

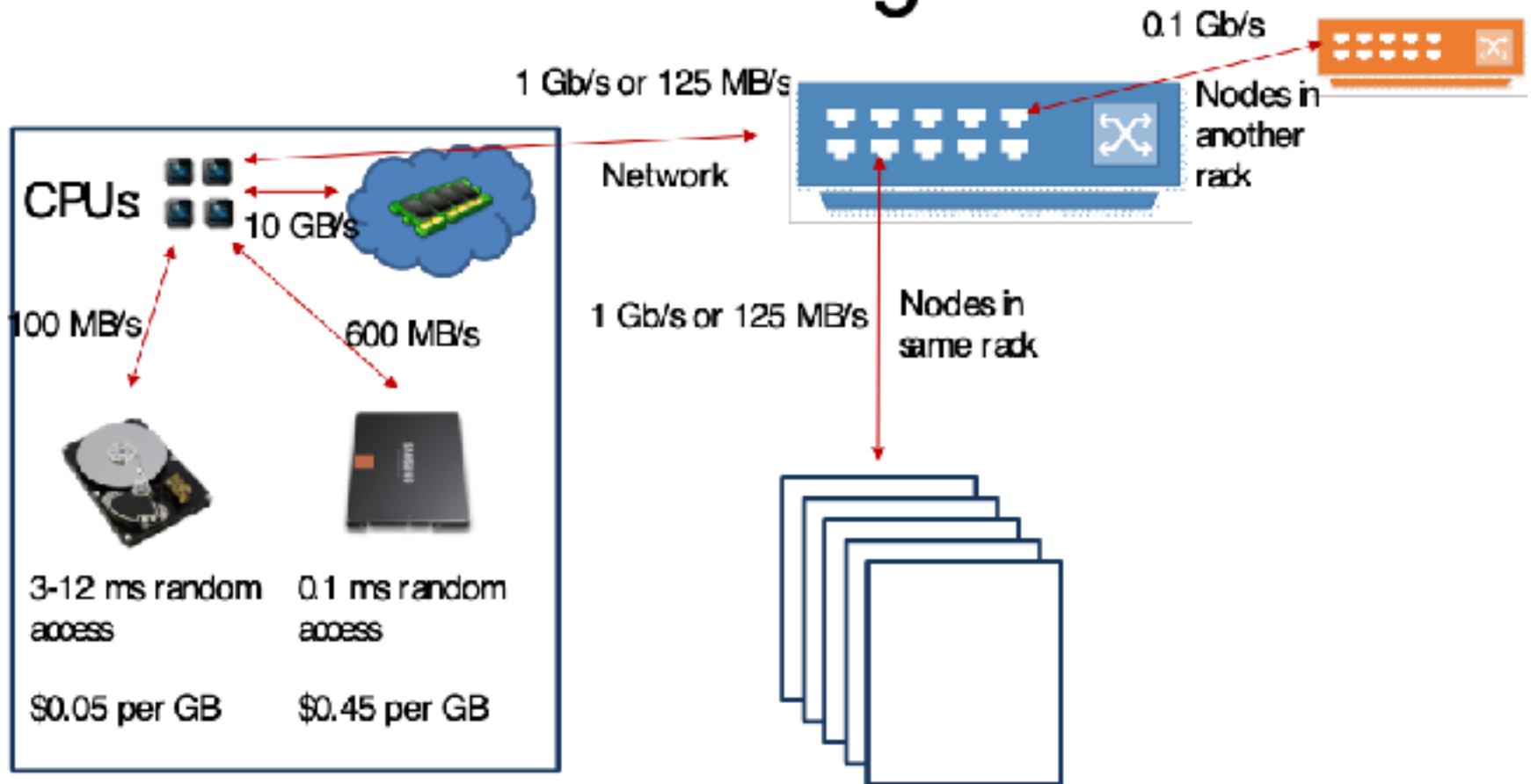
In-Memory Processing with Apache Spark

Vincent Leroy

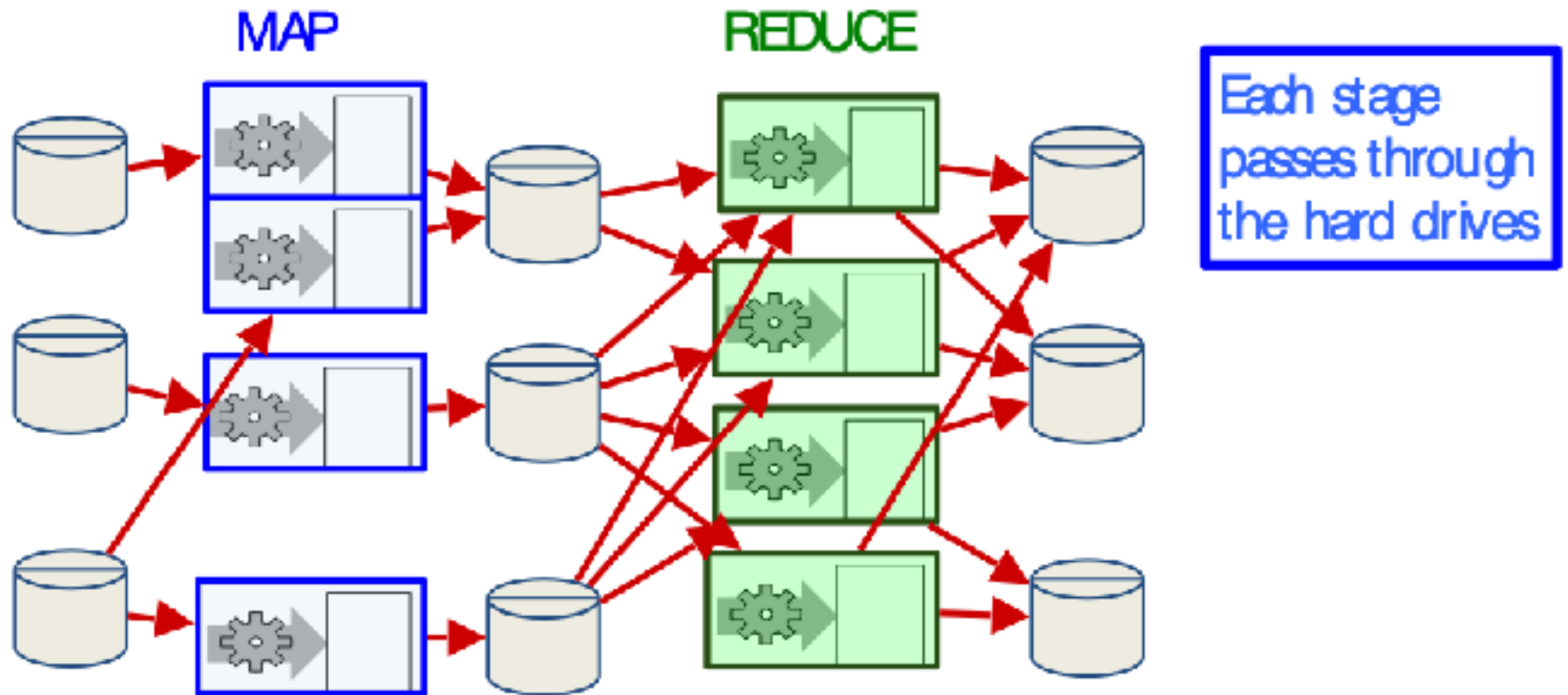
Sources

- [Resilient Distributed Datasets, Henggang Cui](#)
