COMP9313: Big Data Management

Lecturer: Xin Cao

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

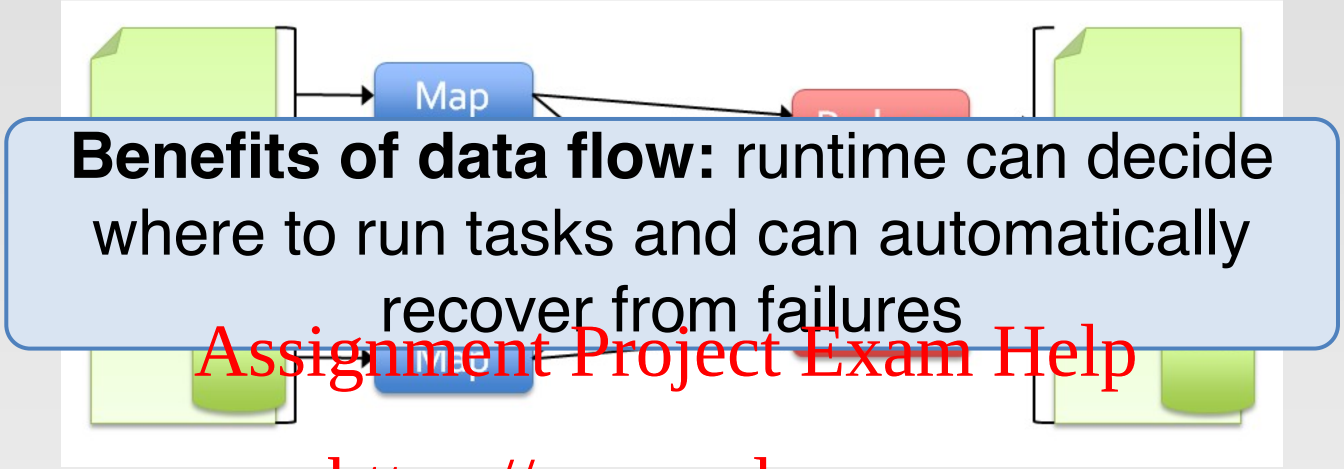
Chapter 6: Spark

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)

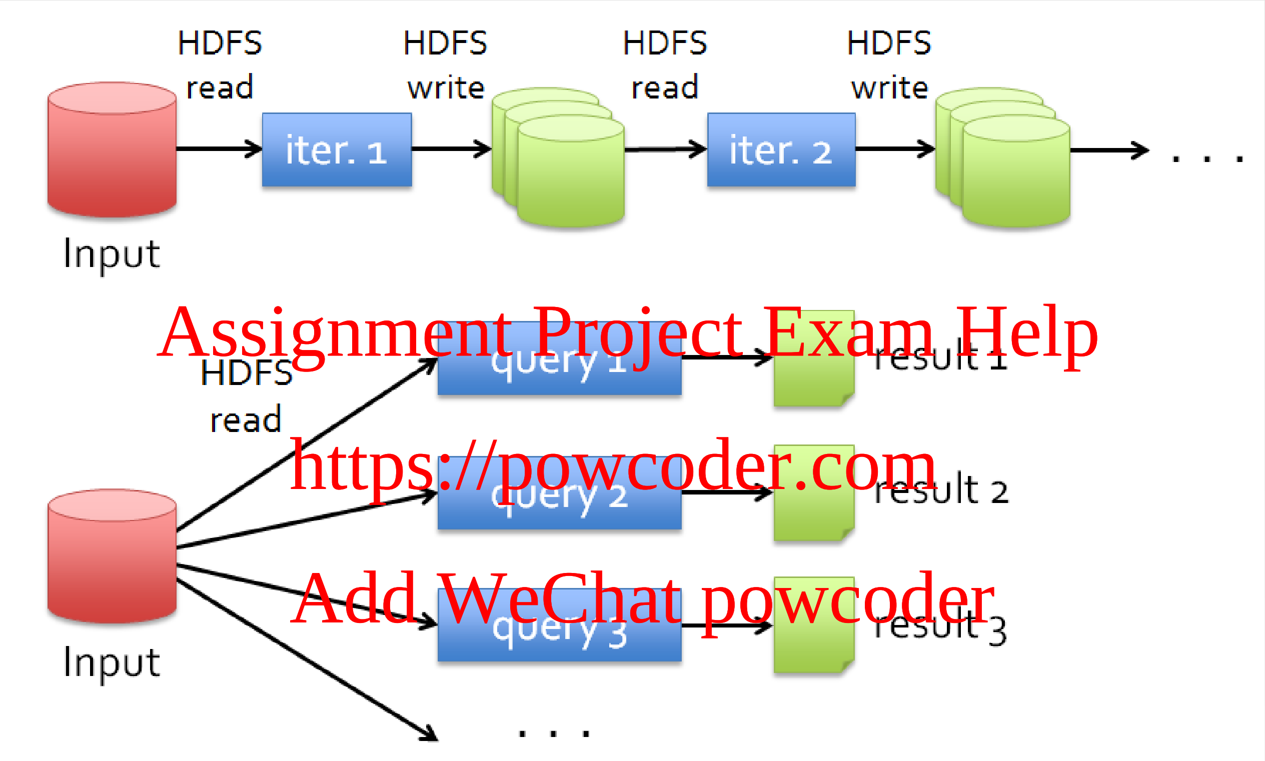
Limitations of MapReduce



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



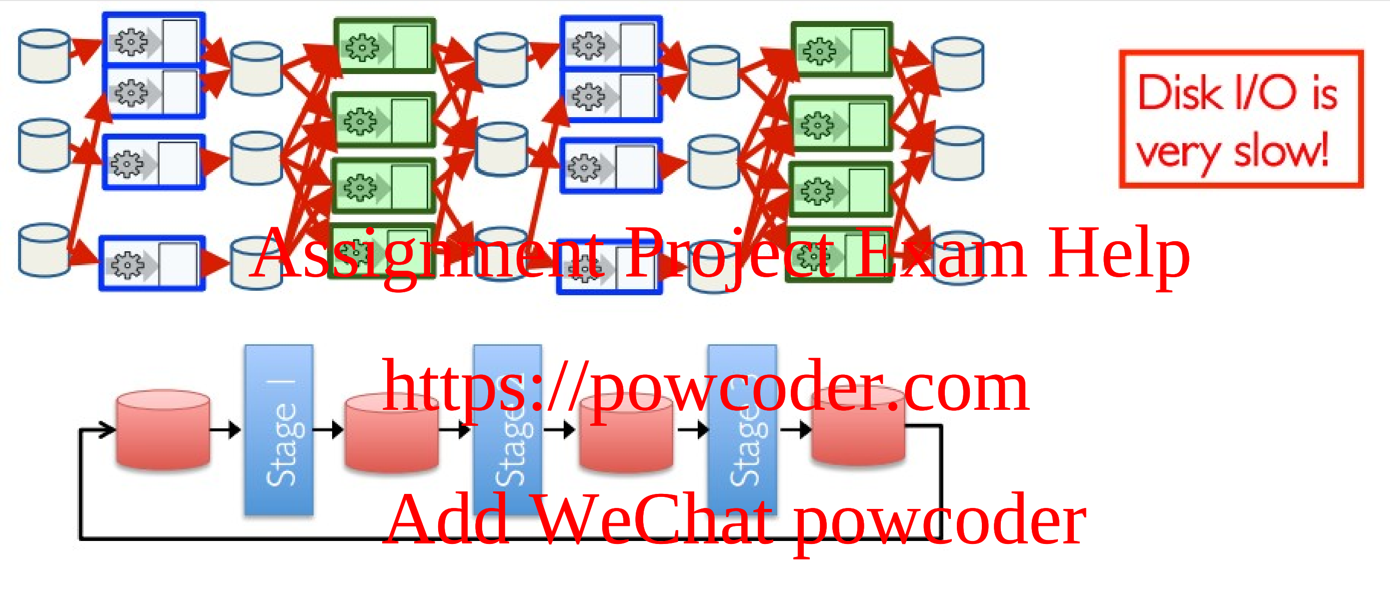
Slow due to replication, serialization, and disk IO

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

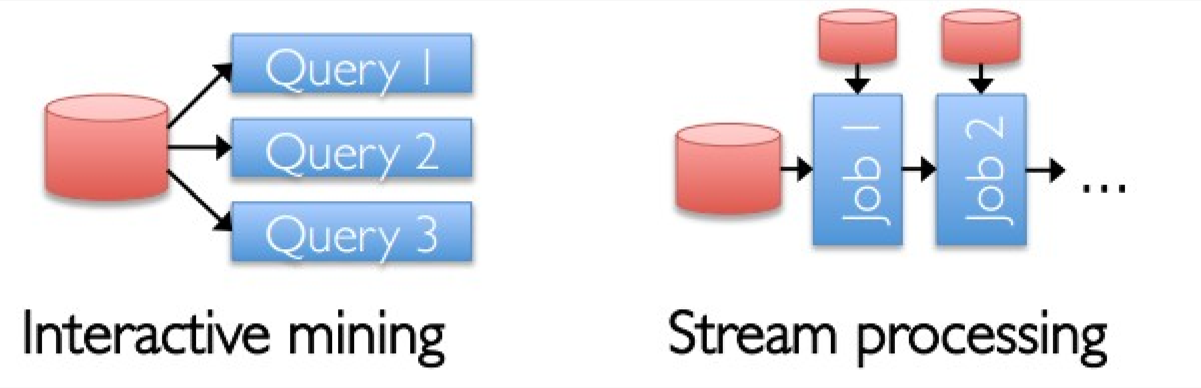
Efficient primitives for **data sharing**

