Int)

val people: RDD[Person]
people.foreach(println)
```

What happens?

Cluster Toplogy

- A simple example with *println*

```
case class Person(name: String, age: Int)

val people: RDD[Person]
people.foreach(println)
```

The driver node: Nothing.

The worker node: Print results.

Why? Recall that foreach is **an action**, with **return type Unit**. Therefore, it will be eagerly executed on the executors. Thus, any calls to *println* are happening on the worker nodes and are not visible in the drive node.

Cluster Topology

- Another simple example with *take*

```
case class Person(name: String, age: Int)

val people: RDD[Person]
people.foreach(println)

val first10 = people.take(10)
```

Where will *first10* end up?

Cluster Topology

- Another simple example with *take*

```scala
case class Person(name: String, age: Int)

val people: RDD[Person]
people.foreach(println)

val first10 = people.take(10)
```

Where will *first10* end up? The driver program.

In general, executing an action involves communication between worker nodes and the node running the driver program.

Why Spark is Good for Data Sci

- In-memory computation

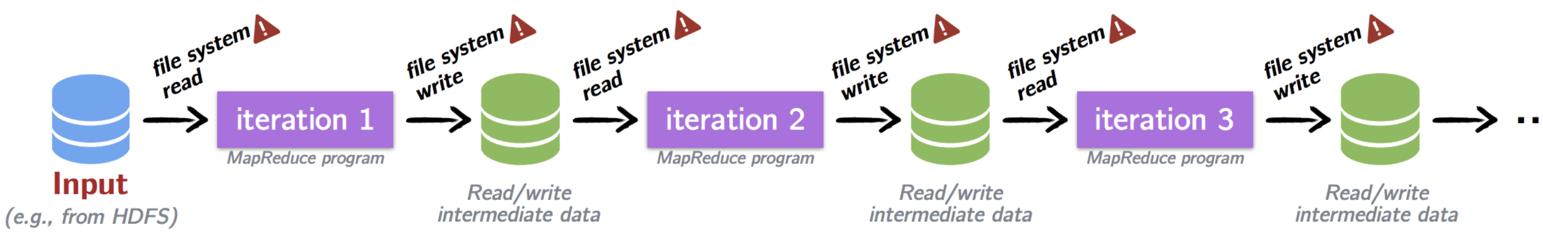
- RDD operations
  - Transformations: Lazy, deferred
  - Actions: Eager, kick off staged transformations

- Why Spark is good for data science?
  - Machine learning algorithms

Iteration

- Most data science problems **involve iterations**

Iteration in Hadoop:



Iteration

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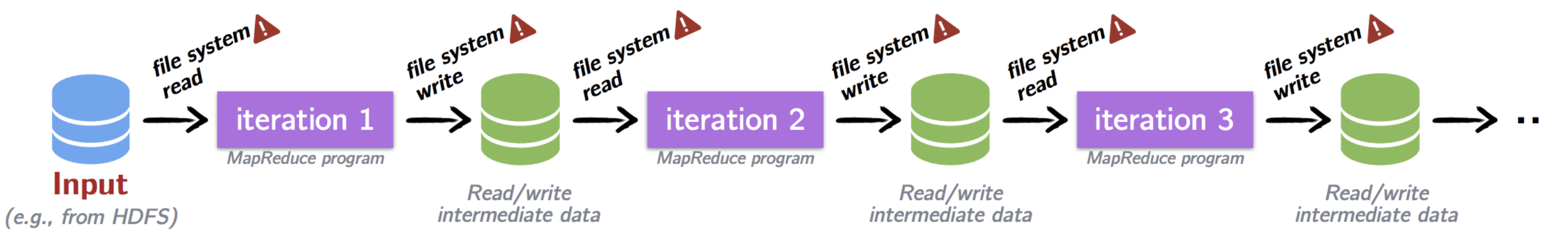
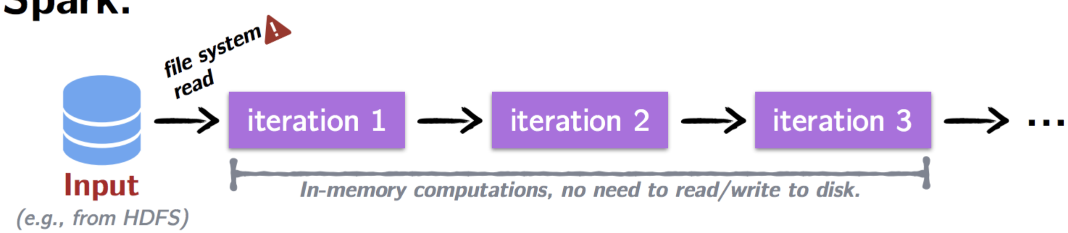
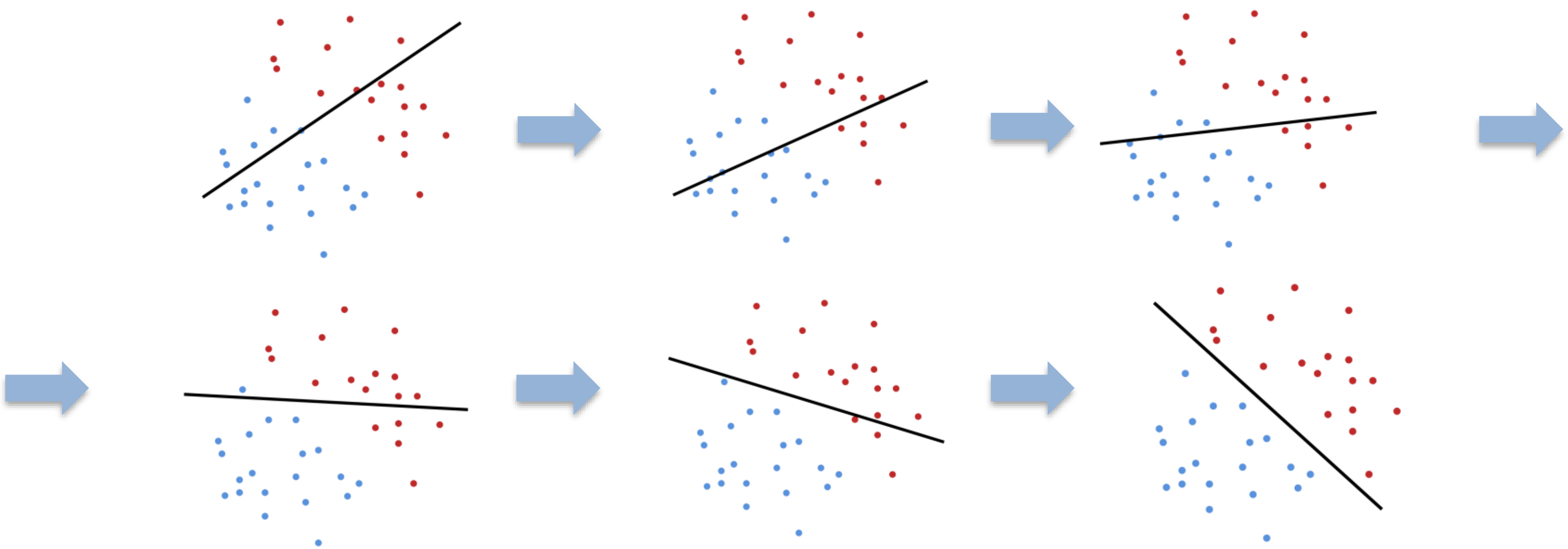


Iteration in Spark:



Iteration
Example: Logistic Regression

- Logistic regression is **an iterative algorithm** typically used for classification. Like most classification algorithms, it **updates weights iteratively** base on the training data.



Iteration
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$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$

Iteration
Example: Logistic Regression

- Logistic regression sample code:

