

# COMP 322: Fundamentals of Parallel Programming

## Lecture 30: Distributed Map-Reduce using Hadoop and Spark Frameworks

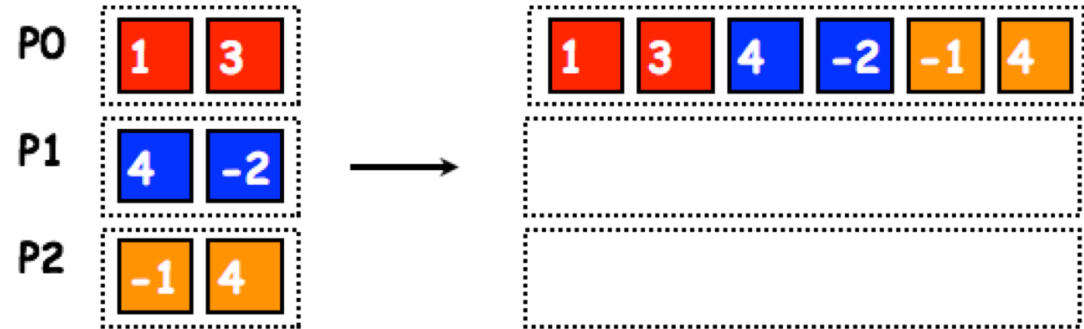
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# Worksheet #29 solution: MPI Gather

Indicate what value should be provided instead of ??? in line 6 to minimize space, and how it should depend on myrank.



```
1. MPI.Init(args) ;
2. int myrank = MPI.COMM_WORLD.Rank() ;
3. int numProcs = MPI.COMM_WORLD.Size() ;
4. int size = ...;
5. int[] sendbuf = new int[size];
6. int[] recvbuf = new int[???];
7. . . . // Each process initializes sendbuf
8. MPI.COMM_WORLD.Gather(sendbuf, 0, size, MPI.INT,
9.                        recvbuf, 0, size, MPI.INT,
10.                       0 /*root*/);
11. . . .
12. MPI.Finalize();
```

**Solution:** `myrank == 0 ? (size * numProcs) : 0`



# Organization of a Distributed-Memory Multiprocessor (Recap)

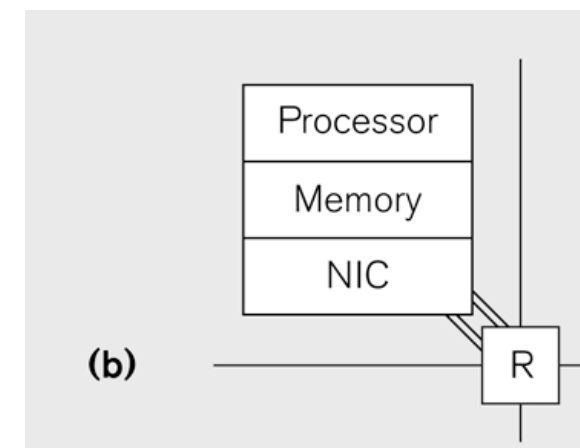
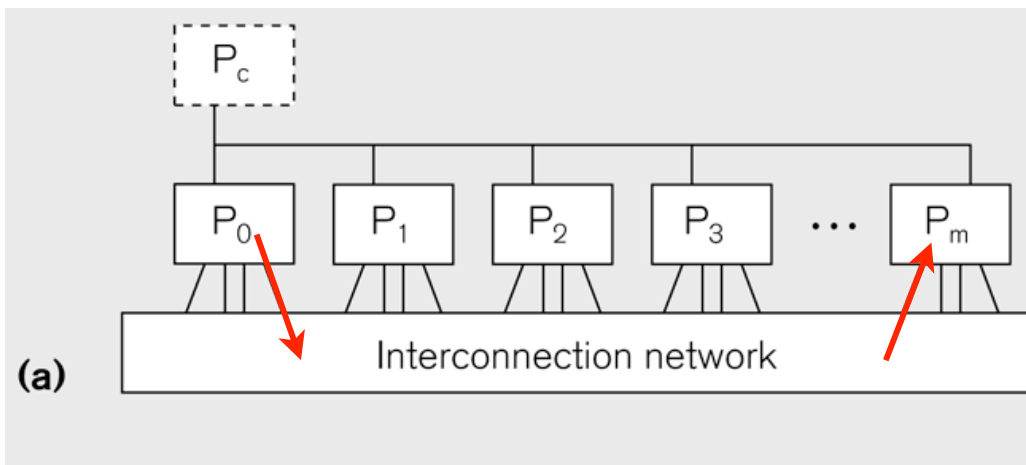
Figure (a)

