Lecture 04

Introduction to Spark

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Reference

- These slides follow to a good measure the book

  "*Learning Spark*" by

  Holden Karau, Andy Konwinski, Patrick Wendell & Mathei Zaharia,
  O'Reilly 2015

Spark

- Spark is yet another one greatest thing ever invented.

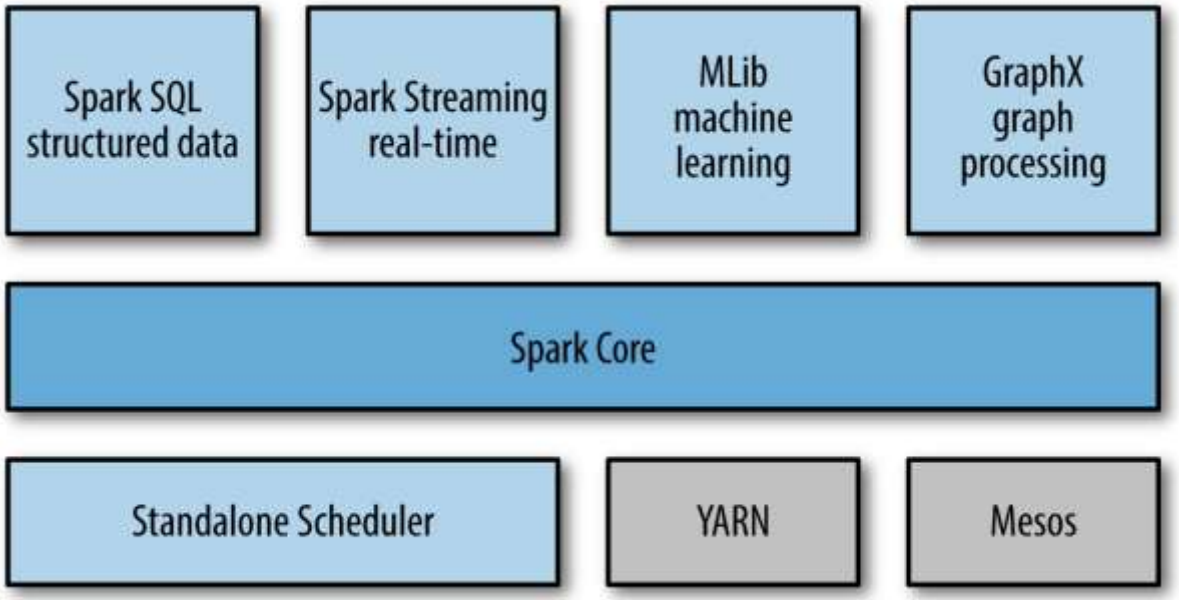
- Spark extends MapReduce model to efficiently support more types of computations, including interactive queries and stream processing.
- Spark is designed to cover a wide range of workloads that previously
- required separate distributed systems, including batch applications, iterative algorithms, interactive queries, and streaming.
- By supporting these workloads in the same engine, Spark makes it easy and inexpensive to *combine* different processing types.
- Spark is designed to be highly accessible, offering simple APIs in Python, Java, Scala, and SQL, and rich built-in libraries.
- Spark integrates closely with other Big Data tools. Spark can run in Hadoop clusters and access any Hadoop data source, including Cassandra.

What is Spark

- **Spark is** an *open-source* software solution that performs rapid calculations on *in-memory distributed datasets.*
- In-memory distributed datasets are referred to as RDDs
- *RDDs are Resilient Distributed Datasets*
  - RDD is the key Spark concept and the basis for what Spark does
  - RDD is a distributed collections of objects that can be cached in memory across cluster and can be manipulated in parallel.
  - RDD could be automatically recomputed on failure
  - RDD is resilient – can be recreated on the fly from known state
  - Immutable – already defined RDDs can be used as a basis to generate derivative RDDs but are never mutated
  - Distributed – the dataset is often partitioned across multiple nodes for increased scalability and parallelism

What is Spark

- Spark is a fast *general* processing engine for large scale data processing
- Spark is designed for iterative computations and interactive data mining.
- Spark supports use of well known languages: Scala, Python and Java
- With Spark streaming the same code can be used on data at rest and data in motion
- Spark has several key modules:



Key Modules

- **Spark Core** contains the basic functionality of Spark, including components for task scheduling, memory management, fault recovery, interacting with storage systems, and others.
- Spark Core is the home to the API that defines *resilient distributed datasets* (RDDs), which are Spark's main programming abstraction. RDDs represent a collection of items distributed across many compute nodes that can be manipulated in parallel.
- **Spark SQL** is Spark's package for working with structured data. I
- Spark SQL allows querying data via SQL as well as the Apache Hive variant of SQL—Hive Query Language (HQL)—and it supports many sources of data, including Hive tables, Parquet, and JSON.
- Spark SQL allows developers to intermix SQL queries with the programmatic data manipulations supported by RDDs in Python, Java, and Scala, all within a single application, thus combining SQL with complex analytics.

Key Modules

- **Spark Streaming** is a Spark component that enables processing of live streams of data. Data streams include log files of web servers, or queues of messages.
- Spark Streaming API for manipulating data streams closely matches the Spark Core's RDD API, making it easy to move between apps that manipulate data in memory, on disk, or arriving in real time.
- Spark Streaming provides the same degree of fault tolerance, throughput, and scalability as Spark Core.
- **MLlib** is a library containing common machine learning (ML) functionality.
- MLlib provides multiple types of machine learning algorithms, including classification, regression, clustering, and collaborative filtering, as well as supporting functionality such as model evaluation and data import.
- MLlib provides some lower-level ML primitives, including a generic gradient descent optimization algorithm. All of ML methods are designed to scale out across a cluster.

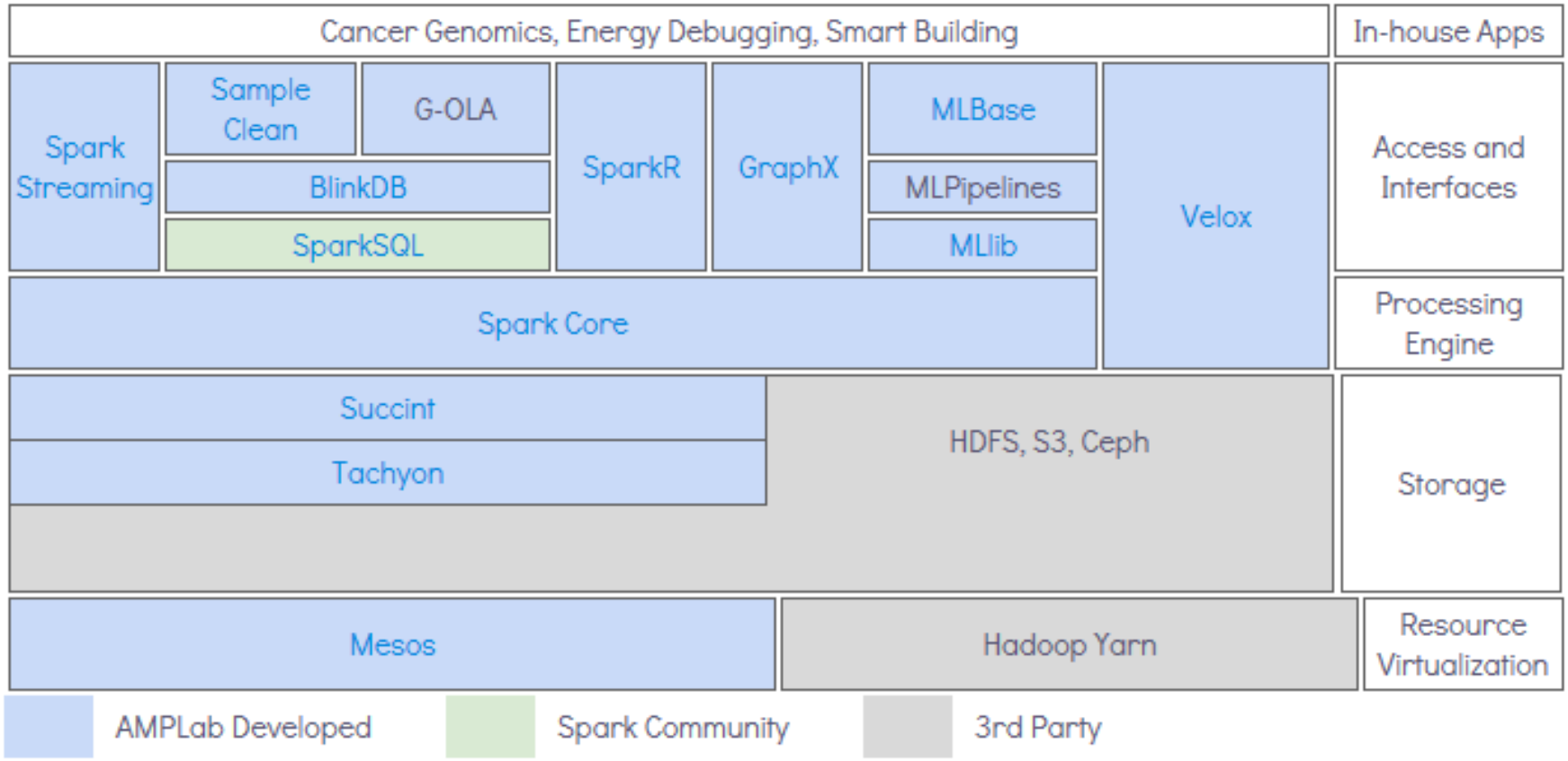
Key Modules

- **GraphX** is a library for manipulating graphs (e.g., a social network's friend graph) and performing graph-parallel computations. GraphX extends the Spark RDD API, allowing us to create a directed graph with arbitrary properties attached to each vertex and edge.
- GraphX also provides various operators for manipulating graphs (e.g., subgraph and mapVertices) and a library of common graph algorithms (e.g., PageRank and triangle counting).

- **Cluster Managers** allow Spark to efficiently scale up from one to many thousands of compute nodes.
- Spark can run over a variety of *cluster managers*, including Hadoop YARN, Apache Mesos, and a simple cluster manager included in Spark itself called the Standalone Scheduler.

Amplab.cs.Berkely Stack

- Spark started at AMPLab: https://amplab.cs.berkeley.edu/
- AMPLab builds BDAS*, the Berkeley Data Analytics Stack*, an open source software stack that integrates many data processing software components. BDAS has a wider scope than Spark itself.



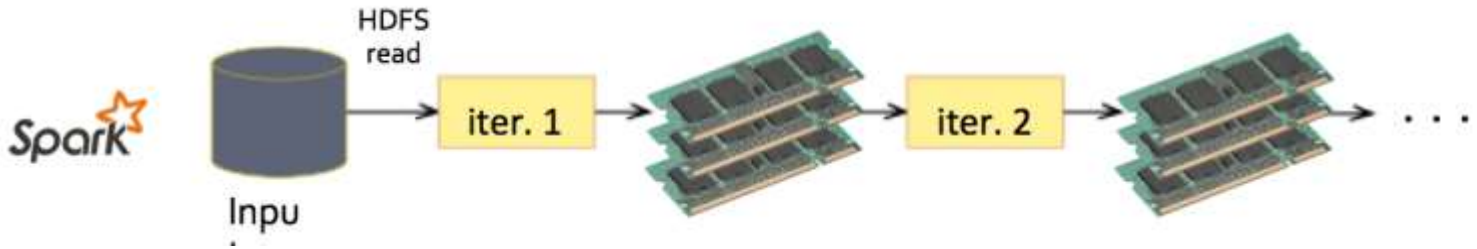
How does Spark Work?

