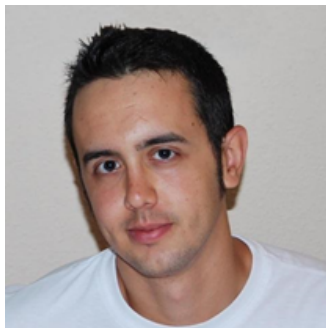


# Distributed computing with



Javier Santos  
April, 13 - 2015

# About me



**Javier Santos** [@jpaniego](#)

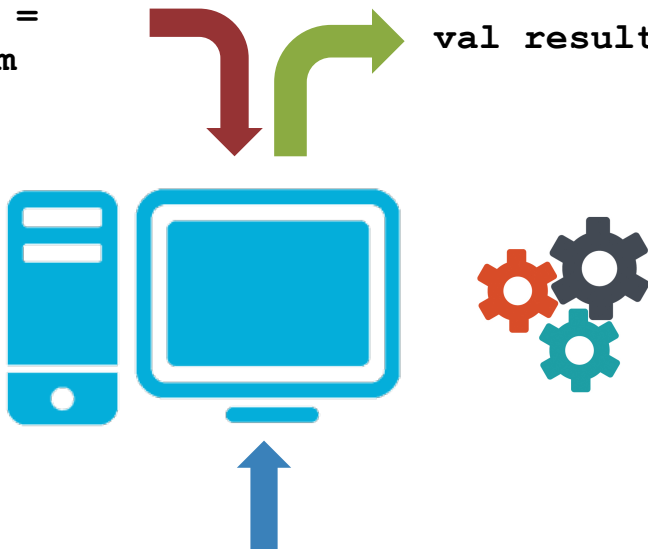
*«Hay dos formas de programar sin  
errores; solo la tercera funciona»*

Alan J Perlis

# What's Spark?

```
val action: Seq[Int] => Int =  
  (seq: Seq[Int]) => seq.sum
```

```
val result: Int = 15
```

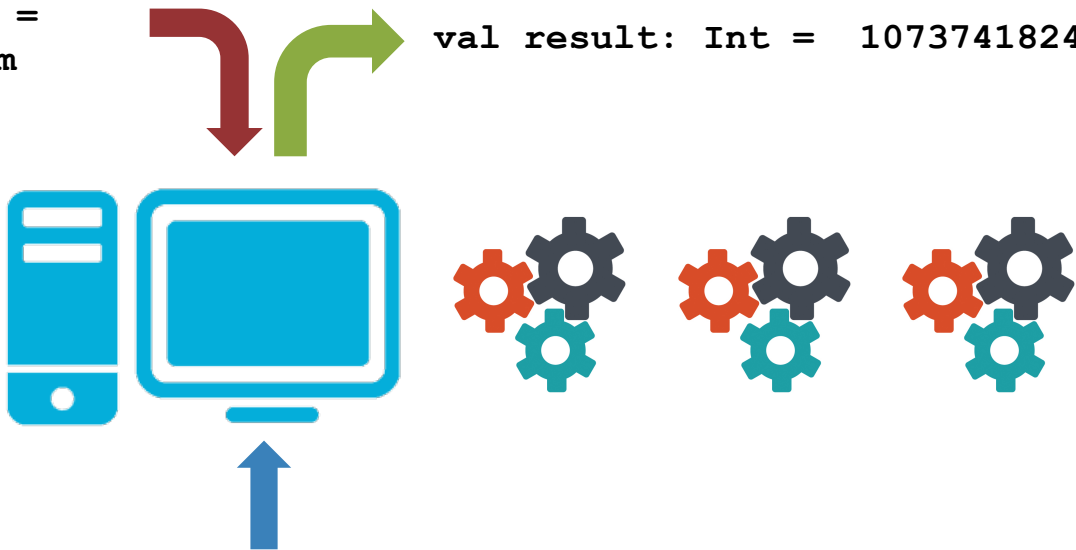


```
val mySeq: Seq[Int] = 1 to 5
```

# What's Spark?

```
val action: Seq[Int] => Int =  
  (seq: Seq[Int]) => seq.sum
```

```
val result: Int = 1073741824
```



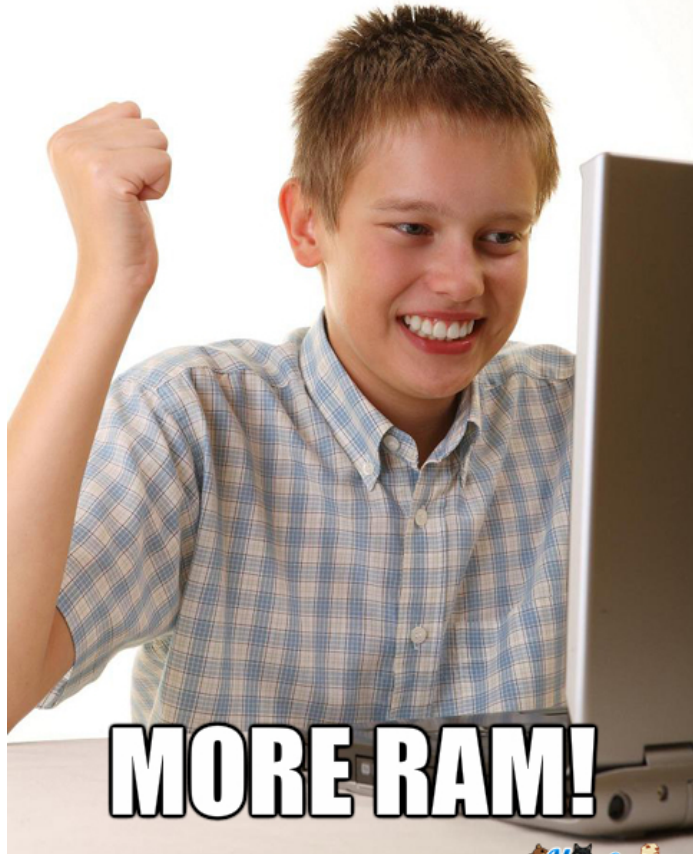
```
val mySeq: Seq[Int] = 1 to Int.MaxValue
```

# What's Spark?

Computing problems:

- Time: Waiting for action results on tons of records
- Space: How do we allocate TB of data?