- Host node ( $P_c$ ) connected to a cluster of processor nodes ( $P_0 \dots P_m$ )
- Processors  $P_0 \dots P_m$  communicate via an interconnection network which could be standard TCP/IP (e.g., for Map-Reduce) or specialized for high performance communication (e.g., for scientific computing)

Figure (b)

- Each processor node consists of a processor, memory, and a Network Interface Card (NIC) connected to a router node (R) in the interconnect

**In MPI, processes communicate by sending messages to each other. Distributed Map-Reduce offers an alternative approach for programming distributed-memory multiprocessors.**



# MapReduce Pattern (Recap from Lecture 8)

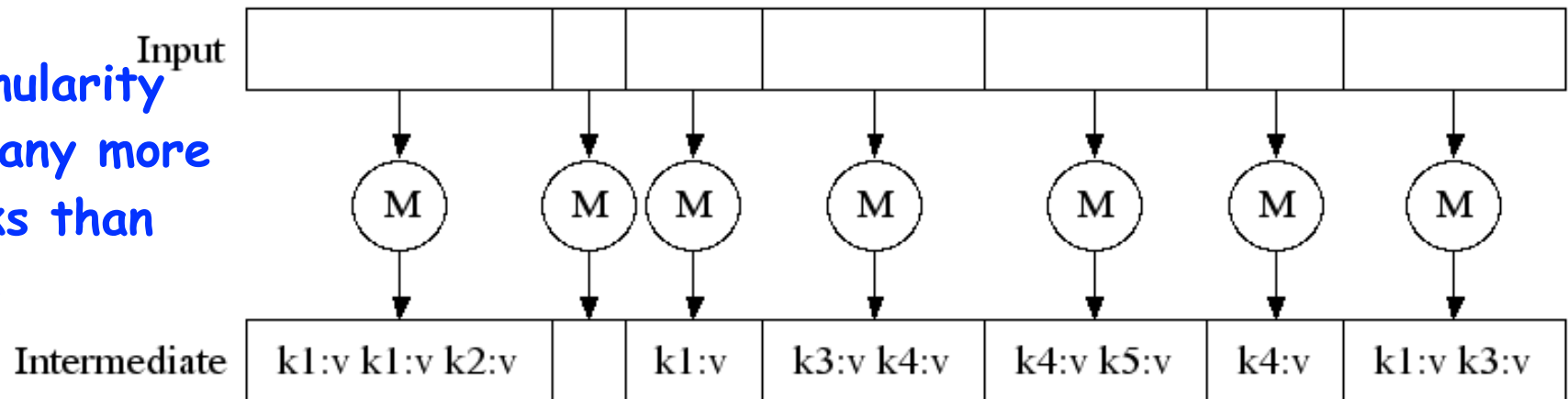
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- Apply **Map** function **f** to user supplied record of key-value pairs
- Compute set of intermediate key/value pairs
- Apply **Reduce** operation **g** to all values that share same key to combine derived data properly
  - Often produces smaller set of values
- User supplies Map and Reduce operations in functional model so that the system can parallelize them, and also re-execute them for fault tolerance
- Distributed Map-Reduce frameworks (Hadoop, Spark) support the Map-Reduce pattern (with extensions) on a distributed-memory multiprocessor

