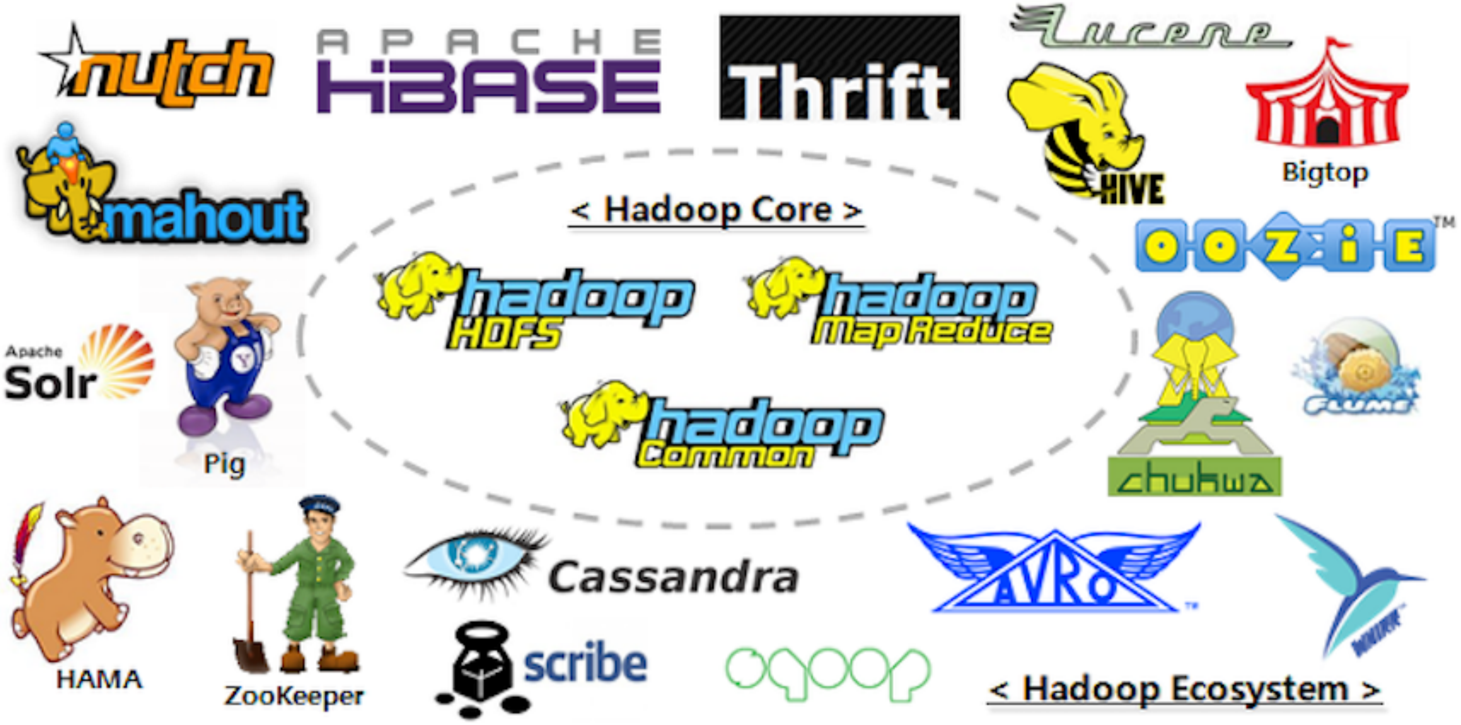
Introduction to Using Spark on the Big Data Cluster

Getting Help

- Submit a ticket to the Helpdesk
- Join the accre-forum Slack team!
  - https://accre-forum.slack.com/signup
  - Use your Vanderbilt email address to register
  - Join the `#bigdata` channel to communicate and collaborate
- Check out our GitHub organization at github.com/bigdata-vandy
- Check out our blog at bigdata-vandy.github.io
- Schedule a meeting for your research group

The Hadoop Ecosystem



How is Big Data different from HPC?

Traditional HPC	Big Data
Move the data to the code	Move the code to the data
Centralized storage via GPFS	Distributed storage via HDFS
Perfomant languages (C/C++, Fortran)	Abstract languages (Java, Scala, Python)
Imperative programming	Functional programming