- [Coursera Introduction to Apache Spark, University of California, Databricks](#)

Datacenter Organization

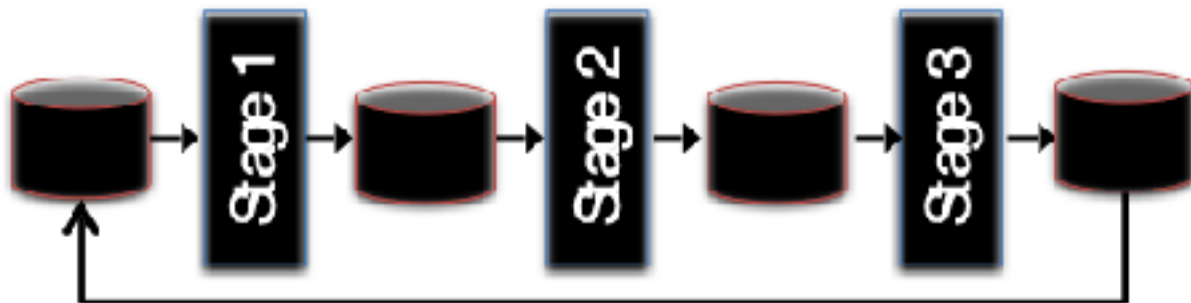
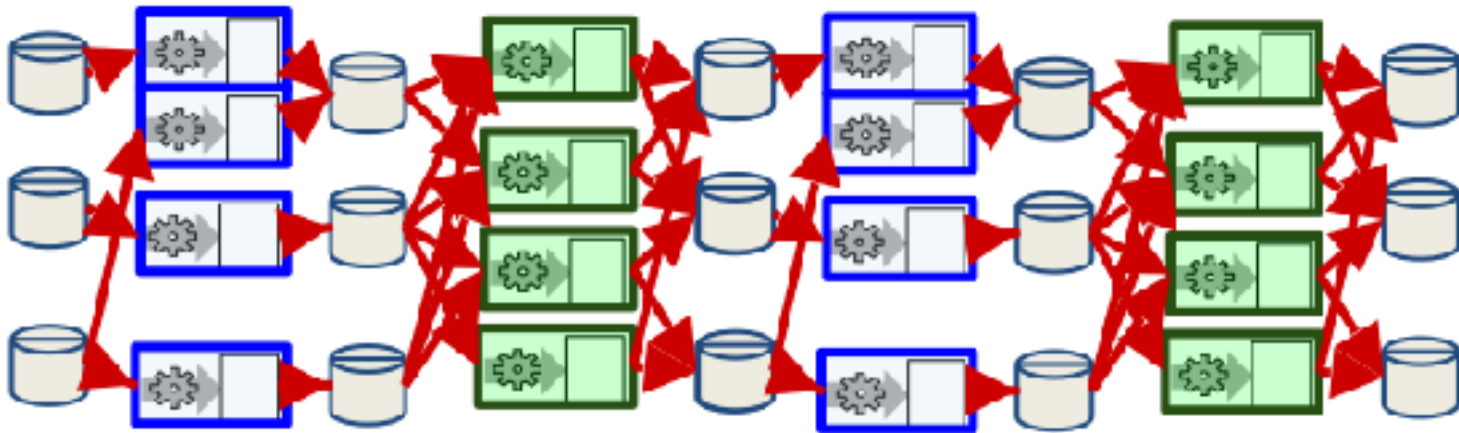