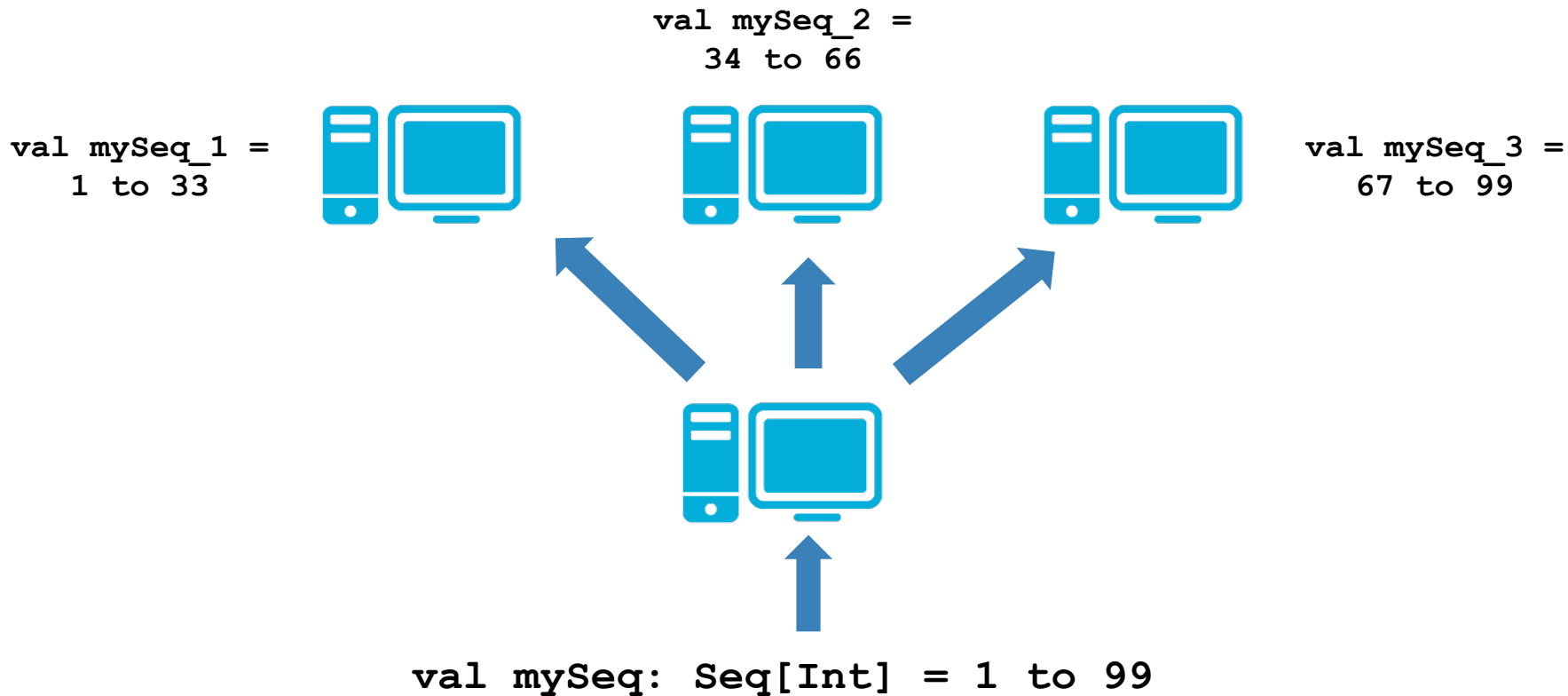
**FINALLY I DOWNLOADED**



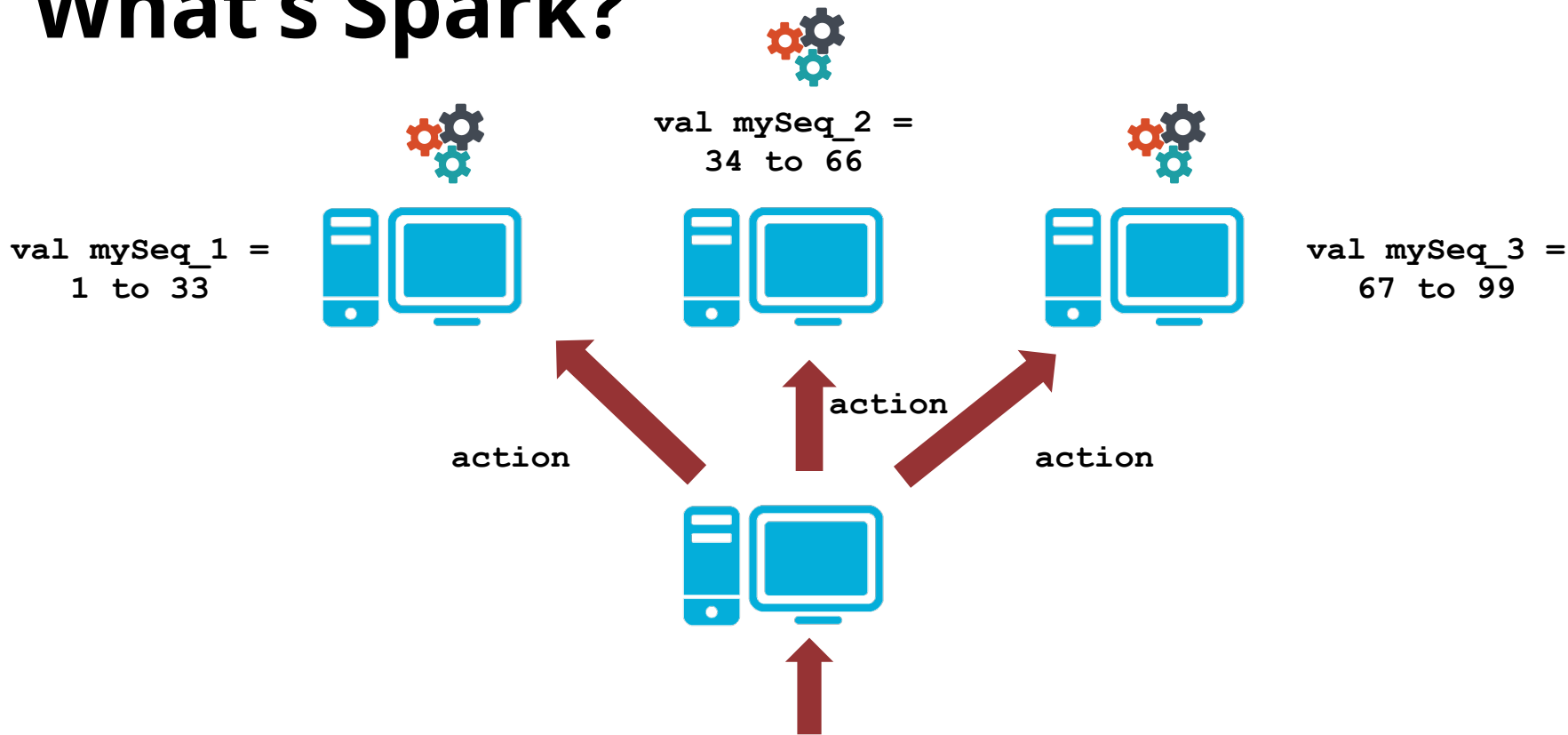
**MORE RAM!**

[downloadmoreram.com](http://downloadmoreram.com)