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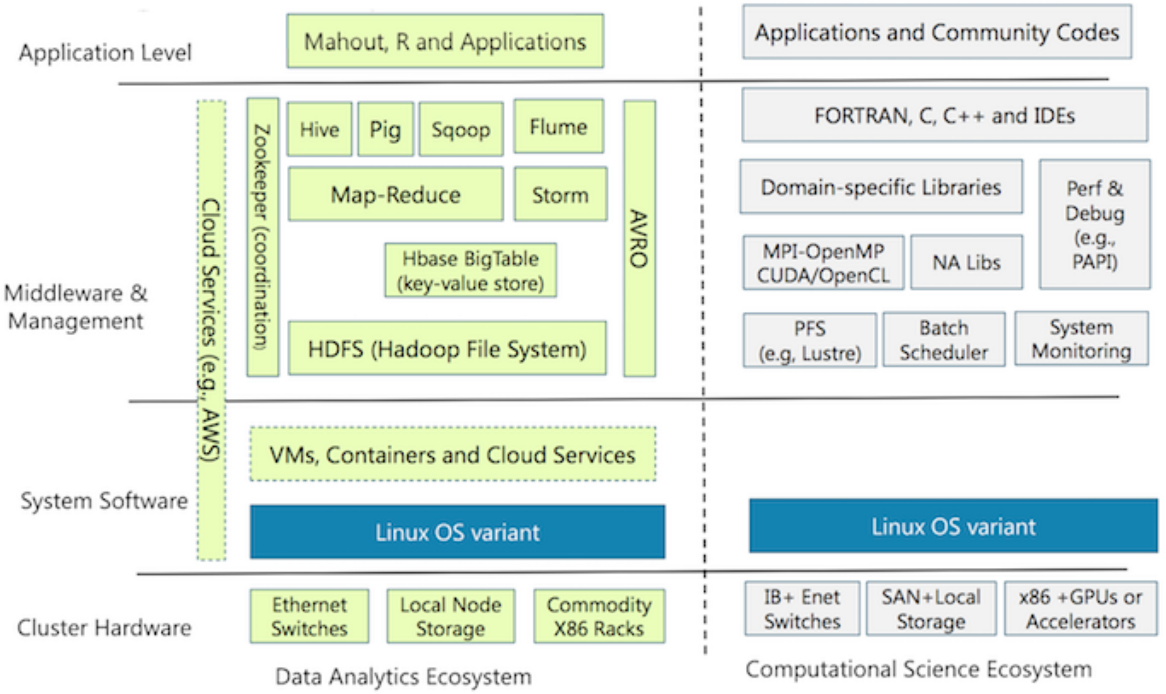
Candidates for Big Data solutions:

- Lots of data
- Embarrasingly parallel data processing
- Machine learning
- Network analysis
- Processing/analysis of streaming data

Divergent Ecosystems



Dan Reed, “Clouds, Big Data, and the Future of Computing,” CASC Fall 2015 Meeting, Washington, D.C.

BigData Test Cluster - Available Now!

Initial deployment for testing, prototyping, and benchmarking only, using recycled hardware

- 3 management nodes
    - 8 CPU cores, 92 GB RAM per node
- 6 data nodes
    - 8 TB, 8 CPU cores, 92 GB RAM per node

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BigData Production Environment - Available Fall 2017

Newly purchased hardware!!

- 4 management nodes
    - 16 CPU cores, 128 GB RAM per node
- 9 data nodes
    - 80 TB, 32 CPU cores, 512 GB RAM per node

BigData Cluster Management with Cloudera

Cloudera Manager is used to deploy, configure, and manage the bigdata cluster

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Service	**Description**
HDFS	Hadoop Distributed File System - replicated, partitioned data
YARN	Yet Another Resource Negotiator
MapReduce 2	MapReduce jobs running on top of YARN
Spark	MapReduce-like + cacheing
Oozie	Web app for scheduling Hadoop jobs
Hue	User interface for constructing Jobs
Hive	ETL transformations expressed as SQL
Impala	Interactive SQL
HBase	Random, realtime read/write access to distributed big data store
Pig	High-level language for expressing data analysis programs
Solr	Text search engine supporting free form queries

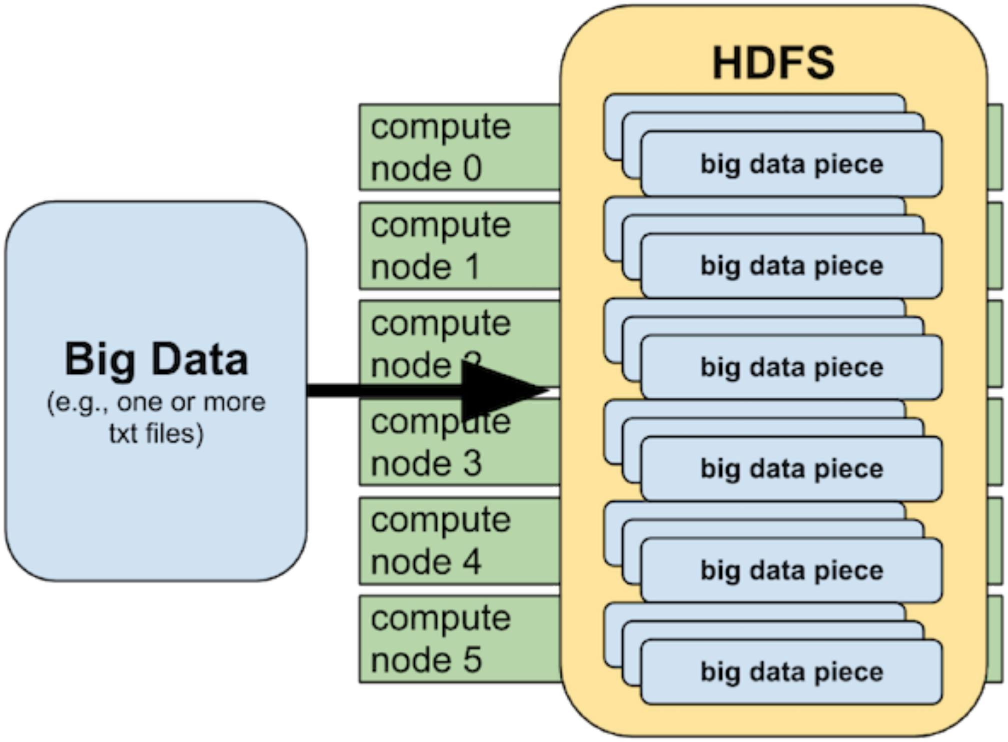
Technologies for this Presentation

Service	Function
HDFS	Store data in a distributed/replicated manner
YARN	Schedule and run jobs, acquiring resources as necessary
Spark	Perform map-reduce with data persistence in memory + much, much more

What is HDFS?