- **RDD**
  - Your data is loaded in parallel into structured collections
- **Actions**
  - Manipulate the state of the working model by forming new RDDs and performing calculations upon them
- **Persistence**
  - Long-term storage of an RDD's state
- **Spark Application is a definition in code of**
  - RDD creation
  - Actions
  - Persistence
- Spark Application results in the creation of a DAG (Directed Acyclic Graph)
- Each DAG is compiled into stages
- Each Stage is executed as a series of Tasks
- Each Task operates in parallel on assigned partitions
- It all starts with the SparkContext 'sc'

Spark vs. Map Reduce

- Map Reduce places every result on disk

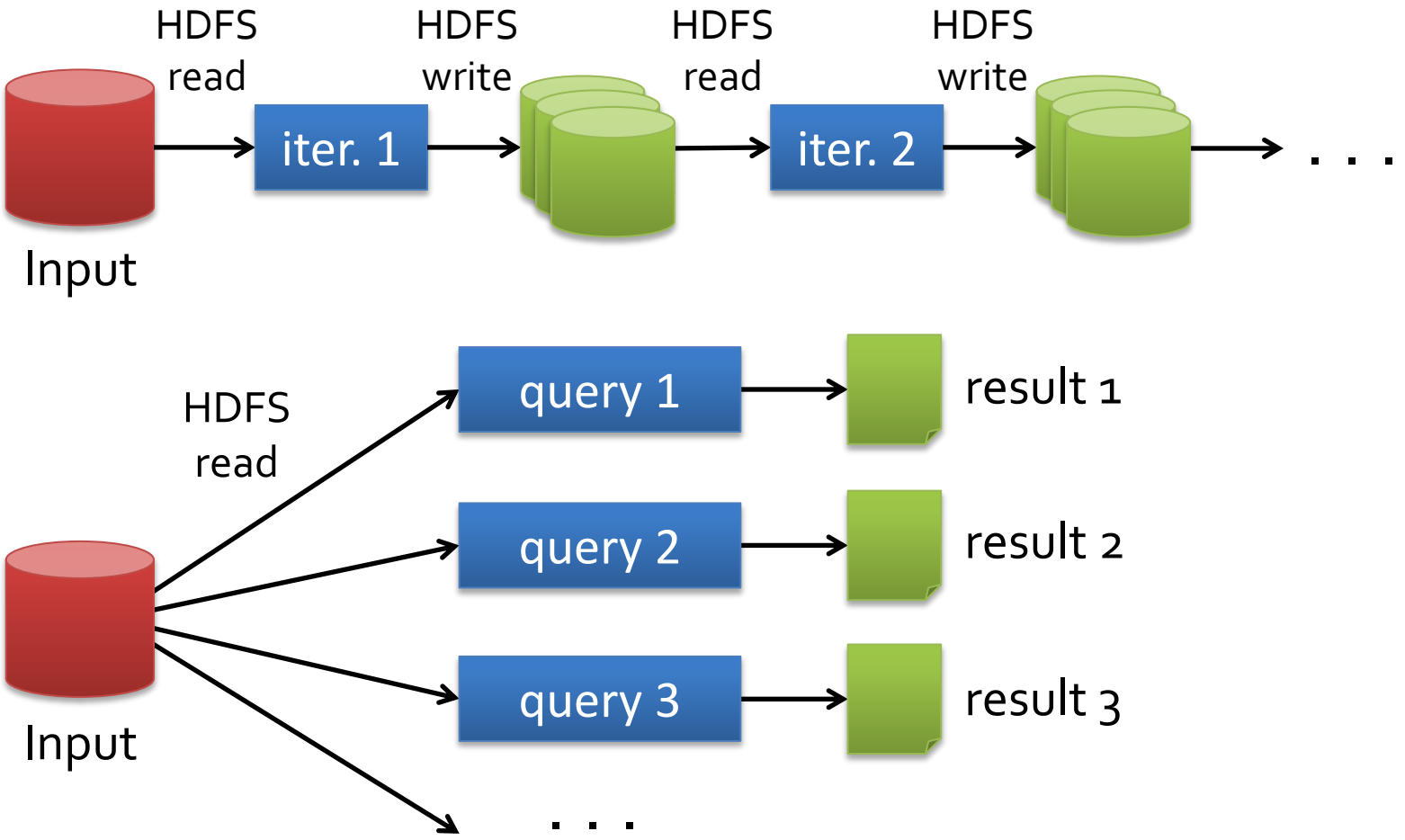
- Spark is much smarter, it keeps all results in memory



  - MapReduce greatly simplified big data analysis
  - But as soon as it got popular, users wanted more:
    - More **complex**, multi-pass analytics (e.g. ML, graph)
    - More **interactive** ad-hoc queries
    - More **real-time** stream processing
  - All need faster **data sharing** across parallel jobs

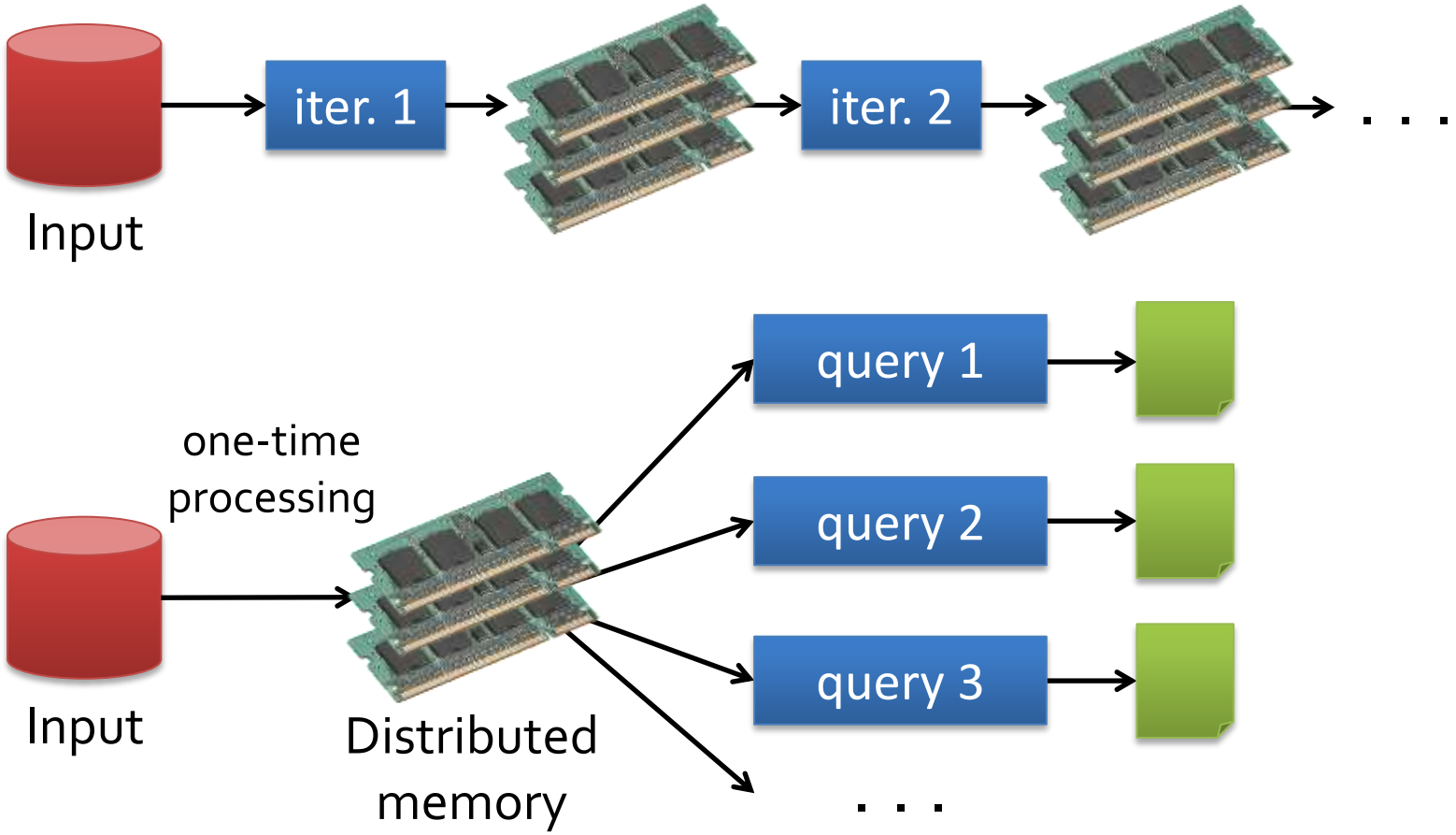
Data Sharing in Map Reduce

- Map Reduce is slow due to replication, serialization and disk IO



Data Sharing in Spark

- Distributed memory is 10-100× faster than network and disk

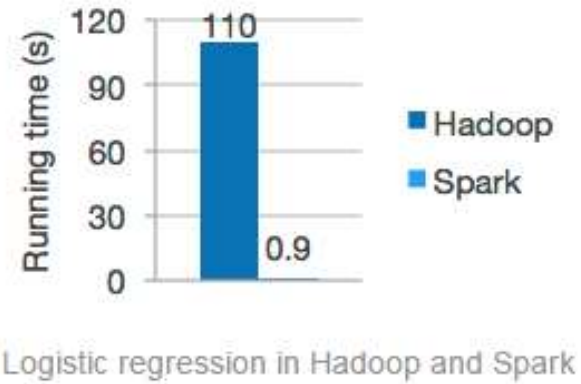


Spark vs. Map Reduce

- Spark extends the popular MapReduce model to efficiently support more types of computations, including interactive queries and stream processing.
- It is said that inventors of Spark noticed that Hadoop (MapReduce) was inefficient for the iterative workflows and they extended Hadoop architecture to make it more efficient.
- Speed is important in processing large datasets, as it means the difference between exploring data interactively and waiting minutes or hours.
- Spark's speed comes from its ability to run computations in memory. Spark appears to be more efficient than MapReduce for complex applications running on disk.
- Spark retains the attractive properties of MapReduce:
  - fault tolerance, data locality, scalability