# What's Spark?



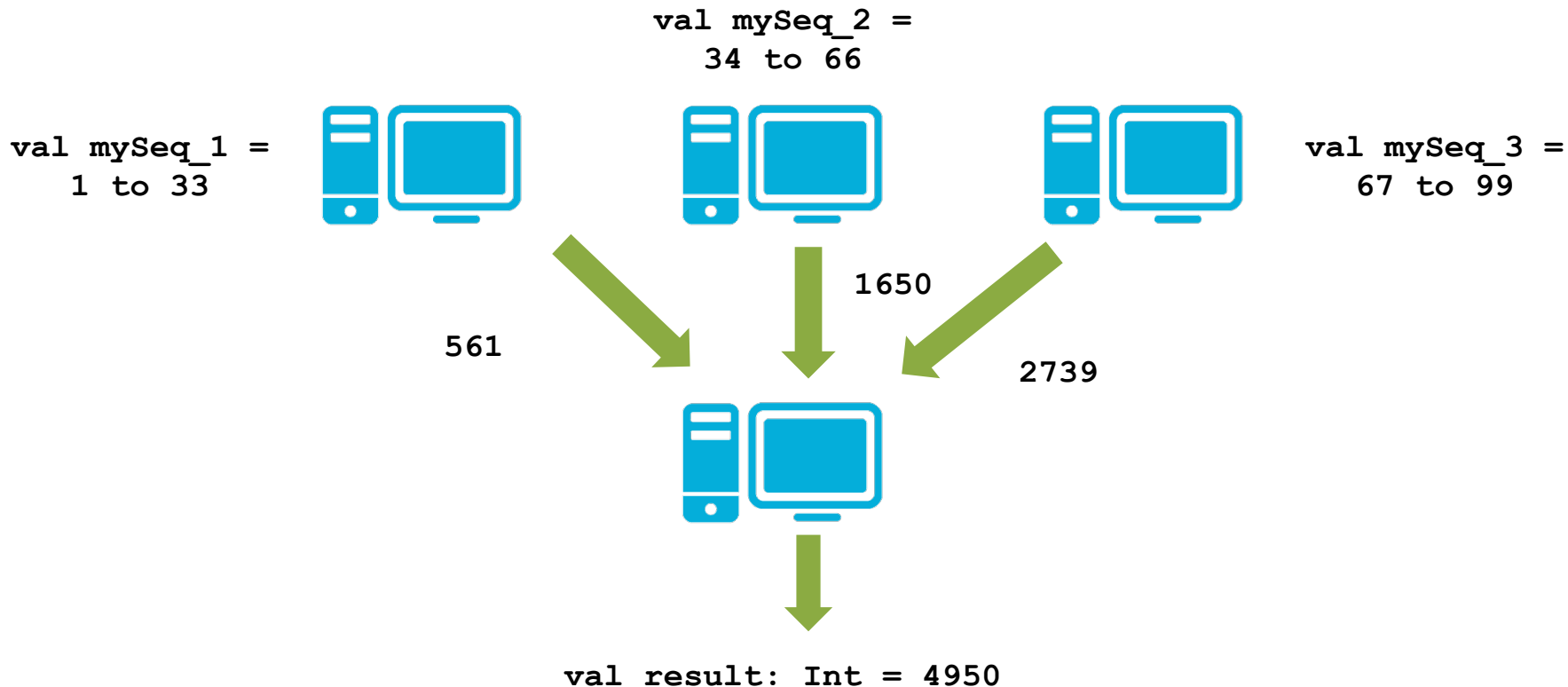
# What's Spark?



```
val action: Seq[Int] => Int = (seq: Seq[Int]) => seq.sum
```



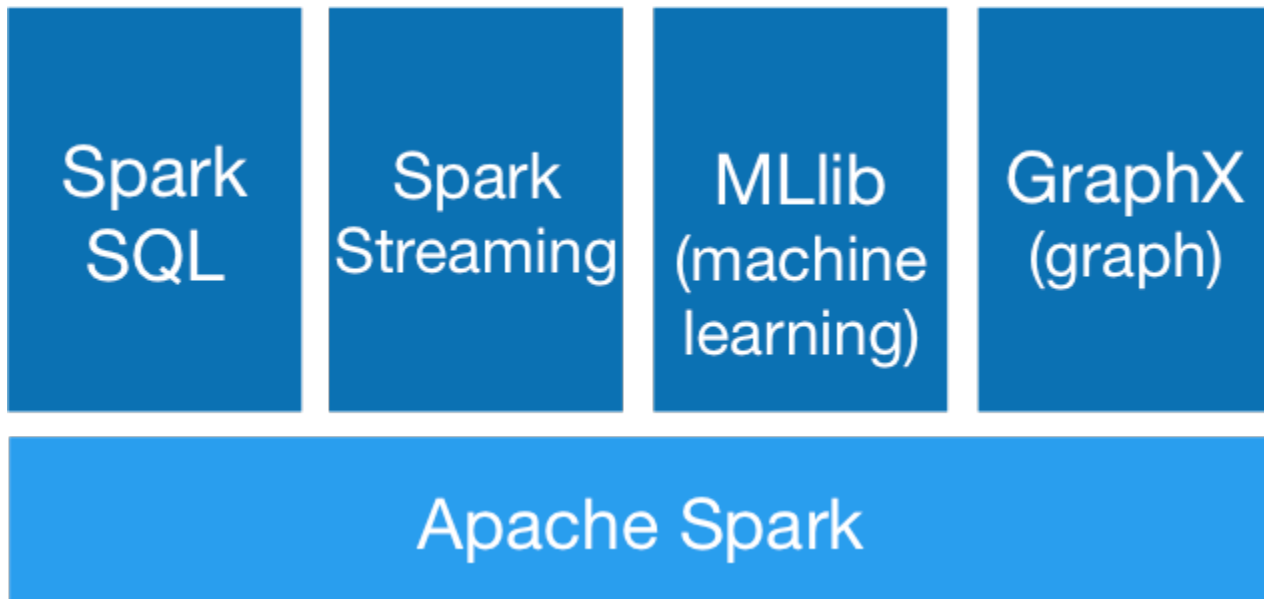
# What's Spark?



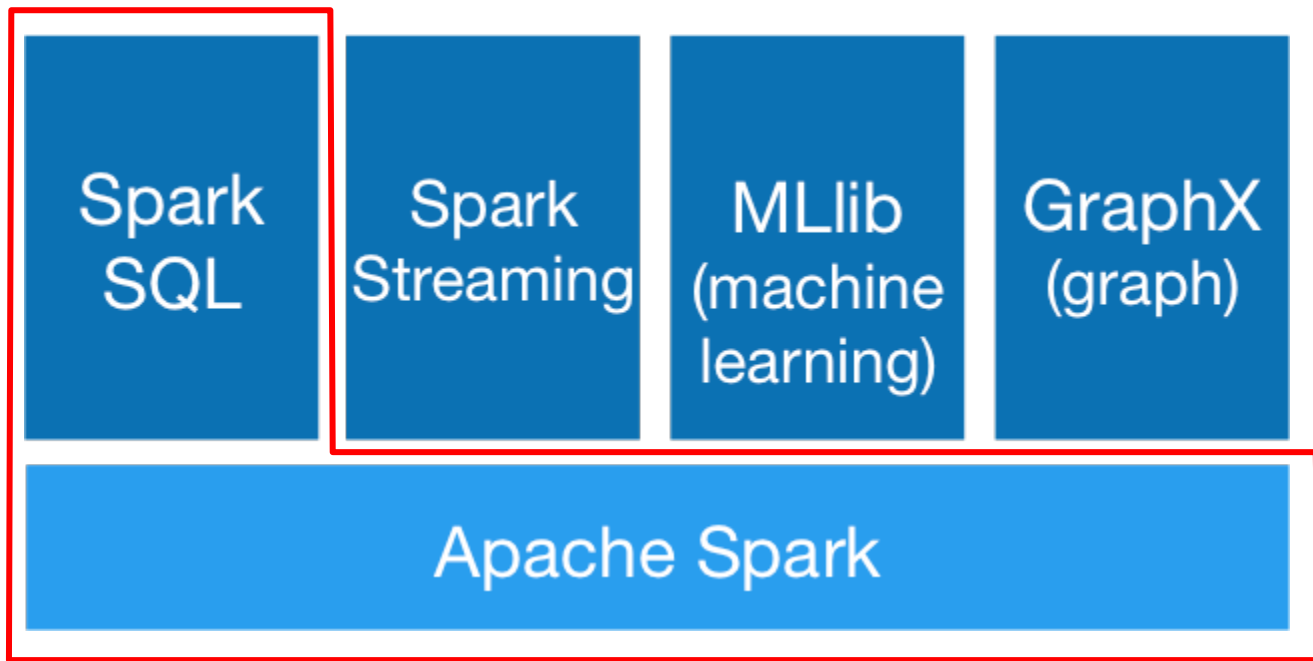
# What's Spark?

