COMP9313: Big Data Management

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Course web site: http://www.cse.unsw.edu.au/~cs9313/

Chapter 5: Spark I

Part 1: Spark Introduction

Motivation of Spark

MapReduce greatly simplified big data analysis on large, unreliable clusters. It is great at one-pass computation.

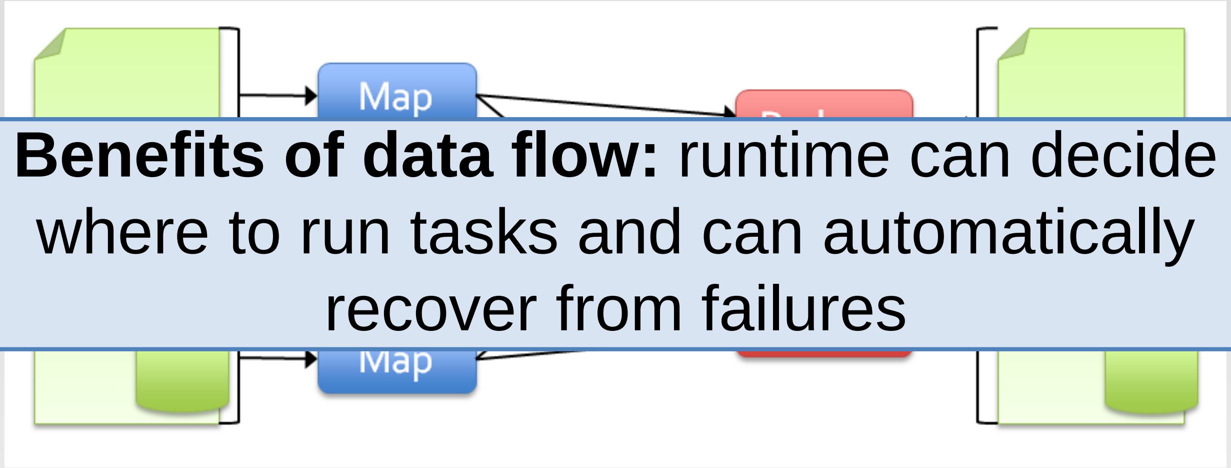
But as soon as it got popular, users wanted more:

- More **complex**, multi-pass analytics (e.g. ML, graph)
- More **interactive** ad-hoc queries
- More **real-time** stream processing

All 3 need faster **data sharing** across parallel jobs

- One reaction: specialized models for some of these apps, e.g.,
  - Pregel (graph processing)
  - Storm (stream processing)

Limitations of MapReduce



Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures

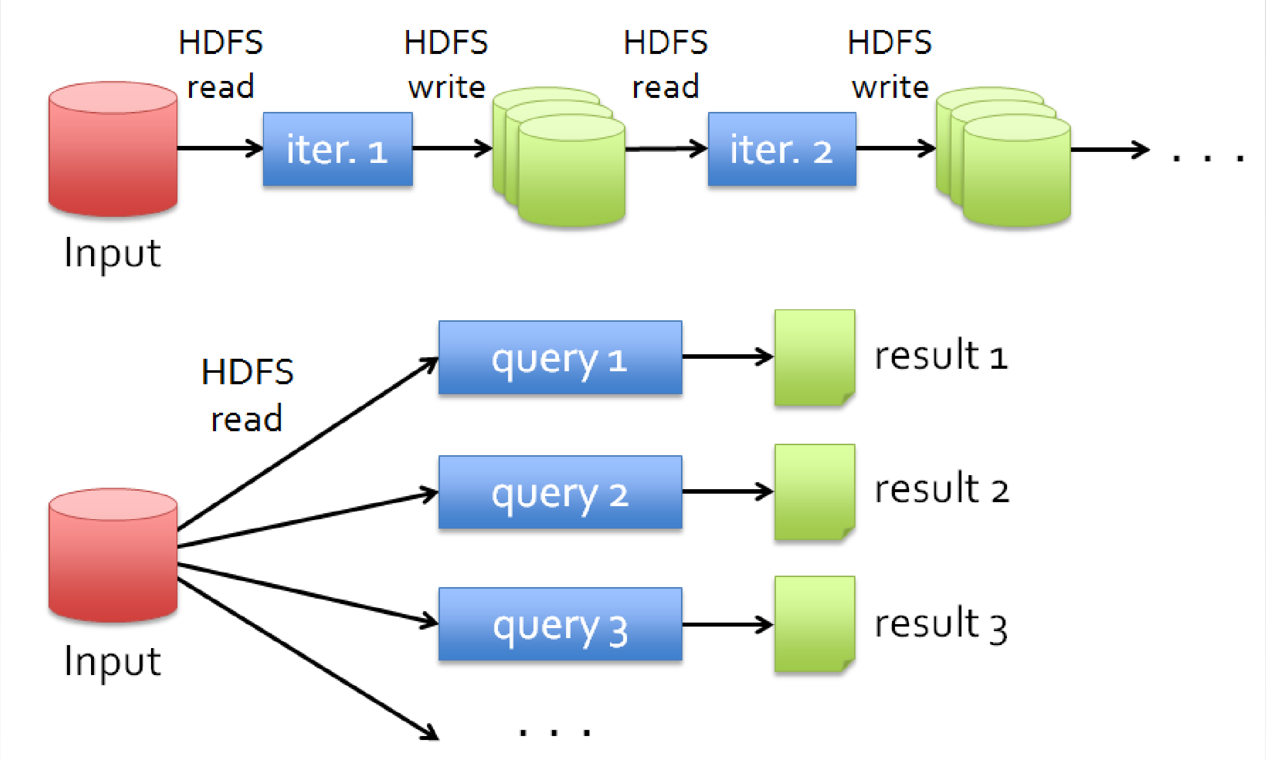
As a general programming model:

- It is more suitable for one-pass computation on a large dataset
- Hard to compose and nest multiple operations
- No means of expressing iterative operations

As implemented in Hadoop

- All datasets are read from disk, then stored back on to disk
- All data is (usually) triple-replicated for reliability
- Not easy to write MapReduce programs using Java

Data Sharing in MapReduce



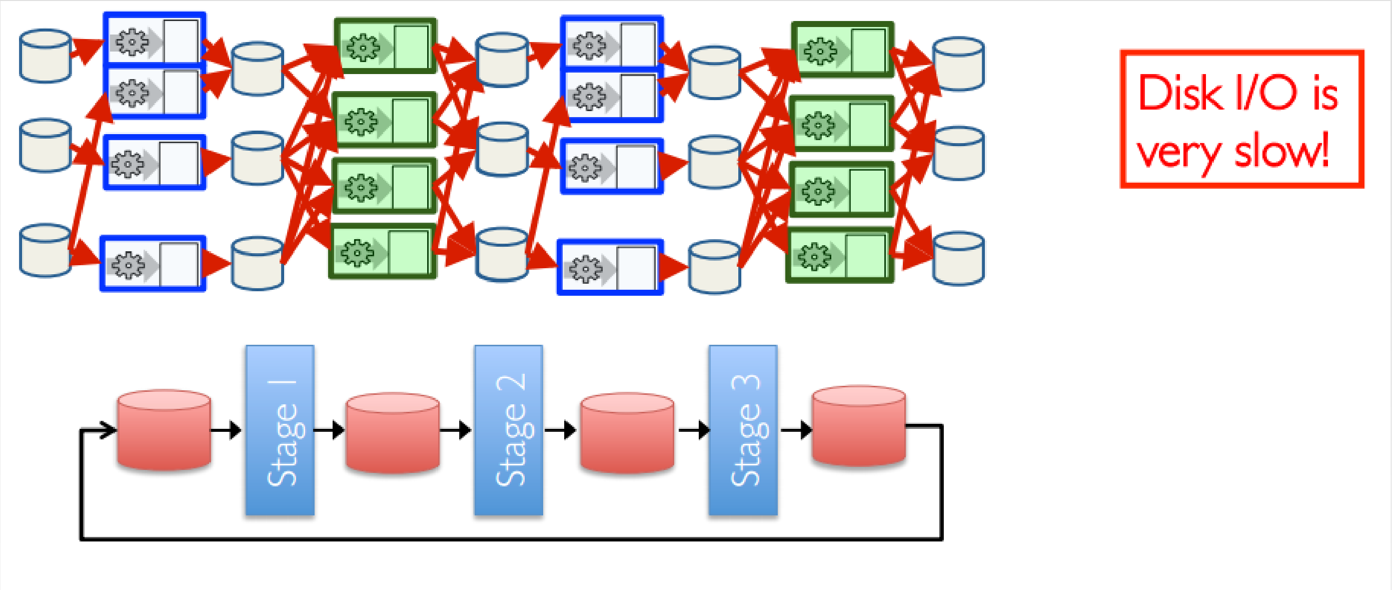
Slow due to replication, serialization, and disk IO

Complex apps, streaming, and interactive queries all need one thing that MapReduce lacks:

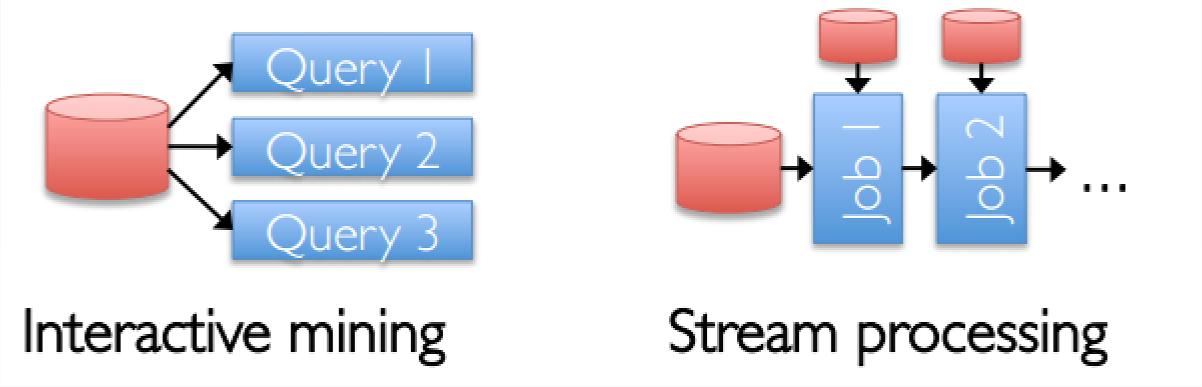
Efficient primitives for **data sharing**

Data Sharing in MapReduce

Iterative jobs involve a lot of disk I/O for each repetition

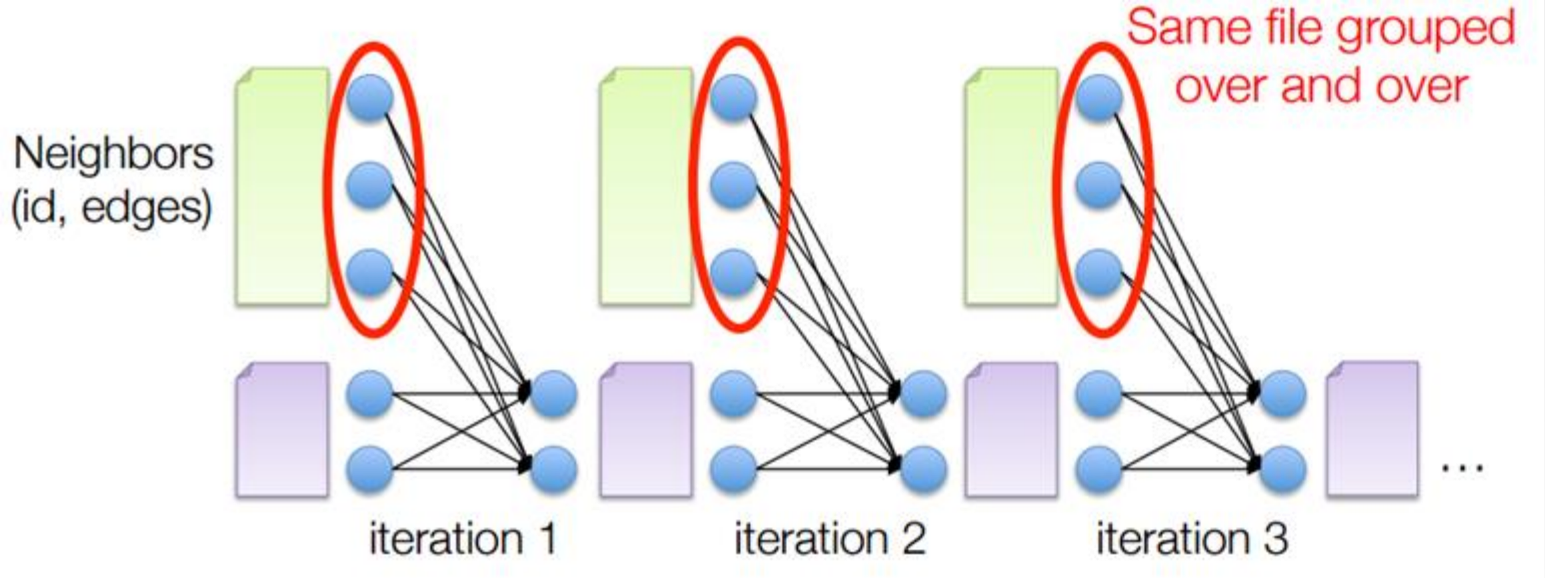


Interactive queries and online processing involves lots of disk I/O



Example: Shortest Path

Repeatedly send graph structure from mapper to reducer



Hardware for Big Data

Lots of hard drives

Lots of CPUs

And lots of memory!

Goals of Spark

Keep more data in-memory to improve the performance!

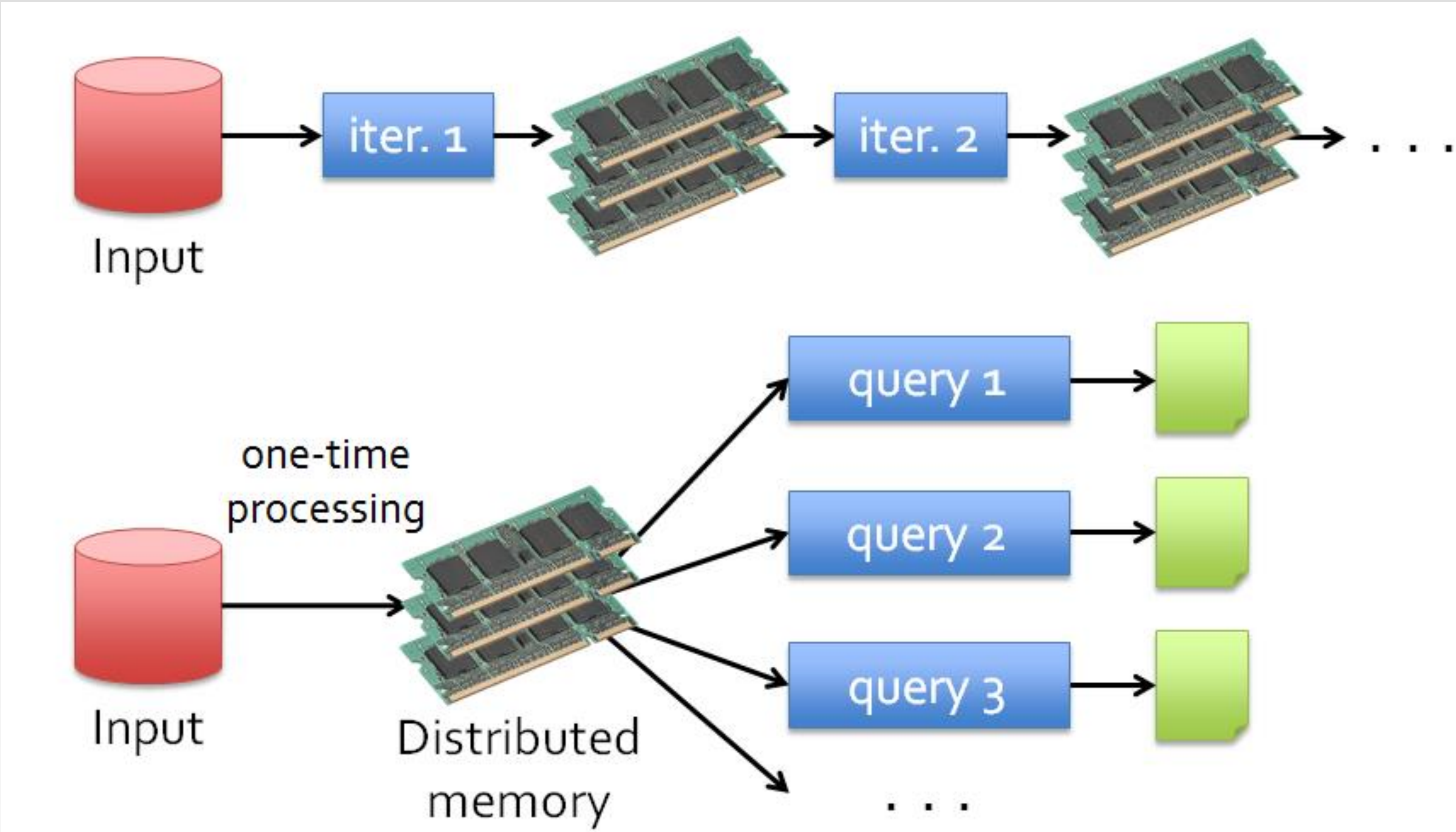
Extend the MapReduce model to better support two common classes of analytics apps:

- Iterative algorithms (machine learning, graphs)
- Interactive data mining

Enhance programmability:

- Integrate into Scala programming language
- Allow interactive use from Scala interpreter

Data Sharing in Spark Using RDD



10-100× faster than network and disk

What is Spark

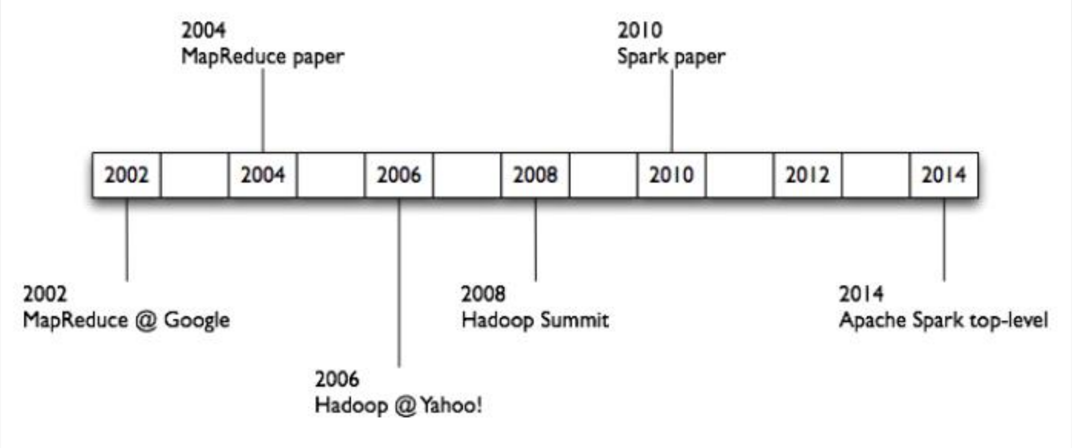
One popular answer to “What’s beyond MapReduce?”