Spark vs. Hadoop

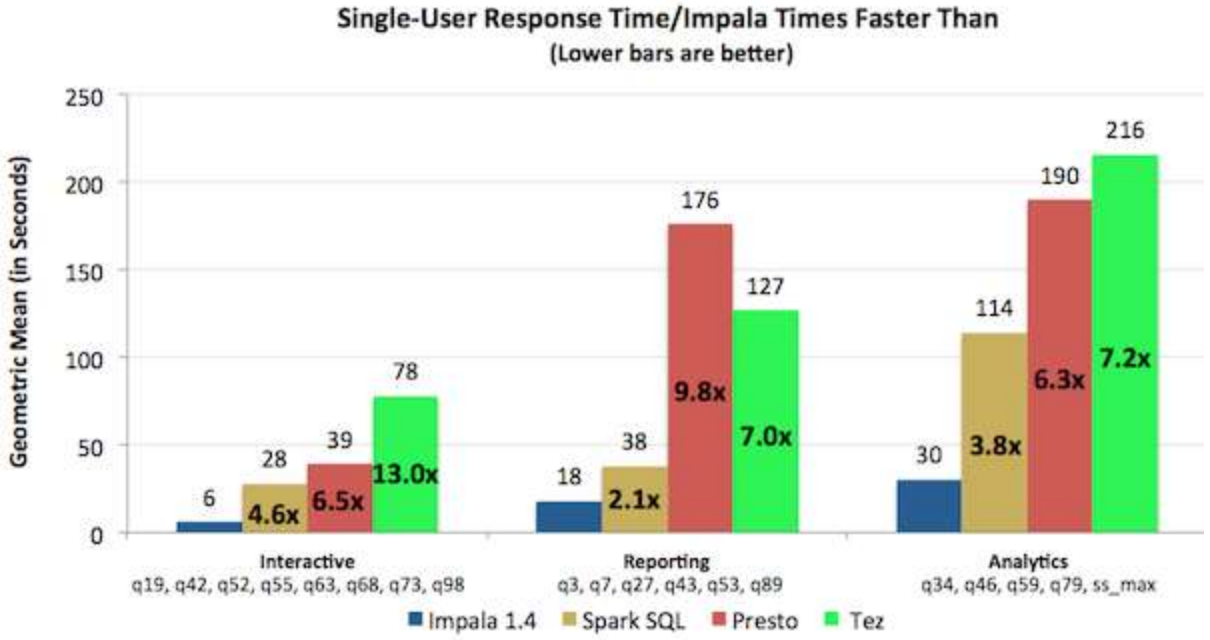
- You will frequently see diagrams like this:



Logistic regression in Hadoop and Spark

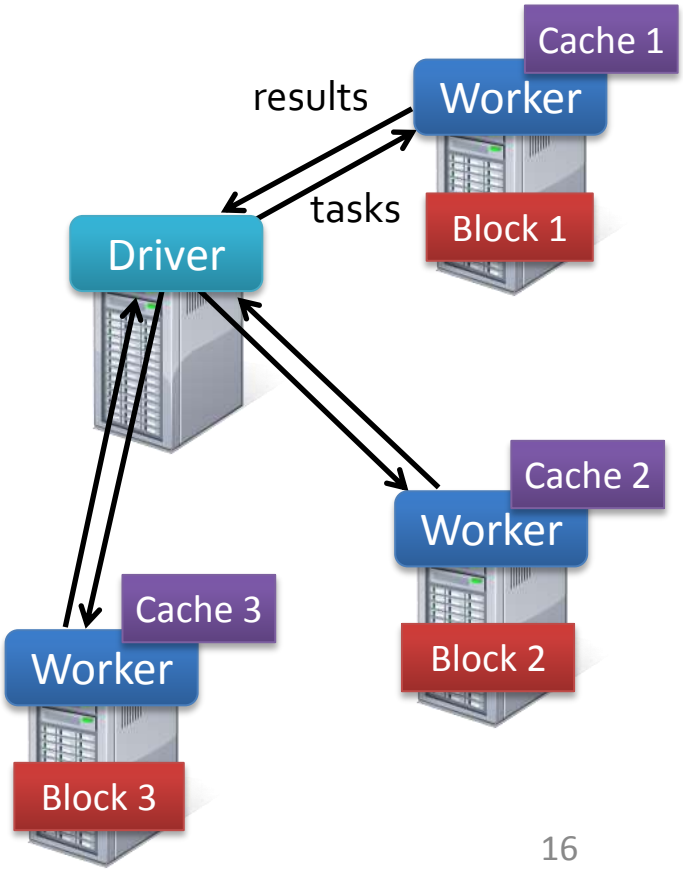
- Do not take them too seriously. Hadoop people will show you the results below which compare Impala, a Hadoop SQL engine, and Spark. Impala is 4 or 6 X faster,….

- Engineers developing Hadoop are learning from Spark just like Spark engineers learned from Hadoop.
- Cycles keep repeating



Distributed Memory Processing

- Just like MapReduce (Hadoop), Spark has a central controller, called Driver (App Master) which distributes tasks to Workers.
- Data (RDD) is split among memories of many workers.
- Data is originally sourced from the disk (HDFS, S3, regular File System). During processing is shared only between memories (if possible).
- Driver, if it detects that a worker is slacking or not working at all could make the worker redo its work or could move processing to another worker.
- Spark is fault tolerant just like Hadoop.



Installation of Spark

- You can go to http://spark.apache.org/downloads and fetch the newest and greatest release of Spark. You have options to download the source code or download binaries. To use the source code you need Mavern.
- Since we are working with Cloudera's VM-s we will do the following:
  - Make sure we have JDK 7+ installed.
  - Make sure we have `hadoop-client` package installed. For example, you could do: `$ sudo yum install hadoop-client`,

    and `yum` will either install the package or tell you it is already there.
  - Make sure all HDFS and YARN services are installed and running. Stop them and start them all.
  - Use `yum` to run installation of Spark, by typing all on one line:

```
$ sudo yum install spark-core spark-master spark-worker spark-history-server spark-python
```

- Be positive. Answer yes to all the questions. For Linux versions other than CentOS, please consult Cloudera documentation. Set your `SPARK_HOME` env. variable to `/usr/lib/spark` and add `$SPARK_HOME/bin` to your `PATH` environmental variable. You are done.
- `yum` made sure that you have Spark version which matches your Hadoop (Yarn) version.
- Without any further changes we will run Spark locally on this single machine.

Spark Shells

- Spark comes with interactive shells that enable ad hoc data analysis.
- Unlike most other shells, which let you manipulate data using the disk and memory on a single machine, Spark's shells allow interaction with data distributed on disks or in memory across many machines.
- Spark can load data into memory on the worker nodes, and distributed computations, even ones that process large volumes of data across many machines, can run in a few seconds. This makes iterative, ad hoc, and exploratory analysis commonly done in shells a good fit for Spark.
- Spark provides both (and only) Python and Scala shells that have been augmented to support access to a cluster of machines.
- In these lecture notes, we will use Python shell, only.
- Python shell opens with `pyspark` command.
- Scala shell is very similar and opens with `spark-shell` command.
- You can program Spark from R using package SparkR

Scala Programming Language (from Wikipedia)

- **Scala** (/ˈskɑːlə/ ***SKAH-lə***) is an object-functional programming language for general software applications. Scala has full support for ***functional programming*** and a very strong static type system. This allows programs written in Scala to be very concise and thus smaller in size than other general-purpose programming languages. Many of Scala's design decisions were inspired by criticism of the shortcomings of Java.
- Scala source code is intended to be compiled to Java bytecode, so that the resulting executable code runs on a Java virtual machine. Java libraries may be used directly in Scala code and vice versa. Like Java, Scala is object-oriented, and uses a curly-brace syntax reminiscent of the C programming language. Unlike Java, Scala has many features of functional programming languages like Scheme, Standard ML and Haskel, including currying, type inference, immutability, lazy evaluation, and pattern matching. It also has an advanced type system supporting algebraic data types, covariance and contravariance, higher-order types, and anonymous types. Other features of Scala not present in Java include operator overloading, optional parameters, named parameters, raw strings, and no checked exceptions.
- *Functional programming* is a subset of declarative programming. Programs written using this paradigm use functions, blocks of code intended to behave like mathematical functions. Functional languages discourage changes in the value of variables through assignment, making a great deal of use of recursion instead.

pyspark

- If you type `pyspark` on the Linux command prompt, you will see the following:

```
[cloudera@localhost conf]$ pyspark
Python 2.6.6 (r266:84292, Jul 23 2015, 15:22:56)
[GCC 4.4.7 20120313 (Red Hat 4.4.7-11)] on linux2
Type "help", "copyright", "credits" or "license" for more information.
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/usr/lib/zookeeper/lib/slf4j-
log4j12-1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/usr/lib/flume-ng/lib/slf4j-log4j12-
1.7.5.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an
explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
Welcome to
      ____              __
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   /__ / .__/\_,_/_/ /_/\_\   version 1.5.0-cdh5.5.1
      /_/

Using Python version 2.6.6 (r266:84292, Jul 23 2015 15:22:56)
SparkContext available as sc, HiveContext available as sqlContext.
>>>
```

Shell verbosity and `log4j.properties` file

- The output is long and annoying. It would have been even longer had we not created `log4j.properties` file in the directory `$SPARK_HOME/conf`.
- You create that file by copying provided file `log4j.properties.template` and by changing line

```
log4j.rootCategory=INFO, console
```

- to read:

```
log4j.rootCategory=ERROR, console
```

- That lowered the logging level so that we see only the ERROR messages, and above. Another option is `WARN`, which is more verbose that ERROR but less than INFO.
- Before we proceed, let us see which files with how many lines we have in HDFS

```
$ hadoop fs –ls ulysis
-rw-r--r-- 1 cloudera 5258688 2015-04-01 14:32 input/4300.txt
$ hadoop fs -cat ulysis/4300.txt | wc
 33056  267980 1573079
```

Load Data (RDD) from HDFS

- In Spark, we express our computation through operations on distributed collections that are automatically parallelized across the cluster.
- These collections are called *resilient distributed datasets*, or RDDs.
- When we load some data, i.e. a file into a shell variable, we are creating an RDD, like

```
>>> lines = sc.textFile("ulysis/4300.txt")
>>> lines.count()
33056
```

- What we've just done is create and populate an RDD named `lines` using a mysterious object "`sc`" and its method `textFile()`. We populated that RDD with data in HDFS file `ulysis/4300.txt`.
- "`sc`" stands for an implicit `SparkContext`. `SparkContext` allows us to communicate with the execution environment.
- It appears that RDD-s are also (Object Oriented) objects and have methods, such as `count()` which gave use the exact number of lines in file `4300.txt`.

Load Data (RDD) from Local File

- We could load the same data from the local operating system.
- We happen to have the `4300.txt` file in `/home/cloudera` directory and could do the following:

```
>>> blines = sc.textFile("file:///home/cloudera/4300.txt")
>>> blines.count()
33056
>>> blines.first()
u'The Project Gutenberg EBook of Ulysses, by James Joyce'
```

- What we did above was create an RDD named `blines` and populate that RDD with data from the local file `/home/cloudera/4300.txt`.
- We also see in action another method of RDD-s, first(), which tells us that the first line in RDD `blines` is some uninterested collection of characters (**`u''`**) .
- Please note that we are not terminating our commands with a semi-colon (";") or anything else aside from the carriage return. Savings on typing all those semi-colons is one of the greatest contributions of Python to the computer science.
- By the way, our commands are in Python.

Load Data (RDD) from the Cloud (AWS S3 Bucket)

- I uploaded the same `4300.txt` file to the Amazon's AWS S3 bucket called `zoran001`.
- On my Linux box (Cloudera VM) I created two new environmental variables in file `.bash_profile`.

```
AWS_ACCESS_KEY_ID=ADTSDYSDUIOSIDOI and
AWS_SECRET_ACCESS_KEY=dsfsfuierfsdfuiorfarifaifaopopa
```

- I source the file:

```
$ source .bash_profile
```

- Then, after reopening Python Spark shell, I issued the command:

```
>>> s3lines = sc.textFile("s3n://zoran001/4300.txt")
>>> s3lines.count()
33056
```

- We did not loose a single line of text while brining the text down from the Cloud.

```
>>> Heaven = s3lines.filter(lambda line: "Heaven" in line)
>>> Heaven.count()
2
>>> heaven = s3lines.filter(lambda line: "heaven" in line)
>>> heaven.count()
50
```

- We also see in action another method of RDD-s, `filter()`, which apparently let us inquire how many times is `heaven` mentioned in the Ulysis. Heaven is mentioned 52 time, i.e. some 0.15% of the time (> Bible)
- If you do not have an AWS account, do filtering examples on local files.