- Distributed file system
- Designed to run on commodity hardware
- Highly fault-tolerant (through replication)
- Suitable for applications that have large data sets

HDFS Magic


Big Data
(e.g., one or more txt files)
compute node 0
compute node 1
compute node 2
compute node 3
compute node 4
compute node 5
HDFS
big data piece
big data piece
big data piece
big data piece
big data piece
big data piece

Interacting with HDFS

The HDFS filesystem uses Unix-like commands for common operations, prefixed with the `hadoop fs` command, e.g.:

```
$ hadoop fs -ls /
Found 5 items
drwxr-xr-x   - hdfs  supergroup          0 2017-04-19 13:47 /data
drwxr-xr-x   - hbase hbase               0 2017-04-02 21:09 /hbase
drwxrwxr-x   - solr  solr                0 2017-02-24 17:20 /solr
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drwxr-xr-x   - hdfs  supergroup          0 2017-02-17 12:14 /user
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$ hadoop fs -ls /data
Found 9 items
-rw-r--r--   3 hdfs    supergroup       3359 2017-02-14 09:57 /data/Spark_README.md
drwxr-xr-x   - hdfs    supergroup          0 2017-03-06 16:25 /data/babs
drwxr-xr-x   - hdfs    supergroup          0 2017-03-06 11:52 /data/capitalbikeshare-data
drwxr-xr-x   - hdfs    supergroup          0 2017-03-06 12:10 /data/citibike-tripdata
drwxr-xr-x   - hdfs    supergroup          0 2017-02-14 21:10 /data/google-ngrams
-rw-r--r--   3 hdfs    supergroup  274188932 2017-04-19 13:47 /data/hadoop-2.5.0-cdh5.2.0.tar.gz
drwxr-xr-x   - hdfs    supergroup          0 2017-01-18 19:06 /data/nyc-tlc
drwxr-xr-x   - hdfs    supergroup          0 2016-12-21 15:14 /data/stack-archives
```

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```

This is not the same `/data` as on GPFS

HDFS

Common arguments for the `hadoop fs` command:

Argument	Description
`cat`	concatenate file contents to stdout
`copyFromLocal`	copy from local filesystem to HDFS
`copyToLocal`	copy from HDFS to local disk
`du`	calculate disk usage
`moveFromLocal`	copy to HDFS and remove local copy
`moveToLocal`	copy to local drive and remove HDFS copy
`rm`	remove files and folders from HDFS

HDFS

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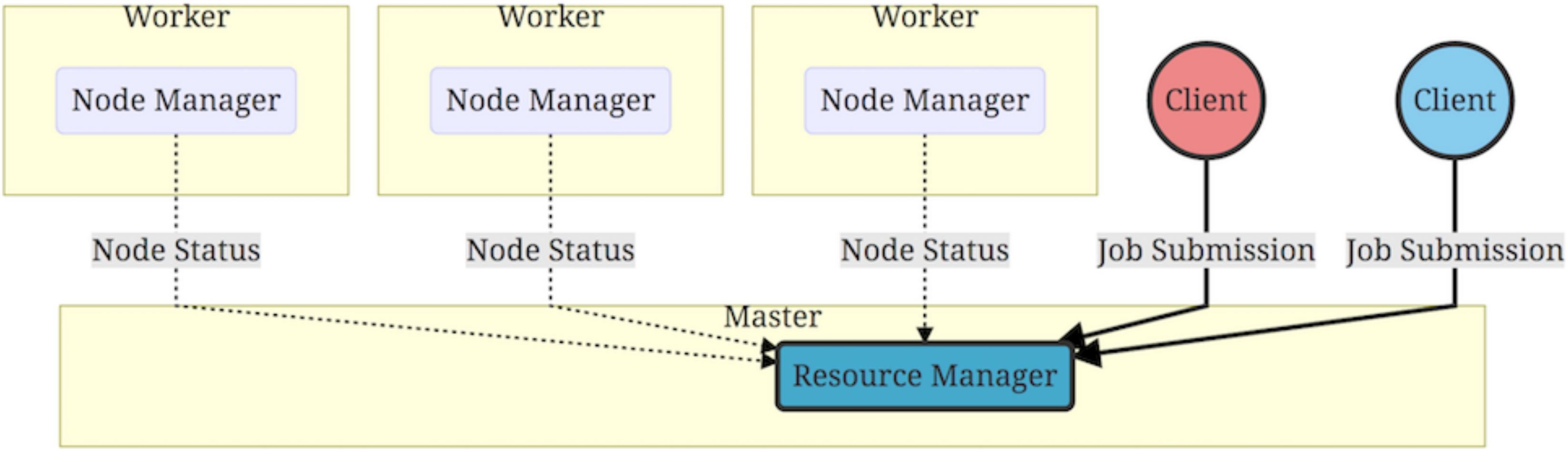
Command outputs can be piped, just like normal Unix commands, for example

```
hadoop fs -cat /user/fido/my-file | head -100
```