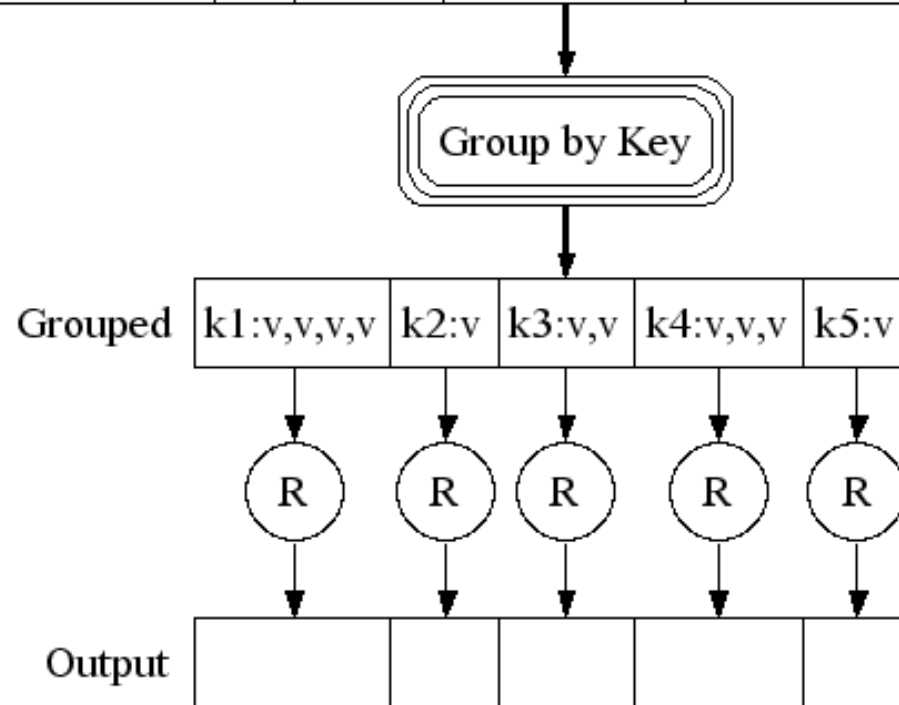


# Distributed MapReduce Execution

Fine granularity tasks: many more map tasks than machines



Bucket sort to get same keys together



E.g. 2000 servers =>  
≈ 200,000 Map Tasks,  
≈ 5,000 Reduce tasks



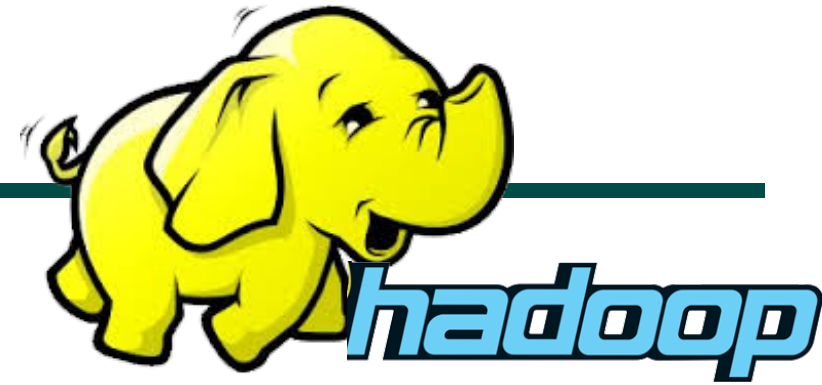
# Apache Hadoop Project

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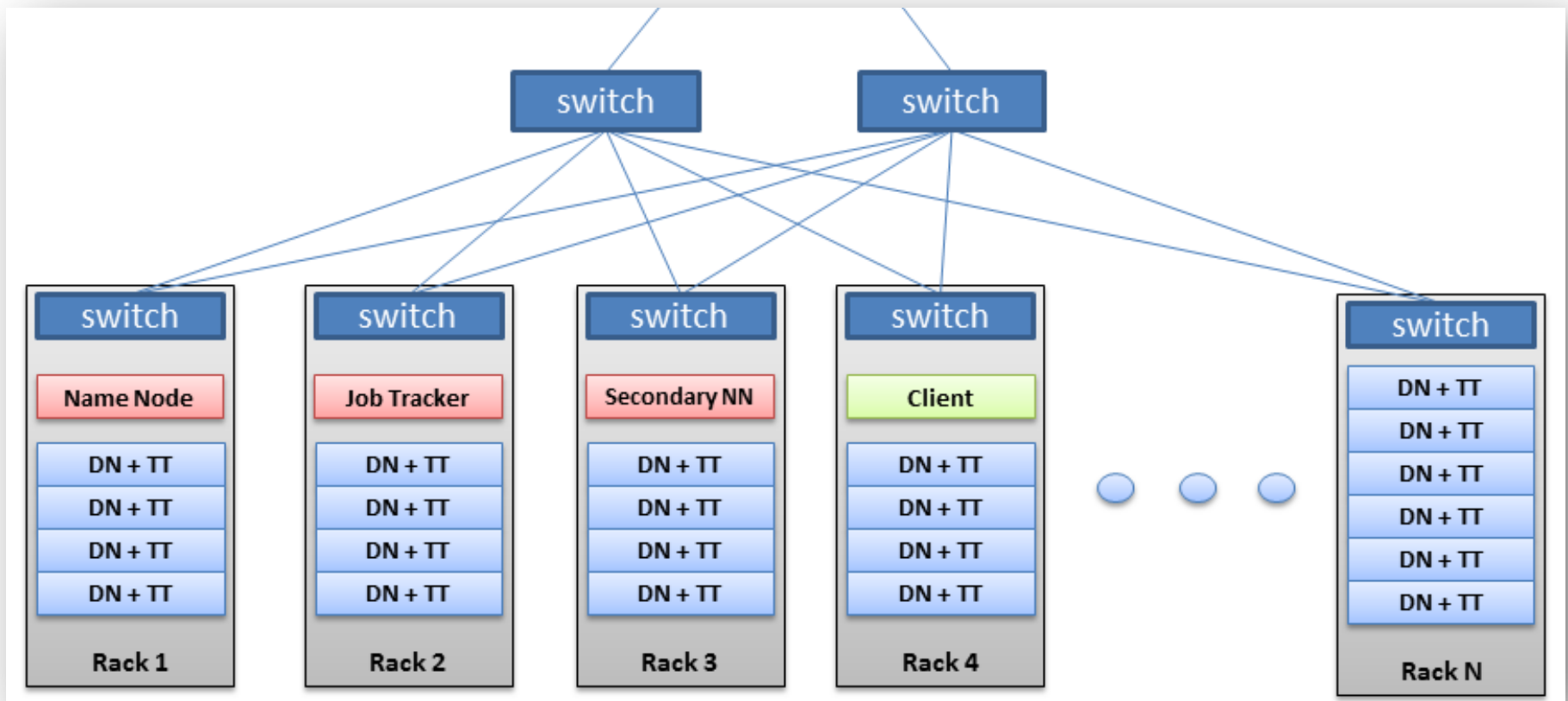
- Hadoop: an open-source software framework that supports data-intensive distributed applications, licensed under the Apache v2 license.
- Goals / Requirements:
  - Abstract and facilitate the storage and processing of large and/or rapidly growing data sets
  - Simple programming models
  - High scalability and availability
  - Fault-tolerance
  - Move computation rather than data
- Distributed design, with some centralization
  - Main nodes of cluster are where most of the computational power and storage of the system lies
  - Main nodes run TaskTracker to accept and reply to MapReduce tasks, and also DataNode to store needed blocks closely as possible
  - Central control node runs NameNode to keep track of HDFS directories & files, and JobTracker to dispatch compute tasks to TaskTracker
- Written in Java, also supports Python and Ruby
- Acknowledgment: slides on Hadoop from UCI CS 237 course by Nalini Venkatasubramanian