Python `lambda` Syntax

- Python supports the creation of anonymous inline functions (i.e. functions that are not bound to a name) at runtime, using a construct called "lambda“.
- The following code shows the difference between a normal function definition ("f") and a lambda function ("g"):

```
>>> def f(x): return x**2
>>> print f(8)
64
>>> g = lambda x: x**2
>>> print g(8)
64
```

- As you can see, `f()` and `g()` do exactly the same thing. The lambda definition does not include a "return" statement. The last expression is returned.
- You can put a lambda definition anywhere a function is expected, and you don't have to assign it to a variable at all.

`filter()` Method

- Method `filter()` takes a function returning `True` or `False` and applies it to a sequence (list) and returns only those members of the sequence for which the function returned `True`.
- So, in the Python code :

```
heavens = s3lines.filter(lambda line: "Heaven" in line)
```

- Method `filter()` acts on the collection `s3lines`, and passes every element of that collection as the variable `line` as the argument to the anonymous function created using lambda construct. That anonymous function uses a simple regular expression to test whether string "`Heaven`" exists in variable `line`. If the regular expression returns `True` for a particular `line`, an element of collection `s3lines`, the anonymous function will return `True` and for that particular `line`, `filter()` will return/add variable `line` building up a new collection called `heavens`.
- You can accomplish the same in Java 1.7 and older with several lines of code. In Java 1.8 you have similarly efficient lambda constructs.

Passing Function to Spark in Python

- We want to convince ourselves that rather than using lambda constructs we could define functions and then pass their names to Spark. For example:

```
>>> def hasLife(line):
. . .       return "life" in line    # At the beginning hit a tab
. . .
>>> lines = sc.textFile("file:///home/cloudera/4300.txt")
>>> lifeLines = lines.filter(hasLife)
>>> lifeLines.count()
203
>>> print lifeLines.first()
u'whom Mulligan was one, and Arius, warring his life long upon
the'
>>>
```

- Function `hasLife()` returns `True` if the line of text in its argument contains string "`life`". We successfully passed that function's name to method `filter()`.
- Above, we have seen a few more crucial features of Python. Python accepted the second line of function definition only when we properly indented `'return "life"…` statement.
- Also, to terminate function definition, we had to hit Carriage Return (Enter) twice.
- Most importantly, there are no semicolons in sight.

Passing Function in Java

- In Java Spark API it is possible to pass functions as well. In that case, functions are defined as Java classes, implementing a Spark interface:

  `org.apache.spark.api.java.function.Function.`

- For example:

```
JavaRDD<String> lifeLines = lines.filter(
    new Function<String, Boolean>() {
     Boolean call(String line){return line.contains("life");}
    }
);
```

- Java 8 introduces shorthand syntax called *`lambdas`* that looks similar to Python.
- The above code in that lambda syntax would look like:

```
JavaRDD<String> lifeLines = lines.filter(line ->
        line.contains("life"));
```

- A lot of Spark's magic is in the fact that function-based operations like `filter()` *also* parallelize across the cluster. That is, Spark automatically takes your function (e.g., `line.contains("Python"))` and ships it to executor nodes.
- You write code in a single driver program and Spark automatically has parts of it running on multiple nodes

Spark Sources and Destinations of Data

- Spark supports a wide range of input and output sources, partly because it builds on the ecosystem made available by Hadoop.
- In particular, Spark can access data through the `InputFormat` and `OutputFormat` interfaces used by Hadoop MapReduce, which are available for many common file formats and storage systems (e.g., S3, HDFS, Cassandra, HBase, etc.).
- For data stored in a local or distributed file system, such as NFS, HDFS, or Amazon S3, Spark can access a variety of file formats including `Text`, `JSON`, `SequenceFiles`, and Google's `Protocol Buffers`.
- The Spark SQL module, provides an efficient API for structured data sources, including JSON and Apache Hive.
- Spark could also use third-party libraries for connecting to Cassandra, HBase, Elasticsearch, and JDBC databases.
- We will analyze some of the above techniques a bit later.

File Formats

- Spark makes it very simple to load and save data in a large number of file formats. Spark transparently handles compressed formats based on the file extension.
- We can use both Hadoop's new and old file APIs for keyed (or paired) data. We can use those only with key/value data.

Format Name	Structured	Comments
Text File	No	Plain old text files. Records assumed to be one per line.
JSON	Semi	Common text-based format, semi-structured; most libraries require one record per line.
CSV	YES	Very common text-based format, often used with spreadsheet applications.
SequenceFile	YES	A common Hadoop file format used for key/value data
Protocol buffer	YES	A fast, space-efficient multi-language format
Object file	YES	Useful for saving data from a Spark job to be consumed by shared code. Breaks if you change your classes, as it relies on Java Serialization.

Standalone Applications

- Spark can be linked into standalone applications in either Java, Scala, or Python. The main difference from using it in the shell is that you need to initialize your own `SparkContext`. After that, the API is the same.
- The process of linking to Spark varies by language. In Java and Scala, you give your application a Maven dependency on the spark-core artifact.
- Maven is a popular package management tool for Java-based languages that lets you link to libraries in public repositories. You can use Maven itself to build your project, or use other tools that can talk to the Maven repositories, including Scala's `sbt` tool or `Gradle`.
- Eclipse also allows you to directly add a Maven dependency to a project.
- In Python, you simply write applications as Python scripts, but you must run them using the `bin/spark-submit` script included in Spark. The `spark-submit` script includes the Spark Python dependencies.
- We simply run your script with the

```
$SPARK_HOME/bin/spark-submit  your_script.py
```

Standalone Application in Python

- To create an application (Python script) we need to import some Python classes and create `SparkContext` object.
- The rest of the application is coded as if you are writing code in PySpark shell

```
from pyspark import SparkConf, SparkContext

conf = SparkConf().setMaster("local").setAppName("MyApp")
sc = SparkContext(conf = conf)
lines = sc.textFile("/ulysis/4300.txt")
lifeLines = lines.filter(lambda line: "life" in line)
print lifeLines.first()
```

- If we invoke the above with:

```
$ spark-submit my_script.py
```

- We get:

```
py4j.protocol.Py4JJavaError: An error occurred while calling
o25.partitions.
: org.apache.hadoop.mapred.InvalidInputException: Input path
does not exist: hdfs://localhost:8020/ulysis/4300.txt
```

Python Applications use full HDFS path

- Apparently, we need to provide the complete HDFS path to our files and the `filter()` line of the script should read:

```
lines = sc.textFile("/user/cloudera/ulysis/4300.txt")
```

- If you recall, in HDFS, every user has a home directory, `/user/cloudera` in our case.
- Modified script will produce the expected output:

```
$ spark-submit your_script.py
whom Mulligan was one, and Arius, warring his life long
upon the
```

- If we want to read `4300.txt` file from the local Linux directory `/home/cloudera`, we should change the above line to:

```
lines = sc.textFile("file:///home/cloudera/4300.txt")
```

Initializing `SparkContext` object

- To initialize `SparkContext` in Scala we would write:

```
import org.apache.spark.SparkConf
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._
val conf = new SparkConf().setMaster("local").setAppName("MyApp")
val sc = new SparkContext(conf)
```

- To initialize `SparkContext` in Java we would write

```
import org.apache.spark.SparkConf;
import org.apache.spark.api.java.JavaSparkContext;
SparkConf conf = new SparkConf().setMaster("local").setAppName("MyApp");
JavaSparkContext sc = new JavaSparkContext(conf);
```

- To initialize `SparkContext` in Python we did:

```
from pyspark import SparkConf, SparkContext
conf = SparkConf().setMaster("local").setAppName("MyApp")
sc = SparkContext(conf = conf)
```

- Only one `SparkContext` may be active per JVM.
- You must `stop()` the active `SparkContext` before creating a new one. To shutdown `SparkContext` call `sc.stop()` or exist the application with `System.exit()` or `sys.exit()`

Initializing `SparkContext`

- Previous examples show the minimal way to initialize a `SparkContext`, where we pass two parameters:
  - *cluster URL*, namely `local` in these examples, which tells Spark how to connect to a cluster. `local` is a special value that runs Spark on one thread on the local machine, without connecting to a cluster.
  - an *application name*, namely `MyApp` in these examples. This will identify your application on the cluster manager's UI if you connect to a cluster.
- Additional parameters exist for configuring how your application executes or add code to be shipped to the cluster.

- `SparkContext` is the main entry point for Spark functionality.

SparkContext Object

- SparkContext represents the connection to a Spark cluster, and can be used to create RDDs, accumulators and broadcast variables on that cluster.
- SparkContext comes with a large number of methods. As you can see from their names in Scala implementation, those methods implement large area of data processing and data manipulation functionality:

- filter(), first(), flatMapValues(), fold(), foldByKey(), **foreach()**, foreachPartition(), fullOuterJoin(), getCheckpointFile(), getStorageLevel(), glom(), **groupBy()**, groupByKey(), groupWith(), histogram(), id(), isCheckpointed(), join(), keyBy(), keys(), leftOuterJoin(), lookup(), **map()**, mapPartitions(), mapPartitionsWithIndex(), mapValues(), max(), mean(), meanApprox(), min(), name(), set(), pipe(), randomSplit(), **reduce()**, reduceByKey(), reduceByKeyLocally(), repartition(), repartitionAndSortWithinPartitions(), **rightOuterJoin()**, sample(), sampleByKey(), sampleStdev(), sampleVariance(), saveAsHadoopDataset(), saveAsHadoopFile() , saveAsNewAPIHadoopDataset(), saveAsNewAPIHadoopFile(), saveAsPickleFile(), saveAsSequenceFile(), saveAsTextFile(), setName(), **sortBy()**, sortByKey(), stats(), subtract(), subtractByKey(), sum(), sumApprox(), take(), takeOrdered(), takeSample(), toDebugString(), treeAggregate(), treeReduce(), union(), unpersist(), variance(), zip(), zipWithIndex(), zipWithUniqueId()
- We will examine a few of the above methods along our way.