Apache Hadoop YARN

- Yet Another Resource Negotiator
- Functionalities:
    - resource management
    - job scheduling/monitoring



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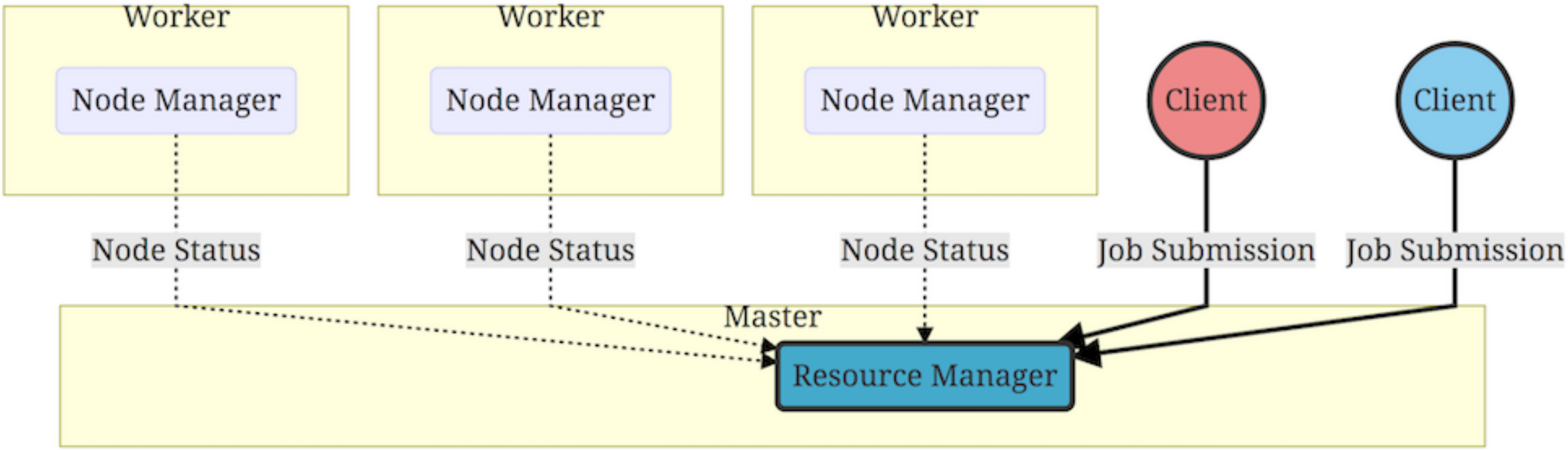
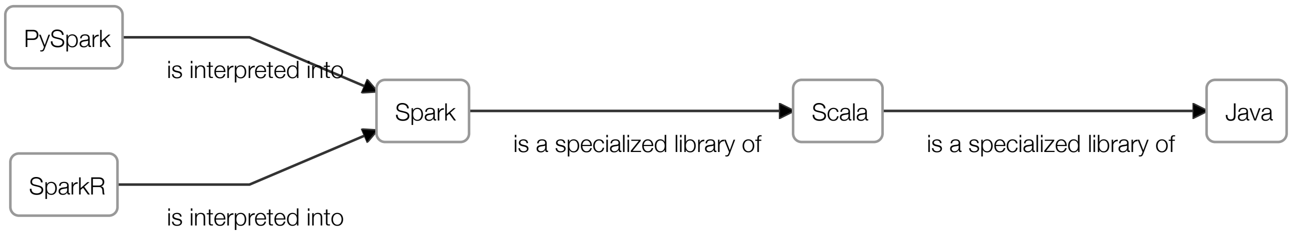


- YARN effectively fills the same role as SLURM
- Resource allocation is essentially transparent to the user

What is Spark?

> Apache Spark is a fast and general-purpose cluster computing system. It provides high-level APIs in Java, Scala, Python and R, and an optimized engine that supports general execution graphs.



Spark can run in:

- Standalone mode, e.g. Spark on GPFS
- on YARN
- on Mesos

How to execute Spark code

- Interactive jobs: Spark REPL, a command line tool to "Read Evaluate Print Loop" Spark/Scala code
    - In general: `$SPARK_HOME/bin/spark-shell`
    - On the cluster:
    - `spark-shell` or `pyspark` (v. 1.6.0)
    - `spark2-shell` or `pyspark2` (v. 2.0.0)

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On the `bigdata` cluster, `spark-submit` calls on YARN to automatically distributes jobs.

Wordcount in Spark

- Wordcount is the "Hello World" application for Hadoop
- Count the occurrences of all words in a text file
- Use the Scala REPL