MapReduce Execution

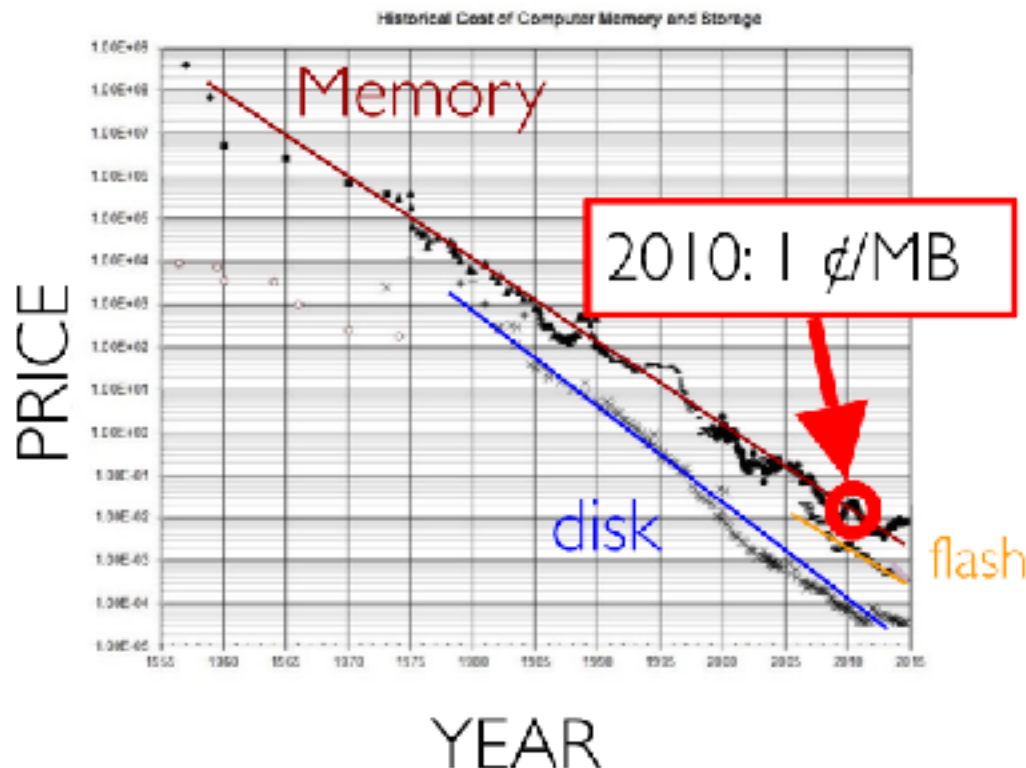


Iterative Jobs

- Disk I/O for each repetition
 - Slow when executing many small iterations



Memory Cost



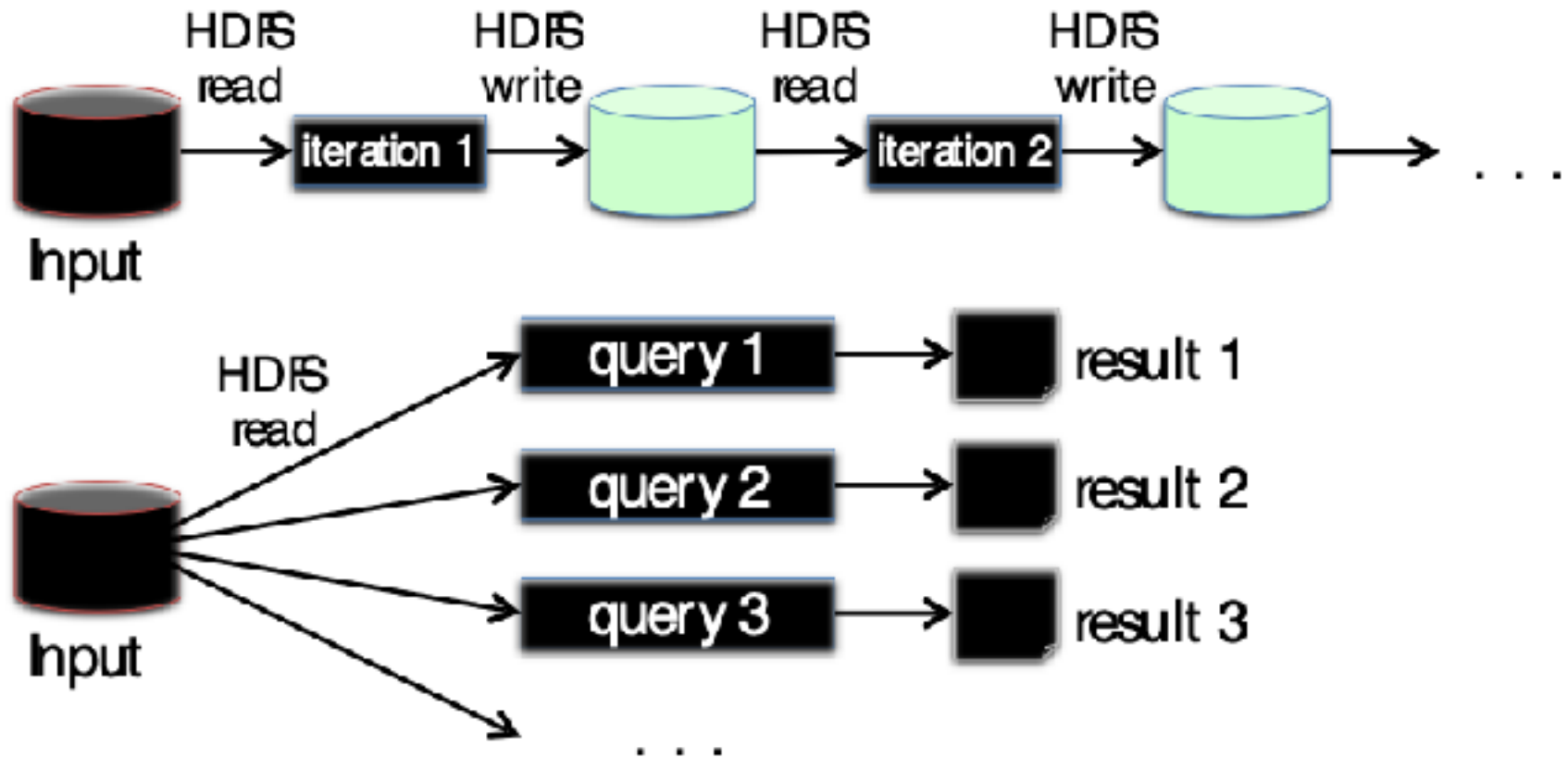
Lower cost means can
put more memory in
each server

In-Memory Processing

- Many datasets fit in memory (of a cluster)
 - Memory is fast and avoid disk I/O
- Spark distributed execution engine