- General engine for large-scale data processing.
- “In-memory” data allocation.
- Target: **data** and **computing** parallelism.
- Mostly developed in Scala.  
It also provides support for Python and Java
- First developed by [AMPLab](#) in UC Berkeley
- Support by [Databricks](#)
- Latest stable version 1.3.0

# Modules



# Modules



# MapReduce model

- Programming model used for supporting parallel-computing and big data sets distribution among computing groups
- Based on two main functional programming methods: Map and reduce.
- Hadoop
  - One of the first open source implementation
  - First implementation lead by Yahoo

# MapReduce model

- Phases



# MapReduce model

- Example (**Map**)

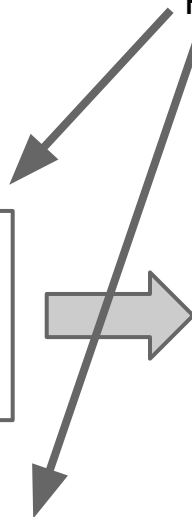
```
"123;SamsungGalaxyIII;14:05;300;34612345678"  
"124;LGNexus4;16:05;121;+34613455678"  
"126;LGNexus4;12:05;23;+3463624678"  
"131;NokiaLumia;14:05;300;+34613246778"
```

```
"125;MotorolaG2;14:05;300;+34612345678"  
"127;NokiaLumia;14:05;300;+34612345678"  
"130;NokiaLumia;14:05;300;+34612345678"
```

Partitions

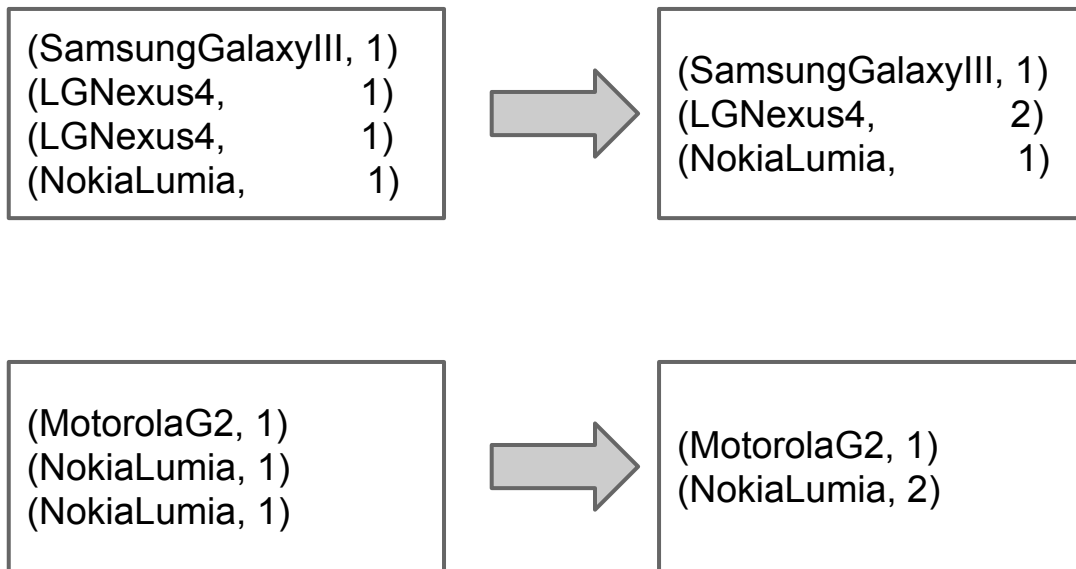
```
(SamsungGalaxyIII, 1)  
(LGNexus4, 1)  
(LGNexus4, 1)  
(NokiaLumia, 1)
```

```
(MotorolaG2, 1)  
(NokiaLumia, 1)  
(NokiaLumia, 1)
```



# MapReduce model

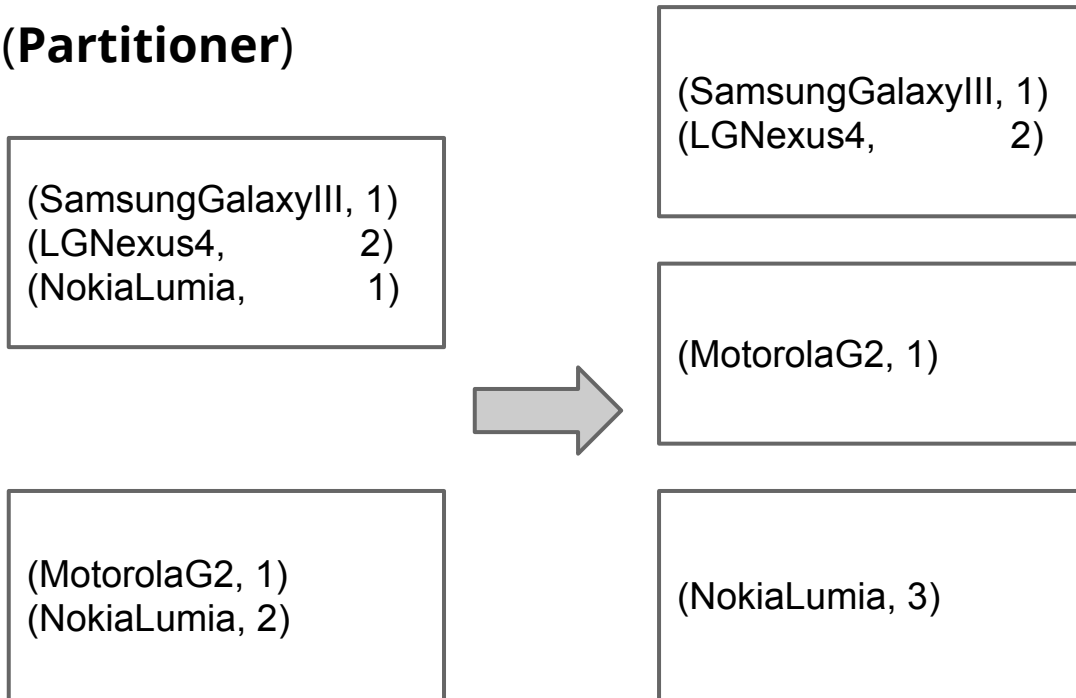
- Example (**Combiner**)





# MapReduce model

- Example (**Partitioner**)



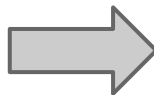
# MapReduce model

- Example (**Reduce**)

(SamsungGalaxyIII, 1)  
(LGNexus4, 2)

(MotorolaG2, 1)

(NokiaLumia, 3)