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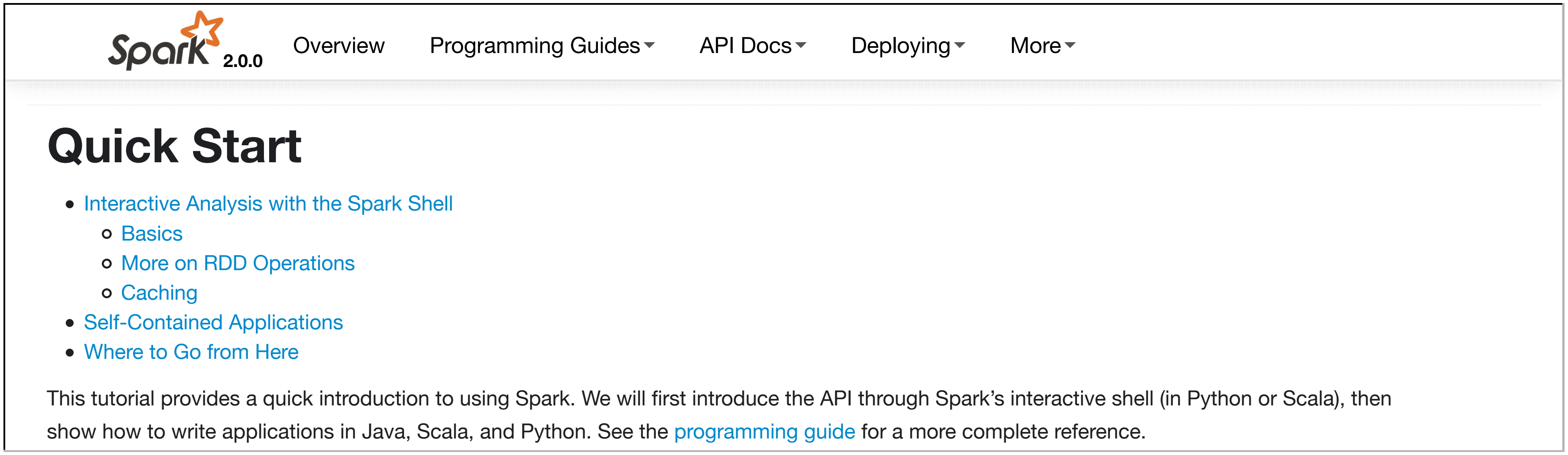
- This content is adapted slightly from the Spark getting started guide.



Quick Start

- Interactive Analysis with the Spark Shell
  - Basics
  - More on RDD Operations
  - Caching
- Self-Contained Applications
- Where to Go from Here

This tutorial provides a quick introduction to using Spark. We will first introduce the API through Spark’s interactive shell (in Python or Scala), then show how to write applications in Java, Scala, and Python. See the programming guide for a more complete reference.

Read in a text file using the SparkContext

- The `SparkContext` class `sc` is the entry point for the Spark API, and is already created in the REPL

```
scala> val linesRDD = sc.textFile("spark_read_me.txt")
linesRDD: org.apache.spark.rdd.RDD[String] = spark_read_me.txt MapPartitionsRDD[1] at textFile at <console>:24
```

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- The value `linesRDD` is an instance of an `RDD` (Resilient Distributed Dataset)
- RDDs are essential to Spark
  - a fault-tolerant collection of elements that can be operated on in parallel
  - parellelism happens *automagically*!

View the contents of the `linesRDD` RDD

- Since RDDs are distributed across nodes, they cannot be viewed directly in the REPL
- To view an RDD, gather all the data at a single node using `collect`.

```
scala> linesRDD.collect.foreach(println)
# Apache Spark

Spark is a fast and general cluster computing system for Big Data. It provides
high-level APIs in Scala, Java, Python, and R, and an optimized engine that
supports general computation graphs for data analysis. It also supports a
rich set of higher-level tools including Spark SQL for SQL and DataFrames,
MLlib for machine learning, GraphX for graph processing,
and Spark Streaming for stream processing.

<http://spark.apache.org/>
.
.
.
```

Map lines from `String` to `Array[String]`

The RDD (and Scala collections) support mapping. For example, the pure Scala expression:

```
scala> val foo: String = "a line with Spark"
```

Can be mapped into an array of strings delimited by whitespace

```
scala> foo.split(" ")
res0: Array[String] = Array(a, line, with, Spark)
```

Counting words per line

The same splitting operation can be applied to each element of the `RDD[String]`

```
scala> val words: RDD[Array[String]] = linesRDD.map(line => line.split(" "))
words: org.apache.spark.rdd.RDD[Array[String]] = MapPartitionsRDD[3] at map at <console>:27
```

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```

Taking the size of each `Array[String]` element of the `RDD` will yield the total words per each line

```
scala> val wordsPerLine: RDD[Int] = words.map(a => a.size)
wordsPerLine: org.apache.spark.rdd.RDD[Int] = MapPartitionsRDD[5] at map at <console>:29

scala> wordsPerLine.take(5).foreach(println)
3
1
14
13
11
```

Total words

To get the total words for the document, we can simply sum up the `wordsPerLine` RDD:

```
scala> val total: Int = wordsPerLine.reduce((a, b) => a + b)
total: Int = 507
```

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- The order of combining the `RDD` elements must not matter

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- The order of combining the RDD elements must not matter

Notice that `total` is no longer an RDD but a regular Scala `Int`.

The MapReduce Paradigm

- Map: transform the data
    - `map`
    - `filter`
    - `flatMap`
    - `join`
    - `union`
    - `intersection`
    - et al.
- Reduce: aggregate the data
    - `reduce`
    - `count`
    - `sample`
    - et al.