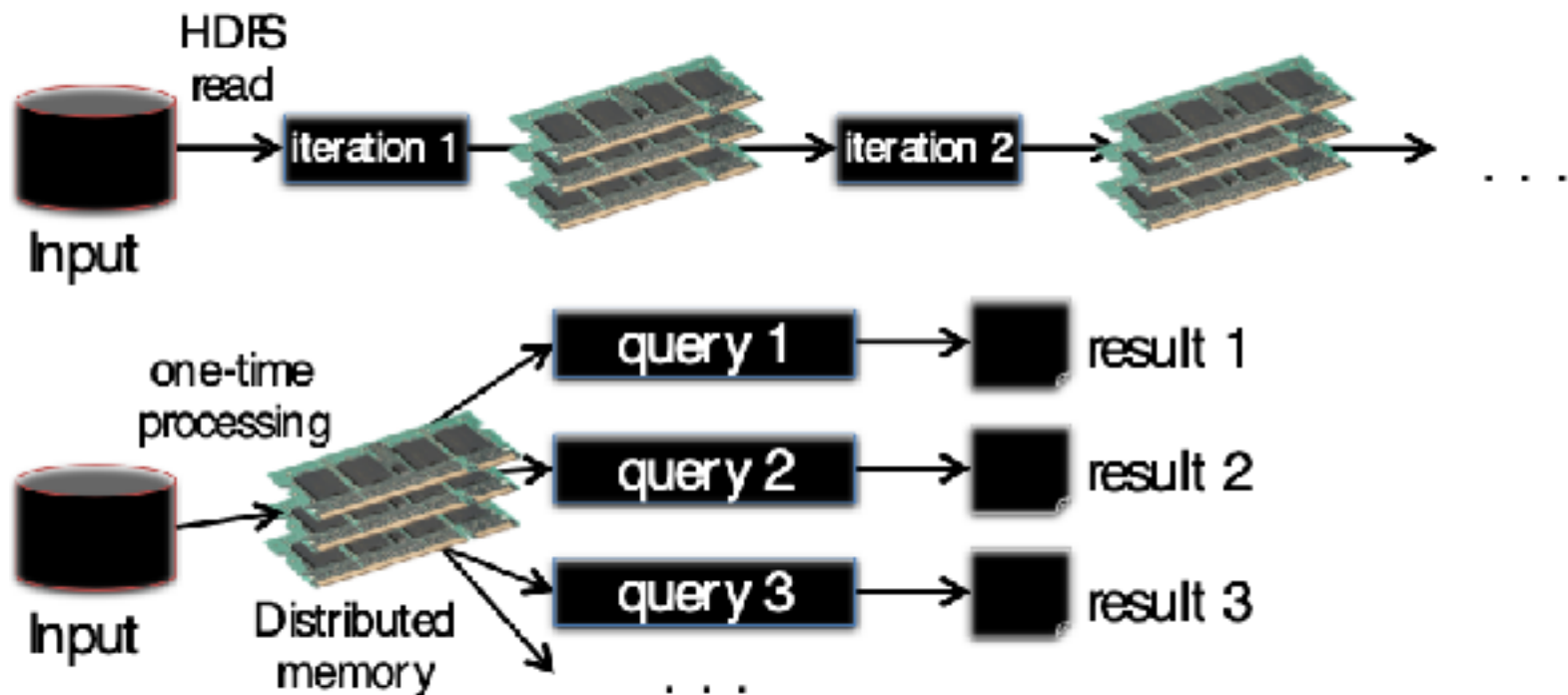


Replace Disk with Memory



Replace Disk with Memory

In-Memory Data Sharing



10-100x faster than network and disk

Spark Architecture

Spark
SQL

Spark
Streaming

MLlib &
ML
(machine
learning)

GraphX
(graph)

Apache Spark

Resilient Distributed Datasets (RDDs)

Resilient Distributed Datasets (RDDs)

- Data Collection
 - Distributed
 - Read-only
 - In-memory
 - Built from stable storage or other RDDs

RDD Creation



Parallelize in Python

```
wordsRDD = sc.parallelize(["fish", "cats", "dogs"])
```

Parallelize

Take an existing in-memory collection and pass it to SparkContext's parallelize method



Read a local txt file in Python

```
linesRDD = sc.textFile("/path/to/README.md")
```