```
val points = sc.textFile(...).map(parsePoint) // case class Point(x: Double, y: Double)
var w = Vector.zero(d)
for(i <- 1 to numIterations) {
  val gradient = points.map {p =>
    g(p) // Apply the function of logistic regression
  }.reduce(_+_)
  w -= alpha * gradient
}
```

$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$

Iteration
Example: Logistic Regression

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$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$

What is the weakness for this code?

Iteration
Example: Logistic Regression

- Logistic regression sample code:

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}
```

Spark starts the execution when the action *reduce* is applied

Iteration
Example: Logistic Regression

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  }.reduce(_+_)
  w -= alpha * gradient
}
```

***points* is being re-evaluated upon every iteration!**
Unnecessary!

Caching and Persistence

- By default, RDDs are recomputed each time you run an action on them. This can be expensive (time-consuming) if you need to use a dataset more than once.

Spark allows you to control what is cached in memory
use *persist()* or *cache()*

cache() : using the default storage level
persist(): can pass the storage level as a parameter,
e.g., "MEMORY_ONLY", "MEMORY_AND_DISK"
default

Iteration
Example: Logistic Regression

- Logistic regression sample code:

```
val points = sc.textFile(...).map(parsePoint).persist() // case class Point(x: Double, y: Double)
var w = Vector.zero(d)
for(i <- 1 to numIterations) {
  val gradient = points.map {p =>
    g(p) // Apply the function of logistic regression
  }.reduce(_+_)
  w -= alpha * gradient
}
```

***points* is evaluated once and is cached in memory.**
It can be re-used on each iteration.

Why Spark is Good for Data Sci

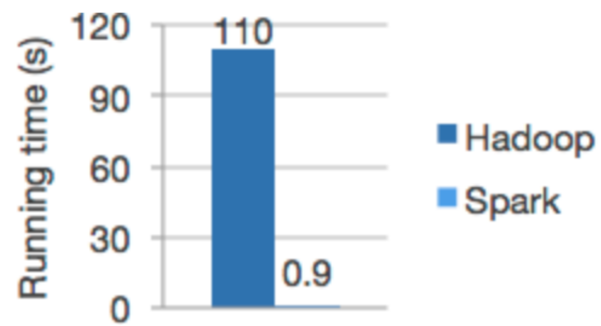
- **The lazy semantics** of RDD transformation operations help improve the performance.

- One of the most common performance bottlenecks for newcomers to Spark arises from unknowingly re-evaluating several transformations when caching could be used.

Spark vs. Hadoop

- **Spark is Faster**
  - When the output of an operation needs to be fed into another operation, Spark passes the data directly without writing to persistent storage
  - Better for some iterative algorithms

  e.g. machine learning algorithms



Logistic regression in Hadoop and Spark

Spark runs programs up to 100x faster than Hadoop MapReduce in memory. [1]

[1] https://spark.apache.org/

Other advantages

- **Easy to use**
  - Write applications quickly in Java, Scala, Python
- **Runs Everywhere**
  - Spark runs on Hadoop, standalone, or in the cloud
  - It can access diverse data sources including HDFS, Cassandra, HBase, and S3
- **Generality**
  - Combine SQL, streaming, and complex analytics

[1] https://spark.apache.org/

What is Scala?

Object-oriented programming language

```scala
class Point(val xc: Int, val yc: Int) {
   var x: Int = xc
   var y: Int = yc

   def move(dx: Int, dy: Int) {
      x = x + dx
      y = y + dy
      println ("Point x location : " + x);
      println ("Point y location : " + y);
   }
}

class Location(override val xc: Int, override val yc: Int,
   val zc :Int) extends Point(xc, yc){
   var z: Int = zc

   def move(dx: Int, dy: Int, dz: Int) {
      x = x + dx
      y = y + dy
      z = z + dz
      println ("Point x location : " + x);
      println ("Point y location : " + y);
      println ("Point z location : " + z);
   }
}
```

```scala
object Demo {
   def main(args: Array[String]) {
      val loc = new Location(10, 20, 15);

      // Move to a new location
      loc.move(10, 10, 5);
   }
}
```

(Singleton) **Object:**
A class that can have only one instance.

Usually we use object to call the main function

What is Scala?

Functional programming language

```
def addInt1( a:Int, b:Int ) : Int = {
    var sum = a + b
    return sum
}
var res1=addInt1(1,2)
```

- **Anonymous Functions**

```
def addInt2=(a: Int, b: Int) => a+b
var res2=addInt2(1,2)
```

- **Higher-Order Functions**

Functions that take other functions as parameters