# Hadoop's Architecture

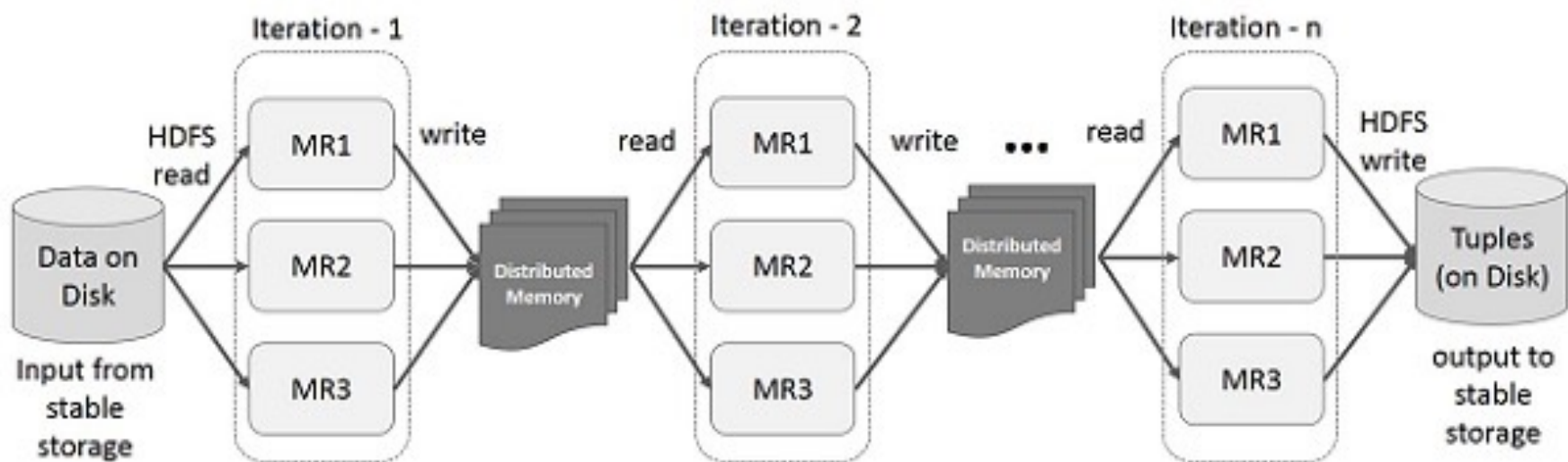


- NN = Name Node
- DN = Data Node
- TT = Task Tracker
- Acknowledgment: [slides on Hadoop](#) from UCI CS 237 course by Nalini Venkatasubramanian



# Spark and Iterative Map/Reduce

- **Apache Spark: General purpose functional programming over a cluster**
  - **Caches results of map/reduce operations in memory so they can be used on subsequent iterations**
  - **Tends to be 10-100 times faster than Hadoop for many applications**