Data Sharing in MapReduce

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

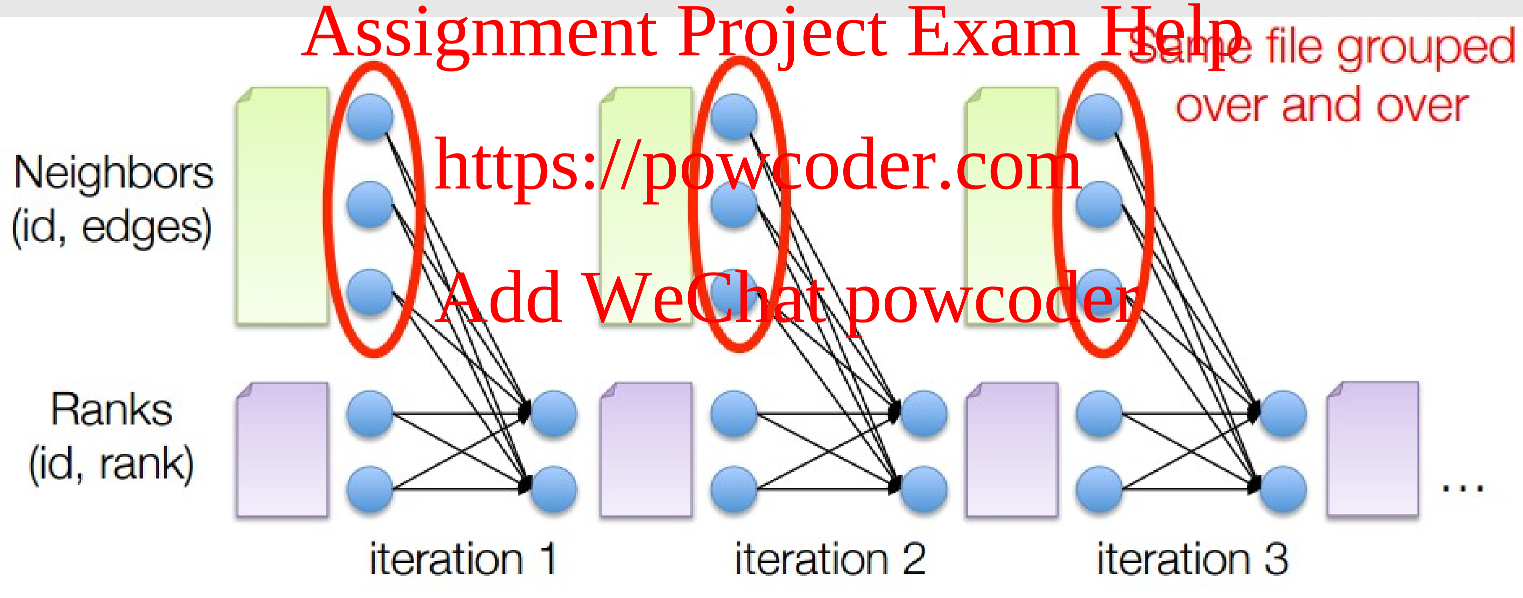


- Interactive queries and online processing involves lots of disk I/O



Example: PageRank

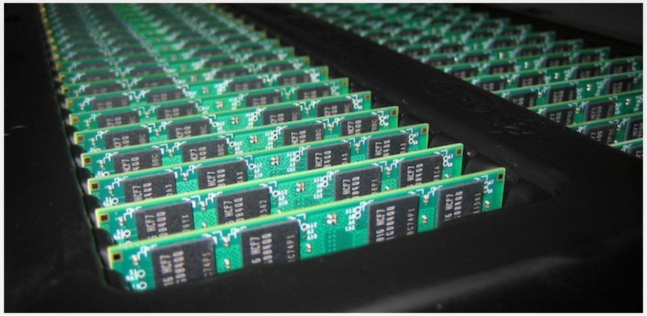
- Repeatedly multiply sparse matrix and vector
- Requires repeatedly hashing together page adjacency lists and rank vector



Hardware for Big Data

Lots of hard drives

Lots of CPUs

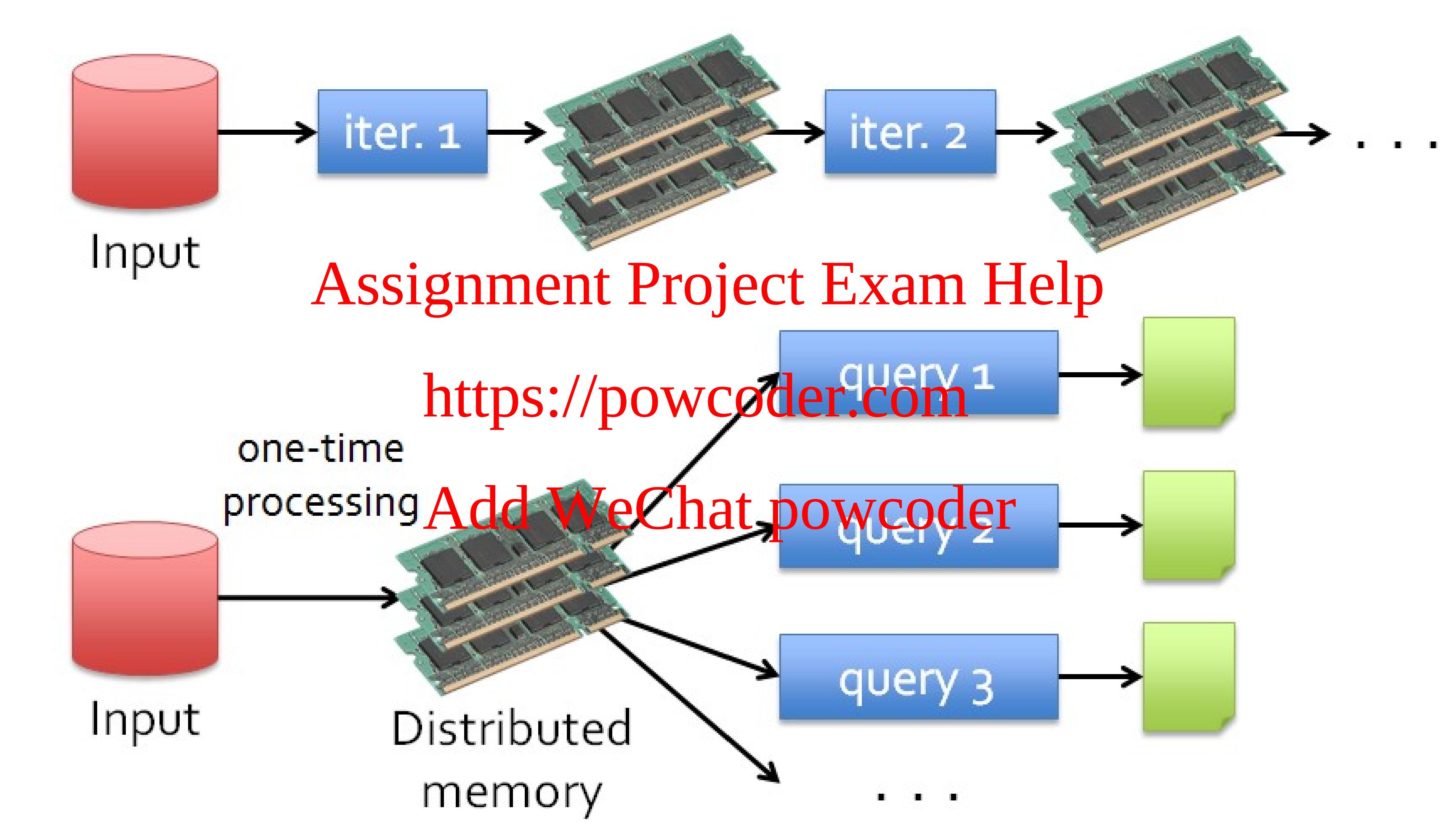


And lots of memory!