```
def output(f: Int => String, v: Int) = f(v)
def layout[A](x: A) = "[" + x.toString() + "]"
println(output( layout, res2))
```

Final output:
[3]

Install Spark

- Download Spark from official website:
  - http://spark.apache.org/downloads.html
  - we will use spark version 2.3.2 (you can find it in Archived Releases)

Download Apache Spark™

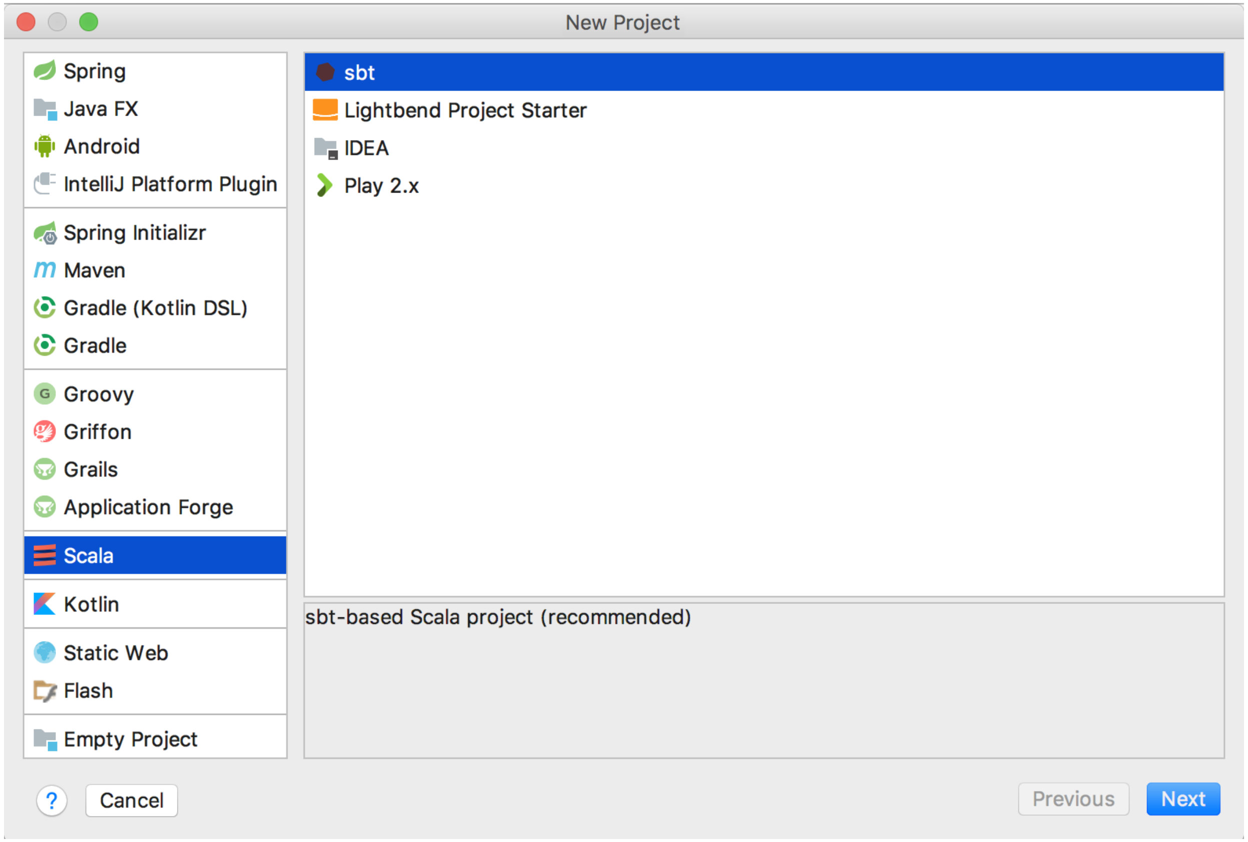
1. Choose a Spark release: 2.3.1 (Jun 08 2018)
2. Choose a package type: Pre-built for Apache Hadoop 2.7 and later
3. Download Spark: spark-2.3.1-bin-hadoop2.7.tgz
4. Verify this release using the 2.3.1 signatures and checksums and project release KEYS.

Install Scala

- IntelliJ IDEA, the compiler:
  – https://www.jetbrains.com/idea/#chooseYourEdition

- Install Scala plugin in the compiler