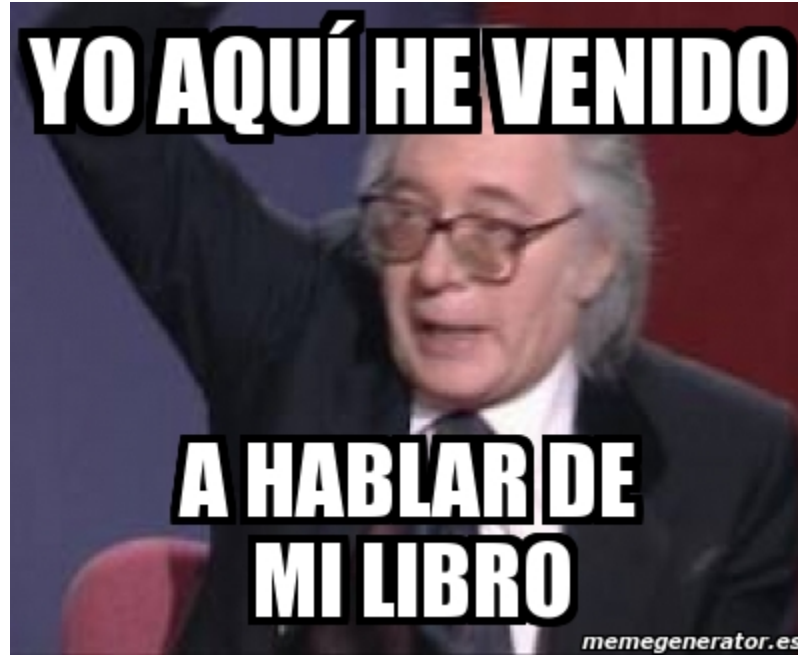


## ReduceFunction

```
f(t1:(String,Int),t2:(String,Int)) =  
  if (t1._2 > t2._2) t1 else t2
```

**(NokiaLumia, 3)**

# So...what about Spark?



# Deployment types

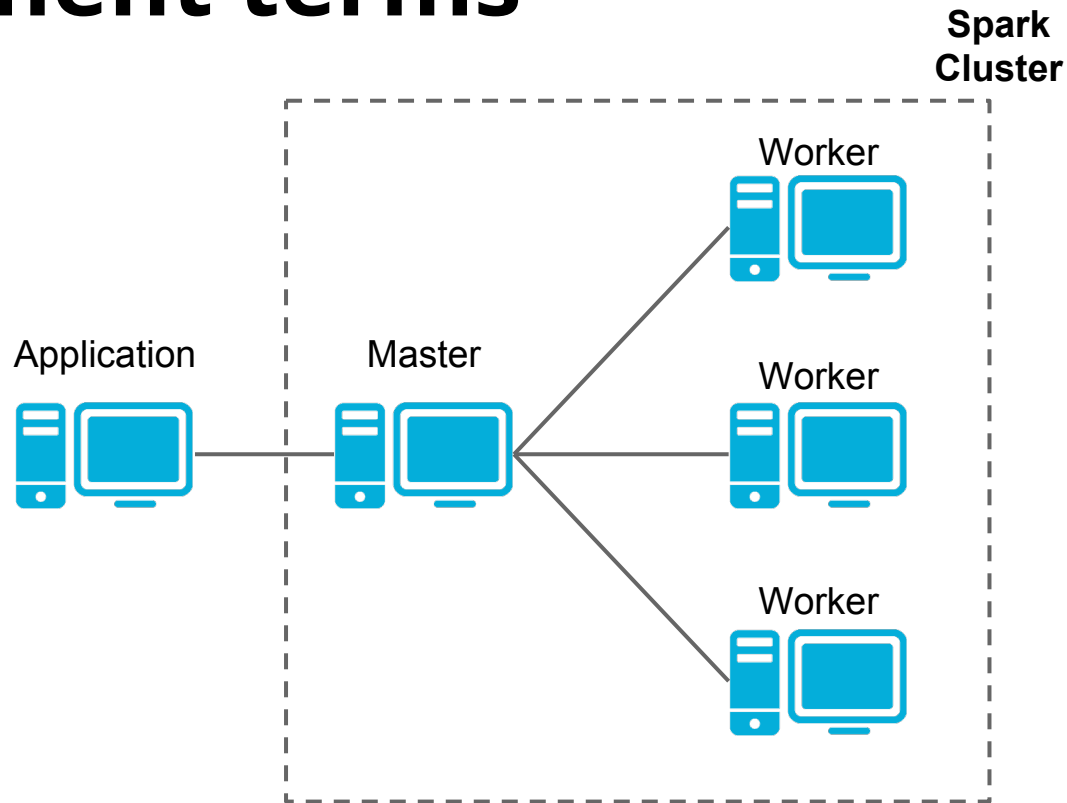
- Local

- `master="local[N]"` (N=Amount of cores)
- Spark master is launched in the same process.  
It's not accessible from web.
- Workers are launched in the same process.

- Standalone

- `master="spark://master-url"`
- Spark master is launched in a cluster machine.
- For deploying workers, it's used 'start-all.sh' script.
- Submit JAR to worker nodes.

# Deployment terms



# Deployment: Cluster managers

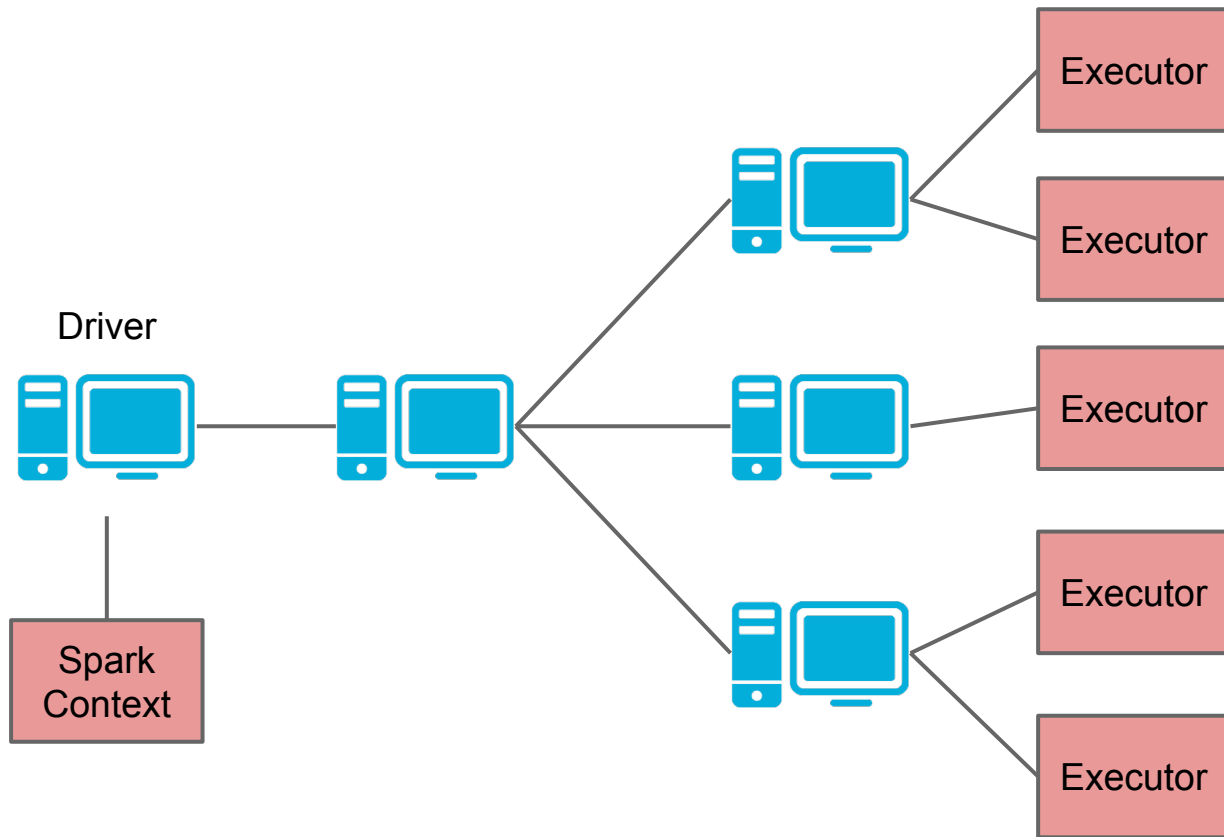
- YARN

- It uses Hadoop Yarn Resource Manager
- Spark app is launched inside a Yarn container
- Several isolated Spark Masters running in cluster possibility.