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

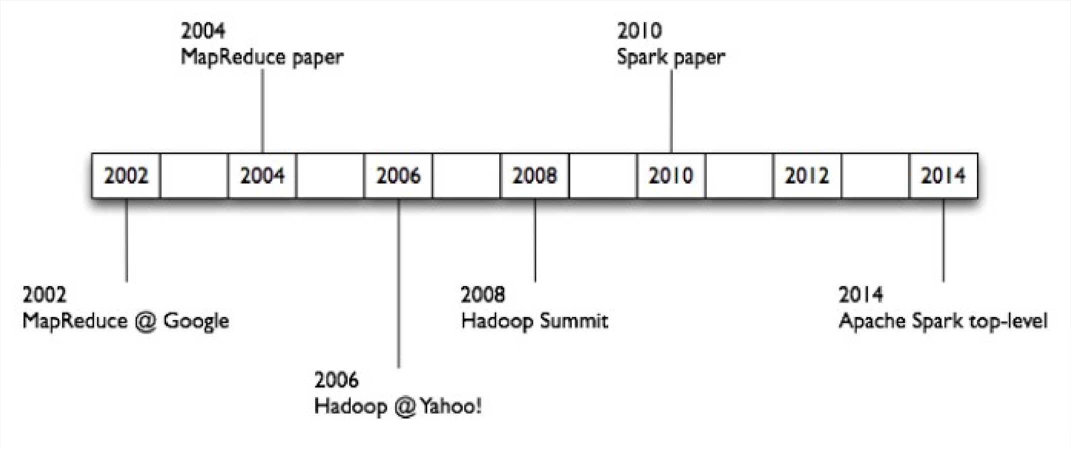
Data Sharing in Spark Using RDD



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



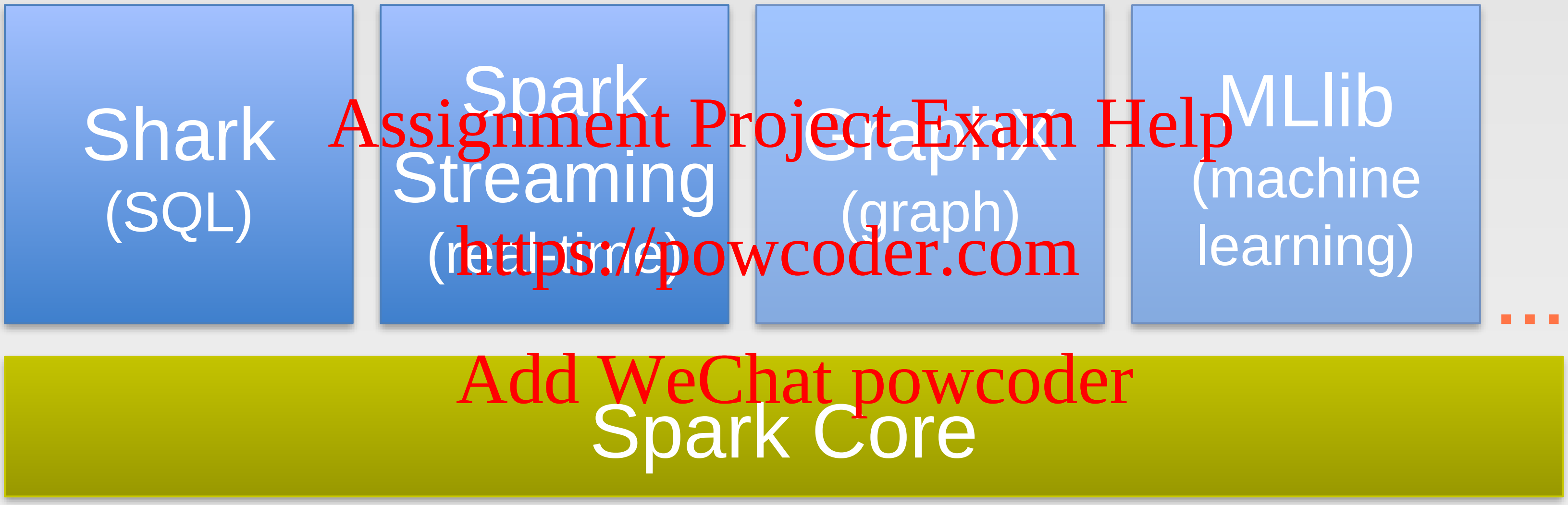
What is Spark

- 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)



Shark (SQL)

Spark Streaming (real-time)

GraphX (graph)

MLlib (machine learning)

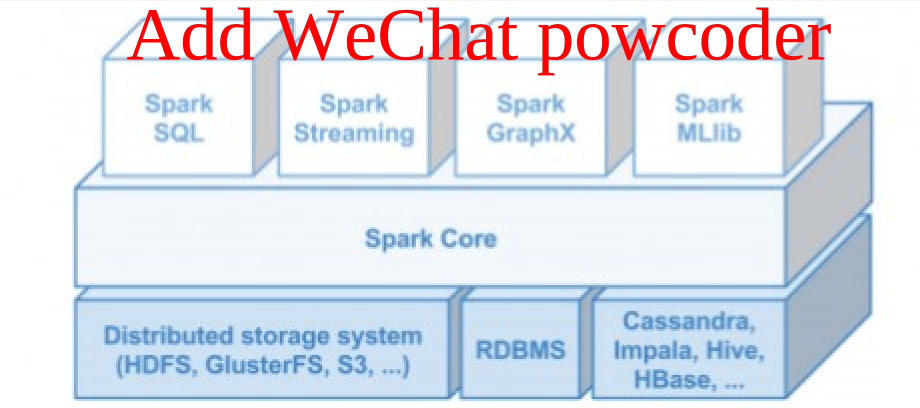
…

Spark Core

- Spark SQL (SQL on Spark)
- Spark Streaming (stream processing)
- GraphX (graph processing)
- MLlib (machine learning library)

Data Sources

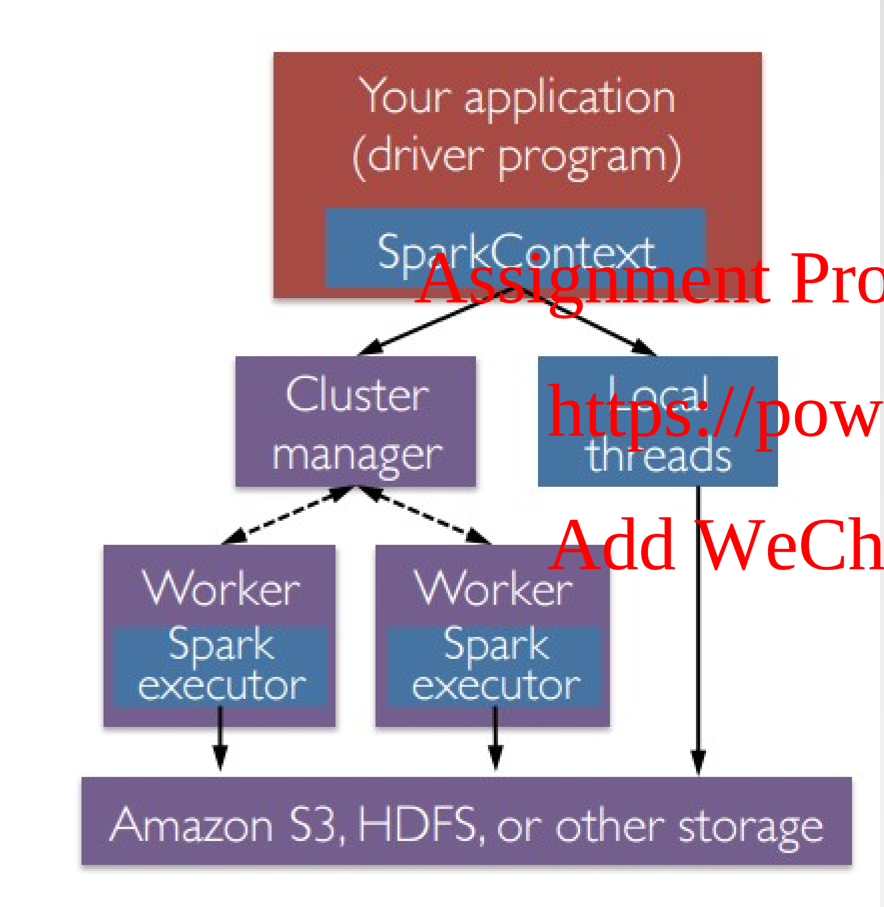
- Local Files
  - file:///opt/httpd/logs/access_log
- S3
- Hadoop Distributed Filesystem
  - Regular files, sequence files, any other Hadoop InputFormat
- HBase, Cassandra, etc.


Spark SQL
Spark Streaming
Spark GraphX
Spark MLlib
Spark Core
Distributed storage system (HDFS, GlusterFS, S3, ...)
RDBMS
Cassandra, Impala, Hive, HBase, ...

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

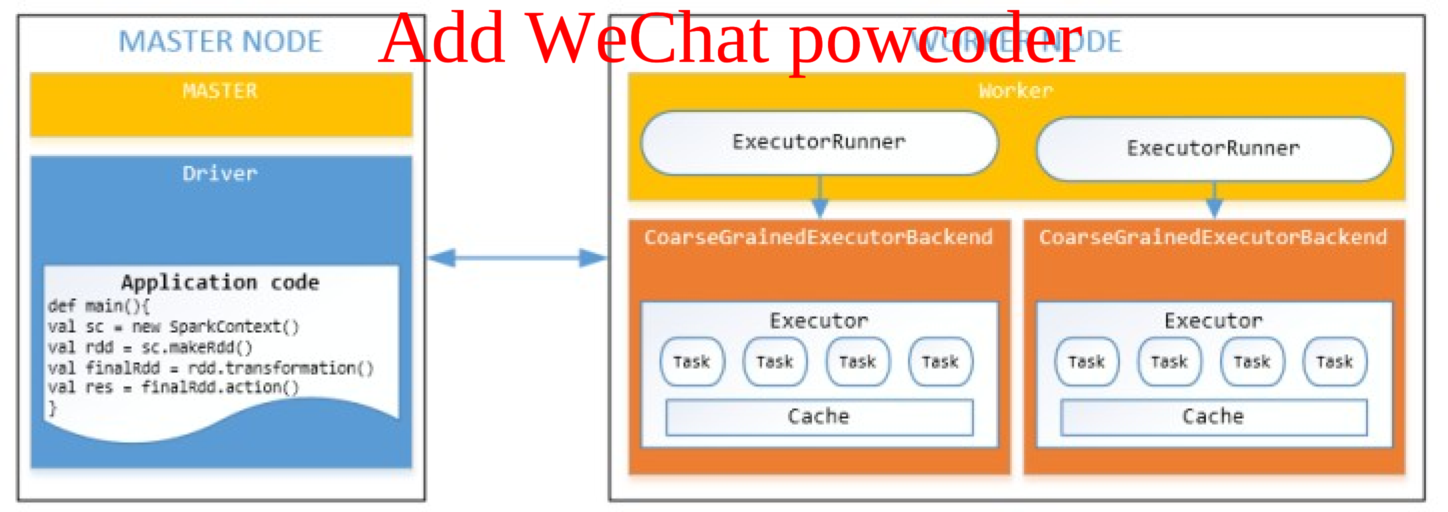
Spark Workflow



- 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



```
def main(){
val sc = new SparkContext()
val rdd = sc.makeRdd()
val finalRdd = rdd.transformation()
val res = finalRdd.action()
}
```