SparkContext API

- Java class implementing SparkContext object is described here:

https://spark.apache.org/docs/1.6.0/api/java/org/apache/spark/SparkContext.html

- Python class implementing SparkContext object is described here:

https://spark.apache.org/docs/1.6.0/api/python/pyspark.html#pyspark.SparkContext

- Scala class implementing SparkContext object is described here:

https://spark.apache.org/docs/1.6.0/api/scala/index.html#org.apache.spark.SparkContext

- R package for working with Spark could be found at:

https://spark.apache.org/docs/1.6.0/api/R/index.html

- While the functionality is almost identical in all supported languages, there does not exist a one-to-one mapping between methods of respective classes in all four languages.
- Most methods one could find in Scala class SparkContext exist in Java class SparkContext. Python's SparkContext has fewer methods. It appears that some are moved to some other Python classes, like RDD, for example.
- Let us try to implement a word count program on a single machine.
- We will do it using both sbt for Scala and Maven for a Java example

Building Spark Applications, `WordCount.java`

```
package edu.hu.example;
import java.util.Arrays; import java.util.List; import java.lang.Iterable;
import scala.Tuple2; import org.apache.commons.lang.StringUtils;
import org.apache.spark.api.java.JavaRDD;
import org.apache.spark.api.java.JavaPairRDD;
import org.apache.spark.api.java.JavaSparkContext;
import org.apache.spark.api.java.function.FlatMapFunction;
import org.apache.spark.api.java.function.Function2;
import org.apache.spark.api.java.function.PairFunction;

public class WordCount {
  public static void main(String[] args) throws Exception {
      String master = args[0];
      JavaSparkContext sc = new JavaSparkContext(
      master, "wordcount", System.getenv("SPARK_HOME"), System.getenv("JARS"));
    JavaRDD<String> rdd = sc.textFile(args[1]);
    JavaPairRDD<String, Integer> counts = rdd.flatMap(
      new FlatMapFunction<String, String>() {
        public Iterable<String> call(String x) {
          return Arrays.asList(x.split(" "));
        }}).mapToPair(new PairFunction<String, String, Integer>(){
            public Tuple2<String, Integer> call(String x){
              return new Tuple2(x, 1);
            }}).reduceByKey(new Function2<Integer, Integer, Integer>(){
                public Integer call(Integer x, Integer y){ return x+y;}});
                 counts.saveAsTextFile(args[2]);
           }
}
```

Building Spark Applications, WordCount.scala

```
/*  Illustrates flatMap + countByValue for wordcount.  */
package edu.hu.examples
import org.apache.spark._
import org.apache.spark.SparkContext._

object WordCount {
    def main(args: Array[String]) {
      val inputFile = args(0)
      val outputFile = args(1)
      val conf = new SparkConf().setAppName("wordCount")
      // Create a Scala Spark Context.
      val sc = new SparkContext(conf)
      // Load our input data.
      val input =  sc.textFile(inputFile)
      // Split up into words.
      val words = input.flatMap(line => line.split(" "))
      // Transform into word and count.
      val counts = words.map(word => (word, 1)).reduceByKey{case (x, y) => x + y}
      // Save the word count back out to a text file, causing evaluation.
      counts.saveAsTextFile(outputFile)
    }
}
```

Building Spark Application

- To build Spark Applications you need Maven for Java and `sbt` tool for Scala apps.
- You download Maven's binary tar.gz file from http://maven.apache.org/download.cgi
- You untar or unzip the archive. On Linux you usually copy the untared folder to `/usr/local`. Then you add to your `.bash_profile` file

```
M2_HOME=/usr/local/apache-maven-3.3.9
export M2_HOME
PATH=$M2_HOME/bin:$PATH
export PATH
```

- Maven's executable is called `mvn`, so you ask for it like:

```
$ which mvn
/usr/local/apache-maven-3.3.9/bin/mvn
```

- Maven does what `ant` does, or what `make` does in the world of C/C++.
- You use Maven to compile (build) your projects.
- Maven also maintains a public repository of all kinds of packages and their versions and if properly instructed it will fetch for your build process any and all software packages (dependencies) you need.
- Maven can do many other manipulations of your files/projects/packages and make little children, if you want it to.

Maven build file `pom.xml`

- Instructions for Maven, what to do and where to get what it needs, are written in a file called `pom.xml`.
- Initially, you copy and past content of that file. At one point you start writing your own.
- This is a file that will help us compile `WordCount.java`

```
<project> <groupId>edu.hu.examples</groupId>
  <artifactId>spark-example</artifactId>
  <modelVersion>4.0.0</modelVersion>
  <name>example</name>
  <packaging>jar</packaging> <version>0.0.1</version>
  <dependencies>
    <dependency> <!-- Spark dependency -->
      <groupId>org.apache.spark</groupId>
      <artifactId>spark-core_2.10</artifactId>
      <version>1.1.0</version>
      <scope>provided</scope>
    </dependency>
  </dependencies>
  <properties><java.version>1.6</java.version>
  </properties>
  <build>
    <pluginManagement>
      <plugins><plugin>
<groupId>org.apache.maven.plugins</groupId>
      <artifactId>maven-compiler-plugin</artifactId>
          <version>3.1</version>
          <configuration>
            <source>${java.version}</source>
            <target>${java.version}</target>
          </configuration>
          </plugin>
      </plugins>
    </pluginManagement>
  </build>
</project>
```

Maven's `pom.xml` file

- **Project Object Model (pom)**
  - Describes a project
  - Name and Version
  - Artifact Type
  - Source Code Locations
  - Dependencies
  - Plugins
  - Profiles (Alternate build configurations)

Building Spark Java Project with Maven

- To build a project we need to create a directory hierarchy for our code artifacts. Below is a possible structure of that hierarchy. Directories `/src` and `/project` are at the same level. Initially, `/project` is empty.

```
/mini-examples
   build.sbt
   pom.xml
   /src
     /main
        /java                                   /scala
            /edu                                    /edu
               /hu                                     /hu
                  /examples                               /examples
                       WordCount.java                          WordCount.scala
   /project
```

```
$ mkdir -p mini-examples/src/main/java/edu/hu/examples
$ mkdir -p mini-examples/src/main/scala/edu/hu/examples
```

- Run Maven from the directory where `pom.xml` resides, i.e. `/mini-examples`, like this:

```
$ mvn clean && mvn compile && mvn package
```

- Build process downloaded a bunch of “dependencies”, compiled class `WordCount.java` and created directory `target`

Structure of Maven's Project

Maven project structure

- `target`: Default work directory
- `src`: All project source files go in this directory
- `src/main`: All sources that go into primary artifact
- `src/test`: All sources contributing to testing project
- `src/main/java`: All java source files
- `src/main/webapp`: All web source files
- `src/main/resources`: All non compiled source files
- `src/test/java`: All java test source files
- `src/test/resources`: All non compiled test source files

Generated Artifacts

- Generated directory `target` contains directory `classes` with the compiled Java classes and a jar file `spark-example-0.0.1.jar`. This jar contains compiled classes coming from the original `src` directory.
- This jar file, in a cluster with more than one machine, will be shipped to various worker nodes.
- The name of the jar file is a concatenation of `pom.xml` elements `<artifactId>` and `<version>`
- Directory `maven-archiver` contains file `pom.properties` which lists values of relevant elements from `pom.xml` file: `version, groupId` and `artifactId`.
- To run compiled code, in the directory where `pom.xml` file resides, we issue the following command, all on one line:

```
$ spark-submit --class edu.hu.examples.WordCount ./target/spark-example-0.0.1.jar ulysis/4300.txt wordcounts
```

- In the above, string `ulysis/4300.txt` is the name of the HDFS input file (`WordCount.java inputFile variable`) and `wordcounts` is the name of the `WordCount.java outputFile` variable, i.e. HDFS output directory.

WordCount.java Spark's Heavenly Output

- Once the run is finished, in HDFS directory `/user/cloudera/wordcounts` we will find files named `part-00000` and `part-00001`. If we open those files, we will see that they contain something that looks like words and counts:

```
(supplied.,1)
(Ah!,14)
(reunion,2)
(bone,5)
(Justifiable,1)
(Hats,1)
(Apart.,1)
(blandly,1)
(fiction.,1)
(Friend,2)
(hem,2)
(stinks,3)
(boats?,1)
(flutiest,1)
(Lost.,1)
(fuller,2)
(jade,1)
```

- If we search for the words `heaven` or `Heaven`, we will find numbers like

```
(heavens,5)
(HeavenS_,1).
```

- We though, there were some `50+ 2 = 52 heavens.`
- They are there, except that neither of our searches was very sophisticated.
- If we do

```
$ egrep –i heaven part-00000
```

- we will get 56 of them.
- What is even better (more) ☺ than the result with simple `filter()` method.

```
(heavens,5)
(heaven._,1)
(Heavenly,1)
(heavens,,1)
(heavenbeast,,1)
(heavenborn,1)
(heavenly,2)
(heaven!,1)
(heavenly.,1)
(heavengrot,,1)
(heaven,,8)
(Heavens_,1)
(heavenman.,1)
(heaven.,8)
(heaventree,1)
(heaven,17)
(heaventree,,1)
(heaven:,1)
(heaven's,1)
(heavenworld,1)
(heavenward.)_,1)
```

Scala Build Tool: `sbt`

- `sbt` is an open source build tool for Scala and Java projects, similar to Java's Maven or Ant.
- `sbt`'s main features are:
  - native support for compiling Scala code and integrating with many Scala test frameworks
  - build descriptions written in Scala using a Domain Specific Language
  - dependency management using Ivy (which supports Maven-format repositories)
  - continuous compilation, testing, and deployment
  - integration with the Scala interpreter for rapid iteration and debugging
  - support for mixed Java/Scala projects

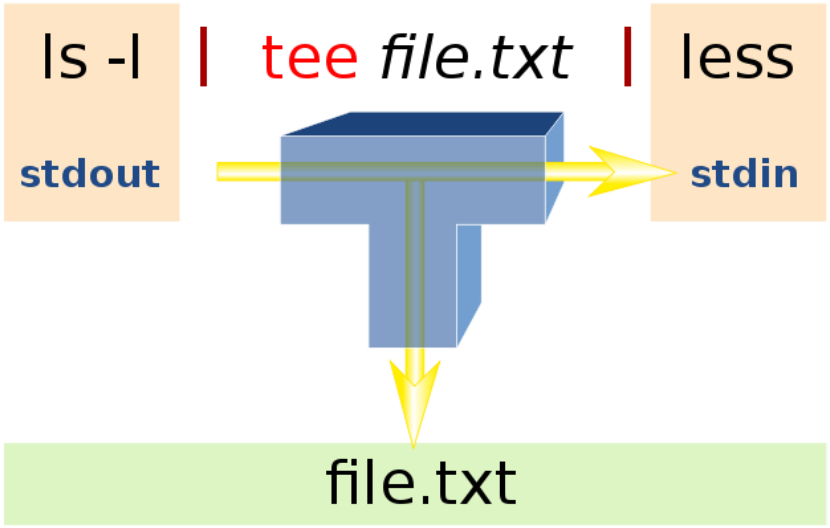
  `sbt` is the *de facto* build tool for the Scala community.

- To install `sbt`, on Red Hat Enterprise Linux (CentOS), run the following command on one line :

```
$ curl https://bintray.com/sbt/rpm/rpm | sudo tee
/etc/yum.repos.d/bintray-sbt-rpm.repo
$ sudo yum install sbt
$ which sbt
/usr/bin/sbt
```

- You are done

Linux `tee` Command



- **Unix-like** Systems

tee [-a] [-i] [File ...] Arguments:

File One or more files that will receive the "tee-d" output.

Flags:

-a Appends the output to the end of File instead of writing over it.

-i Ignores interrupts.

The command returns the following exit values (exit status):

0 The standard input was successfully copied to all output files.

>0 An error occurred.

Building Spark Scala Project with `sbt`

- We want to build a Spark application from file `WordCount.scala` residing in directory `mini-examples/src/main/scala/edu/hu/examples`
- `sbt` also needs a file to tell it what to do.
- That file is called `build.sbt` and in our case reads:

```
name := "mini-example"
                              # these empty lines are significantcd
version := "0.0.1"
                              # these empty lines are significant
scalaVersion := "2.10.4"
                              # these empty lines are significant
// additional libraries
libraryDependencies ++= Seq(
     "org.apache.spark" %% "spark-core" % "1.1.0" % "provided")
```

- To build Spark application from `WordCount.scala` type:

```
$ sbt clean package    # in the directory containing build.sbt file
```

- Build process created a bunch of directories. We are interested in the directory `../mini-example/target/scala-2.10`. In that directory there appears a jar file `mini-example_2.10-0.0.1.jar`. That jar file contains our `WordCount.class` and will be distributed among members of the cluster if you have a cluster with more than one machine.