WordCount: Count the occurrences of each word in a document

- Pseudocode:
    - Map each line into an array of words
    - Map each word into a word-value *pair*, or `Tuple`, e.g. `(the, 101)`
        - First element is the *key* which serves as identifier
        - Second element is the *value* which, in this case, signifies that each word has occurred one time.
    - Group all word-value pairs by word, and sum up the values for each word

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  - Group all word-value pairs by word, and sum up the values for each word
- Key-Value pairs: mechanism for allowing `groupBy` operations
  - All the RDD elements of a given key are guaranteed to on the same worker during aggregations
  - `reduceByKey` combines values of a given key:

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- Key-Value pairs: mechanism for allowing `groupBy` operations
  - All the RDD elements of a given key are guaranteed to on the same worker during aggregations
  - `reduceByKey` combines values of a given key:

```
scala> val wordFrequencies = linesRDD.flatMap( line => line.split(" ").map(word => (word, 1)) ).
     | reduceByKey((a, b) => a + b)
wordFrequencies: org.apache.spark.rdd.RDD[(String, Int)] = ShuffledRDD[7] at reduceByKey at <console>:28
```

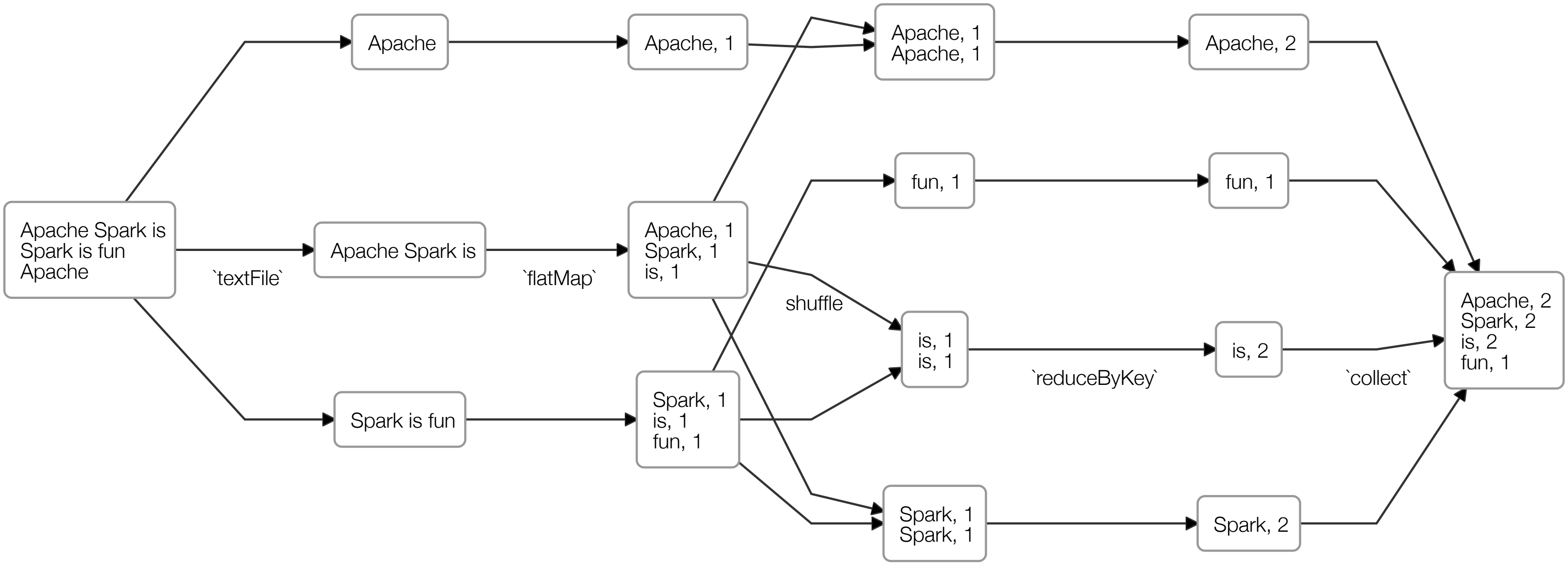
--

Note that `wordFrequencies` is now a `ShuffledRDD`

WordCount

```
scala> wordFrequencies.takeOrdered(20).foreach(println)
(,67)
("local",1)
("local[N]",1)
("yarn",1)
(#,1)
(##,8)
((You,1)
(-DskipTests,1)
(./bin/pyspark,1)
(./bin/run-example,2)
(./bin/spark-shell,1)
(./dev/run-tests,1)
(1000).count(),1)
(1000:,2)
(<class>,1)
(<http://spark.apache.org/>,1)
(>>>,1)
(A,1)
(APIs,1)
(About,1)
```

Under the Hood of Map-Reduce



Spark higher-level tools

Library	Function
Spark SQL	SQL and structured data processing
MLlib	machine learning
GraphX	graph processing
Spark Streaming	real-time analysis of data streams