  – Open *Preference* -> Choose [*Plugins] ->* Click [*Install JetBrains plugin] (at bottom) ->* Search *Scala* and Install

Create an SBT project



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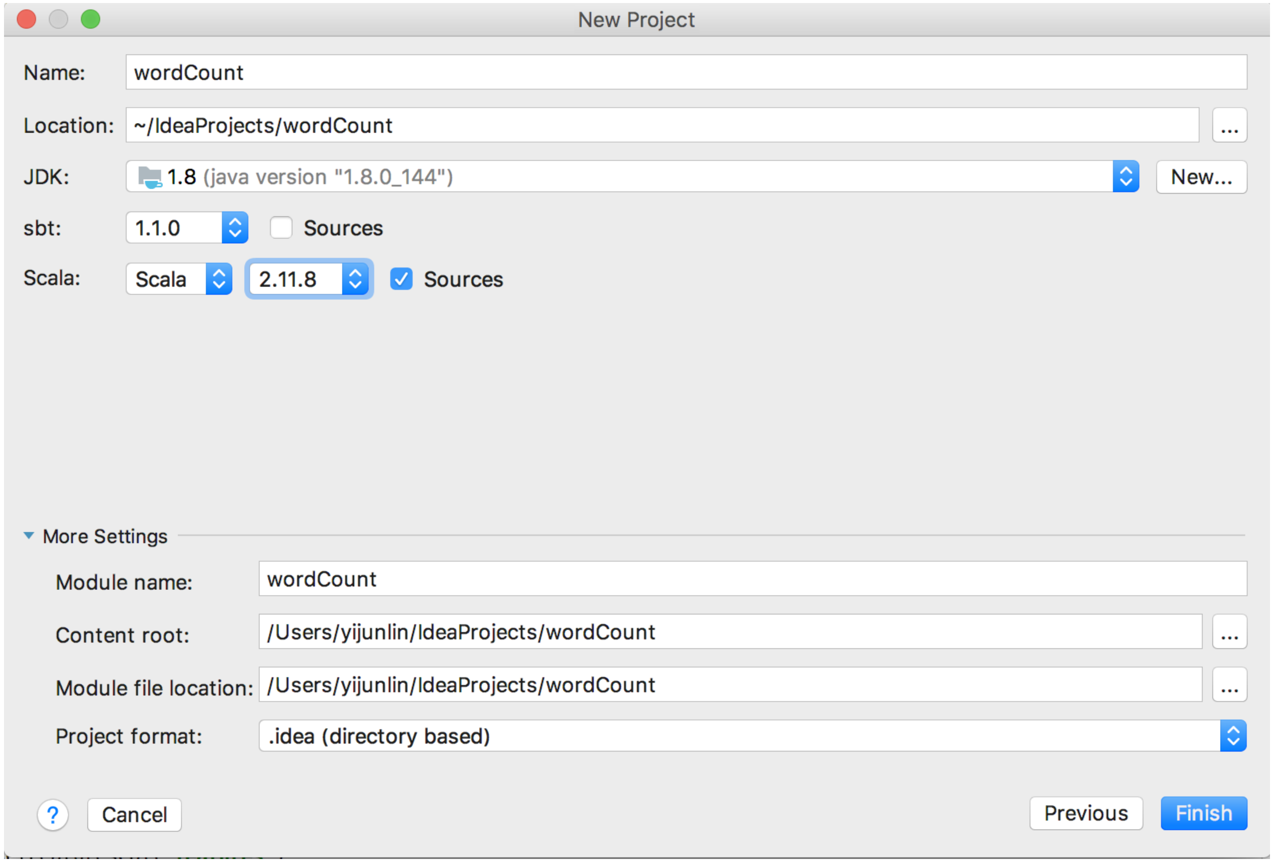
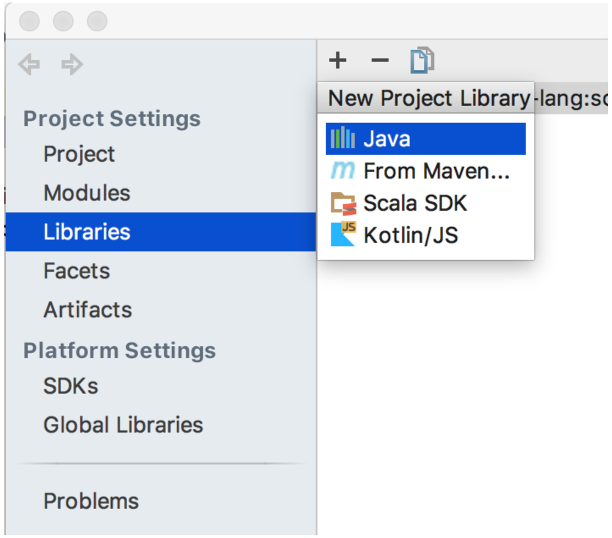
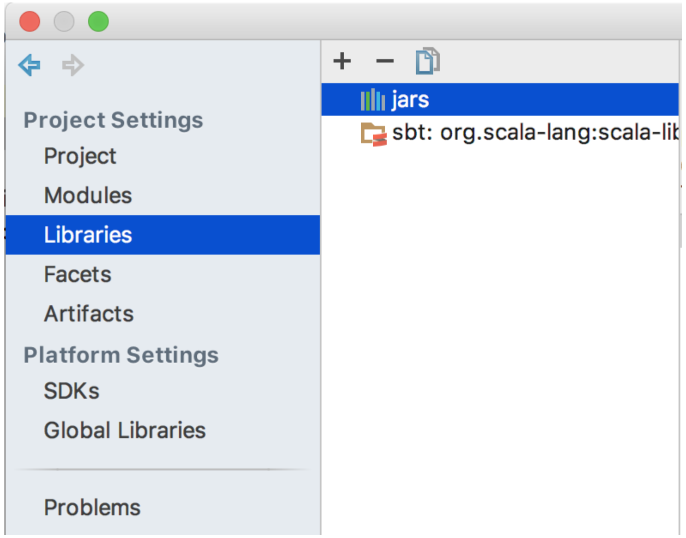


Add Spark Environment

- You can add Spark either in **External Libraries** or through build.sbt
  - External Libraries:
  - Click [File] -> [Project Structure] -> [Libraries] -> [+] Java library -> Add the **jar package/.jar file** from the Spark you download





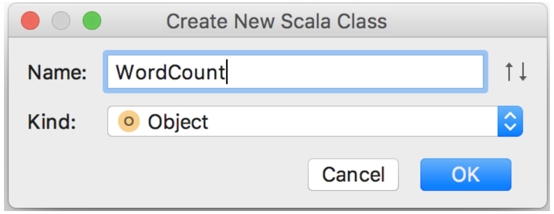
Add Spark Environment

- You can also add Spark **through build.sbt**
  - build.sbt (we will use spark version 2.3.2)

build.sbt