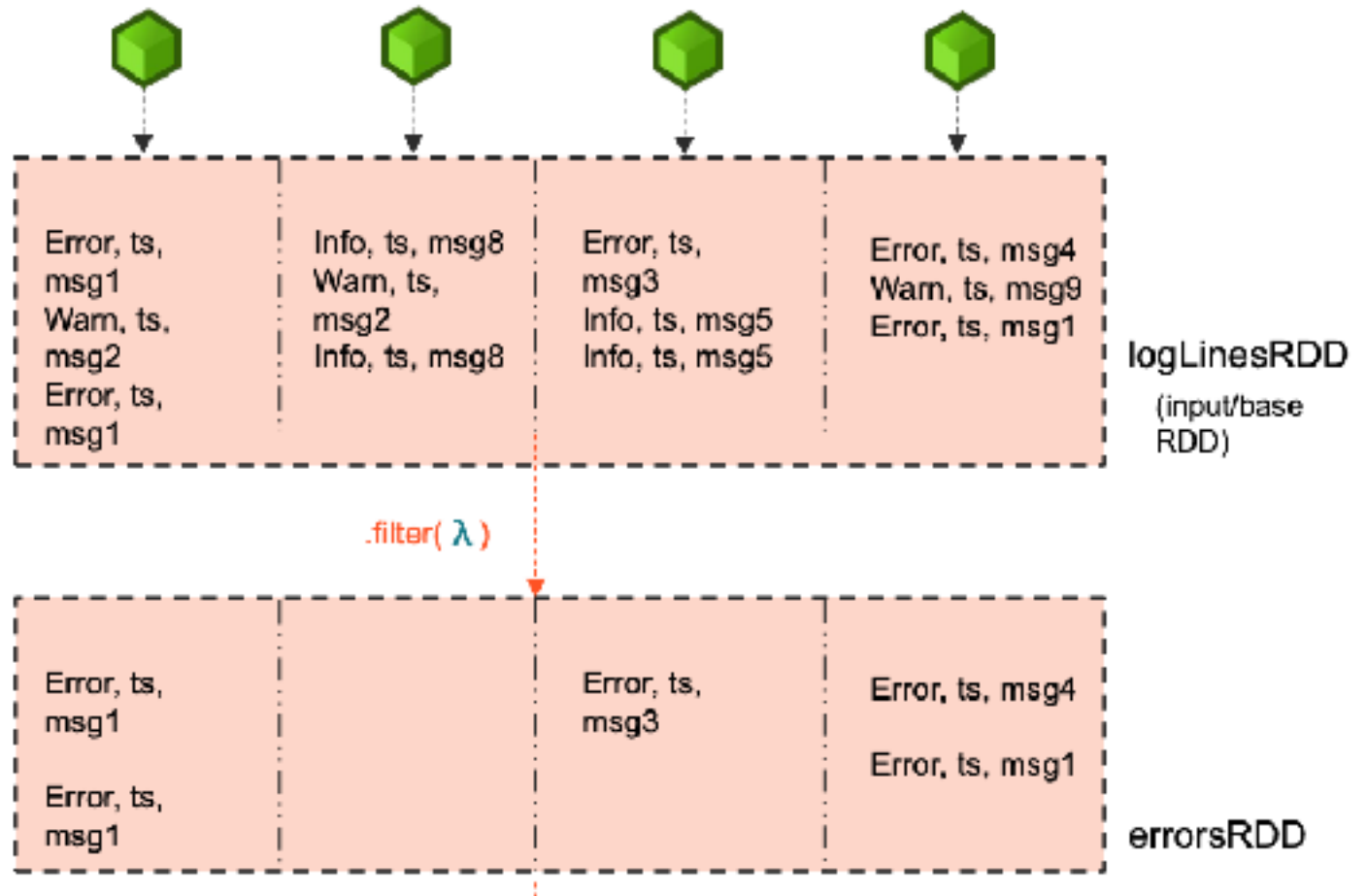
Read from Text File

There are other methods to read data from HDFS, C*, S3, HBase, etc.

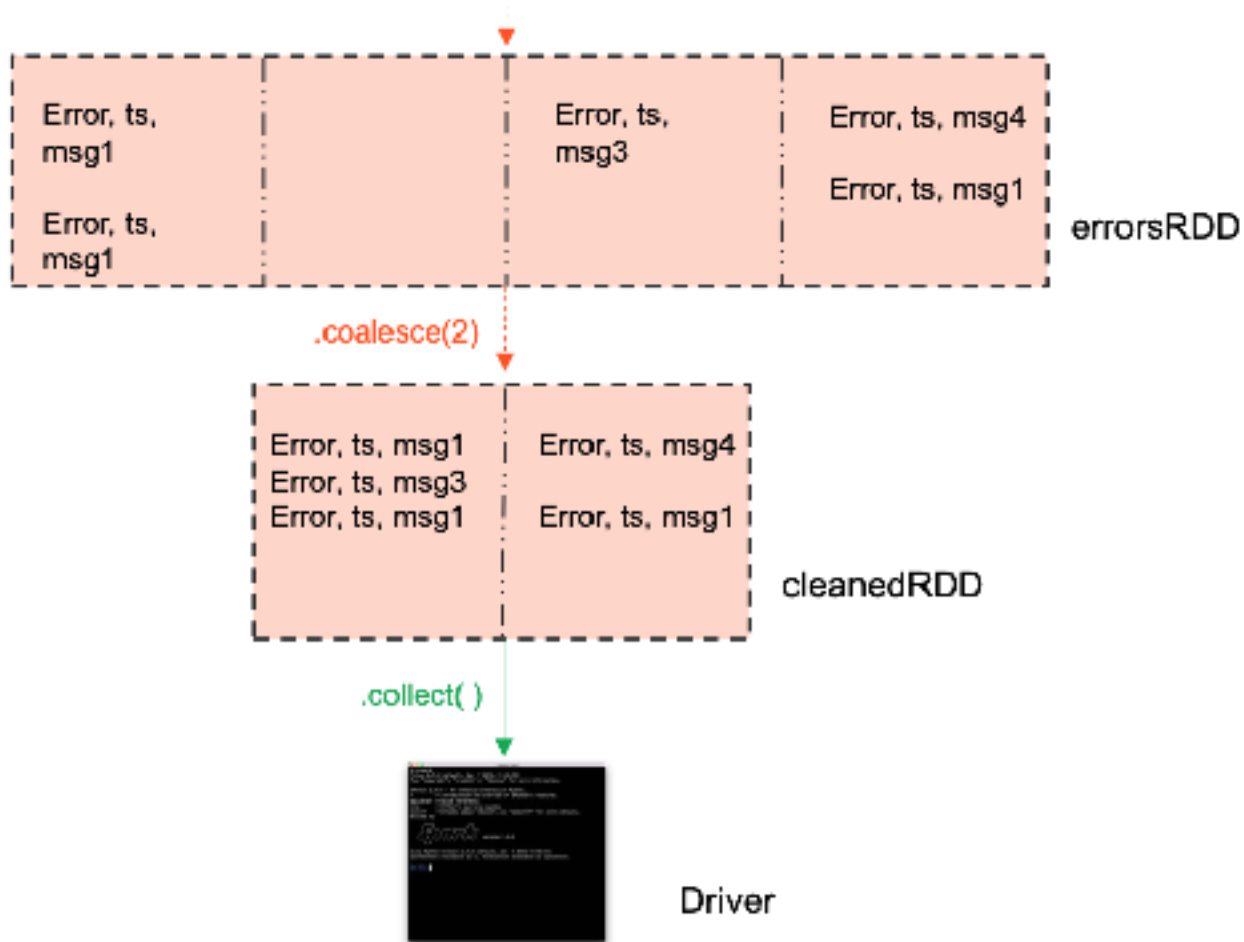
Operations on RDDs

- Transformations: lazy execution
 - Map, filter, intersection, groupByKey, zipWithIndex ...
- Actions: trigger execution of transformations
 - Collect, count, reduce, saveAsTextFile ...