Open-source engine for large-scale data processing

- Supports generalized dataflows
- Written in Scala, with bindings in Java and Python

Brief history:

- Developed at UC Berkeley AMPLab in 2009
- Open-sourced in 2010
- Became top-level Apache project in February 2014
- Commercial support provided by DataBricks



What is Spark

Fast and expressive cluster computing system interoperable with Apache Hadoop

Improves efficiency through:

- **In-memory** computing primitives → Up to 100 × faster (10 × on disk)
- General computation graphs

Improves usability through:

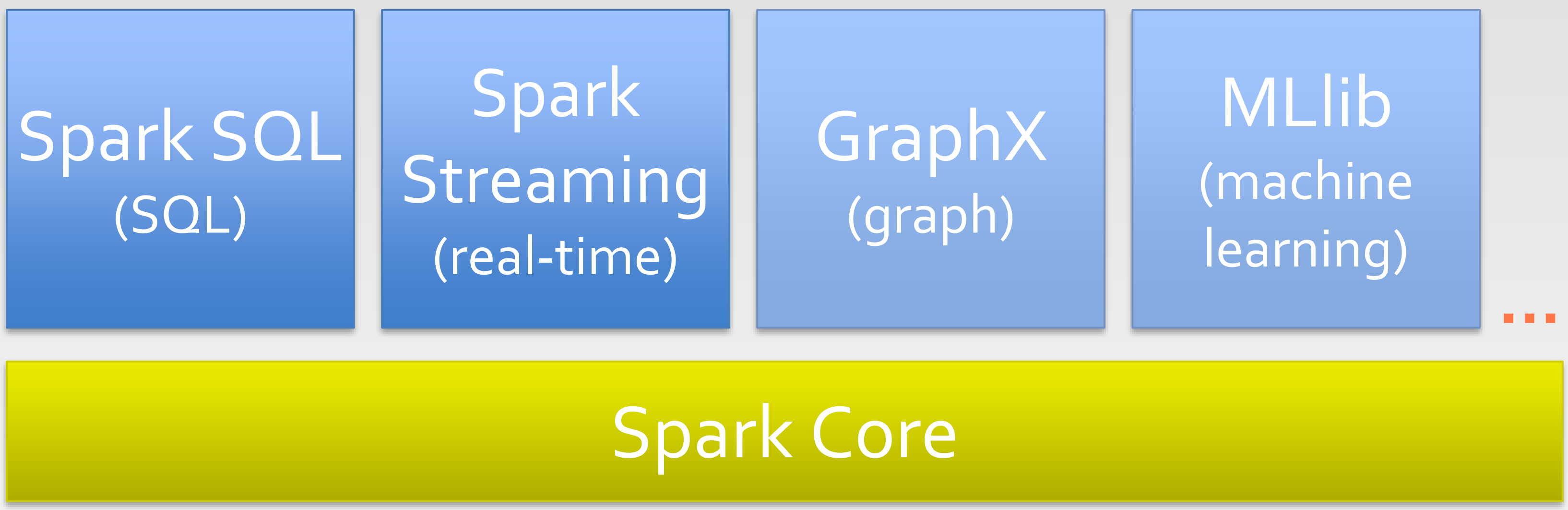
- Rich APIs in Scala, Java, Python
- Interactive shell → Often 5 × less code

Spark is not

- a modified version of Hadoop
- dependent on Hadoop because it has its own cluster management
- Spark uses Hadoop for storage purpose only

What is Spark

Spark is the basis of a wide set of projects in the Berkeley Data Analytics Stack (BDAS)



Spark SQL (SQL on Spark)

Spark Streaming (stream processing)

GraphX (graph processing)

MLlib (machine learning library)

Data Sources

Local Files

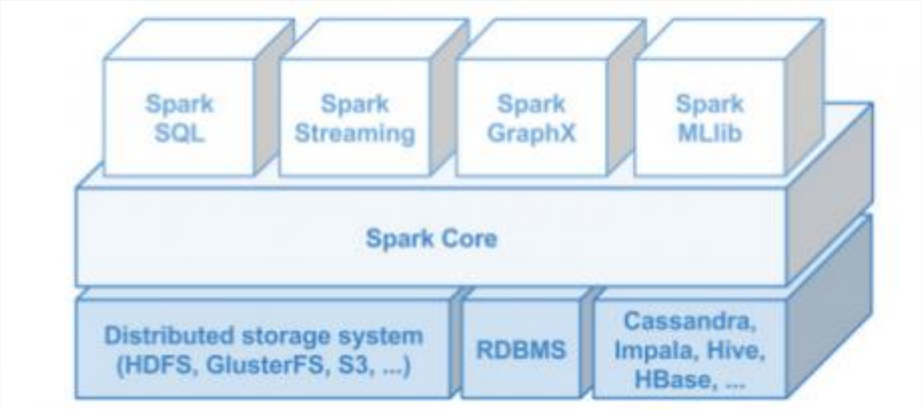
file:///opt/httpd/logs/access_log

S3

Hadoop Distributed Filesystem

Regular files, sequence files, any other Hadoop InputFormat

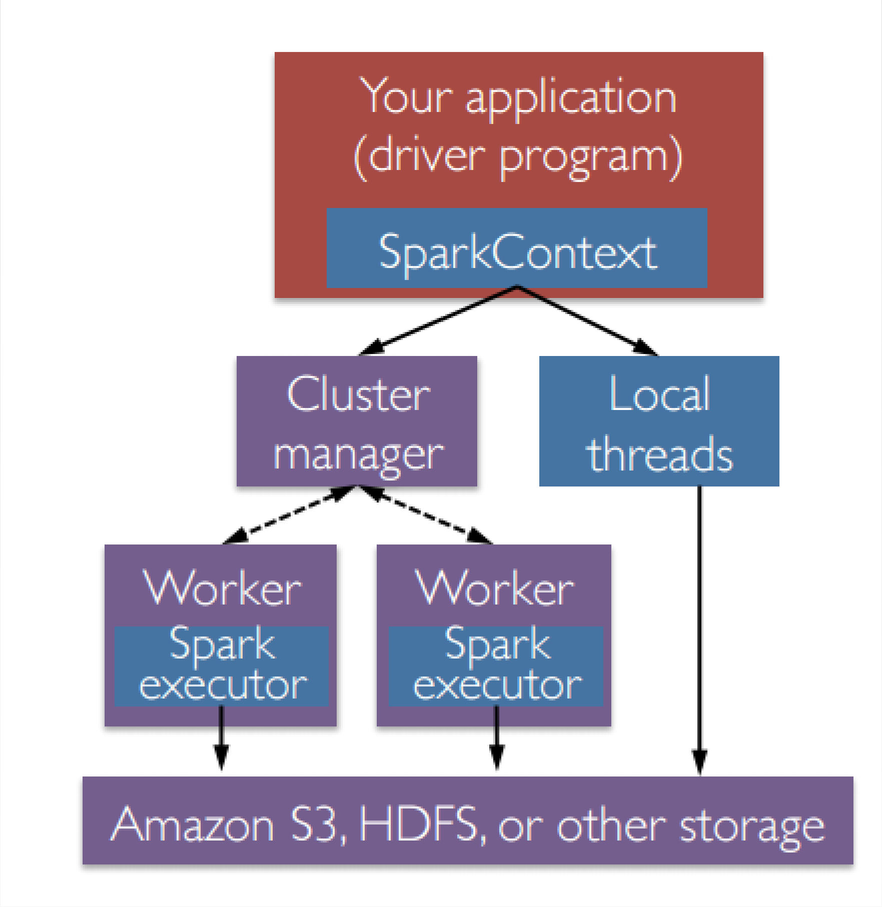
HBase, Cassandra, etc.



Spark Ideas

- Expressive computing system, not limited to map-reduce model
- Facilitate system memory
  - avoid saving intermediate results to disk
  - cache data for repetitive queries (e.g. for machine learning)
- Layer an in-memory system on top of Hadoop.
- Achieve fault-tolerance by re-execution instead of replication

Spark Workflow



A Spark program first creates a SparkContext object

- Tells Spark how and where to access a cluster
- Connect to several types of cluster managers (e.g., YARN, Mesos, or its own manager)

Cluster manager:

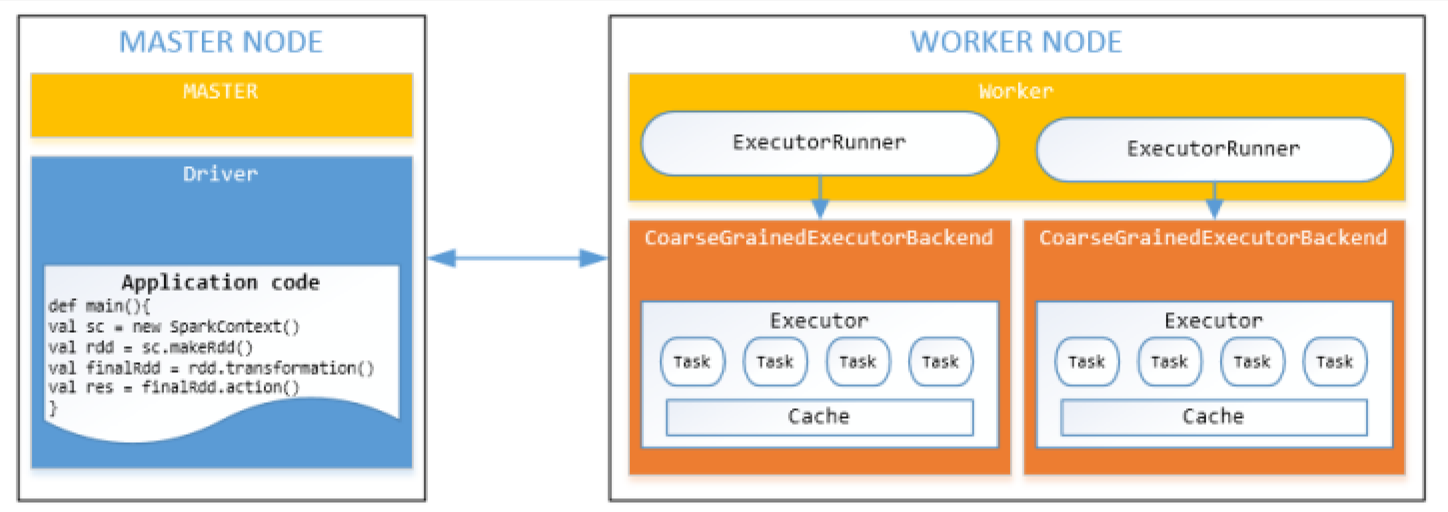
- Allocate resources across applications