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, 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

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

```
// 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
  }
}
```

```
// 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;
  }
}
```

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, …

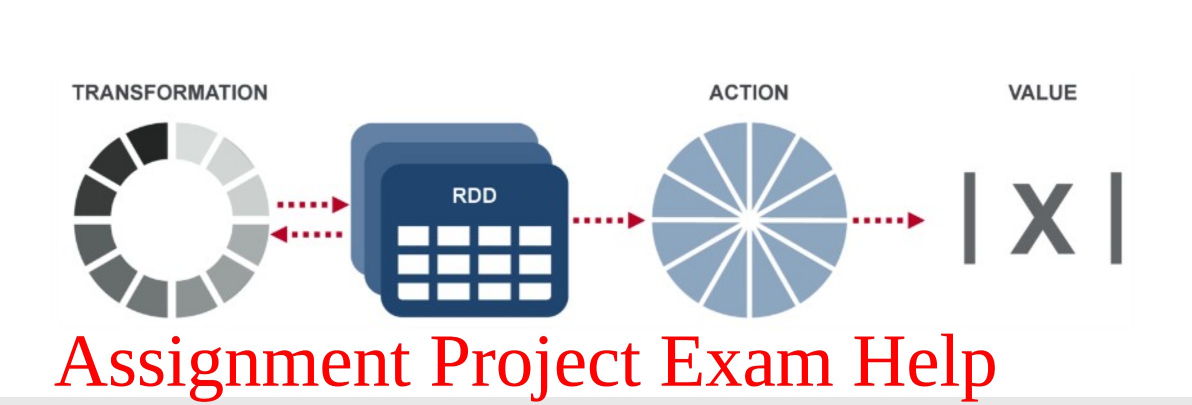
What is RDD

- 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).

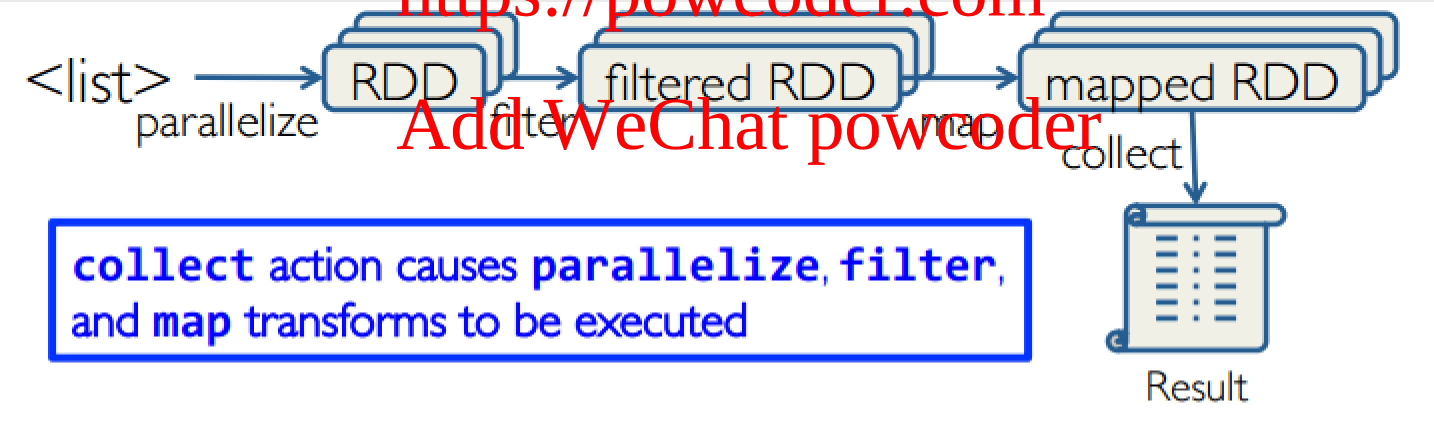
RDD Operations



- **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

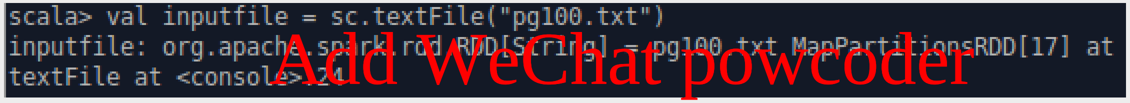


collect action causes **parallelize**, **filter**, and **map** transforms to be executed

- 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

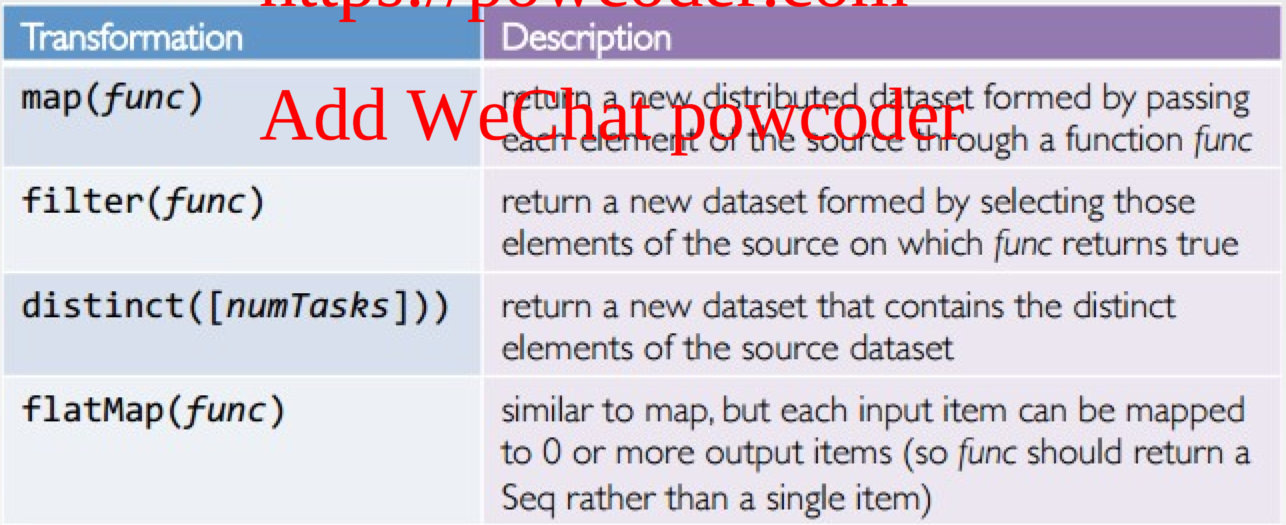


```
scala> val inputfile = sc.textFile("pg100.txt")
inputfile: org.apache.spark.rdd.RDD[String] = pg100.txt MapPartitionsRDD[17] at
textFile at <console>:24
```

- 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

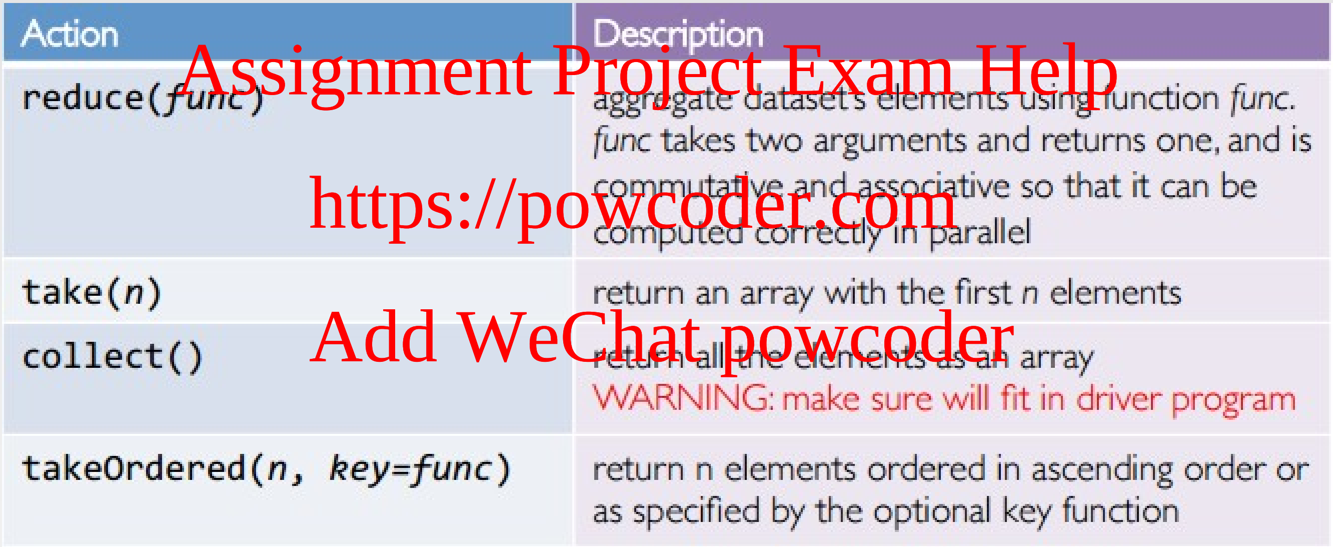
- Create new datasets from an existing one
- Use lazy evaluation: results not computed right away – instead Spark remembers set of transformations applied to base dataset
  - Spark optimizes the required calculations
  - Spark recovers from failures
- Some transformation functions