```
name := "wordCount"

version := "0.1"

scalaVersion := "2.11.8"

val sparkVersion = "2.1.0"

resolvers ++= Seq(
  "apache-snapshots" at "http://repository.apache.org/snapshots/"
)

libraryDependencies ++= Seq(
  "org.apache.spark" %% "spark-core" % sparkVersion,
  "org.apache.spark" %% "spark-sql" % sparkVersion,
  "org.apache.spark" %% "spark-mllib" % sparkVersion,
  "org.apache.spark" %% "spark-streaming" % sparkVersion,
  "org.apache.spark" %% "spark-hive" % sparkVersion
)

```

Write Scala Code

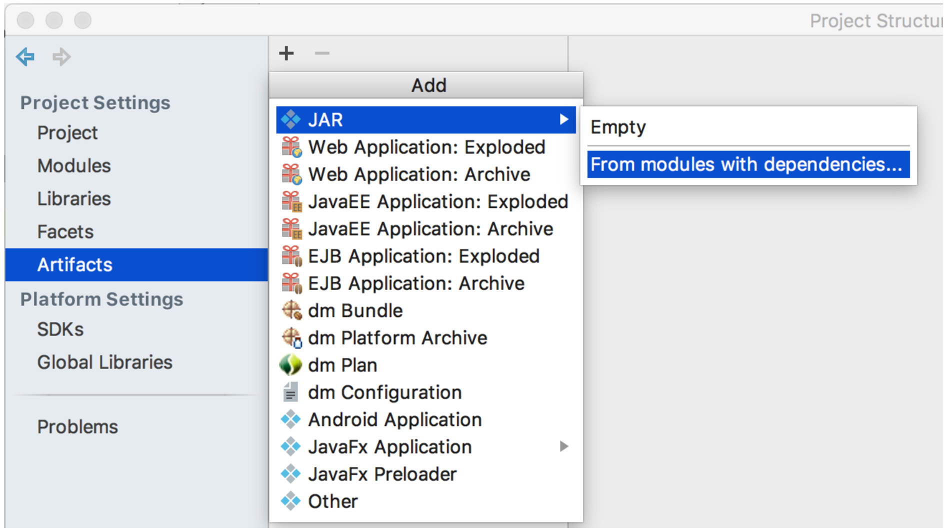


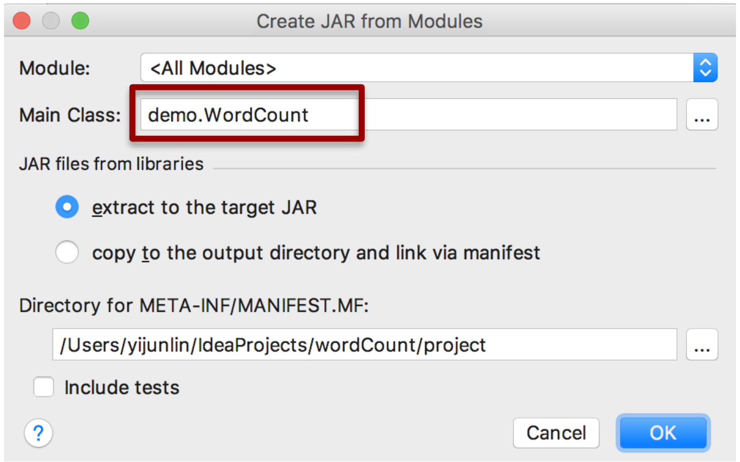
Create new Scala object

```scala
import org.apache.log4j.{Level, Logger}
import org.apache.spark.sql.SparkSession


object wordCount {

  def main(args:Array[String]): Unit = {

    Logger.getLogger("org").setLevel(Level.INFO)

    val ss = SparkSession // Configure your Spark job here
      .builder()
      .appName("wordCount")
      .config("spark.master", "local[*]")
      .getOrCreate()

    val sc = ss.sparkContext
    val textRDD = sc.textFile("./text.txt")
    val counts = textRDD.flatMap(line => line.split(" ")).map(x => (x, 1)).reduceByKey(_+_).collect()

    counts.foreach(println)