- Mesos

- Another cluster manager
- Not so much used like Yarn with Spark.
- Several isolated Spark Masters running in cluster possibility.

# Execution terms



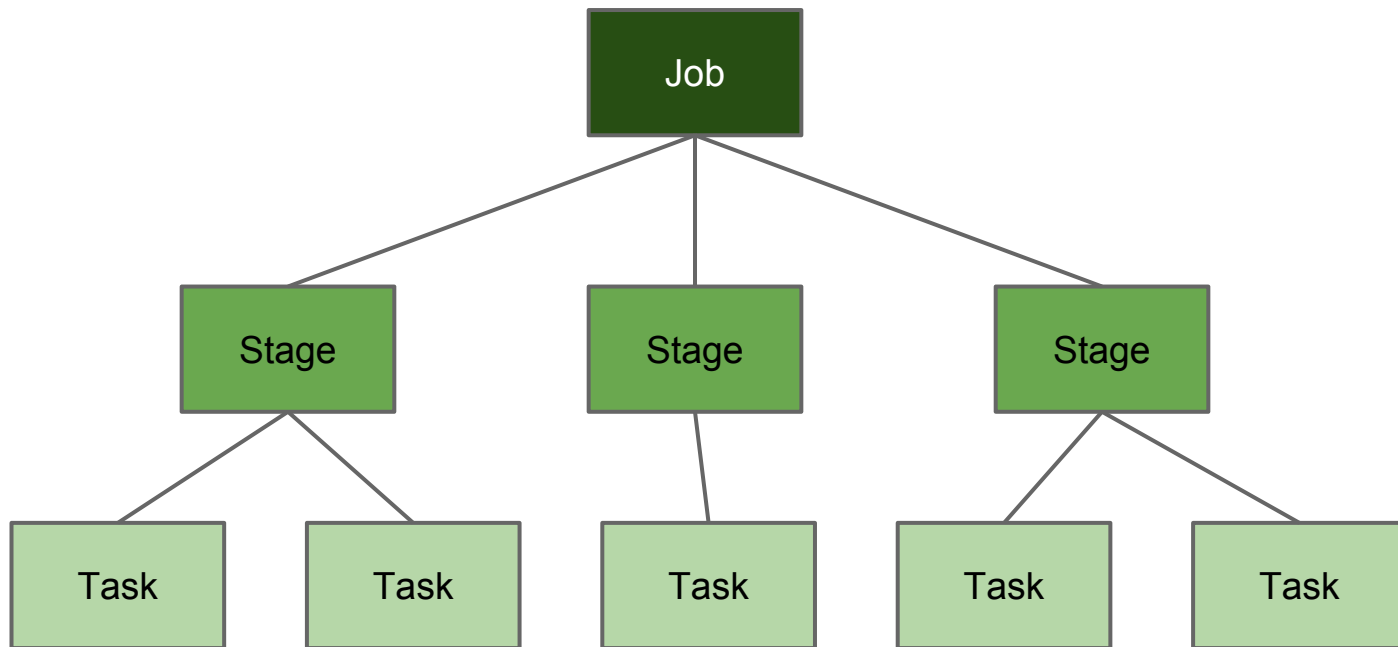
# Execution terms :

## SparkContext & Executor

- SparkContext
  - Spark cluster connection
  - Necessary for SQLContext, StreamingContext, ...
  - Isolated: Two Spark Contexts cannot exchange data (without external help).
- Executor
  - Individual execution unit
  - 1 core ~ 2 executor
  - Each application has its owns.



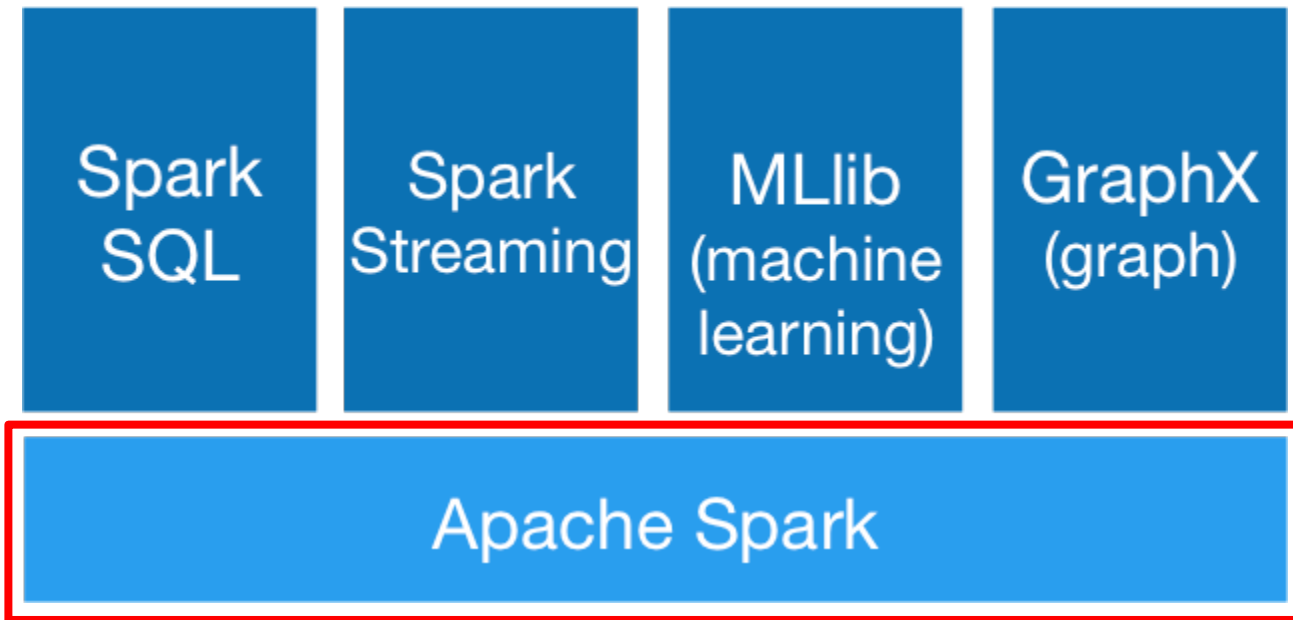
# Job terms



# Job terms

- Job
  - Individual executed action
  - It's composed by a set of tasks arranged in stages
- Stage
  - Job split based on last cached action or shuffle event.
- Task
  - Minimum execution unit sent to executors.
  - Task ~ Partition correlation

# Modules



# RDD

- **R**esilient **D**istributed **D**ataset. Basic abstraction in Spark
- Think of it like a huge collection **partitioned** and distributed in different machines.
- Lazy evaluated
- Basically composed of
  - A list of partitions
  - A function for computing each split
  - A list of dependencies on other RDDs

# RDD

- Basic example:

```
val myRdd: RDD[String] = sc.parallelize(  
    "this is a sample string".split(" ").toList)
```

- For creating a new RDD is necessary to implement:
  - compute (How to get RDD population)
  - getDependencies (RDD lineage)
  - getPartitions (How to split the data)

# RDD

- An RDD may be created from

- A file / set of files:

```
sc.textFile("myFile")
```

```
sc.textFile("file1,file2")
```

- A bunch of memory-storaged data:

```
sc.parallelize(List(1,2,3))
```

Another RDD:

```
myRdd.map(_.toString)
```

# RDD - Partitions

- Partition : RDD chunk
- A worker node may contain 1 or more partitions of some RDD.
- It's important to choose a best-performance partitioning.
- Repartitioning
  - It implies shuffling all RDD data among worker nodes
  - There will surely be tons of network traffic among all worker nodes!