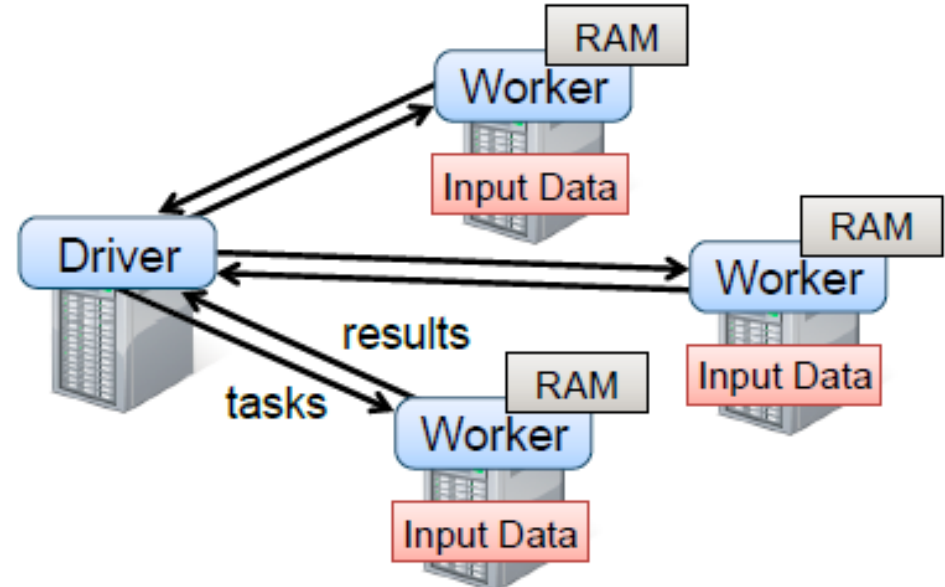




# Apache Spark Project

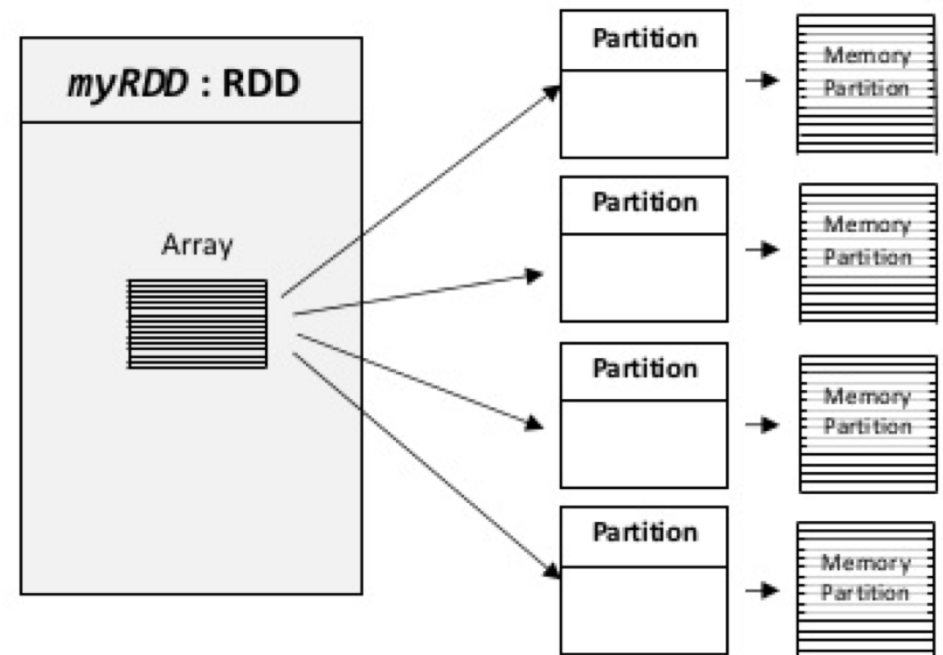


- Spark is a data parallel processing framework, which means it will execute tasks as close to where the data lives as possible (i.e. minimize data transfer).
- Spark follows a paradigm of keeping as much data in-memory and spilling excess to disk rather than pulling data from disk when needed.
- Spark decomposes your program into tasks and handles dispatching and scheduling of these tasks on worker nodes in your cluster.
- Spark revolves around the concept of a resilient distributed datasets (RDD).



# Resilient Distributed Datasets

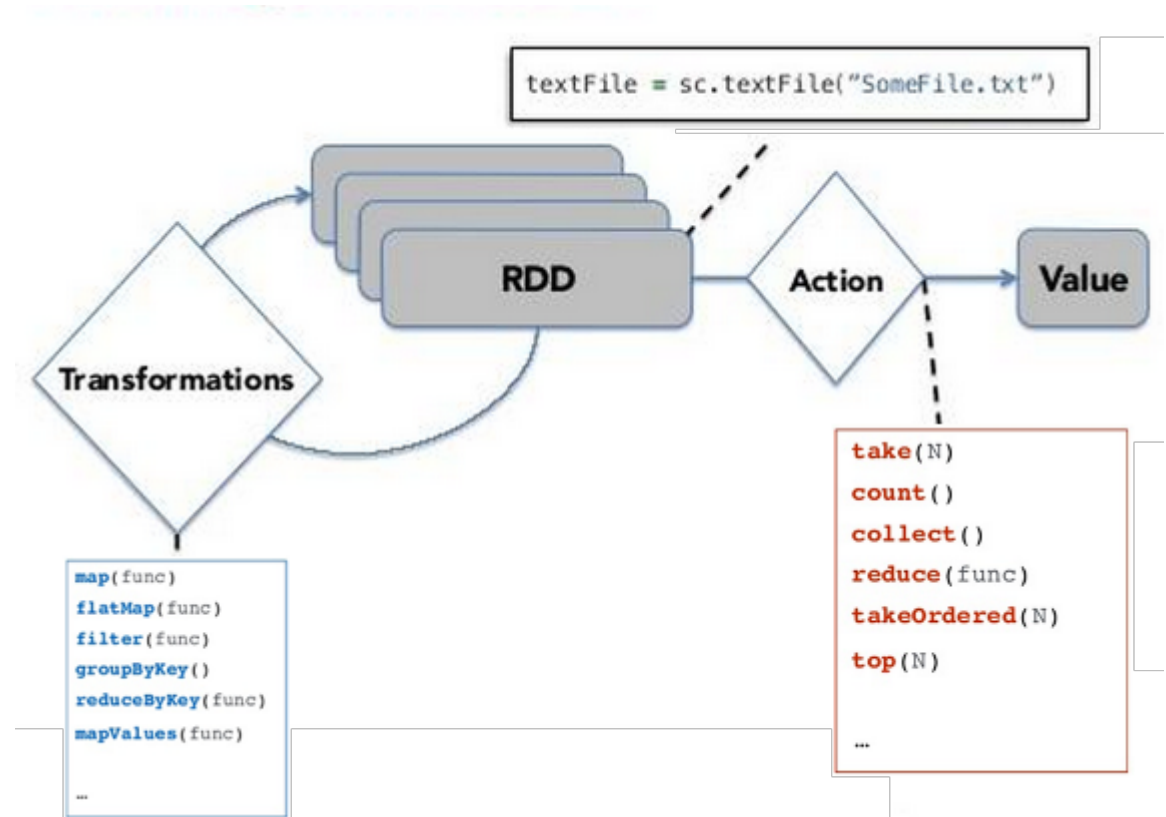
- The key construct in Spark is the Resilient Distributed Dataset (RDD)
  - RDDs can be thought of as a collection of key-value pairs
- An RDD is a giant immutable collection, distributed in a redundant way over all the machines in a cluster
- The types of the elements in the RDD can be arbitrary elements
- If the elements are pairs, then the RDD acts like a table
- Computations on an RDD (including Map/Reduce) can be expressed as functional programming operations