Run Scala version of `WordCount`

- To run built project, in directory `../mini-example` we type, all on one line:

```
$ spark-submit --class edu.hu.examples.WordCount ./target/scala-2.10/mini-example_2.10-0.0.1.jar ulysis/4300.txt scalacounts
```

If we examine HDFS directory `scalacounts` we will see a results file `part-00000`. We can copy that file to the local system

```
$ hadoop fs –get scalacounts/part-00000 scalacounts
```

- And then see how are heavens doing this time

```
$ cd scalacounts
$ egrep –i heaven scalacounts/part-00000

   (heavens,5)
   (heaven._,1)
   (Heavenly,1)
   (heavens,,1)
   (heavenbeast,,1)
   (heavenborn,1)
   (heavenly,2)
   (heaven!,1)
   (heavenly.,1)
   (heavengrot,,1)
   (heaven,,8)
   (Heavens_,1)
   (heavenman.,1)
   (heaven.,8)
   (heaventree,1)
   (heaven,17)
   (heaventree,,1)
   (heaven:,1)
   (heaven's,1)
   (heavenworld,1)
   (heavenward.)_,
   1)
   )
```

`WordCount` in Python

- You can do WordCounting in Python as well

```
file = sc.textFile("/user/cloudera/ulysis/4300.txt")

counts = lines.flatMap(lambda line: line.split(" ")) \
 .map(lambda word: (word, 1)).reduceByKey(lambda a, b: a +b)
>>> counts.saveAsTextFile("pycounts")
```

- In HDFS directory `pycounts` you will find file `part-00000` and `part-00001`

Programming with RDDs

- An RDD in Spark is simply an immutable distributed collection of objects.
- Each RDD is split into multiple *partitions*, which may be computed on different nodes of the cluster. RDDs can contain any type of Python, Java, or Scala objects, including user defined classes.
- Users create RDDs in two ways: by loading an external dataset, or by distributing a collection of objects (e.g., a list or set) in their driver program. We have already seen loading a text file as an RDD of strings using `SparkContext.textFile()`.
- Once created, RDDs offer two types of operations: *transformations* and *actions*.
- *Transformations* construct a new RDD from a previous one. For example, one common transformation is filtering data that matches a predicate. In our text file example, we can use this to create a new RDD holding just the strings that contain the word *Heaven* . Transformations always return an RDD.
- *Actions*, on the other hand, compute a result based on an RDD, and either return it to the driver program or save it to an external storage system (e.g., HDFS). One example of an action we called earlier is first(), which returns the first element in an RDD. Actions return other types.

Lazy Compute

- Spark computes RDDs only in a *lazy* fashion—that is, the first time they are used in an action. If Spark were to load and store all the lines in the file as soon as we define an RDD, it would waste a lot of storage space, given that we might filter out many lines. Instead, once Spark sees the whole chain of transformations, it can compute just the data needed for its result. In fact, for the first() action, Spark scans the file only until it finds the first matching line; it doesn't even read the whole file.
- Finally, Spark's RDDs are by default recomputed each time you run an action on them. If you would like to reuse an RDD in multiple actions, you can ask Spark to *persist* it using RDD.persist().
- We can ask Spark to persist our data in a number of different places. After computing it the first time, Spark will store the RDD contents in memory (partitioned across the machines in your cluster), and reuse them in future actions. Persisting RDDs on disk instead of memory is also possible.
- In practice, you will often use persist() to load a subset of your data into memory and query it repeatedly.

```
>>> pythonLines.persist
>>> pythonLines.count()
2
>>> pythonLines.first()
```

Creating RDDs

- We already know how to create RDDs by loading data from external files.
- Another way to create RDDs is to take an existing collection in your program and pass it to SparkContext's `parallelize()` method. Like:
- *parallelize() method in Python*

```
lines = sc.parallelize(["Heaven", "Earth"])
```

- *parallelize() method in Scala*

```
val lines = sc.parallelize(List ("Heaven", "Earth"))
```

- *parallelize() method in Java*

```
JavaRDD<String> lines = sc.parallelize(Arrays.asList ("Heaven",
"Earth"));
```

Transformations

- Suppose that we have a logfile, *log.txt*, with a number of messages, and we want to select only the error messages. We can use the `filter()` transformation seen before.
- *filter() transformation in Python*

```
inputRDD = sc.textFile("log.txt")
errorsRDD = inputRDD.filter(lambda x: "error" in x)
```

- *filter() transformation in Scala*

```
val inputRDD = sc.textFile("log.txt")
val errorsRDD = inputRDD.filter(line =>
line.contains("error"))
```

- *filter() transformation in Java*

```
JavaRDD<String> inputRDD = sc.textFile("log.txt");
JavaRDD<String> errorsRDD = inputRDD.filter(
   new Function<String, Boolean>() {
      public Boolean call(String x) { return x.contains("error"); }
   }
});
```

- `filter()` operation does not mutate the existing `inputRDD`. Instead, it returns a pointer to an entirely new RDD. `inputRDD` can still be reused later in the program

`union()` Transformation

- If we need to print the number of lines that contained either *error* or *warning*, we could use union() function, which is identical in all three languages. Text that follows is in Python:

```
errorsRDD = inputRDD.filter(lambda x: "error" in x)
warningsRDD = inputRDD.filter(lambda x: "warning" in x)
badLinesRDD = errorsRDD.union(warningsRDD)
```

- union() is a bit different than filter(), in that it operates on two RDDs instead of one.
- Transformations can operate on any number of input RDDs.

Actions

- at some point, we'll want to actually *do something* with our dataset. Actions are the second type of RDD operation. They are the operations that return a final value to the driver program or write data to an external storage system.
- Actions force the evaluation of the transformations required for the RDD they were called on, since they need to actually produce output.
- Continuing the log example from the previous section, we might want to print out some information about the `badLinesRDD`. To do that, we'll use two actions, `count()`, which returns the count as a number, and `take()`, which collects a number of elements from the RDD,.
- In the following example, we will use method take() to retrieve a small number of elements (sample of 10) in the RDD at the driver program. We then iterate over them locally to print out information at the driver.
- RDDs also have a collect() function to retrieve the entire RDD. This can be useful if your program filters RDDs down to a very small size and you'd like to deal with it locally. The entire dataset must fit in memory on a single machine to use collect() on it.

Actions, `count()`, `take()`

- *Python error count and sample display using actions*

```
print "Input had " + badLinesRDD.count() + " concerning lines"
print "Here are 10 examples:"
for line in badLinesRDD.take(10):
print line
```

- *Scala error count and smaple display using actions*

```
println("Input had " + badLinesRDD.count() + " concerning lines")
println("Here are 10 examples:")
badLinesRDD.take(10).foreach(println)
```

- *Java error count and sample display using actions*

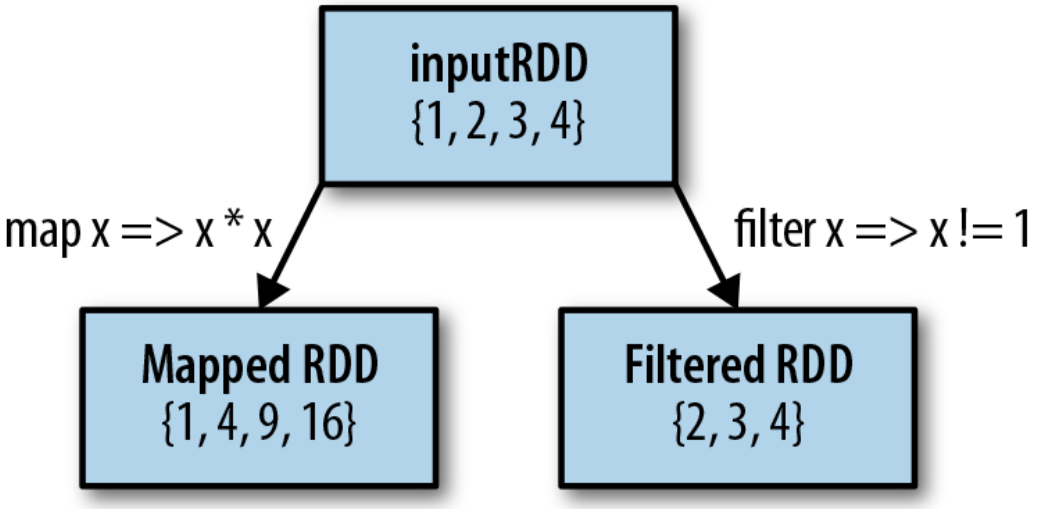
```
System.out.println("Input had " + badLinesRDD.count() + "
concerning lines")
System.out.println("Here are 10 examples:")
for (String line: badLinesRDD.take(10)) {
   System.out.println(line);
}
```

- If RDDs can't be `collect()`ed to the driver because they are too large, it is common to write data out to a distributed storage system such as HDFS or Amazon S3.
- You can save the contents of an RDD using the `saveAsTextFile()` action, saveAsSequenceFile(), or any of a number of actions for various built-in formats.

Common Transformations and Actions

Element-wise transformations:

- The two most common transformations we use are map() and filter().
- The map() transformation takes in a function and applies it to each element in the RDD with the result of the function being the new value of each element in the resulting RDD.
- The filter() transformation takes in a function and returns an RDD that only has elements that pass the filter() function.



- map()'s return type does not have to be the same as its input type.

map() Examples

- *Python squaring the values in an RDD*

```
nums = sc.parallelize([1, 2, 3, 4])
squared = nums.map(lambda x: x * x).collect()
for num in squared:
print "%i " % (num)
```

- *Scala squaring the values in an RDD*

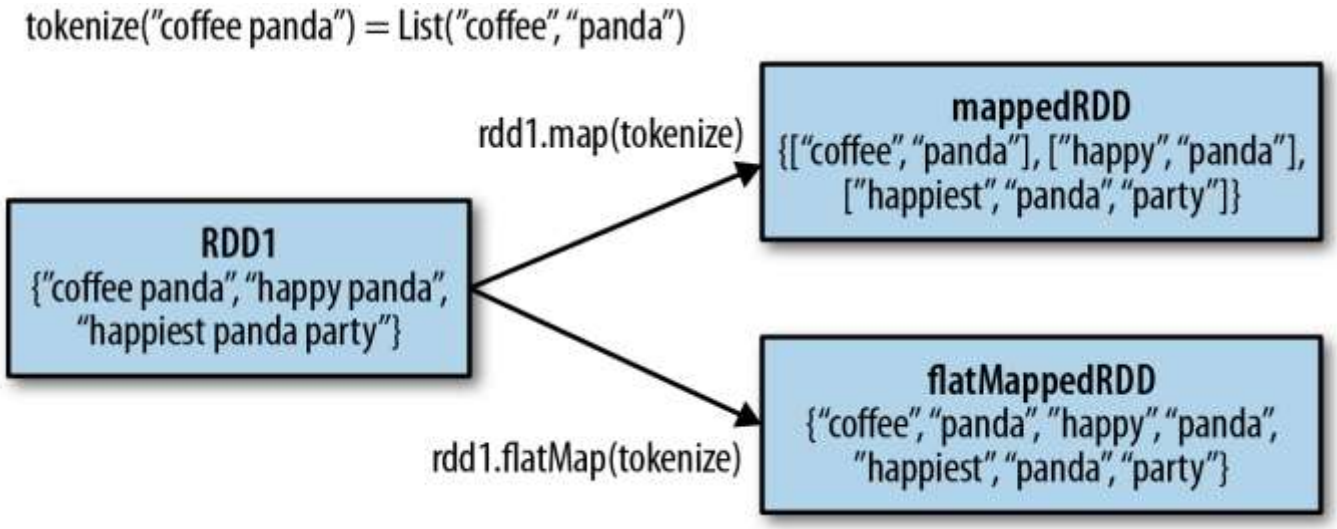
```
val input = sc.parallelize(List(1, 2, 3, 4))
val result = input.map(x => x * x)
println(result.collect().mkString(","))
```