Spark executor:

- Run computations
- Access data storage

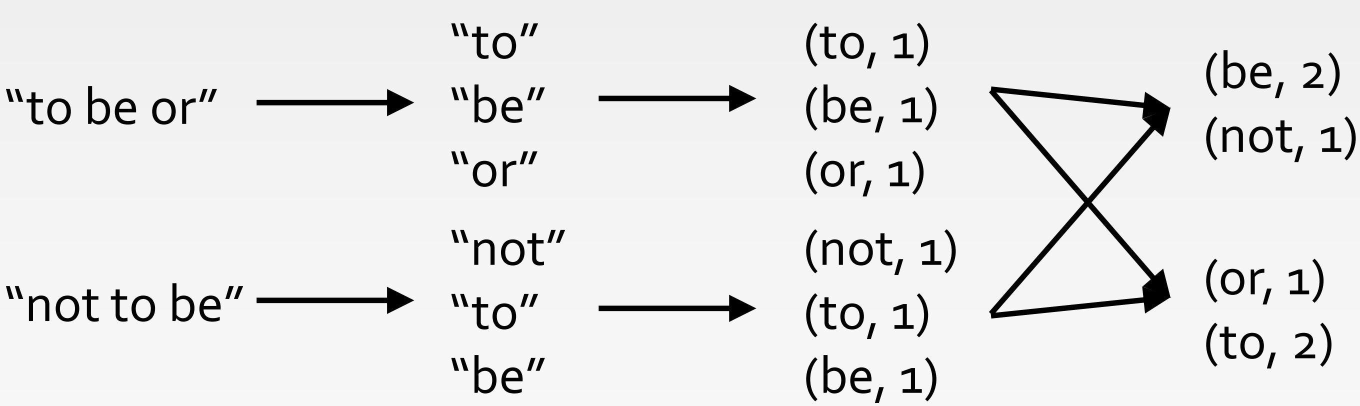
Worker Nodes and Executors

- Worker nodes are machines that run executors
  - Host one or multiple Workers
  - One JVM (1 process) per Worker
  - Each Worker can spawn one or more Executors
- Executors run tasks
  - Run in child JVM (1 process）
  - Execute one or more task using threads in a ThreadPool



Word Count in Spark

```
val file = sc.textFile("hdfs://...")

val counts = file.flatMap(line => line.split(" "))
    .map(word => (word,1))
    .reduceByKey(_ + _)

counts.saveAsTextFile("hdfs://...")
```



Part 2: Scala Introduction

Scala (Scalable language)

Scala is a *general-purpose programming language* designed to express common programming patterns in a concise, elegant, and type-safe way

Scala supports both Object Oriented Programming and Functional Programming

Scala is Practical

- Can be used as drop-in replacement for Java
  - Mixed Scala/Java projects
- Use existing Java libraries
- Use existing Java tools (Ant, Maven, JUnit, etc…)
- Decent IDE Support (NetBeans, IntelliJ, Eclipse)

Why Scala

Scala supports object-oriented programming. Conceptually, every value is an object and every operation is a method-call. The language supports advanced component architectures through classes and traits

Scala is also a functional language. Supports functions, immutable data structures and preference for immutability over mutation

Seamlessly integrated with Java

Being used heavily for Big data, e.g., Spark, Kafka, etc.

Scala Basic Syntax

When considering a Scala program, it can be defined as a collection of objects that communicate via invoking each other’s methods.

Object − same as in Java

Class − same as in Java

Methods − same as in Java

Fields − Each object has its unique set of instant variables, which are called fields. An object's state is created by the values assigned to these fields.

Traits − Like Java Interface. A trait encapsulates method and field definitions, which can then be reused by mixing them into classes.

Closure − A **closure** is a function, whose return value depends on the value of one or more variables declared outside this function.

closure = function + enviroment

Object-Oriented Programming in Scala

Scala is object-oriented, and is based on Java's model

An `object` is a singleton object (there is only one of it)

- Variables and methods in an `object` are somewhat similar to Java's `static` variables and methods
- Reference to an `object`'s variables and methods have the syntax ***ObjectName*.*methodOrVariableName***
- The name of an `object` should be capitalized

A `class` may take parameters, and may describe any number of objects

- The class body *is* the constructor, but you can have additional constructors
- With correct use of `val` and `var`, Scala provides getters and setters for class parameters

Scala is Statically Typed

You don't have to specify a type in most cases

Type Inference

```
val sum = 1 + 2 + 3
val nums = List(1, 2, 3)
val map = Map("abc" -> List(1,2,3))
```

Explicit Types

```
val sum: Int = 1 + 2 + 3
val nums: List[Int] = List(1, 2, 3)
val map: Map[String, List[Int]] = ...
```

Scala is High level

```
// Java – Check if string has uppercase character
boolean hasUpperCase = false;
for(int i = 0; i < name.length(); i++) {
    if(Character.isUpperCase(name.charAt(i))) {
        hasUpperCase = true;
         break;
    }
}

// Scala
val hasUpperCase = name.exists(_.isUpper)
```

Scala is Concise

```java
// Java
public class Person {
  private String name;
  private int age;
  public Person(String name, Int age) {
    this.name = name;
     this.age = age;
  }
  public String getName() {              // name getter
    return name;
  }
  public int getAge() {                  // age getter
    return age;
  }
  public void setName(String name) {     // name setter
    this.name = name;
  }
  public void setAge(int age) {          // age setter
    this.age = age;
  }
}
```

```scala
// Scala
class Person(var name: String, private var _age: Int) {
  def age = _age              // Getter for age
  def age_=(newAge:Int) {  // Setter for age
    println("Changing age to: "+newAge)
    _age = newAge
  }
}
```

Variables and Values

Variables: values stored can be changed

```
var foo = "foo"
foo = "bar"  // okay
```

Values: immutable variable

```
val foo = "foo"
foo = "bar" // nope
```

Scala is Pure Object Oriented

```
// Every value is an object
1.toString
// Every operation is a method call
1 + 2 + 3  →  (1).+(2).+(3)
// Can omit . and ( )
"abc" charAt 1  →  "abc".charAt(1)
// Classes (and abstract classes) like Java
abstract class Language(val name:String) {
  override def toString = name
}
// Example implementations
class Scala extends Language("Scala")
// Anonymous class
val scala = new Language("Scala") { /* empty */ }
```

Scala Traits

```
// Like interfaces in Java
trait JVM {
  // But allow implementation
 override def toString = super.toString+" runs on JVM" }
trait Static {
 override def toString = super.toString+" is Static" }

// Traits are stackable
class Scala extends Language with JVM with Static {
  val name = "Scala"
}
println(new Scala) → "Scala runs on JVM is Static"
```

Scala is Functional

First-Class Functions. Functions are treated like objects:

- passing functions as arguments to other functions
- returning functions as the values from other functions
- assigning functions to variables or storing them in data structures

```
// Lightweight anonymous functions
(x:Int) => x + 1

// Calling the anonymous function
val plusOne = (x:Int) => x + 1
plusOne(5)  →  6
```

Scala is Functional

Closures: a function whose return value depends on the value of one or more variables declared outside this function.

```
// plusFoo can reference any values/variables in scope
var foo = 1
val plusFoo = (x:Int) => x + foo

plusFoo(5)   → 6

// Changing foo changes the return value of plusFoo
foo = 5
plusFoo(5)   → 10
```

Scala is Functional

Higher Order Functions

A function that does at least one of the following:

- takes one or more functions as arguments
- returns a function as its result

```
val plusOne = (x:Int) => x + 1
val nums = List(1,2,3)
// map takes a function: Int => T
nums.map(plusOne)       →  List(2,3,4)
// Inline Anonymous
nums.map(x => x + 1)    →  List(2,3,4)
// Short form
nums.map(_ + 1)         →  List(2,3,4)
```

More Examples on Higher Order Functions

```
val nums = List(1,2,3,4)
// A few more examples for List class
nums.exists(_ == 2)          → true
nums.find(_ == 2)            → Some(2)
nums.indexWhere(_ == 2)      → 1

// functions as parameters, apply f to the value “1”
def call(f: Int => Int) = f(1)

call(plusOne)      → 2
call(x => x + 1)   → 2
call(_ + 1)        → 2
```

More Examples on Higher Order Functions

```
val basefunc = (x:Int) => ((y:Int) => x + y)
// interpreted by:
   basefunc(x){
       sumfunc(y){ return x+y;}
       return sumfunc;
   }

val closure1 = basefunc(1)    closure1(5) = ?
                                             6
val closure2 = basefunc(4)    closure2(5) = ?
                                             9
```

basefunc returns a function, and closure1 and closure2 are of function type.