  }
}
```

Build jar

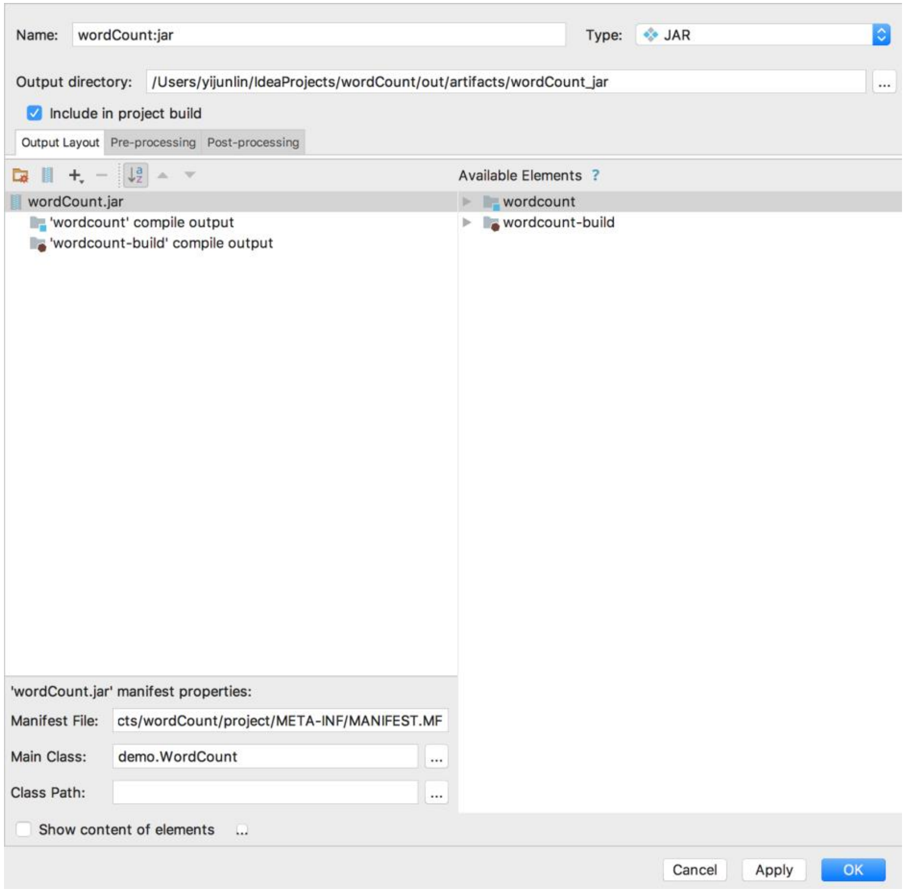
- Click [File] -> [Project Structure] -> [Artifacts] -> [+] JAR -> [From modules with dependencies] -> Put the Main Class of your code (or you can leave it to be empty) -> [OK]





Build jar

- You need to **delete all the spark libraries** or other unrelated libraries that you would not use in your program; Have "Include in project build" checked; Click [OK]



- Click [Build] -> [Build Artifacts] -> [Build] -> produce the package *out*, the jar file is in it!

Run jar on Spark - command line