- *Java squaring the values in an RDD*

```
JavaRDD<Integer> rdd = sc.parallelize(
    Arrays.asList(1, 2, 3, 4));
JavaRDD<Integer> result = rdd.map(
  new Function<Integer, Integer>() {
   public Integer call(Integer x) { return x*x; }
});
System.out.println(StringUtils.join(result.collect(),
","));
```

flatMap()

- Sometimes we want to produce multiple output elements for each input element. The operation to do this is called flatMap().
- As with map(), the function we provide to flatMap() is called individually for each element in our input RDD. Instead of returning a single element, we return an iterator with our return values.
- Rather than producing an RDD of iterators, we get back an RDD that consists of the elements from all of the iterators. A simple usage of flatMap() is splitting up an input string into words.
- The difference between map() and flatMap() is presented bellow.



flatMap() Examples

- *flatMap() in Python, splitting lines into words*

```
lines = sc.parallelize(["hello world", "hi"])
words = lines.flatMap(lambda line: line.split(" "))
words.first() # returns "hello"
```

- *flatMap() in Scala, splitting lines into multiple words*

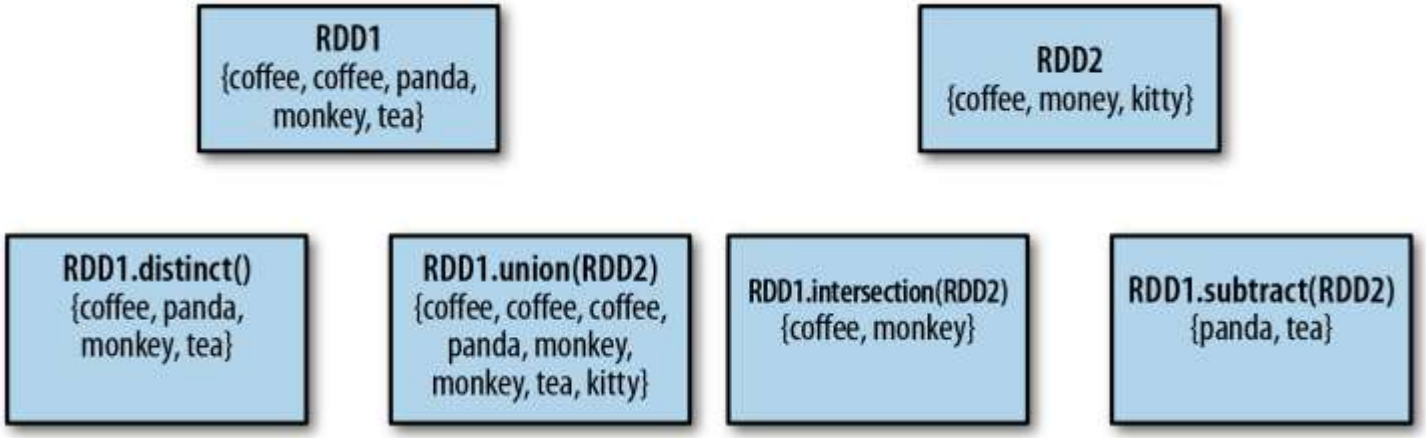
```
val lines = sc.parallelize(List("hello world", "hi"))
val words = lines.flatMap(line => line.split(" "))
words.first() // returns "hello"
```

- *flatMap() in Java, splitting lines into multiple words*

```
JavaRDD<String> lines = sc.parallelize(
     Arrays.asList("hello world", "hi"));
JavaRDD<String> words = lines.flatMap(
 new FlatMapFunction<String, String>() {
  public Iterable<String> call(String line) {
    return Arrays.asList(line.split(" "));
  }
});
words.first(); // returns "hello"
```

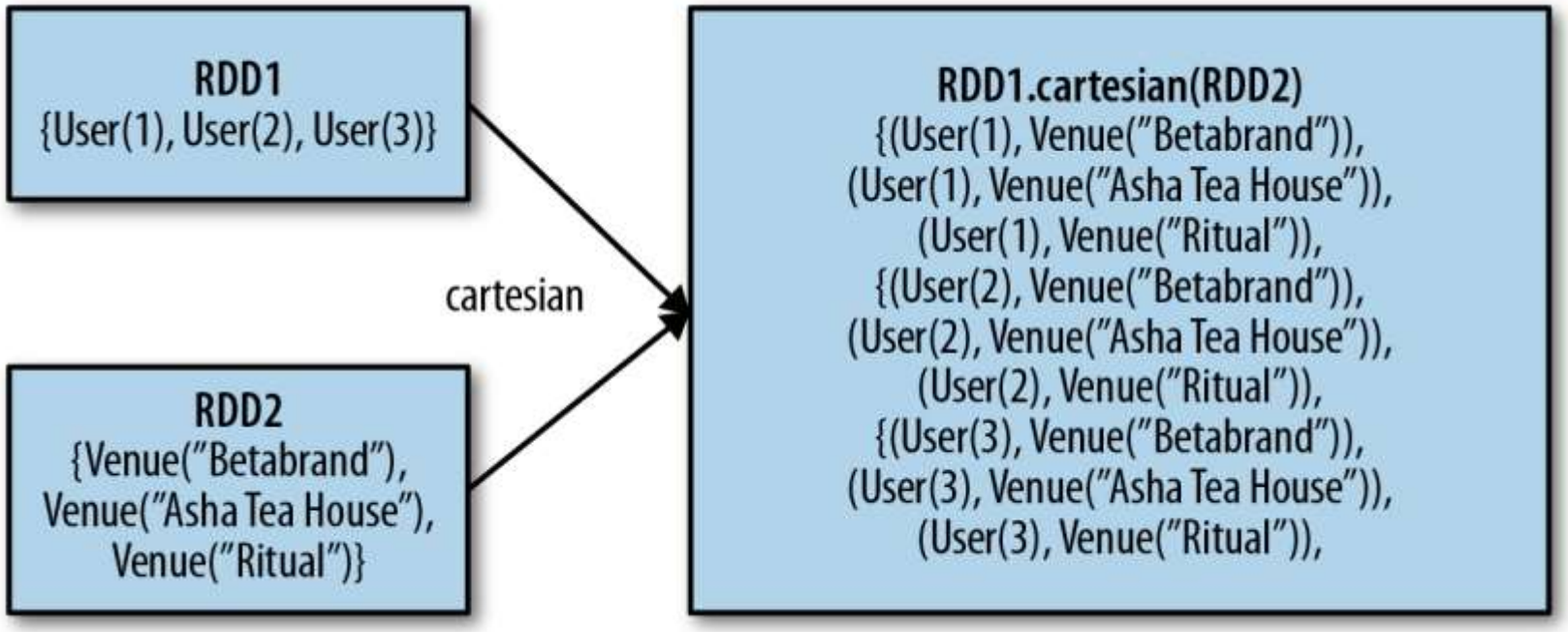
Pseudo set operations

- RDDs support many of the operations of mathematical sets, such as union and intersection, even when the RDDs themselves are not proper sets.
- All set operations require that the RDDs being operated on have elements of the same type.
- The set property most frequently missing from RDDs is the uniqueness of elements, as we often have duplicates.
- Below we illustrate four set operations: distinct(), union(), intersection() and subtract()



Cartesian Product between RDDs

- The cartesian(other) transformation returns all possible pairs of (a, b) where a is in the source RDD and b is in the other RDD.



Actions, `reduce()`

- The most common action on basic RDDs you will likely use is reduce(), which takes a function that operates on two elements of the type in your RDD and returns a new element of the same type.
- A simple example of such a function is +, which we can use to sum our RDD. With reduce(), we can easily sum the elements of our RDD, count the number of elements, and perform other types of aggregations.
- *reduce() in Python*

```
sum = rdd.reduce(lambda x, y: x + y)
```

- *reduce() in Scala*

```
val sum = rdd.reduce((x, y) => x + y)
```

- *reduce() in Java*

```
Integer sum = rdd.reduce(
  new Function2<Integer, Integer, Integer>() {
     public Integer call(Integer x, Integer y) { return x + y; }
  });
```

- `reduce()` requires that the return type of our result be the same type as that of the elements in the RDD we are operating over.

fold()

- Similar to reduce() is fold(), which also takes a function with the same signature as needed for reduce(), but in addition takes a “zero value” to be used for the initial call on each partition.
- The zero value you provide should be the identity element for your operation; that is, applying it multiple times with your function should not change the value (e.g., 0 for +, 1 for *, or an empty list for concatenation).
- fold() requires that the return type of our result be the same type as that of the elements in the RDD we are operating over. This works well for operations like sum, but sometimes we want to return a different type.
- For example, when computing a running average, we need to keep track of both the count so far and the number of elements, which requires us to return a pair. We could work around this by first using map() where we transform every element into the element and the number 1, which is the type we want to return, so that the reduce() function can work on pairs.

aggregate()

- The aggregate() function frees us from the constraint of having the return be the same type as the RDD we are working on. With aggregate(), like fold(), we supply an initial zero value of the type we want to return. We then supply a function to combine the elements from our RDD with the accumulator. Finally, we need to supply a second function to merge two accumulators, given that each node accumulates its own results locally.
- We can use aggregate() to compute the average of an RDD, avoiding a map() before the fold().
- *aggregate() in Python*

```
sumCount = nums.aggregate((0, 0),
(lambda acc, value: (acc[0] + value, acc[1] + 1),
(lambda acc1, acc2: (acc1[0] + acc2[0], acc1[1] + acc2[1]))))
return sumCount[0] / float(sumCount[1])
```

- *aggregate() in Scala*

```
val result = input.aggregate((0, 0))(
(acc, value) => (acc._1 + value, acc._2 + 1),
(acc1, acc2) => (acc1._1 + acc2._1, acc1._2 + acc2._2))
val avg = result._1 / result._2.toDouble
```

aggregate() in Java

```
class AvgCount implements Serializable {
    public AvgCount(int total, int num) {
    this.total = total; this.num = num;
}
public int total; public int num;
    public double avg() { return total / (double) num;
    }
}
Function2<AvgCount, Integer, AvgCount> addAndCount =
    new Function2<AvgCount, Integer, AvgCount>() {
    public AvgCount call(AvgCount a, Integer x) {
    a.total += x; a.num += 1; return a;
    }
};
Function2<AvgCount, AvgCount, AvgCount> combine =
    new Function2<AvgCount, AvgCount, AvgCount>() {
    public AvgCount call(AvgCount a, AvgCount b) {
    a.total += b.total; a.num += b.num; return a;
    }
};
AvgCount initial = new AvgCount(0, 0);
AvgCount result = rdd.aggregate(initial, addAndCount, combine);
System.out.println(result.avg());
```