While closure1 and closure2 refer to the same function basefunc, the associated environments differ, and the results are different

The Usage of "_" in Scala

In anonymous functions, the "_" acts as a placeholder for parameters

```
nums.map(x => x + 1)
```

is equivalent to:

```
nums.map(_ + 1)
```

```
List(1,2,3,4,5).foreach(print(_))
```

is equivalent to:

```
List(1,2,3,4,5).foreach( a => print(a) )
```

You can use two or more underscores to refer different parameters.

```
val sum = List(1,2,3,4,5).reduceLeft(_+_)
```

is equivalent to:

```
val sum = List(1,2,3,4,5).reduceLeft((a, b) => a + b)
```

The reduceLeft method works by applying the function/operation you give it, and applying it to successive elements in the collection

Part 3: RDD Introduction

Challenge

Existing Systems

Existing in-memory storage systems have interfaces based on fine-grained updates

- Reads and writes to cells in a table
- E.g., databases, key-value stores, distributed memory

Requires replicating data or logs across nodes for fault tolerance

-> expensive!

- 10-100x slower than memory write

How to design a distributed memory abstraction that is both **fault-tolerant** and **efficient**?

Solution: Resilient Distributed Datasets

Resilient Distributed Datasets (RDDs)

- Distributed collections of objects that can be cached in memory across cluster
- Manipulated through parallel operators
- Automatically recomputed on failure based on lineage

RDDs can express many parallel algorithms, and capture many current programming models

- Data flow models: MapReduce, SQL, …
- Specialized models for iterative apps: Pregel, …

What is RDD

Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. Matei Zaharia, et al. NSDI'12

RDD is a **distributed** memory abstraction that lets programmers perform **in-memory** computations on large clusters in a **fault-tolerant** manner.

Resilient

Fault-tolerant, is able to recompute missing or damaged partitions due to node failures.

Distributed

Data residing on multiple nodes in a cluster.

Dataset

A collection of partitioned elements, e.g. tuples or other objects (that represent records of the data you work with).

RDD is the primary data abstraction in Apache Spark and the core of Spark. It enables operations on collection of elements in parallel.

RDD Traits

In-Memory, i.e. data inside RDD is stored in memory as much (size) and long (time) as possible.

Immutable or **Read-Only**, i.e. it does not change once created and can only be transformed using transformations to new RDDs.

Lazy evaluated, i.e. the data inside RDD is not available or transformed until an action is executed that triggers the execution.

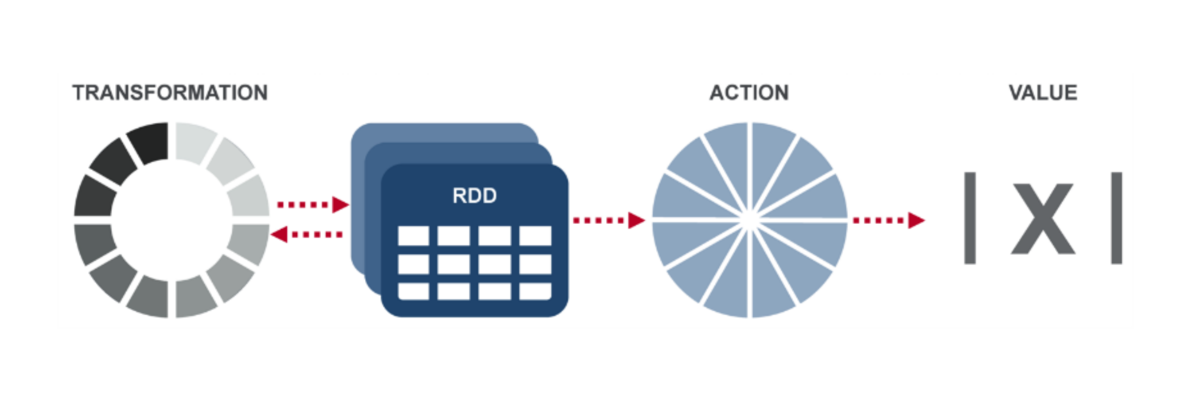
Cacheable, i.e. you can hold all the data in a persistent "storage" like memory (default and the most preferred) or disk (the least preferred due to access speed).

Parallel, i.e. process data in parallel.

Typed, i.e. values in a RDD have types, e.g. RDD[Long] or RDD[(Int, String)].

Partitioned, i.e. the data inside a RDD is partitioned (split into partitions) and then distributed across nodes in a cluster (one partition per JVM that may or may not correspond to a single node).

RDD Operations



Transformation: returns a new RDD.

Nothing gets evaluated when you call a Transformation function, it just takes an RDD and return a new RDD.

Transformation functions include *map, filter, flatMap, groupByKey, reduceByKey, aggregateByKey, filter, join, etc.*

Action: evaluates and returns a new value.

When an Action function is called on a RDD object, all the data processing queries are computed at that time and the result value is returned.

Action operations include *reduce, collect, count, first, take, countByKey, foreach, saveAsTextFile, etc.*

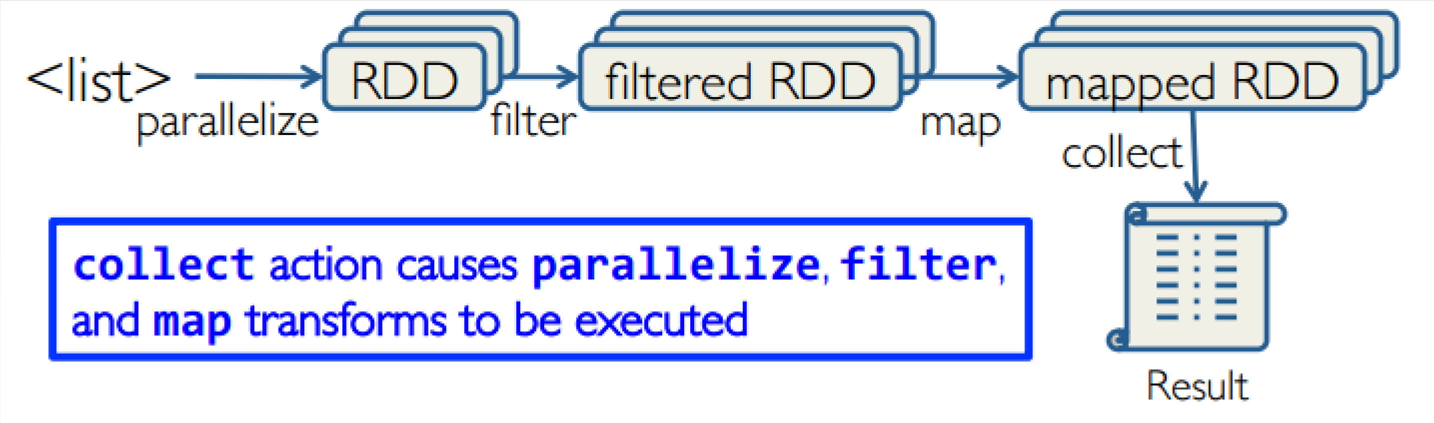
Working with RDDs

Create an RDD from a data source

- by parallelizing existing collections (lists or arrays)
- by transforming an existing RDDs
- from files in HDFS or any other storage system

Apply transformations to an RDD: e.g., map, filter

Apply actions to an RDD: e.g., collect, count



Users can control two other aspects:

- Persistence
- Partitioning

Creating RDDs

From HDFS, text files, Amazon S3, Apache HBase, SequenceFiles, any other Hadoop InputFormat

Creating an RDD from a File

- val inputfile = sc.textFile("...", 4)
  - RDD distributed in 4 partitions
  - Elements are lines of input
  - Lazy evaluation means no execution happens now

```
scala> val inputfile = sc.textFile("pg100.txt")
inputfile: org.apache.spark.rdd.RDD[String] = pg100.txt MapPartitionsRDD[17] at
textFile at <console>:24
```

Turn a collection into an RDD

- sc.parallelize([1, 2, 3]), creating from a Python list
- sc.parallelize(Array(“hello”, “spark”)), creating from a Scala Array

Creating an RDD from an existing Hadoop InputFormat

- sc.hadoopFile(keyClass, valClass, inputFmt, conf)

Spark Transformations

Create new datasets from an existing one

Use lazy evaluation: results not computed right away – instead Spark remembers set of transformations applied to base dataset

- Spark optimizes the required calculations
- Spark recovers from failures

Some transformation functions

Transformation	Description
`map(`*func*`)`	return a new distributed dataset formed by passing each element of the source through a function *func*
`filter(`*func*`)`	return a new dataset formed by selecting those elements of the source on which *func* returns true
`distinct([`*numTasks*`]))`	return a new dataset that contains the distinct elements of the source dataset
`flatMap(`*func*`)`	similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item)

Spark Actions

Cause Spark to execute recipe to transform source

Mechanism for getting results out of Spark

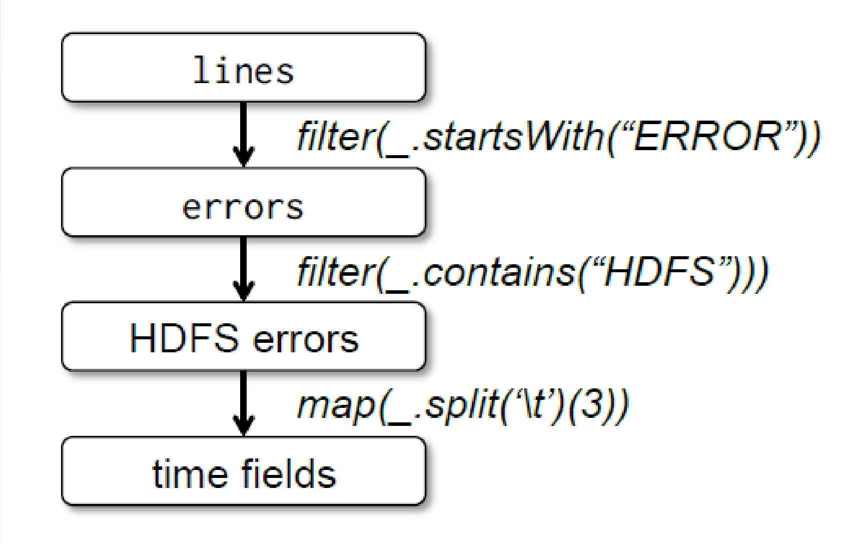
Some action functions

Action	Description
`reduce(func)`	aggregate dataset's elements using function *func*. *func* takes two arguments and returns one, and is commutative and associative so that it can be computed correctly in parallel
`take(n)`	return an array with the first *n* elements
`collect()`	return all the elements as an array WARNING: make sure will fit in driver program
`takeOrdered(n, key=func)`	return n elements ordered in ascending order or as specified by the optional key function

Example: words.collect().foreach(println)

Example

Web service is experiencing errors and an operators want to search terabytes of logs in the Hadoop file system to find the cause.