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

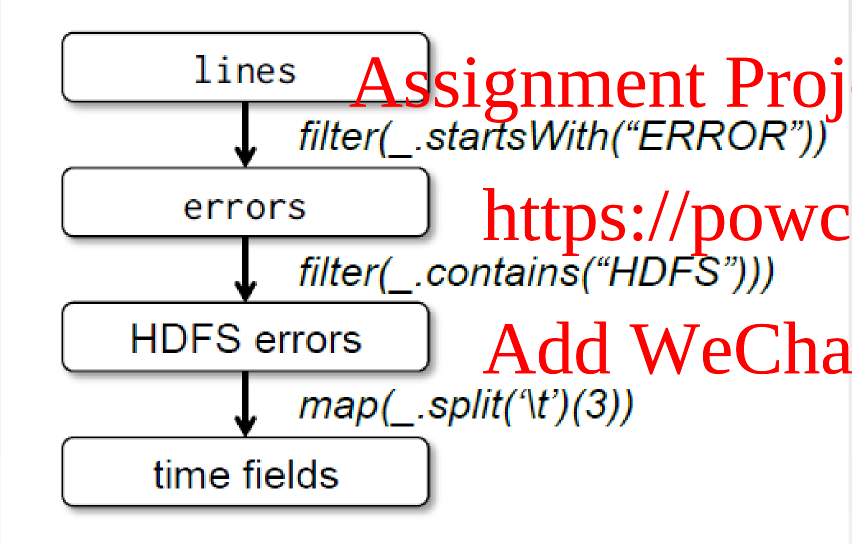


Action	Description
`reduce(func)`	aggregate dataset's elements using function *func*. *func* takes two arguments and returns one, and is commutative and associative so that it can be computed correctly in parallel
`take(n)`	return an array with the first *n* elements
`collect()`	return all the elements 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.

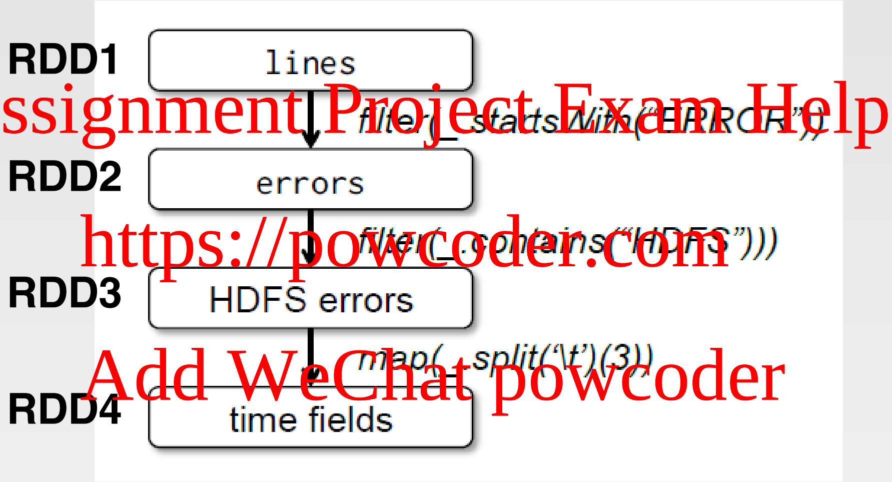


```
//base RDD

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)

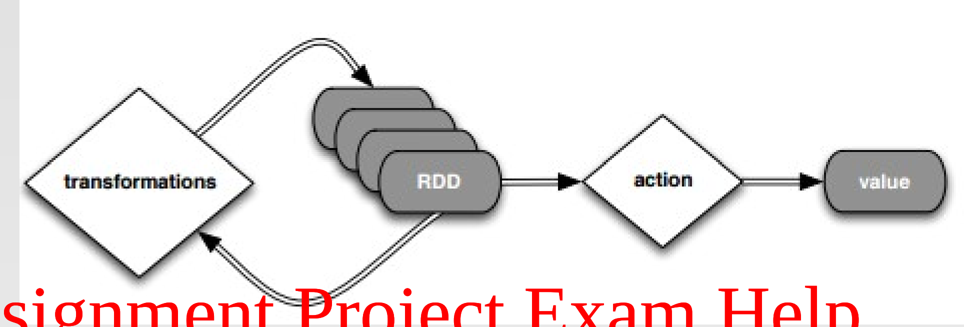
Lineage Graph

- 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
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//Transformed RDD
val errors = lines.filter(_.startsWith("Error"))
errors.persist()
errors.count()
errors.filter(_.contains("HDFS"))
        .map(_.split('\t')(3))
        .collect()
```
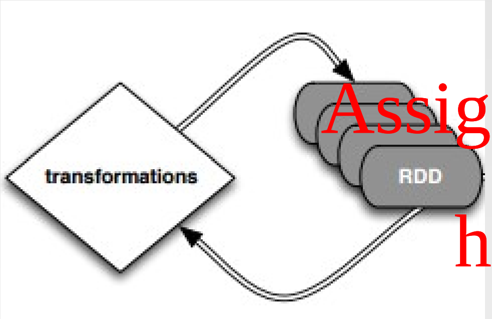

Deconstructed

//base RDD

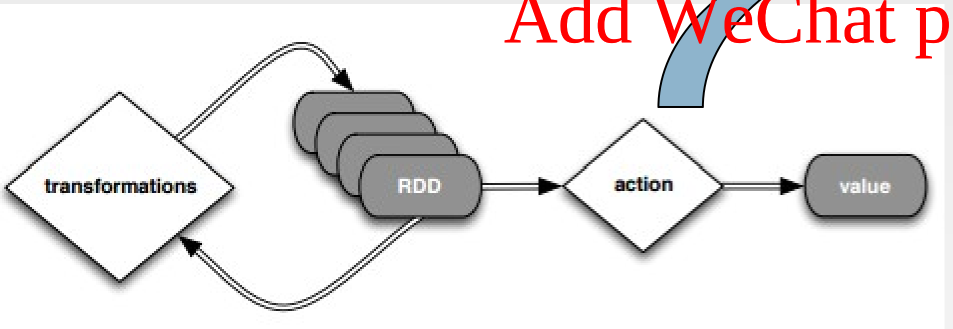
val lines = sc.textFile(“hdfs://…”)



//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()
```

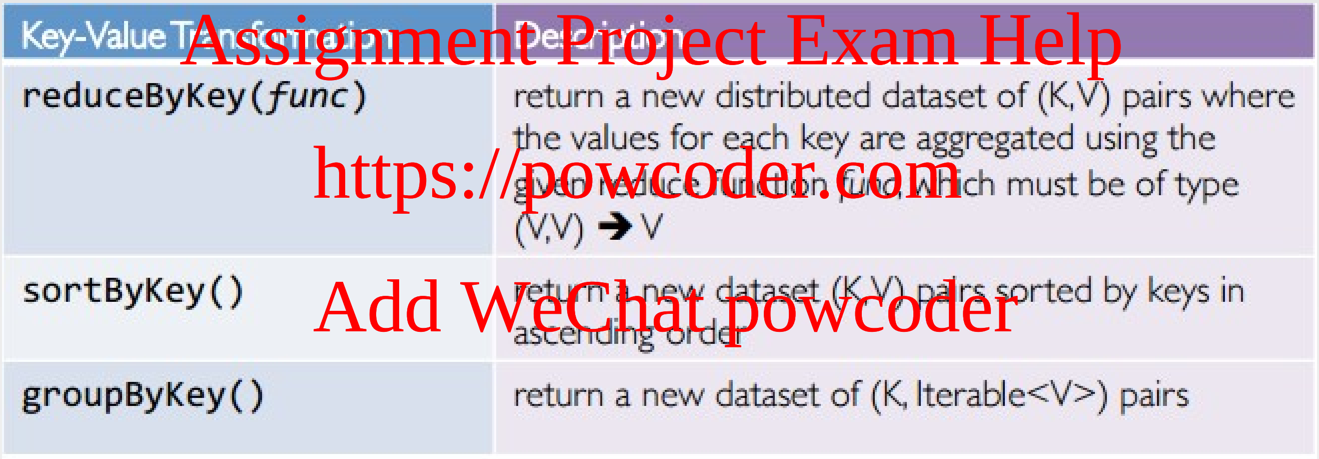
- If you do errors.count() again, the file will be loaded again and computed again.

- 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)
```