Spark DataFrames

- Analogous to data frames in R and Pandas
- Can be automatically created from CSV, Parquet, JSON lines files

```
val df: DataFrame = spark.read
    .option("header", true)
    .option("treatEmptyValuesAsNulls", true)
    .option("inferSchema", true)
    .csv("/data/nyc-tlc/yellow_tripdata_2016-04.csv")

df.show()
```

```
    +---------+-------------------+-------------------+---------------+-------------+----------------+
    |vendor_id|    pickup_datetime|   dropoff_datetime|passenger_count|trip_distance|pickup_longitude|
    +---------+-------------------+-------------------+---------------+-------------+----------------+
    |      CMT|2013-01-01 15:11:48|2013-01-01 15:18:10|              4|          1.0|      -73.978165|
    |      CMT|2013-01-06 00:18:35|2013-01-06 00:22:54|              1|          1.5|       -74.00668|
    |      CMT|2013-01-05 18:49:41|2013-01-05 18:54:23|              1|          1.1|      -74.004711|
    |      CMT|2013-01-07 23:54:15|2013-01-07 23:58:20|              2|          0.7|        -73.9746|
    |      CMT|2013-01-07 23:25:03|2013-01-07 23:34:24|              1|          2.1|      -73.976252|
    |      CMT|2013-01-07 15:27:48|2013-01-07 15:38:37|              1|          1.7|      -73.966743|
    |      CMT|2013-01-08 11:01:15|2013-01-08 11:08:14|              1|          0.8|      -73.995801|
    |      CMT|2013-01-07 12:39:18|2013-01-07 13:10:56|              3|         10.7|      -73.989937|
    |      CMT|2013-01-07 18:15:47|2013-01-07 18:20:47|              1|          0.8|      -73.980071|
    |      CMT|2013-01-07 15:33:28|2013-01-07 15:49:26|              2|          2.5|      -73.977937|
    |      CMT|2013-01-08 13:11:52|2013-01-08 13:19:50|              1|          1.3|      -73.982456|
    |      CMT|2013-01-08 09:50:05|2013-01-08 10:02:54|              1|          0.7|      -73.995561|
```

SQL queries on Spark DataFrames

```
scala> val coords = df.select("pickup_longitude", "pickup_latitude")
coords: org.apache.spark.sql.DataFrame = [pickup_longitude: string, pickup_latitude: string]
scala> coords.show(5)
+-------------------+------------------+
|   pickup_longitude|   pickup_latitude|
+-------------------+------------------+
|-73.990211486816406|40.750968933105469|
|-73.935188293457031| 40.80072021484375|
|-73.963752746582031|40.767936706542969|
|-73.997177124023438|40.742168426513672|
|-74.006843566894531|40.730266571044922|
+-------------------+------------------+
only showing top 5 rows
```

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+-------------------+------------------+
|   pickup_longitude|   pickup_latitude|
+-------------------+------------------+
|-73.990211486816406|40.750968933105469|
|-73.935188293457031| 40.80072021484375|
|-73.963752746582031|40.767936706542969|
|-73.997177124023438|40.742168426513672|
|-74.006843566894531|40.730266571044922|
+-------------------+------------------+
only showing top 5 rows
```

- DataFrames cast to RDDs return RDDs of rows

```
scala> val dist = df.select("trip_distance").rdd.map({ case Row(d: String) => d.toDouble }).mean
dist: Double = 15.7432129086462
```

Spark MLLib

- Spark's machine learning library
- Spark MLLib - RDD API (code maintenance only)
- Spark ML - DataFrame API
- Provides many common clustering and classification algorithms

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```
val training: DataFrame

val lr = new LogisticRegression()
  .setMaxIter(10)
  .setRegParam(0.3)
  .setElasticNetParam(0.8)

// Fit the model
val lrModel = lr.fit(training)

// Print the coefficients and intercept for logistic regression
println(s"Coefficients: ${lrModel.coefficients} Intercept: ${lrModel.intercept}")
```