//base RDD

val lines = sc.textFile("hdfs://…")

//Transformed RDD

val errors = lines.filter(_.startsWith("Error"))

errors.persist()

errors.count()

errors.filter(_.contains("HDFS"))

.map(_.split('\t')(3))

.collect()

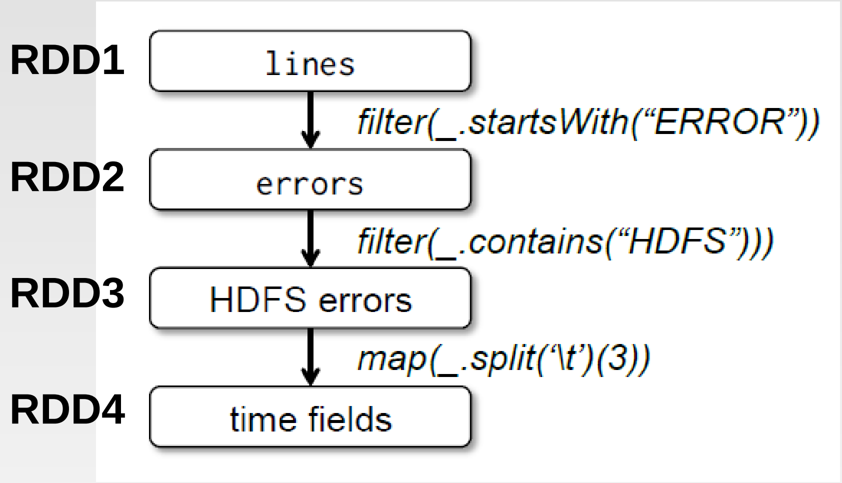
Line1: RDD backed by an HDFS file (base RDD lines not loaded in memory)

Line3: Asks for errors to persist in memory (errors are in RAM)

Lineage Graph

RDDs keep track of *lineage*

RDD has enough information about how it was derived from to compute its partitions from data in stable storage.

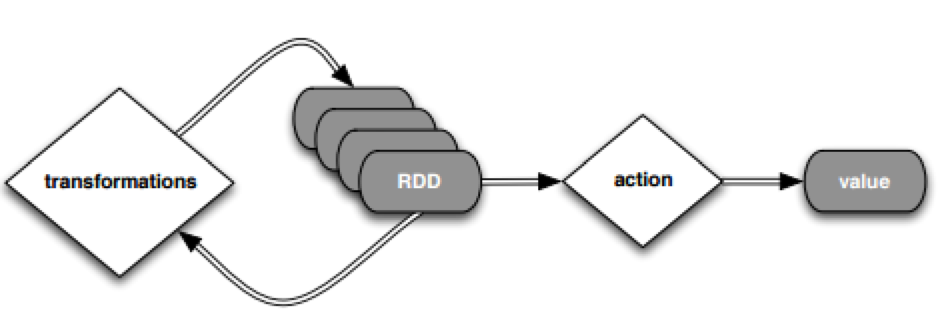


Example:

If a partition of errors is lost, Spark rebuilds it by applying a filter on only the corresponding partition of lines.

Partitions can be recomputed in parallel on different nodes, without having to roll back the whole program.

Deconstructed

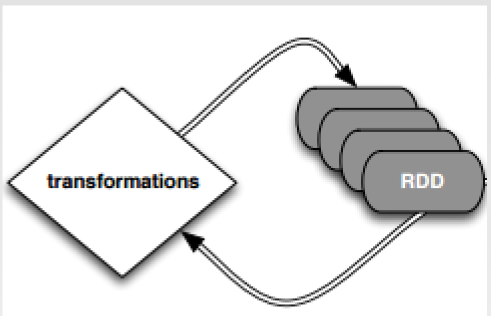



```
//base RDD
val lines = sc.textFile("hdfs://…")
//Transformed RDD
val errors = lines.filter(_.startsWith("Error"))
errors.persist()
errors.count()
errors.filter(_.contains("HDFS"))
        .map(_.split('\t')(3))
        .collect()
```

Deconstructed

//base RDD

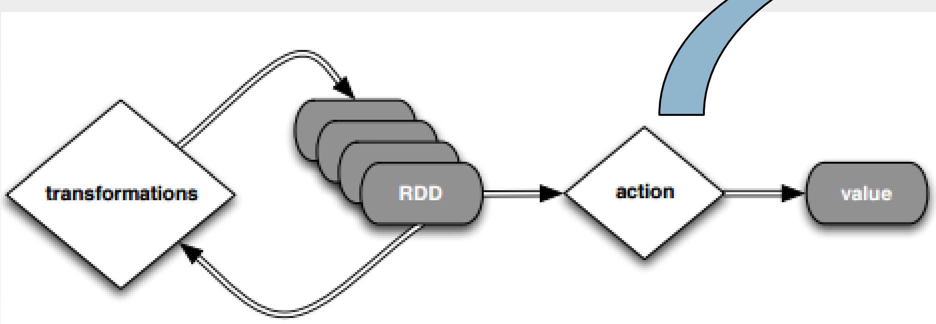
val lines = sc.textFile("hdfs://…")



//Transformed RDD

val errors = lines.filter(_.startsWith("Error"))

errors.persist()



errors.count()

count() causes Spark to: 1) read data; 2) sum within partitions; 3) combine sums in driver

Put transform and action together:

errors.filter(_.contains("HDFS")).map(_split('\t')(3)).collect()

SparkContext

SparkContext is the entry point to Spark for a Spark application.

Once a SparkContext instance is created you can use it to

- Create RDDs
- Create accumulators
- Create broadcast variables
- access Spark services and run jobs

A Spark context is essentially a client of Spark's execution environment and acts as the *master of your Spark application*

The first thing a Spark program must do is to create a SparkContext object, which tells Spark how to access a cluster

In the Spark shell, a special interpreter-aware SparkContext is already created for you, in the variable called *sc*

RDD Persistence: Cache/Persist

One of the most important capabilities in Spark is *persisting* (or *caching*) a dataset in memory across operations.

When you persist an RDD, each node stores any partitions of it. You can reuse it in other actions on that dataset

Each persisted RDD can be stored using a different *storage level,* e.g.

MEMORY_ONLY:

- Store RDD as deserialized Java objects in the JVM.
- If the RDD does not fit in memory, some partitions will not be cached and will be recomputed when they're needed.
- This is the default level.

MEMORY_AND_DISK:

- If the RDD does not fit in memory, store the partitions that don't fit on disk, and read them from there when they're needed.

cache() = persist(StorageLevel.MEMORY_ONLY)

Why Persisting RDD?

```
val lines = sc.textFile("hdfs://…")
val errors = lines.filter(_.startsWith("Error"))
errors.persist()
errors.count()
```

- If you do errors.count() again, the file will be loaded again and computed again.
- Persist will tell Spark to cache the data in memory, to reduce the data loading cost for further actions on the same data
- erros.persist() will do nothing. It is a lazy operation. But now the RDD says "read this file and then cache the contents". The action will trigger computation and data caching.

Spark Key-Value RDDs

Similar to Map Reduce, Spark supports Key-Value pairs

Each element of a *Pair RDD* is a pair tuple

Some Key-Value transformation functions:

Key-Value Transformation	Description
`reduceByKey(`*func*`)`	return a new distributed dataset of (K,V) pairs where the values for each key are aggregated using the given reduce function *func*, which must be of type (V,V) ➔ V
`sortByKey()`	return a new dataset (K,V) pairs sorted by keys in ascending order
`groupByKey()`	return a new dataset of (K, Iterable<V>) pairs

More Examples on Pair RDD

Create a pair RDD from existing RDDs

```
val pairs = sc.parallelize( List( (“This”, 2), (“is”, 3), (“Spark”, 5), (“is”, 3) ) )
pairs.collect().foreach(println)
```

Output?

reduceByKey() function: reduce key-value pairs by key using give *func*

```
val pair1 = pairs.reduceByKey((x,y) => x + y)
pairs1.collect().foreach(println)
```

Output?

mapValues() function: work on values only

```
val pair2 = pairs.mapValues( x => x -1 )
pairs2.collect().foreach(println)
```

Output?

groupByKey() function: When called on a dataset of (K, V) pairs, returns a dataset of (K, Iterable<V>) pairs

```
pairs.groupByKey().collect().foreach(println)
```

Setting the Level of Parallelism

All the pair RDD operations take an optional second parameter for number of tasks

```
> words.reduceByKey((x,y) => x + y, 5)
> words.groupByKey(5)
```

Spark


Steven Luscher
@steveluscher
Map/filter/reduce in a tweet:
map([, ,], cook)
=> [, ,]
filter([, ,], isVegetarian)
=> [,]
reduce([,], eat)
=>
RETWEETS
6,472
LIKES
6,357

Part 4: Spark Programming Model

How Spark Works

User application create RDDs, transform them, and run actions.