Examples, Actions

Basic actions on an RDD containing {1, 2, 3, 3}

Function name	Purpose	Example	Result
collect()	Return all elements from the RDD.	rdd.collect	{1, 2,3,3}
Count()	Return all elements from the RDD.	rdd.count()	4
countByValue()	Number of times each element occurs in the RDD.	rdd.countByValue()	{(1,1),(2,1),(3,2)}
take(num)	Return num elements from the RDD.	rdd.take(2)	{1,2}
top(num)	Return the top num elements the RDD.	rdd.top(2)	{3,3}
takeOrdered(num)(ordering)	Return num elements based on provided ordering.	rdd.takeOrdered(2)(myOrdering)	{3,3}
takeSample(withReplacement,num,[seed])	Return num elements at random.	rdd.takeSample(false, 1)	nondeterministic
reduce()	Combine the elements of the RDD together in parallel (e.g., sum).	rdd.reduce((x, y) => x + y)	9
fold(zero)(func)	Same as reduce() but with the provided zero value.	rdd.fold(0)((x, y) => x + y)	9
aggregate(zeroValue)(seqOp, combOp)	Similar to reduce() but used to return a different type.	rdd.aggregate((0, 0)) ((x, y) => (x._1 + y, x._2 + 1), (x, y) => (x._1 + y._1, x._2 + y._2))	(9,4)
foreach(func)	Apply the provided function to each element of the RDD.	rdd.foreach(func)	

Working with Key/Value Pairs

- While Spark tries to distinguish itself from MapReduced, most calculation in Spark rely on key/value pairs data types.
- Key/value RDDs are commonly used to perform aggregations.
- Key/value RDDs expose new operations (e.g., counting up reviews for each product, grouping together data with the same key, and grouping together two different RDDs).
- Spark introduces an advanced feature, *partitioning,* that lets users control the layout of pair RDDs across nodes. Using controllable partitioning, applications can sometimes greatly reduce communication costs by ensuring that data will be accessed together on the same node.
- Spark provides special operations on RDDs containing key/value pairs. These RDDs are called *pair RDDs*. *Pair RDDs* are a useful building block in many programs, as they expose operations that allow you to act on each key in parallel or regroup data across the network.
- For example, pair RDDs have a `reduceByKey()` method that can aggregate data separately for each key, and a `join()` method that can merge two RDDs together by grouping elements with the same key.

Creating Pair RDDs

- There are a number of ways to get pair RDDs in Spark. Many import formats will directly return pair RDDs for their key/value data.
- In other cases we have a regular RDD that we want to turn into a pair RDD. We can do this by running a map() function that returns key/value pairs.
- To illustrate, we show code that starts with an RDD of lines of text and keys the data by the first word in each line.
- The way to build key-value RDDs differs by language.
- In Python, for the functions on keyed data to work we need to return an RDD composed of tuples.
- *Creating a pair RDD using the first word as the key in Python*

```
pairs = lines.map(lambda x: (x.split(" ")[0], x))
```

- In Scala, for the functions on keyed data to be available, we also need to return tuples. An implicit conversion on RDDs of tuples exists to provide the additional key/value functions.
- *Creating a pair RDD using the first word as the key in Scala*

```
val pairs = lines.map(x => (x.split(" ")(0), x))
```

Creating Pair RDD in java

- Java doesn't have a built-in tuple type, so Spark's Java API has users create tuples using the scala.Tuple2 class. This class is very simple: Java users can construct a new tuple by writing new Tuple2(elem1, elem2) and can then access its elementswith the ._1() and ._2() methods.
- Java users also need to call special versions of Spark's functions when creating pair RDDs. For instance, the mapToPair() function should be used in place of the basic map() function.
- *Creating a pair RDD using the first word as the key in Java*

```
PairFunction<String, String, String> keyData =
   new PairFunction<String, String, String>() {
     public Tuple2<String, String> call(String x) {
        return new Tuple2(x.split(" ")[0], x);
     }
   };
JavaPairRDD<String, String> pairs =
lines.mapToPair(keyData);
```

Transformations on Pair RDDs

- Since pair RDDs contain tuples, we need to pass functions that operate on tuples rather than on individual elements.
- *Transformations on one pair RDD (example: {(1, 2), (3, 4), (3, 6)})*

Function name	Purpose	Example	Result
reduceByKey(func)	Compbine values with the same key	rdd.reduceByKey(x,y) => x + y	{(1,2),(3,10)}
groupByKey()	Group values with the same key	rdd.groupByKey()	{(1,[2]),(3,[4,6])}
mapValues(func)	Apply a function to each value of a pair RDD without changing the key.	rdd.mapValues(x => x+1)	{(1, 3), (3, 5), (3,7)}
flatMapValues(func)	Apply a function that returns an iterator to each value of a pair RDD, and for each element returned, produce a key/value entry with the old key. Often used for tokenization.	rdd.flatMapValues(x => (x to 5)	{(1,2), (1,3), (1,4), (1, 5), (3, 4), (3,5)}
keys()	Return an RDD of just the keys.	rdd.keys()	{1,3,5}
values()	Return an RDD just of values	rdd.values()	{2,4,6}
sortByKey()	Return and RD sorted by the key	Rdd.sortByKey()	{(1,2),(3,4)(3,6)}

Transformations on two pair RDD

- Two pair *RDDs (rdd = {(1, 2), (3, 4), (3, 6)} other = {(3, 9)})*

Function name	Purpose	Example	Result
substractByKey	Remove elements with a key present in the other RDD	Rdd.substractByKey(other)	{(1,2)}
join	Perform an inner join between two RDDs	Rdd.join(other)	{(3,(4,9)),(3,(6,9))}
rightOuterJoin	Perform a join between two RDDs where the key must be present in the first RDD	Rdd.rightOuterJoin(other)	{(3,(Some(4),9)), (3,(Some(6),9))}
leftOuterJoin	Perform a join between two RDDs where the key must be present in the other RDD.	rdd.leftOuterJoin(other)	{(1,(2,None)), (3, (4,Some(9))), (3, (6,Some(9)))}
cogroup	Group data from both RDDs sharing the same key.	rdd.cogroup(other)	{(1,([2],[])), (3, ([4, 6],[9]))}

- Sometimes working with pairs can be awkward if we want to access only the value part of our pair RDD.
- Since this is a common pattern, Spark provides the mapValues(func) function, which is the same as map{case (x, y): (x, func(y))}.

Pair RDDs are RDDs

- Pair RDDs are also still RDDs (of Tuple2 objects in Java/Scala or of Python tuples), and thus support the same functions as RDDs. For instance, we can take our pair RDD from the previous section and filter out lines longer than 20 characters:
- *Simple filter on second element in Python*

```
result = pairs.filter(lambda keyValue: len(keyValue[1]) < 20)
```

- *Simple filter on second element in Scala*

```
pairs.filter{case (key, value) => value.length < 20}
```

- *Simple filter on second element in Java*

```
Function<Tuple2<String, String>, Boolean> longWordFilter =
  new Function<Tuple2<String, String>, Boolean>() {
    public Boolean call(Tuple2<String, String> keyValue) {
      return (keyValue._2().length() < 20);
    }
  };
JavaPairRDD<String, String> result= pairs.filter(longWordFilter);
```

Aggregations

- When datasets are described in terms of key/value pairs, it is common to want to aggregate statistics across all elements with the same key. We have looked at the `fold()`, `combine()`, and `reduce()` actions on basic RDDs, and similar per-key transformations exist on pair RDDs.
- Spark has a similar set of operations that combines values that have the same key. These operations return RDDs and thus are transformations rather than actions.
- `reduceByKey()` is quite similar to `reduce()`; both take a function and use it to combine values. `reduceByKey()` runs several parallel reduce operations, one for each key in the dataset, where each operation combines values that have the same key. Because datasets can have very large numbers of keys, `reduceByKey()` is not implemented as an action that returns a value to the user program. Instead, it returns a new RDD consisting of each key and the reduced value for that key.
- `foldByKey()` is quite similar to fold(); both use a zero value of the same type of the data in out RDD and combination function.

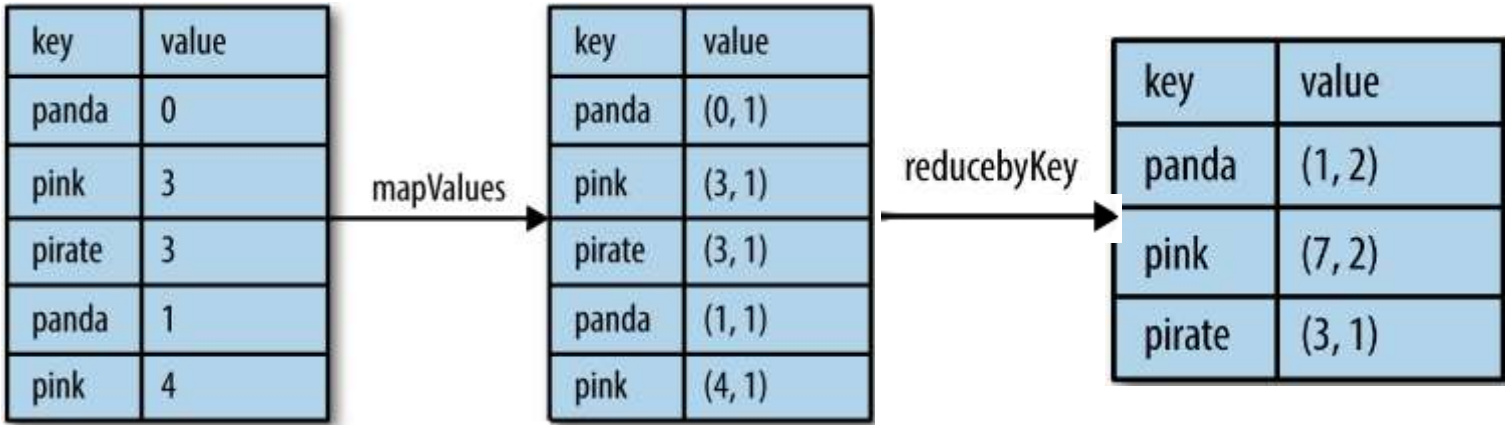
Aggregation Examples

- The following examples demonstrate, we can use reduceByKey() along with mapValues() to compute the per-key average in a very similar manner to how fold() and map() can be used to compute the entire RDD average.
- *Per-key average with reduceByKey() and mapValues() in Python*

```
rdd.mapValues(lambda x: (x, 1)).reduceByKey(
     lambda x, y: (x[0] + y[0], x[1] + y[1]))
```

- *Per-key average with reduceByKey() and mapValues() in Scala*

```
rdd.mapValues(x => (x, 1)).reduceByKey(
     (x, y) => (x._1 + y._1, x._2 + y._2))
```



Aggregation Example, Word count

- We will use `flatMap()` so that we can produce a pair RDD of words and the number 1 and then sum together all of the words using `reduceByKey()`
- *Word count in Python*

```
rdd = sc.textFile("s3://...")
words = rdd.flatMap(lambda x: x.split(" "))
result = words.map(lambda x: (x, 1)).reduceByKey(lambda x, y: x + y)
```

- *Word count in Scala*

```
val input = sc.textFile("s3://...")
val words = input.flatMap(x => x.split(" "))
val result = words.map(x => (x, 1)).reduceByKey((x, y) => x + y)
```

- *Word count in Java*

```
JavaRDD<String> input = sc.textFile("s3://...")
JavaRDD<String> words = rdd.flatMap(new FlatMapFunction<String, String>() {
   public Iterable<String> call(String x) { return Arrays.asList(x.split(" ")); }
});
JavaPairRDD<String, Integer> result = words.mapToPair(
   new PairFunction<String, String, Integer>() {
     public Tuple2<String, Integer> call(String x) { return new Tuple2(x, 1); }
}).reduceByKey(
     new Function2<Integer, Integer, Integer>() {
     public Integer call(Integer a, Integer b) { return a + b; }
});
```