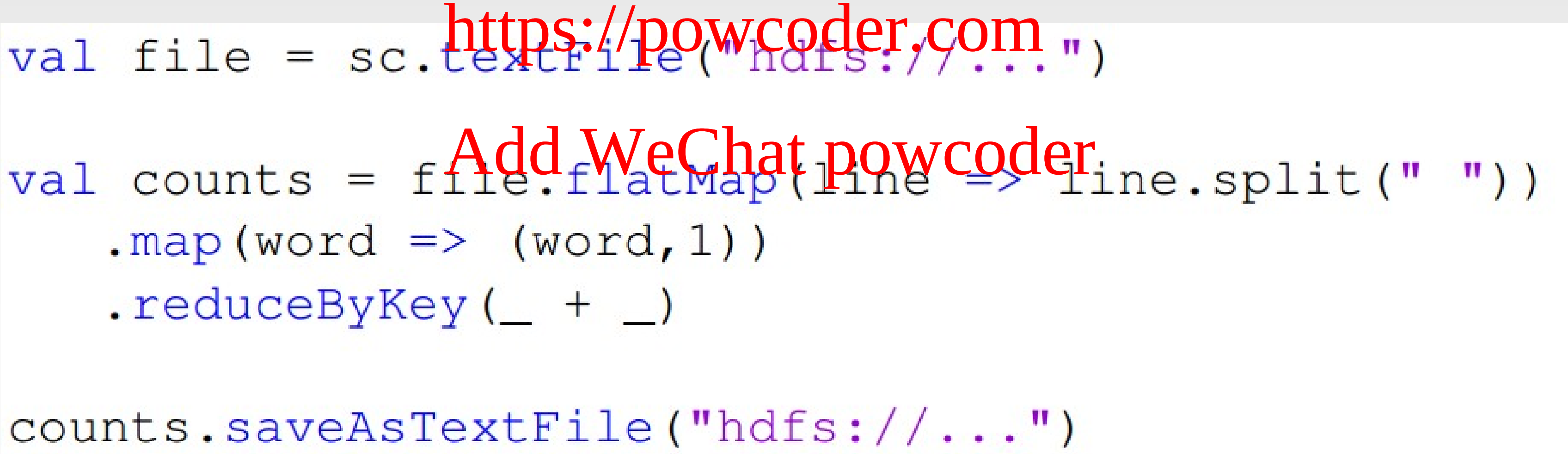
Setting the Level of Parallelism

- All the pair RDD operations take an optional second parameter for number of tasks
  - `words.reduceByKey((x,y) => x + y, 5)`
  - `words.groupByKey(5)`

Part 4: Spark Programming Model

How Spark Works

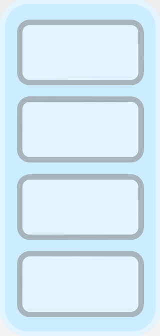
- User application create RDDs, transform them, and run actions.
- This results in a DAG (Directed Acyclic Graph) of operators.
- DAG is compiled into stages
- Each stage is executed as a series of Task (one Task for each Partition).



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

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

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

Word Count in Spark

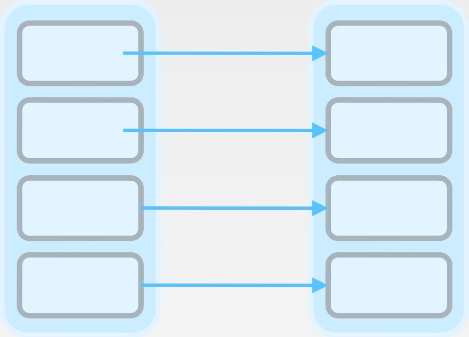
val file = sc.textFile("hdfs://…", 4)   RDD[String]



textFile

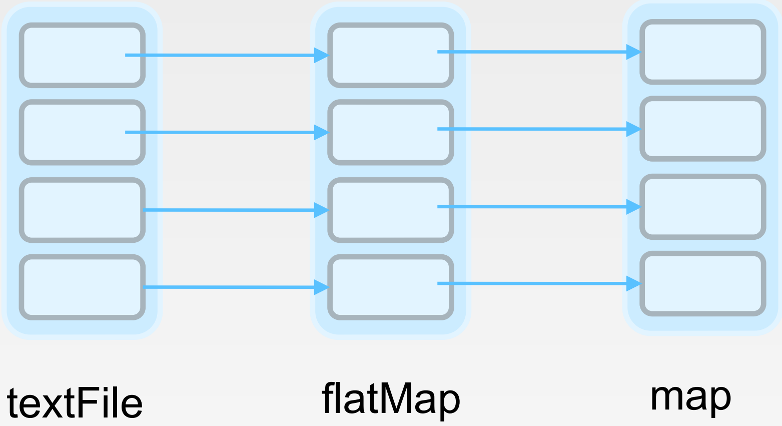
Word Count in Spark

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



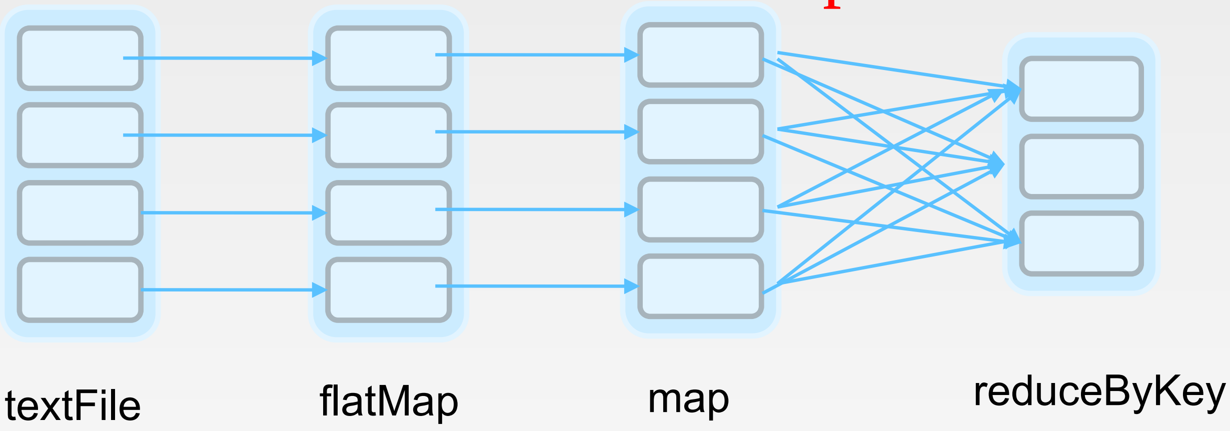
Word Count in Spark

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



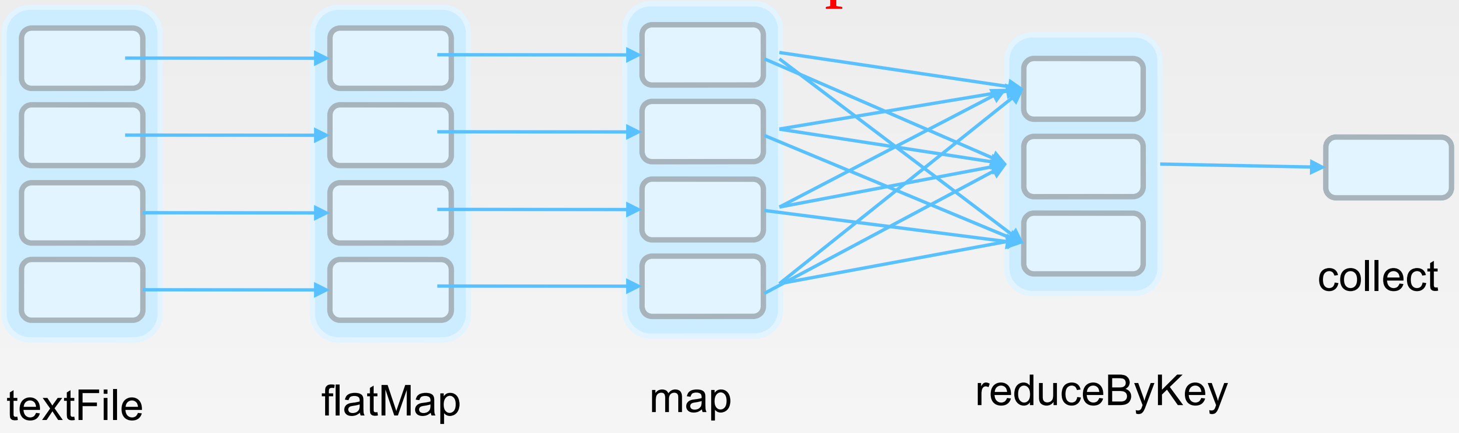
Word Count in Spark

```
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)]
```