This results in a DAG (Directed Acyclic Graph) of operators.

DAG is compiled into stages

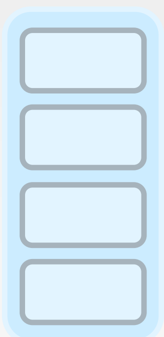
Each stage is executed as a series of Task (one Task for each Partition).

```
val file = sc.textFile("hdfs://...")

val counts = file.flatMap(line => line.split(" "))
   .map(word => (word,1))
   .reduceByKey(_ + _)

counts.saveAsTextFile("hdfs://...")
```

Word Count in Spark

```
val file = sc.textFile("hdfs://…", 4)
```

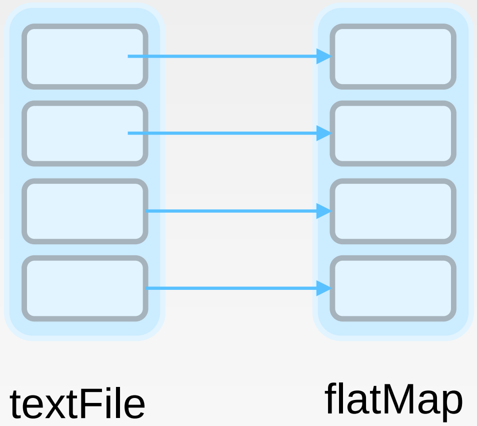
RDD[String]



textFile

Word Count in Spark

```
val file = sc.textFile("hdfs://...", 4)          RDD[String]
val words = file.flatMap(line =>                  RDD[List[String]]
        line.split(" "))
```



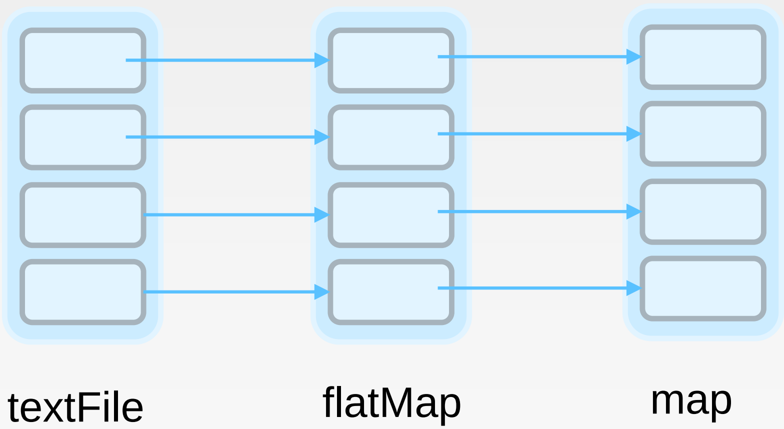
Word Count in Spark

```
val file = sc.textFile("hdfs://...", 4)
val words = file.flatMap(line =>
        line.split(" "))
val pairs = words.map(t => (t, 1))
```

RDD[String]

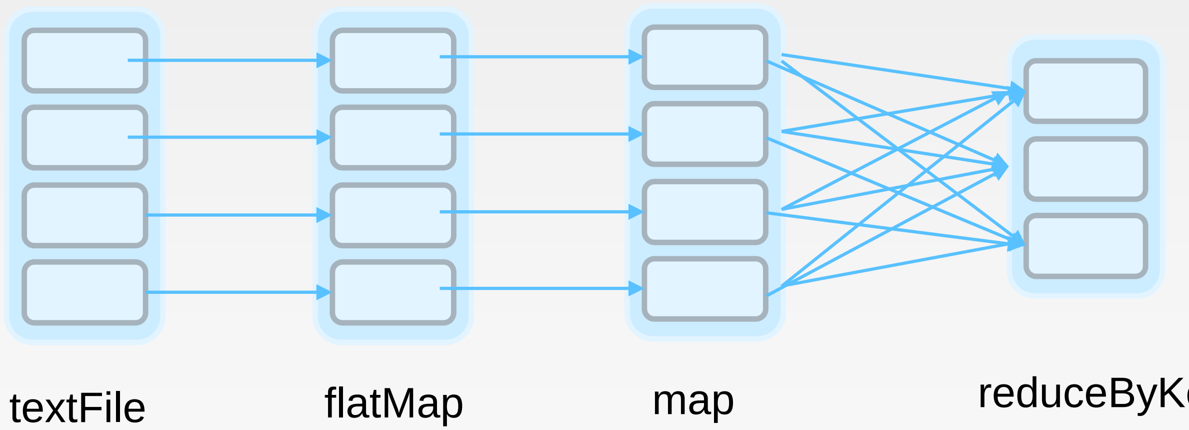
RDD[List[String]]

RDD[(String, Int)]



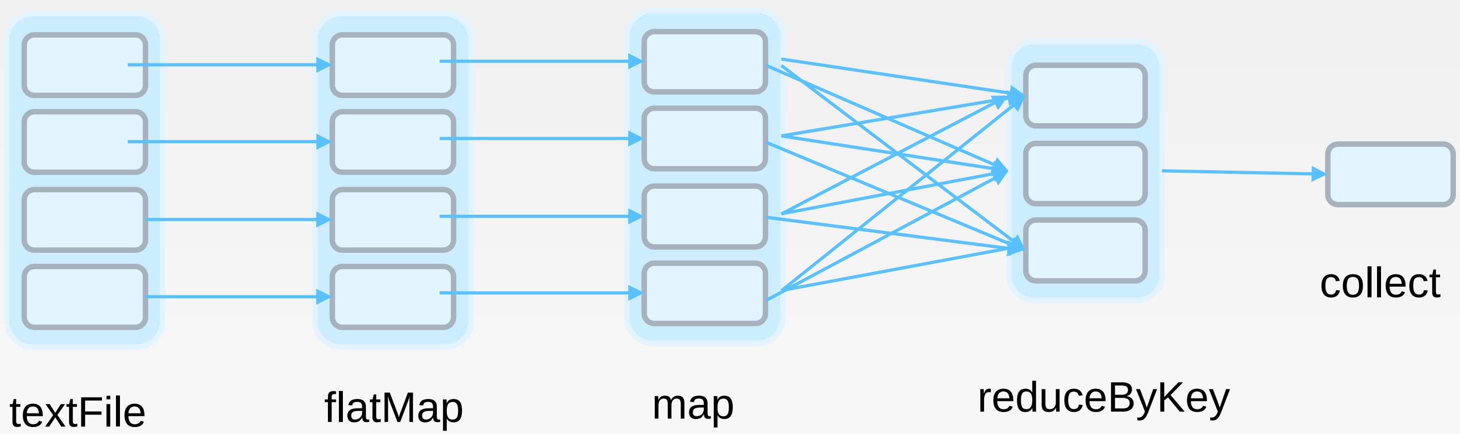
Word Count in Spark

```
val file = sc.textFile(“hdfs://…”, 4)          RDD[String]
val words = file.flatMap(line =>               RDD[List[String]]
          line.split(“ ”))
val pairs = words.map(t => (t, 1))             RDD[(String, Int)]
val count = pairs. reduceByKey(_+_)            RDD[(String, Int)]
```

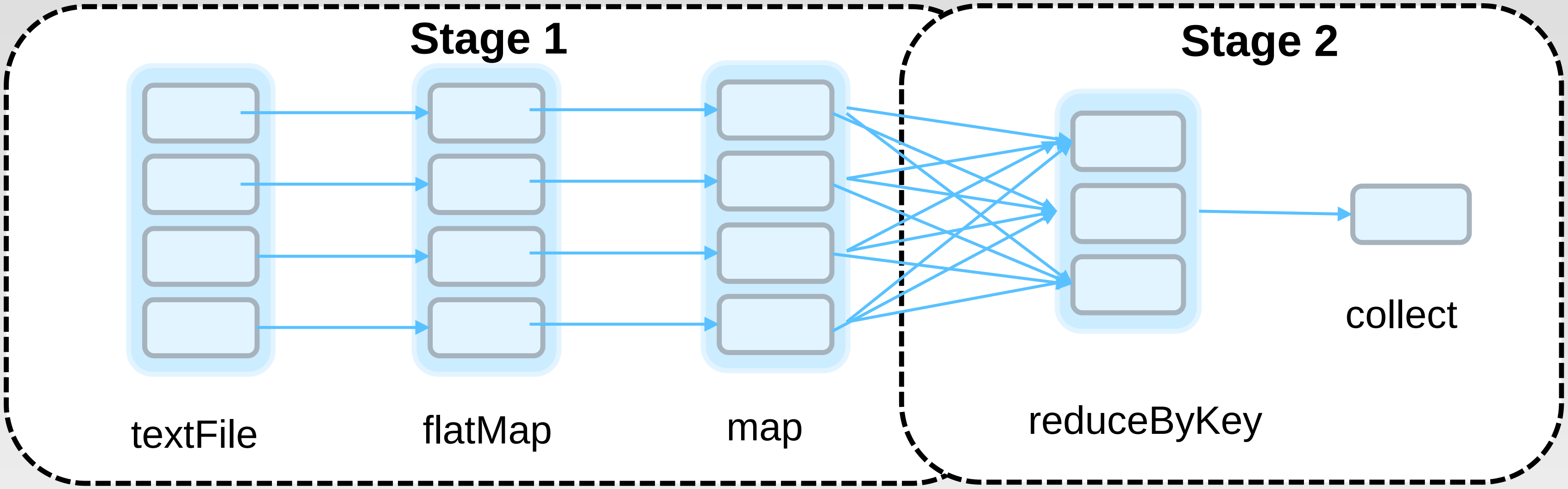


Word Count in Spark

```
val file = sc.textFile("hdfs://…", 4)          RDD[String]
val words = file.flatMap(line =>                RDD[List[String]]
            line.split(" "))
val pairs = words.map(t => (t, 1))              RDD[(String, Int)]
val count = pairs. reduceByKey(_+_)             RDD[(String, Int)]
count.collect()                                 Array[(String, Int)]
```