# RDD - Lineage

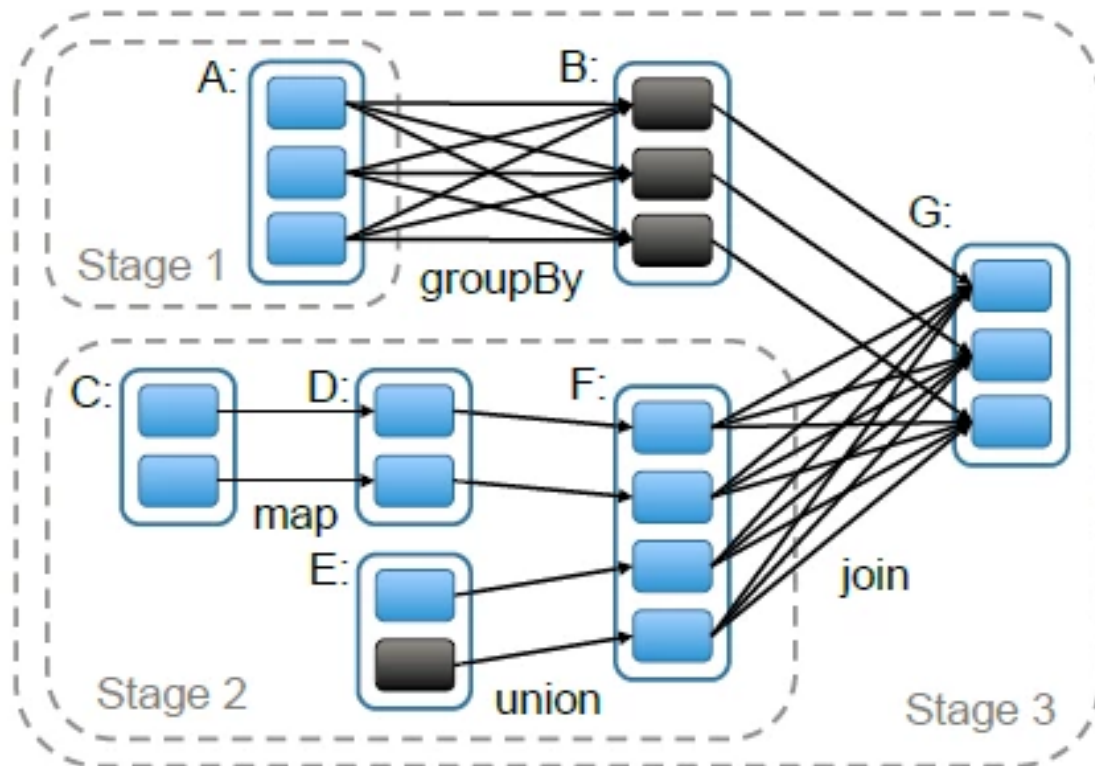
- An RDD may be built from another one.
- Base RDD : Has no parent
- Ex:

```
val base: RDD[Int] = sc.parallelize(List(1,2,3,4))  
val even: RDD[Int] = myRDD.filter(_%2==0)
```

- DAG (**D**irected **A**cyclic **G**raph) : Represents the RDD lineage (inheritance, mutations, ...).
- DAGScheduler: High level layer used that schedules stages among all related RDDs



# RDD - Lineage



# RDD - Transformations

- It applies a change to some RDD, returning a new one.
- It's not immediately evaluated.
- Think of it like a "Call-by-name" function.
- Adds a new node in Lineage DAG.

# RDD - Transformations

- Most frequently used:

- **map**

```
val myRDD: RDD[Int] = sc.parallelize(List(1,2,3,4))  
val myStrinRDD: RDD[String] = myRDD.map(_.toString)
```

- **flatMap**

```
val myRDD: RDD[Int] =  
    sc.parallelize(List(1,null,3,null))  
val myNotNullInts: RDD[Int] =  
    myRdd.flatMap(n => Option(n))
```

# RDD - Transformations

- Most frequently used:

- **filter**

```
val myRDD: RDD[Int] = sc.parallelize(List(1,2,3,4))  
val myStrinRDD: RDD[Int] = myRDD.filter(_%2==0)
```

- **union**

```
val odd: RDD[Int] = sc.parallelize(List(1,3,5))  
val even: RDD[Int] = sc.parallelize(List(2,4,6))  
val all: RDD[Int] = odd.union(even)
```

# RDD - Actions

- It launches the RDD evaluation,
  - returning some data to the driver
  - or persisting to some external storage system
- It's evaluated partially on each worker node, and results are merged in the Driver
- There are mechanisms to make cheaper computing several times the same RDD (like `persist()` or `cache()` )

# RDD - Actions

- Examples:

- **count**

- ```
val myRdd: Rdd[Int] = sc.parallelize(List(1,2,3))
```

- ```
val size: Int = myRdd.count
```

- Counting implies processing whole RDD*

- **take**

- ```
val myRdd: Rdd[Int] = sc.parallelize(List(1,2,3))
```

- ```
val List(1,2) = myRdd.take(2).toList
```

- **collect**

- ```
val myRdd: Rdd[Int] = sc.parallelize(List(1,2,3))
```

- ```
val data: Array[Int] = myRdd.collect
```

- Beware! Executing 'collect' on big collections might end into a memory leak*

# Demo1 : Most retweeted

- [Most Retweeted example](#)
- Bunch of tweets (1000 json records)
- Find out which is the most retweeted tweet.

# Key-Value RDDs

- Particular case of `RDD[T]` where  $T = (U,V)$
- It allows grouping, combining, aggregating values by some key.
- In Scala it's only needed to  
`import org.apache.spark.SparkContext._`
- In Java, it's mandatory to use `PairRDD` class.