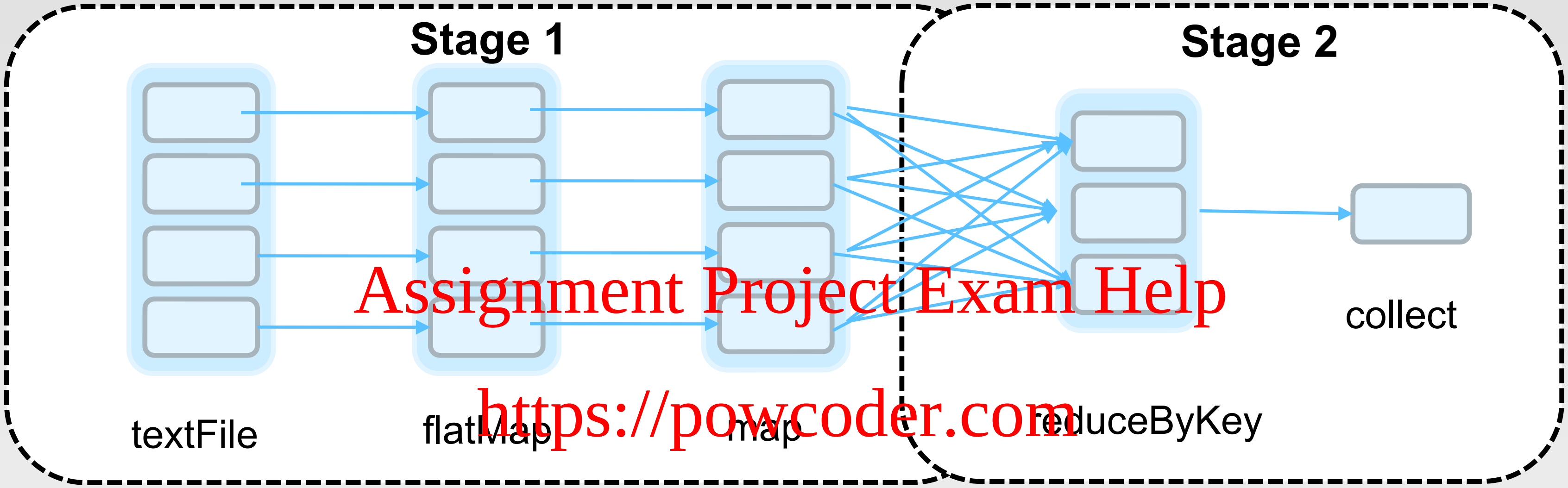


Word Count in Spark

```
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)]
```

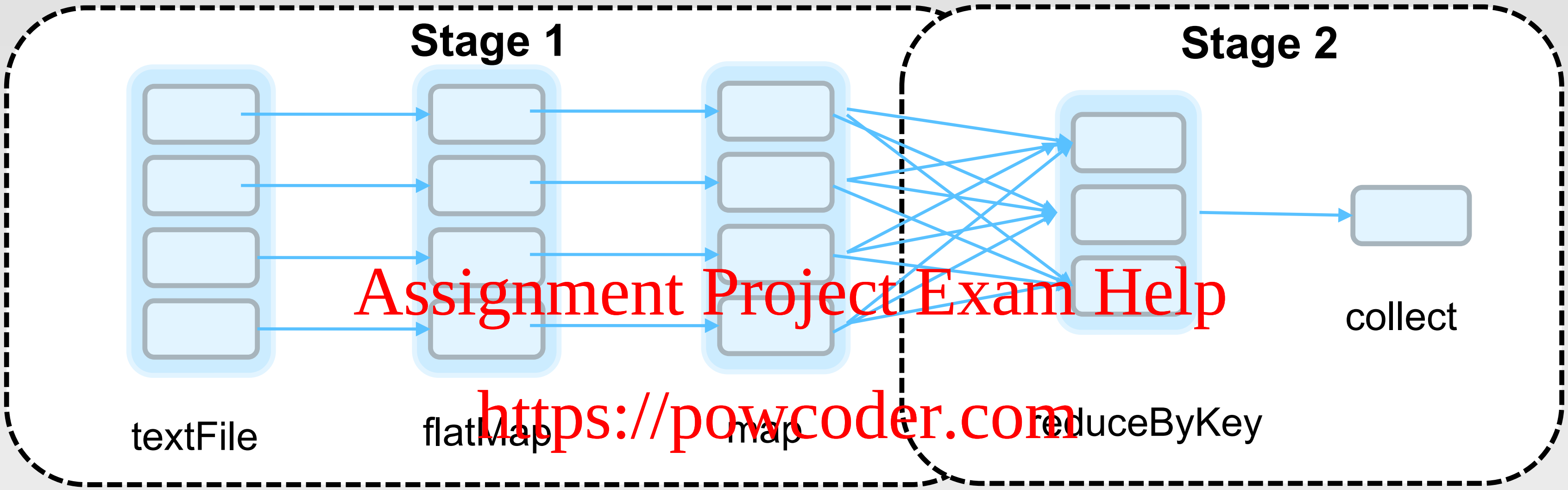


Execution Plan

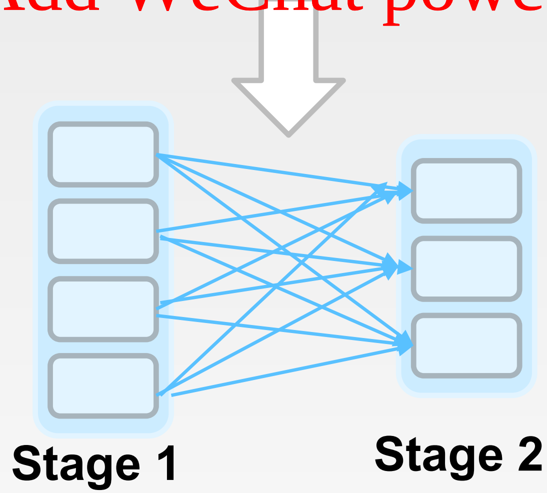


- The scheduler examines the RDD’s lineage graph to build a DAG of stages.
- Stages are sequences of RDDs, that don’t have a Shuffle in between
- The boundaries are the shuffle stages.

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

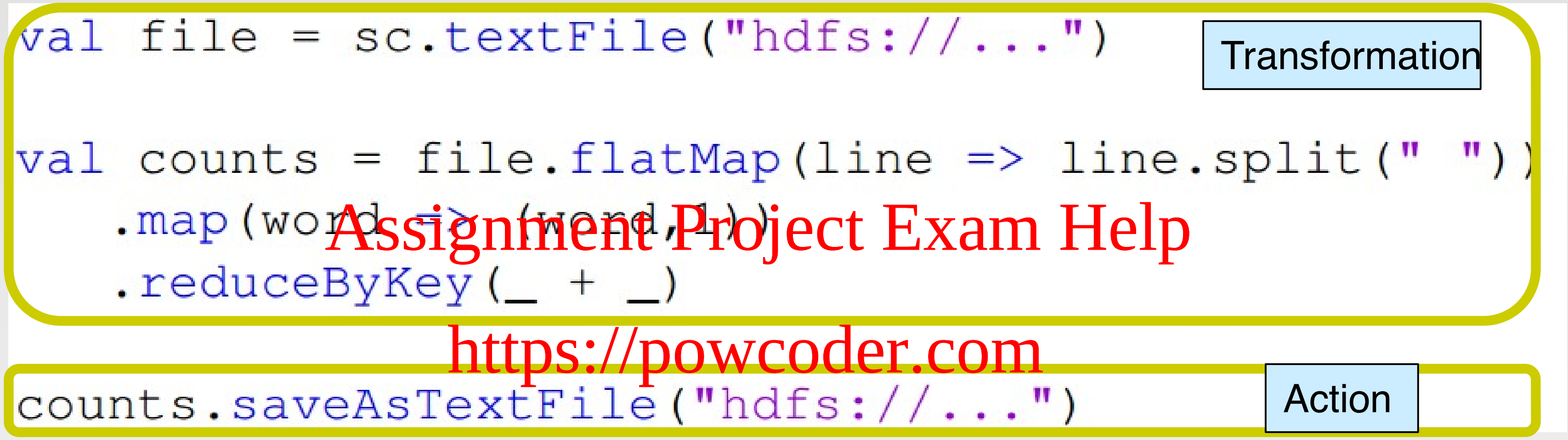
Task 1
Task 2
Task 3
Task 4

- 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)

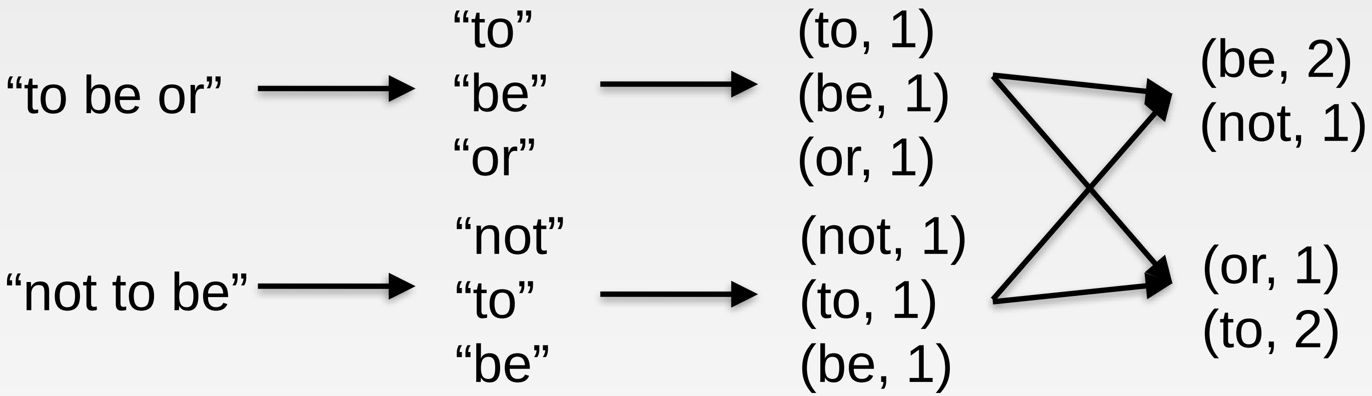
- Word Count using Scala in Spark



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

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

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

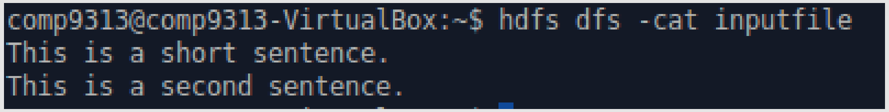
Transformation

Action

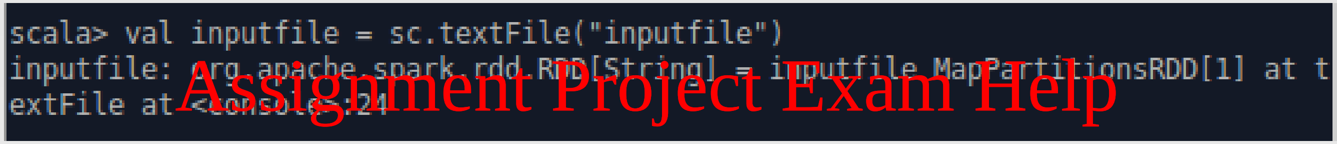


map vs. flatMap

- Sample input file:

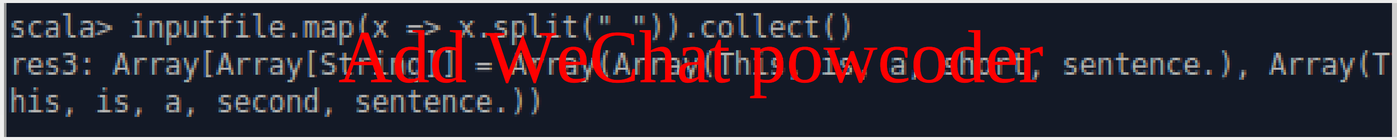


```
comp9313@comp9313-VirtualBox:~$ hdfs dfs -cat inputfile
This is a short sentence.
This is a second sentence.
```



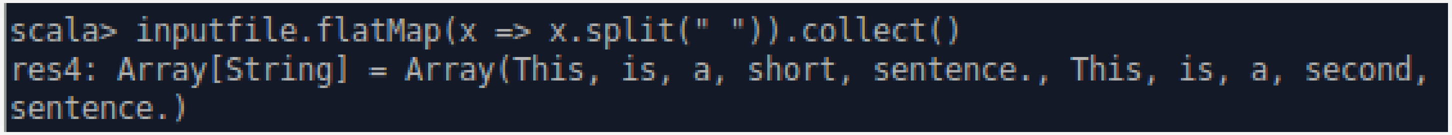
```
scala> val inputfile = sc.textFile("inputfile")
inputfile: org.apache.spark.rdd.RDD[String] = inputfile MapPartitionsRDD[1] at t
extFile at <console>:24
```

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



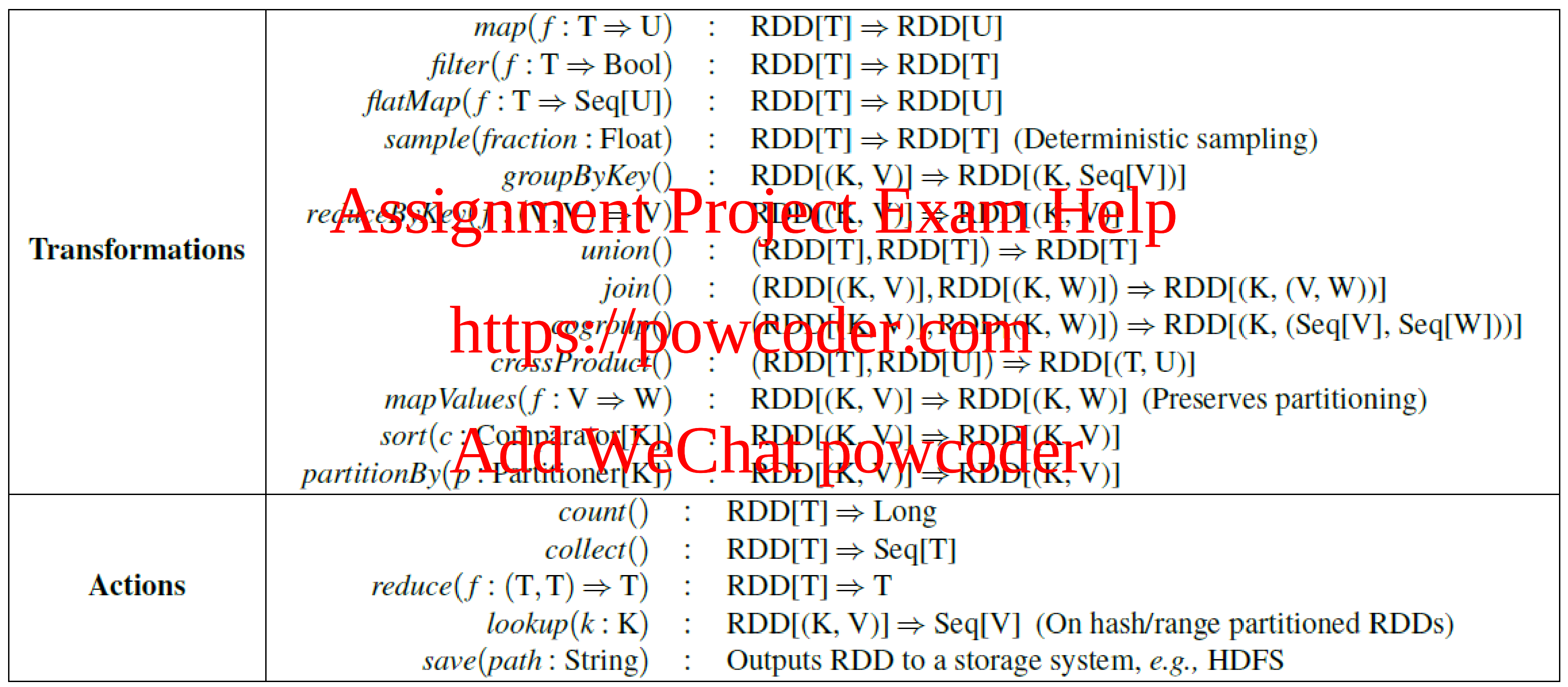
```
scala> inputfile.map(x => x.split(" ")).collect()
res3: Array[Array[String]] = Array(Array(This, is, a, short, sentence.), Array(T
his, is, a, second, sentence.))
```

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

Spark RDD API Examples:

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

Using Local Variables

- Any external variables you use in a closure will automatically be shipped to the cluster:

```
> query = sys.stdin.readline()
> pages.filter(x => x.contains(query)).count()
```

- Some caveats:
  - Each task gets a new copy (updates aren't sent back)
  - Variable must be Serializable

Shared Variables

- When you perform transformations and actions that use functions (e.g., map(f: T=>U)), Spark will automatically push a closure containing that function to the workers so that it can run at the workers.

- Any variable or data within a closure or data structure will be distributed to the worker nodes along with the closure

- When a function (such as map or reduce) is executed on a cluster node, it works on **separate** copies of all the variables used in it.

- Usually these variables are just constants but they cannot be shared across workers efficiently.

Shared Variables

- Consider These Use Cases
  - Iterative or single jobs with large global variables
    - Sending large read-only lookup table to workers
    - Sending large feature vector in a ML algorithm to workers
    - Problems? Inefficient to send large data to each worker with each iteration
    - Solution: Broadcast variables
  - Counting events that occur during job execution
    - How many input lines were blank?
    - How many input records were corrupt?
    - Problems? Closures are one way: driver -> worker
    - Solution: Accumulators

Broadcast Variables

- Broadcast variables allow the programmer to keep a read-only variable cached on each machine rather than shipping a copy of it with tasks.
  - For example, to give every node a copy of a large input dataset efficiently
- Spark also attempts to distribute broadcast variables using efficient broadcast algorithms to reduce communication cost
- Broadcast variables are created from a variable **v** by calling **SparkContext.broadcast(v)**. Its value can be accessed by calling the **value** method.

```
scala > val broadcastVar =sc.broadcast(Array(1, 2, 3))
broadcastVar: org.apache.spark.broadcast.Broadcast[Array[Int]] = Broadcast(0)
scala > broadcastVar.value
res0: Array[Int] = Array(1, 2, 3)
```

- The broadcast variable should be used instead of the value **v** in any functions run on the cluster, so that **v** is not shipped to the nodes more than once.

Accumulators

- Accumulators are variables that are only “added” to through an associative and commutative operation and can therefore be efficiently supported in parallel.
- They can be used to implement counters (as in MapReduce) or sums.
- Spark natively supports accumulators of numeric types, and programmers can add support for new types.
- Only driver can read an accumulator’s value, not tasks
- An accumulator is created from an initial value **v** by calling **SparkContext.accumulator(v)**.

```
scala> val accum = sc.longAccumulator("My Accumulator")
accum: org.apache.spark.util.LongAccumulator = LongAccumulator(id: 0, name:
Some(My Accumulator), value: 0)
scala> sc.parallelize(Array(1, 2, 3, 4)).foreach(x => accum.add(x))
... 10/09/29 18:41:08 INFO SparkContext: Tasks finished in 0.317106 s
scala> accum.value
res2: Long = 10
```

Accumulators Example (Python)

- Counting empty lines

```
file = sc.textFile(inputFile)
# Create Accumulator[Int] initialized to 0
blankLines = sc.accumulator(0)

def extractCallSigns(line):
        global blankLines # Make the global variable accessible
        if (line == ""):
                blankLines += 1
        return line.split(" ")

callSigns = file.flatMap(extractCallSigns)
print "Blank lines: %d" % blankLines.value
```

  - blankLines is created in the driver, and shared among workers
  - Each worker can access this variable

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