```
Yijuns-MacBook-Pro:~ yijunlin$ Tools/spark-2.1.0-bin-hadoop2.7/bin/spark-submit
--class demo.WordCount --master local[2] ./IdeaProjects/wordCount/out/artifacts/
wordCount_jar/wordCount.jar
```

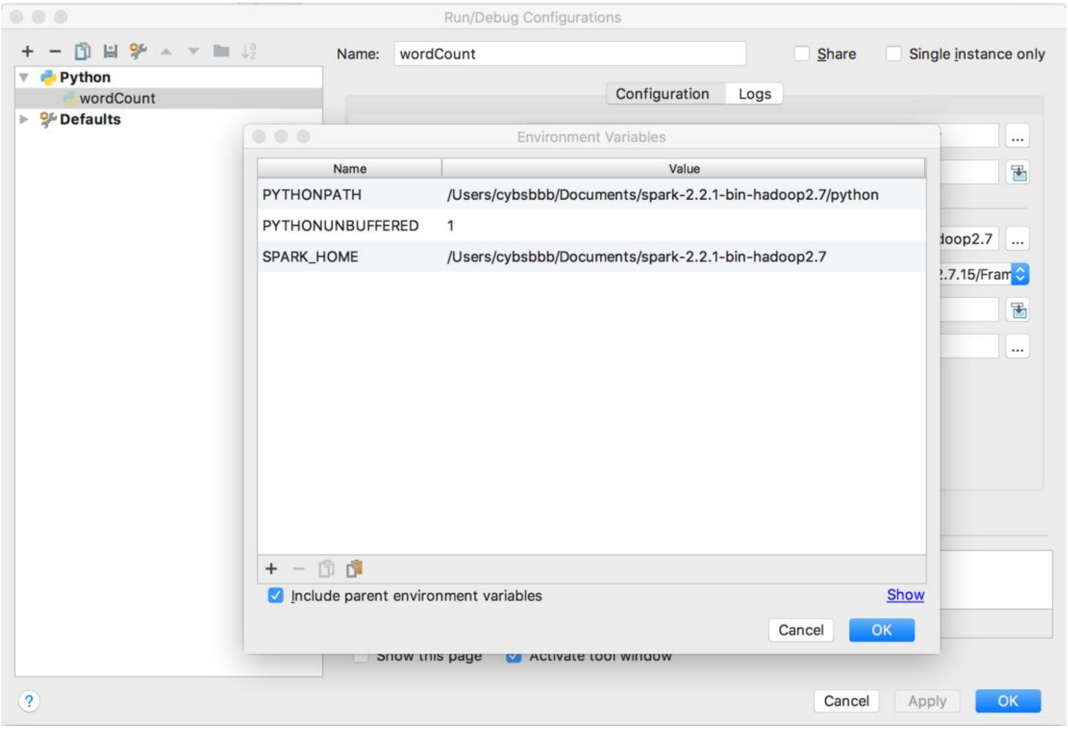
Show the Result:

```
(event,3)
(customized,1)
(rate,1)
(video,2)
(Figure,1)
(range,,1)
(integrating,1)
((4),1)
(Event:,1)
(content,2)
(demonstrates,1)
```

```
(conditions.,1)
(satellite,1)
(geographical,1)
(for,3)
(decision-making,1)
(detecting,1)
(Nearest,1)
(meter:,1)
((e.g.,,4)
(5,400,1)
(buses,1)
```

pyspark

- You can use pip to install pyspark in commandline
- Or config in PyCharm ide:
  - click[Run] -> [Edit Configurations] -> Add[Environment variables]



pyspark

- Make sure keep the same python version for driver and worker
- Try the word_count.py to test the environment

word_count.py × text.txt ×

```python
from pyspark import SparkContext
import os

os.environ['PYSPARK_PYTHON'] = '/usr/local/bin/python3.6'
os.environ['PYSPARK_DRIVER_PYTHON'] = '/usr/local/bin/python3.6'

sc = SparkContext('local[*]', 'wordCount')

input_file_path = './text.txt'
textRDD = sc.textFile(input_file_path)

counts = textRDD.flatMap(lambda line: line.split(' ')) \
    .map(lambda word: (word, 1)).reduceByKey(lambda a, b: a+b).collect()

for each_word in counts:
    print(each_word)
```

```
('Apache', 1)
('Spark', 2)
('is', 1)
('general-purpose', 1)
('It', 2)
('provides', 1)
('high-level', 1)
('APIs', 1)
('in', 1)
('Scala,', 1)
('Java,', 1)
('Python', 1)
('make', 1)
('parallel', 1)
('write,', 1)
('an', 1)
('optimized', 1)
('engine', 1)
('supports', 2)
('computation', 1)
```

Run python on Spark
- command line

- Make sure keep the same python version for driver and worker
  - Edit ./conf/spark-env.sh (copy from ./conf/spark-env.sh.template)
  - Add environment variables

```
export PYSPARK_PYTHON=/usr/local/bin/python3.6
export PYSPARK_DRIVER_PYTHON=/usr/local/bin/python3.6
```

```
vpn-052-143:spark-2.3.1-bin-hadoop2.7 yijunlin$ bin/spark-submit ../../PycharmProjects/inf553sp
ring2019/word_count.py
```

Configuration on Linux and Windows

- Install python version
  - You can find many tutorial on Google
- Install JDK
  - Download jdk and config PATH in bash file
- Download Spark and config PATH
  - SPARK_HOME and PYTHONPATH

Programming Environment

- Python – 3.6
- Spark - 2.3.2
- Scala – 2.11

If you want to learn more…

- Official documentation
  - http://spark.apache.org/docs/latest/
- Online course
  - Coursera: Big Data Analysis with Scala and Spark
- Books
  - *Learning Spark, O' Reilly*
  - Advanced Analytics with Spark: Patterns for Learning from Data at Scale, *O' Reilly*
  - *Machine Learning with Spark, Packt*