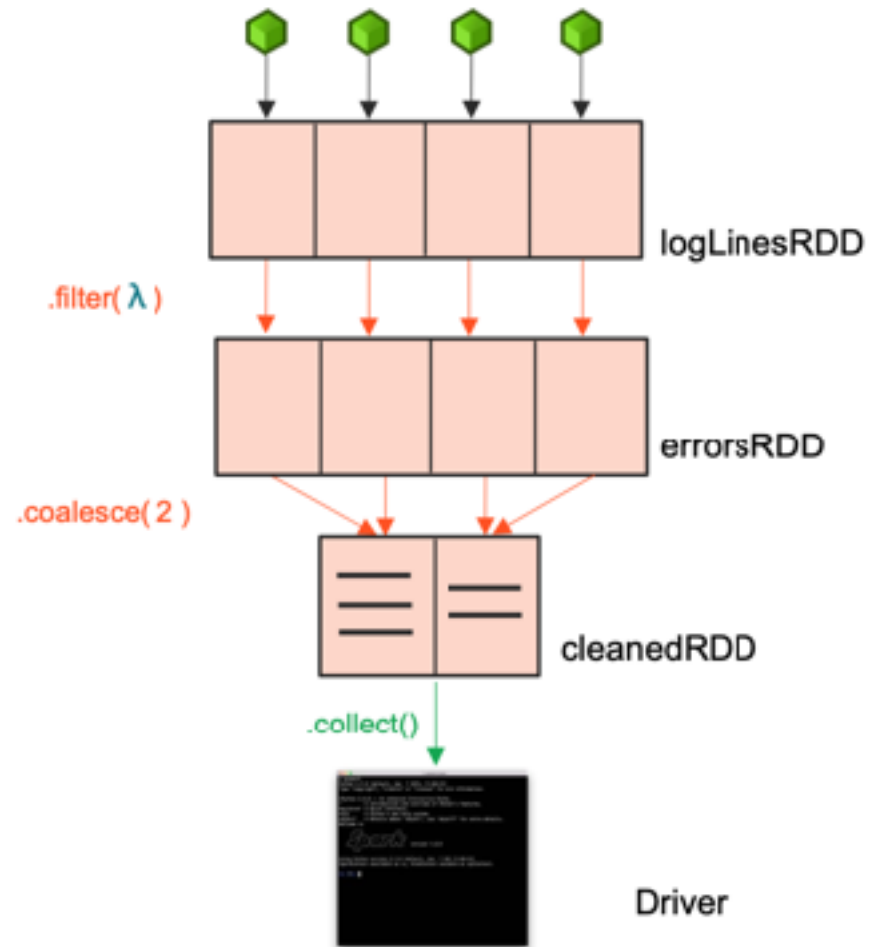
RDD Example



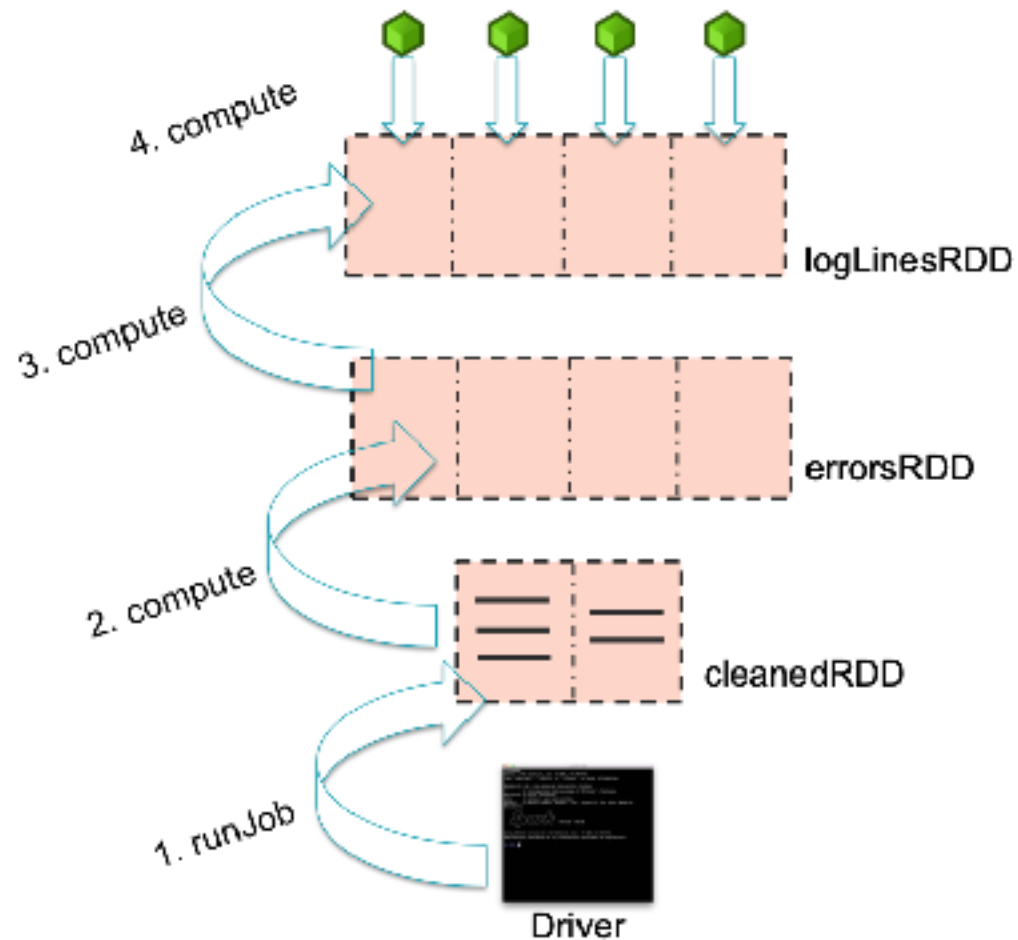
RDD Example



RDD Lineage



Execution



Lazy transformation

- Transformations only when action necessary
- Examples of gain
 - `read file + first()` => only one line read
 - `read file + filter()` => object created only with the matching lines

RDD Fault Tolerance

- Hadoop conservative/pessimistic approach
 - Go to disk / stable storage (HDFS)
- Spark optimistic
 - Don't "waste" time writing to disk, re-compute in case of crash using lineage

Caching

- Lazy execution
 - Process all transformations in a chain until action
 - Does not store intermediate results!
- Multiple actions on the same RDD
 - Re-compute RDD
- Caching
 - Avoids re-computing by storing a copy in memory/
on disk

Narrow Dependencies: the Map family

- $\text{map}(f: X \rightarrow Y)$: transform elements of a RDD using f
 - 1 for 1 transformation
- $\text{flatMap}(f: X \rightarrow \text{Iterable}[Y])$: transform elements of RDD using f
 - 1 to many transformation (like Hadoop map)
- $\text{filter}(f: X \rightarrow \text{Boolean})$: keep only elements for which f returns true
- ...