Execution Plan

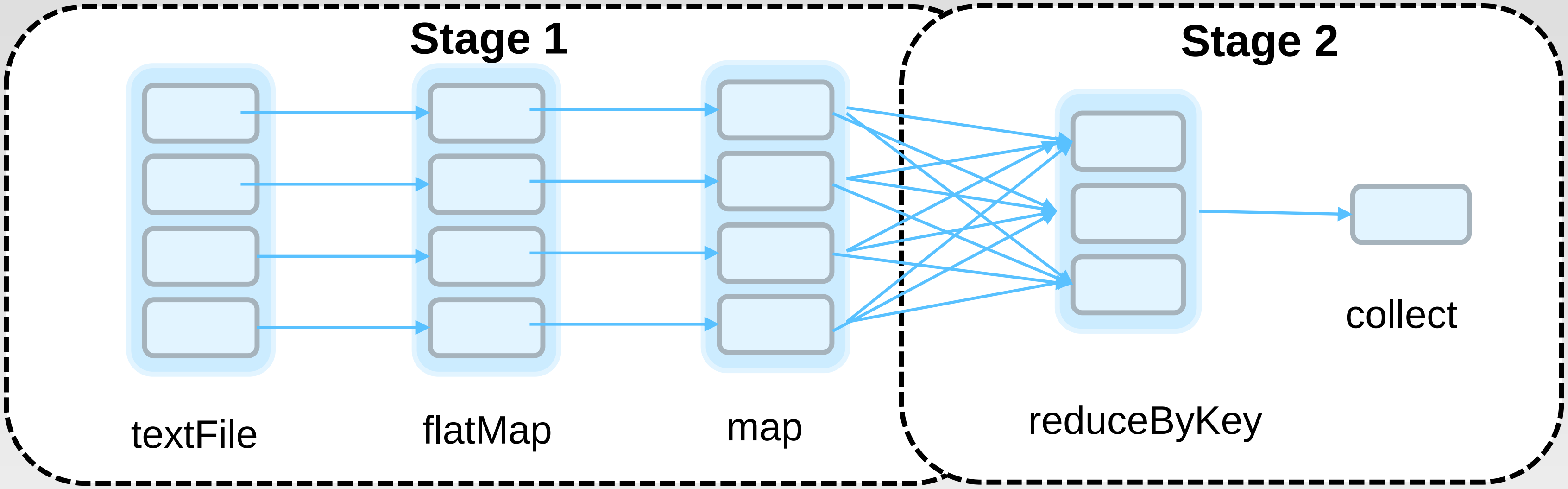


The scheduler examines the RDD's lineage graph to build a DAG of stages.

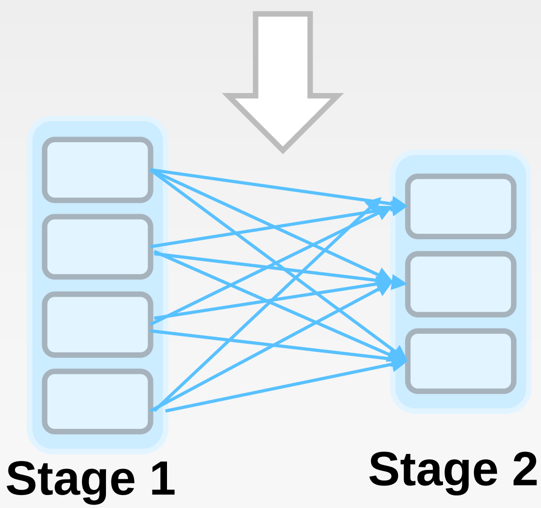
Stages are sequences of RDDs, that don't have a Shuffle in between

The boundaries are the shuffle stages.

Execution Plan



1. Read HDFS split
2. Apply both the maps
3. Start Partial reduce
4. Write shuffle data



1. Read shuffle data
2. Final reduce
3. Send result to driver program

Stage Execution

Create a task for each Partition in the new RDD

Serialize the Task

Schedule and ship Tasks to Slaves

All this happens internally

Word Count in Spark (As a Whole View)

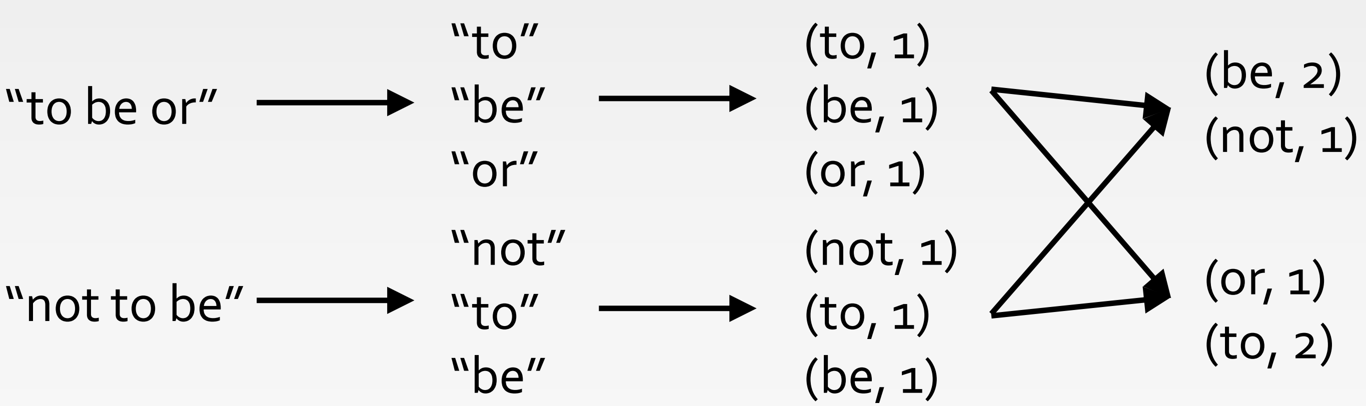
Word Count using Scala in Spark

Transformation

```
val file = sc.textFile("hdfs://...")

val counts = file.flatMap(line => line.split(" "))
    .map(word => (word,1))
    .reduceByKey(_ + _)
```

Action

```
counts.saveAsTextFile("hdfs://...")
```



map vs. flatMap

Sample input file:

```
comp9313@comp9313-VirtualBox:~$ hdfs dfs -cat inputfile
This is a short sentence.
This is a second sentence.
```

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

map: Return a new distributed dataset formed by passing each element of the source through a function *func*.

```
scala> inputfile.map(x => x.split(" ")).collect()
res3: Array[Array[String]] = Array(Array(This, is, a, short, sentence.), Array(T
his, is, a, second, sentence.))
```

flatMap: Similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item).

```
scala> inputfile.flatMap(x => x.split(" ")).collect()
res4: Array[String] = Array(This, is, a, short, sentence., This, is, a, second,
sentence.)
```

RDD Operations

Transformations	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	: RDD[T] $\Rightarrow$ RDD[U]
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	: RDD[T] $\Rightarrow$ RDD[T]
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	: RDD[T] $\Rightarrow$ RDD[U]
	$sample(fraction : \mathrm{Float})$	: RDD[T] $\Rightarrow$ RDD[T] (Deterministic sampling)
	$groupByKey()$	: RDD[(K, V)] $\Rightarrow$ RDD[(K, Seq[V])]
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	: RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
	$union()$	: (RDD[T], RDD[T]) $\Rightarrow$ RDD[T]
	$join()$	: (RDD[(K, V)], RDD[(K, W)]) $\Rightarrow$ RDD[(K, (V, W))]
	$cogroup()$	: (RDD[(K, V)], RDD[(K, W)]) $\Rightarrow$ RDD[(K, (Seq[V], Seq[W]))]
	$crossProduct()$	: (RDD[T], RDD[U]) $\Rightarrow$ RDD[(T, U)]
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	: RDD[(K, V)] $\Rightarrow$ RDD[(K, W)] (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	: RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
	$partitionBy(p : \mathrm{Partitioner[K]})$	: RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
Actions	$count()$	: RDD[T] $\Rightarrow$ Long
	$collect()$	: RDD[T] $\Rightarrow$ Seq[T]
	$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	: RDD[T] $\Rightarrow$ T
	$lookup(k : \mathrm{K})$	: RDD[(K, V)] $\Rightarrow$ Seq[V] (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	: Outputs RDD to a storage system, *e.g.*, HDFS

Spark RDD API Examples:

http://homepage.cs.latrobe.edu.au/zhe/ZhenHeSparkRDDAPIExamples.html

References

http://spark.apache.org/docs/latest/index.html

http://www.scala-lang.org/documentation/

http://www.scala-lang.org/docu/files/ScalaByExample.pdf

A Brief Intro to Scala, by Tim Underwood.

Learning Spark. Chapters 1-7.

End of Chapter 6