# Key-Value RDDs

- `keyBy`: Generates a `PairRDD`

```
val myRDD: RDD[Int] =  
  sc.parallelize(List(1,2,3,4,5))
```

```
val kvRDD: RDD[(String,Int)] =  
  myRDD.keyBy(  
    n => if (n%2==0) "even" else "odd")
```

*"odd" -> 1, "even" -> 2, "odd" -> 3, "even" -> 4, "odd" -> 5*

# Key-Value RDDs

- keys: Gets keys from PairRDD

```
val myRDD: RDD[(String,Int)] =  
  sc.parallelize("odd" -> 1,"even" -> 2,"odd" -> 3)  
val keysRDD: RDD[String] = myRDD.keys
```

*"odd","even","odd"*

- values: Gets values from PairRDD

# Key-Value RDDs

- mapValues: map PairRDD values, omitting keys.

```
val myRDD: RDD[(String,Int)] =  
  sc.parallelize("odd" -> 1,"even" -> 2,"odd" -> 3)  
val mapRDD: RDD[(String,String)] =  
  myRDD.mapValues(_.toString)
```

*"odd" -> "1", "even" -> "2", "odd" -> "3"*

- flatMapValues: flatMap PairRDD values

# Key-Value RDDs

- join: Return a new RDD with both RDD joined by key.

```
val a = sc.parallelize(List("dog", "salmon", "salmon", "rat", "elephant"), 3)
val b = a.keyBy(_.length)
val c = sc.parallelize(List("dog","cat","gnu","salmon","rabbit","turkey","wolf","bear","bee"), 3)
val d = c.keyBy(_.length)
b.join(d).collect
```

```
res0: Array[(Int, (String, String))] = Array((6,(salmon,salmon)), (6,(salmon,rabbit)),
(6,(salmon,turkey)), (6,(salmon,salmon)), (6,(salmon,rabbit)), (6,(salmon,turkey)), (3,
(dog,dog)), (3,(dog,cat)), (3,(dog,gnu)), (3,(dog,bee)), (3,(rat,dog)), (3,(rat,cat)),
(3,(rat,gnu)), (3,(rat,bee)))
```

# Key-Value RDDs - combineByKey

- combineByKey:

```
def combineByKey[C] (  
  createCombiner: V => C,  
  mergeValue: (C, V) => C,  
  mergeCombiners: (C, C) => C) : RDD[ (K, C) ]
```

- Think of it as *something-like-but-not* a foldLeft over each partition

# Key-Value RDDs - combineByKey

- It's composed by:
  - `createCombiner( V => C )`: Sets the way to mutate initial RDD [V] data into new data type used for aggregating values (C). This will be called Combinator.
  - `mergeValue( (C, V) => C )`: Defines how to aggregate initial V values to our Combiner type C, returning a new combiner type C.
  - `mergeCombiners( (C, C) => C )`: Defines how to merge two combiners into a new one.

# Key-Value RDDs - combineByKey

- Example:

```
val a = sc.parallelize(List("dog", "cat", "gnu", "salmon", "rabbit", "turkey", "wolf", "bear", "bee"), 3)
val b = sc.parallelize(List(1,1,2,2,2,1,2,2,2), 3)
val c = b.zip(a)
val d = c.combineByKey(List(_), (x:List[String], y:String) => y :: x,
  (x:List[String], y:List[String]) => x ::: y)
d.collect
```

*res16: Array[(Int, List[String])] = Array((1,List(cat, dog, turkey)), (2,List(gnu, rabbit, salmon, bee, bear, wolf)))*

# Key-Value RDDs - aggregateByKey

- **aggregateByKey** : Aggregate the values of each key, using given combine functions and a neutral “zero value”.
- *Beware!* Zero value is evaluated in each partition.

```
def aggregateByKey[U:ClassTag](zeroValue: U) (
  seqOp: (U,V) => U, combOp: (U,U) => U) : RDD[(K,U)] =
  combineByKey(
    (v: V) => seqOp(zeroValue,v),
    seqOp,
    combOp)
```



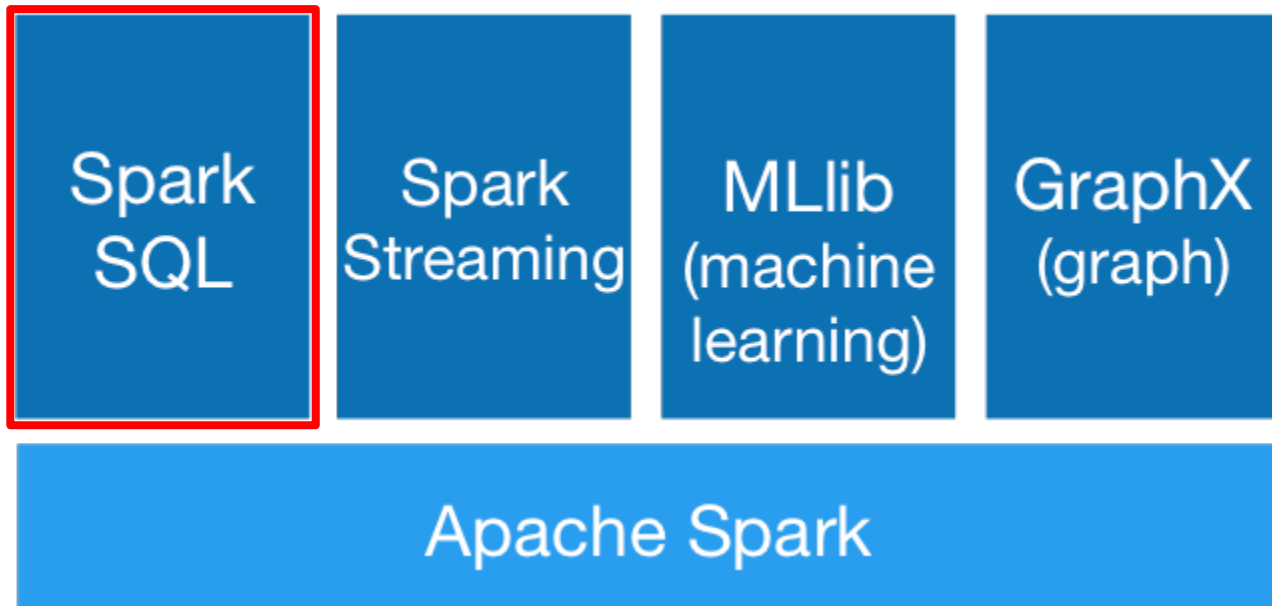
# Key-Value RDDs - groupByKey

- **groupByKey**: Group all values with same key into a Iterable of values

```
def groupByKey(): RDD[(Key, Iterable[Value])] =  
  combineByKey[List[Value]](  
    (v: V) => List(v),  
    (list: List[V], v: V) => list += v,  
    (l1: List[V], l2: List[V]) => l1 ++ l2)
```

*Note: GroupByKey actually uses CompactBuffer instead of list.*

# Modules



**INVENTS MAPREDUCE**

**DOESN'T SHARE HIGH-LEVEL  
LANGUAGE SUPPORT**

# SparkSQL

- [Shark](#) successor (Berkeley)

- Alternative to Hive + Hadoop

- Query language

- HiveQL
- Future: Support full SQL92

- SQLContext

```
val sqlContext = new SQLContext(sparkContext)
val hiveContext = new HiveContext(sparkContext)
```

# SparkSQL

- Different datasources

- JSON
- Parquet
- CSV

- New implementations

- Cassandra
- ElasticSearch
- MongoDB

- Unified API in Spark 1.3.0

```
val students: DataFrame = sqlContext.load(  
    "students", "org.apache.sql.parquet", Map(...))
```

# SparkSQL - DataFrame

- DataFrame = RDD[org.apache.spark.sql.Row] + Schema
- A Row holds both column values and their types.
- This allows unifying multiple datasources with the same API.  
*i.e, we could join two tables, one declared on Mongo and another on ElasticSearch.*

# Demo2 : Most retweeted(SparkSQL)

- [Most Retweeted Example \(SparkSQL\)](#)
- Same bunch of tweets (1000 json records)
- Find out which is the most retweeted tweet using SparkSQL

# Who uses it?

amazon

 databricks

YAHOO!

ebay™

Almaden  
Institute  


Nokia  
Networks

 **JPL**  
National Aeronautics and Space  
Administration  
Jet Propulsion Laboratory  
California Institute of Technology



STRATIO

cloudera®



TREND  
MICRO™

 Simba  
technologies



# Distributed computing with



Javier Santos  
April 2015