Narrow dependencies demo

```
val textRdd: RDD[String] = sc.parallelize(Array("hello", "spark exercise"))
val upText: RDD[String] = textRdd.map(text => text.toUpperCase())
upText.take(10).foreach(println)
//HELLO
//SPARK EXERCISE
val wordRdd: RDD[String] = textRdd.flatMap(text => text.split("\\s"))
wordRdd.take(10).foreach(println)
//hello
//spark
//exercise
val longTextRdd = textRdd.filter(text => text.length() > 8)
longTextRdd.take(10).foreach(println)
//spark exercise
```

Wide Dependencies: the Reduce family

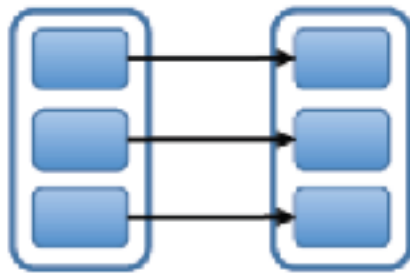
- `reduceByKey(f X,X → X)`: aggregate values having the same key
 - Input and output have the same type
- `groupByKey`: group values having the same key
 - Similar to Hadoop's shuffle and sort phase
- `combineByKey(f1,f2,f3)`: general form of `reduceByKey` where output can have a different type
- ...

Wide dependencies demo

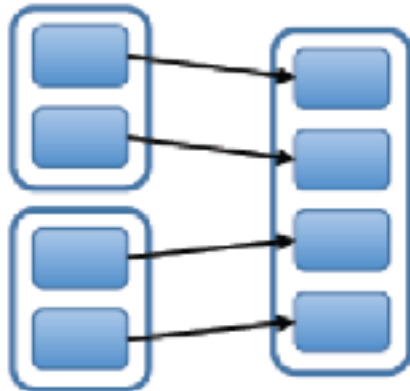
```
val pairRdd: RDD[(String, Int)] = sc.parallelize(Array(("hello", 1), ("spark", 1), ("hello", 2)))
val sumByKey = pairRdd.reduceByKey((x, y) => x + y)
sumByKey.take(10).foreach(println)
//(hello,3)
//(spark,1)
val gByK = pairRdd.groupByKey()
gByK.take(10).foreach(println)
//(hello,CompactBuffer(1, 2))
//(spark,CompactBuffer(1))
val gToS = pairRdd.combineByKey(x => Set(x),
  (s: Set[Int], x: Int) => s + x,
  (s1: Set[Int], s2: Set[Int]) => s1 ++: s2)
gToS.take(10).foreach(println)
//(hello,Set(1, 2))
//(spark,Set(1))
```

RDD Dependencies

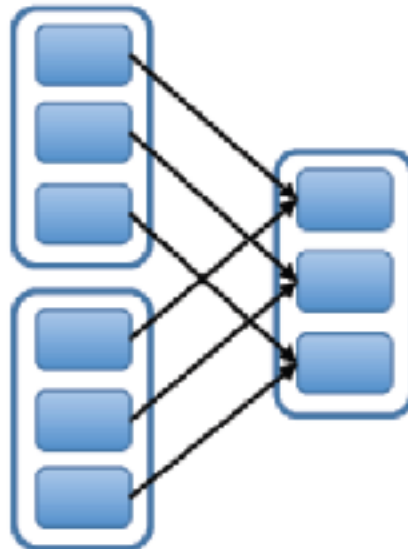
Narrow Dependencies:



map, filter



union



join with inputs
co-partitioned

Wide Dependencies:



groupByKey



join with inputs not
co-partitioned

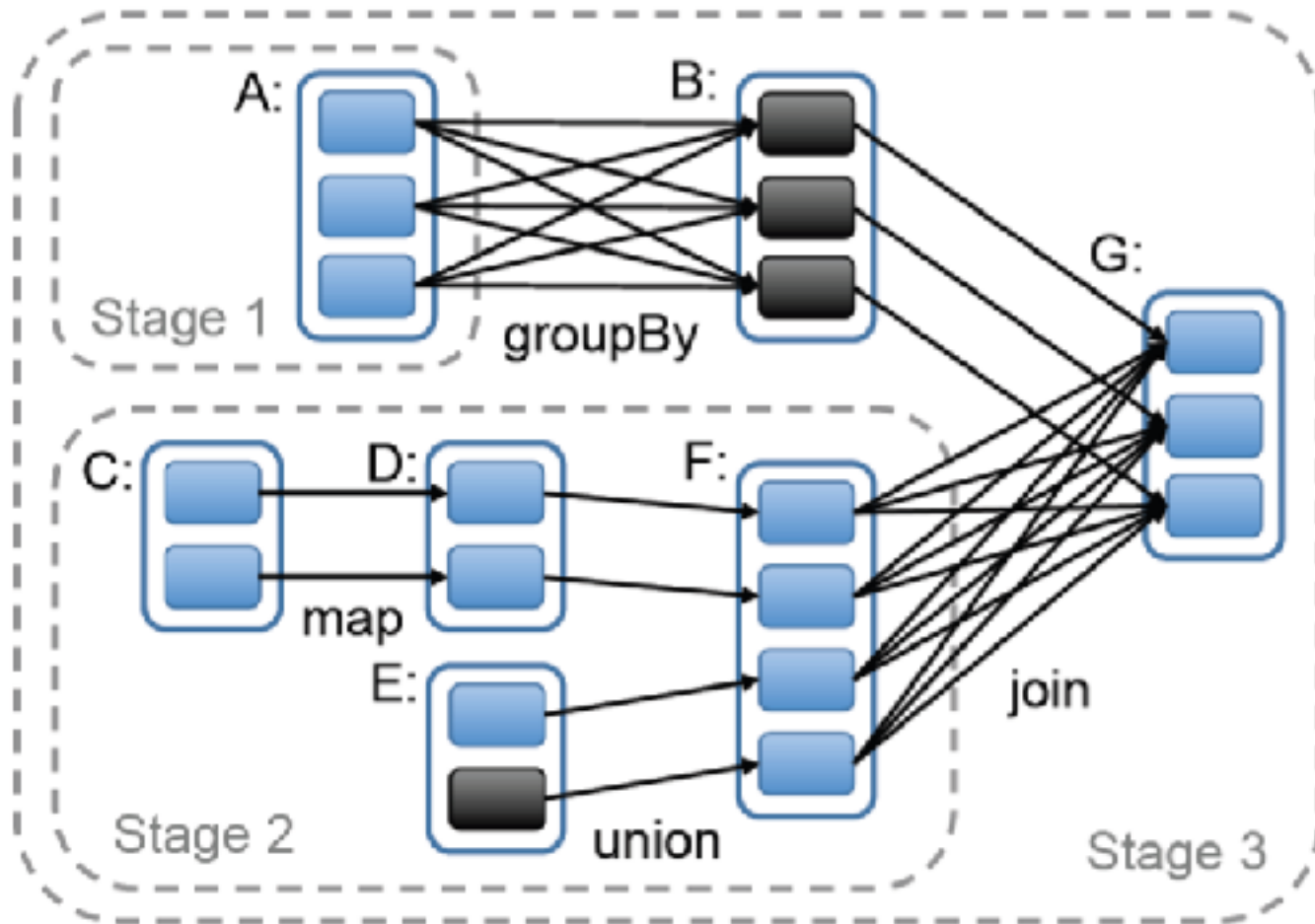
RDD Dependencies

- Narrow dependencies
 - allow for pipelined execution on one cluster node
 - easy fault recovery
- Wide dependencies
 - require data from all parent partitions to be available and to be shuffled across the nodes
 - a single failed node might cause a complete re-execution.

Job Scheduling


- To execute an action on an RDD
 - scheduler decide the stages from the RDD's lineage graph
 - each stage contains as many pipelined transformations with narrow dependencies as possible

Job Scheduling



Spark Interactive Shell

```
scala> val wc = lesMiserables.flatMap(_.split(" ")).map((_,1)).reduceByKey(_+_)
wc: org.apache.spark.rdd.RDD[(String, Int)] = ShuffledRDD[5] at reduceByKey at <console>:14
scala> wc.take(5).foreach(println)
(créanciers;,1)
(abondent.,1)
(plaisir,,5)
(déplaçaient,1)
(sociale,,7)
scala> val cw = wc.map(p => (p._2, p._1))
cw: org.apache.spark.rdd.RDD[(Int, String)] = MappedRDD[5] at map at <console>:16
scala> val sortedCW = cw.sortByKey(false)
sortedCW: org.apache.spark.rdd.RDD[(Int, String)] = ShuffledRDD[11] at sortByKey at <console>:18
scala> sortedCW.take(5).foreach(println)
(16757,de)
(14683,)
(11025,La)
(9794,et)
(8471,Le)
scala> sortedCW.filter(x => "Cosette".equals(x._2)).collect.foreach(println)
(353,Cosette)
```



Wordcount e

DataFrames

Definition

- Data collection
 - Organized in columns
 - Has a schema (column name and type)
 - similar to RDBMS
- Implementation
 - Relies on RDDs (fault tolerance ...)
 - Allows higher level languages like SQL
 - query optimizer (pushing selects ...)

A few notions of Scala



Scala

- Functional programming language
 - Static type
 - Compiles to Java ByteCode
 - Can be mixed with Java
- Developed at EPFL
 - Used by many industrial and open-source systems (Spark, Twitter, Swisscom)

Sample Spark/Scala code

```
object Ex2RDD {  
  def main(args: Array[String]): Unit = {  
    println("hello")  
    var spark: SparkSession = null  
    try {  
      spark = SparkSession.builder().master("local[4]").appName("Flickr using dataframes").getOrCreate()  
      val originalFlickrMeta: RDD[String] = spark.sparkContext.textFile("/Users/vleray/Documents/cours/BigData/TPIntroHadoop/FlickrSample.txt")  
      originalFlickrMeta.take(5).foreach(println)  
      println("nb lines " + originalFlickrMeta.count())  
      val pictures: RDD[Picture] = originalFlickrMeta.map(line => line.split("\t")).map(t => new Picture(t)).filter(c => c.isValidCountry && c.hasTags)  
      pictures.take(5).foreach(println)  
      val picturesByCountry: RDD[(Country, Iterable[Picture])] = pictures.groupBy(p => p.c)  
      picturesByCountry.take(5).foreach(println)  
      val tagsByCountry: RDD[(Country, Iterable[String])] = picturesByCountry.map(cp => (cp._1, cp._2.flatten(p => p.userTags)))  
      tagsByCountry.take(5).foreach(println)  
      val topFreqByCountry: RDD[(Country, Map[String, Int])] = tagsByCountry.map(cp => (cp._1, cp._2.groupBy(identity).mapValues(_.size).map(identity)))  
      tagsByCountry.take(5).foreach(println)  
    } catch {  
      case e: Exception => throw e  
    } finally {  
      spark.stop()  
    }  
    println("done")  
  }  
}
```

Le TP

- Manipulations de base avec Spark en Scala
 - analyse de tweets
 - en utilisant spark-shell (plus léger)
- Installation éventuelle de Spark
 - informations sur le site web