Image Classification

spark-sem-classify on GitHub

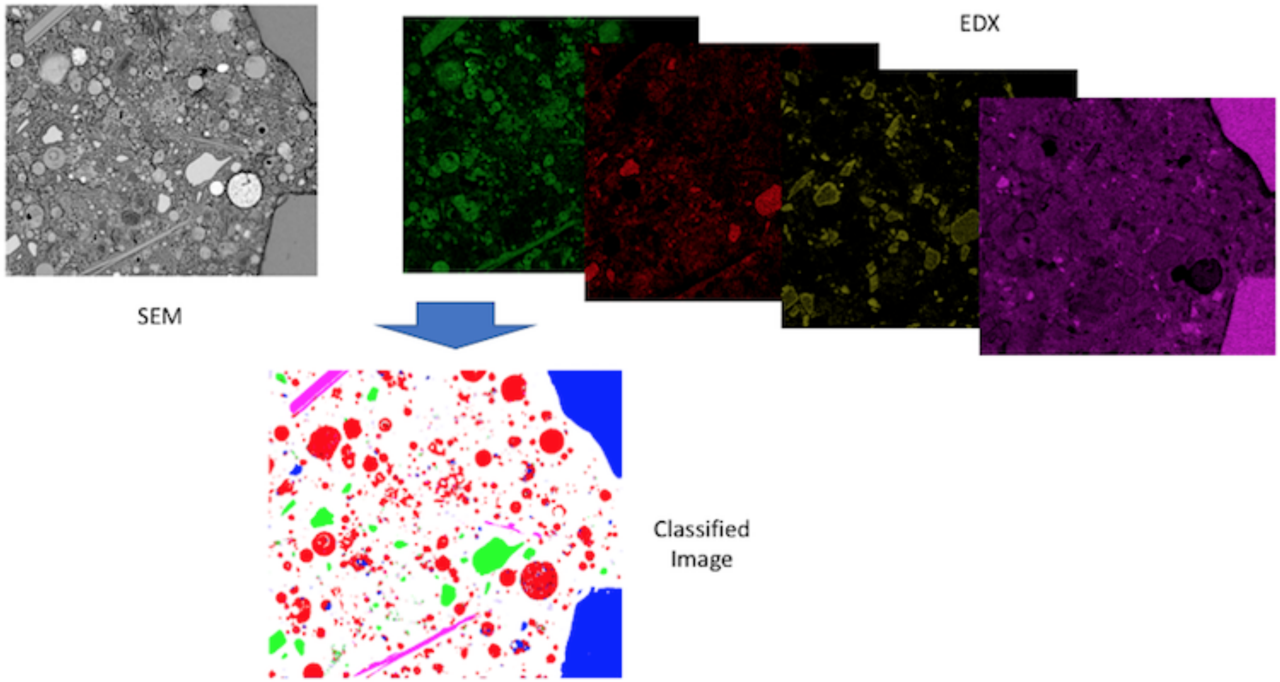

Image Classification

```
// Assemble feature columns into a single column
val assembler =  new VectorAssembler()
    .setInputCols(Array("bse", "ca", "si", "al", "mg",
      "o", "s", "k", "na", "fe"))
    .setOutputCol("features")

// Index labels, adding metadata to the label column.
val labelIndexer = new StringIndexer()
    .setInputCol("label")
    .setOutputCol("indexedLabel")
    .fit(data)

// Specify a RandomForest model.
val rf = new RandomForestClassifier()
    .setFeaturesCol("features")
    .setLabelCol("indexedLabel")
    .setNumTrees(30)

// Convert indexed labels back to original labels.
val labelConverter = new IndexToString()
    .setInputCol("prediction")
    .setOutputCol("predictionLabel")
    .setLabels(labelIndexer.labels)

// Chain indexers and forest in a Pipeline
val pipeline = new Pipeline()
    .setStages(Array(assembler, labelIndexer, rf, labelConverter))
```

Image Classification

```
// We now treat the Pipeline as an Estimator, wrapping it in a CrossValidator instance.
// This will allow us to jointly choose parameters for all Pipeline stages.
// A CrossValidator requires an Estimator, a set of Estimator ParamMaps, and an Evaluator.
// Note that the evaluator here is a BinaryClassificationEvaluator and its default metric
// is areaUnderROC.
val cv = new CrossValidator()
    .setEstimator(pipeline)
    .setEvaluator(evaluator)
    .setEstimatorParamMaps(paramGrid)
    .setNumFolds(3)  // Use 3+ in practice

// Train model.  This also runs the indexers.
val cvModel = cv.fit(trainData)
```

Spark GraphX

- Graph-parallel computation

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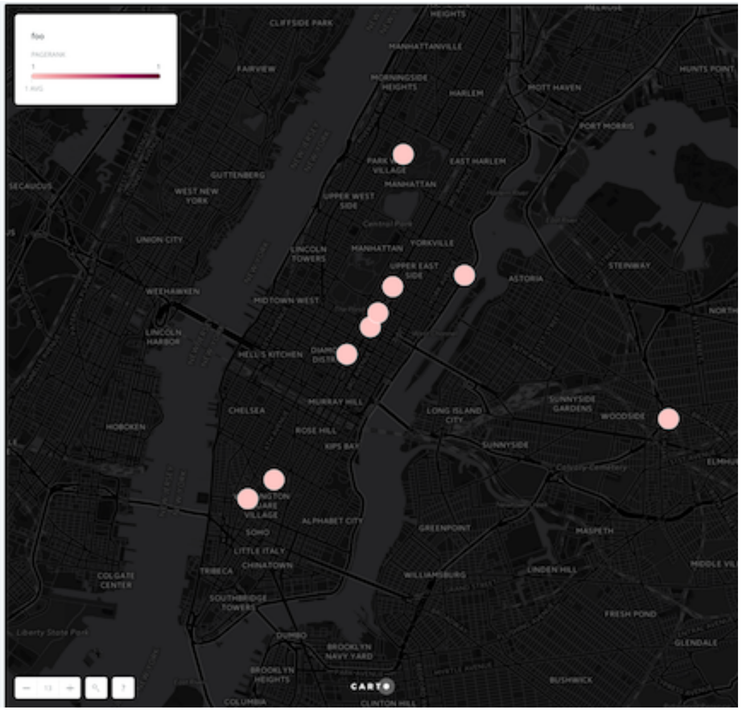
- For example, calculate the most popular taxi pickup/dropoff location in NYC using PageRank



Network Analysis

```
// Construct the edges
// Join the dropoff with it's index
val edges: RDD[Edge[String]] = pickups.map {
    case (_, (Row(_: Point, p1: Point), v0: Long)) =>
        (p1.round, v0)
} .join(indexed).values
        .map { case (v0: Long, v1: Long) => Edge(v0, v1, "foo") }

// Reformat indexed to be vertices
val vertices: RDD[(VertexId, Point)] = indexed.map({
    case (p: Point, v: Long) => (v, p)
})

// Specify default point
val defaultPoint = Point(-1.0, -1.0)

// Create the graph
val graph = Graph(vertices, edges, defaultPoint)

// Run PageRank
val ranks = graph pageRank 0.0001 vertices

ranks take 10 foreach println
```

Pro Tips

1. Read the docs!

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3. Use a good IDE!!!

    - type-checking
    - syntax highlighting
    - tab-completion
    - suggestions: IntelliJ IDEA CE and PyCharm CE