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# Working with RDDs

- There are two kinds of operations one can perform over an RDD.
- Transformations: Operations like `map`, `filter`, `join` etc. that just return another RDD. They are *lazy* operations.
- Actions: These are operations that *actually produce* results like `count`, `collect`, `save` etc. These operations don't return an RDD.
- Similar to *intermediate* and *terminal* operations in Java 8 Streams.



# Advantages of Immutability

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- **The distributed nature of RDDs is not evident in the programming model.**
- **RDD elements can be replicated for fault tolerance.**
- **Purely functional operations can be easily defined on RDDs**
- **Because RDDs are immutable, all the operations from purely functional programming can be applied and parallelized in a straightforward way.**
- **The runtime has great flexibility in scheduling operations on RDDs and executing them in parallel on partitions.**
- **Partitions of RDDs can be recomputed from their lineage.**



# Word Count in Apache Spark

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```
JavaRDD<String> file = context.textFile(inputFile);

JavaPairRDD<String, Integer> counter =
    file.flatMap(s -> Arrays.asList(s.split(" ")))
        .mapToPair(s -> new Tuple2<>(s, 1))
        .reduceByKey((a, b) -> a + b);

counter.collect().foreach(System.out::println);

// Definition of "flatMap"
// x.flatMap(f) = x.map(f).flatten()

// Definition of "reduceByKey"
// x.reduceByKey(f) = x.groupByKey()
//                      .map(xs -> xs.reduce(f))
```



# Word Count in Apache Spark

---

```
["this is a line",  
 "this is another line",  
 "this is yet another line"]  
.map(s -> Arrays.asList(s.split(" ")))  
.flatten()  
-->  
[["this", "is", "a", "line"],  
 ["this", "is", "another", "line"],  
 ["this", "is", "yet", "another", "line"]]  
.flatten()  
-->  
["this", "is", "a", "line", "this", "is",  
 "another", "line", "this", "is", "yet",  
 "another", "line"]
```



# Word Count in Apache Spark

---

```
["this", "is", "a", "line", "this", "is",  
 "another", "line", "this", "is", "yet",  
 "another", "line"]  
.map(s -> new Tuple2<>(s, 1))
```

→

```
[["this",1], ["is",1], ["a",1], ["line",1],  
 ["this",1], ["is",1], ["another",1],  
 ["line",1], ["this",1], ["is",1],  
 ["yet",1], ["another",1], ["line",1]]
```



# Word Count in Apache Spark

---

```
[["this",1], ["is",1], ["a",1], ["line",1],  
 ["this",1], ["is",1], ["another",1],  
 ["line",1], ["this",1], ["is",1],  
 ["yet",1], ["another",1], ["line",1]]  
.groupByKey().map(xs -> xs.reduce(  
    (a,b) -> a + b))
```

—>

```
[["this", [1,1,1]],  
 ["is", [1,1,1]],  
 ["a", [1]],  
 ["line", [1,1,1]],  
 ["another", [1,1]],  
 ["yet", [1]]].map(xs -> xs.reduce((a,b) -> a + b))
```





# Word Count in Apache Spark

---

```
[["this", [1,1,1]],  
 ["is", [1,1,1]],  
 ["a", [1]],  
 ["line", [1,1,1]],  
 ["another", [1,1]],  
 ["yet", [1]]].map(xs -> xs.reduce(  
                                     (a,b) -> a + b)
```

—>

```
[["this", [1,1,1]].reduce((a,b) -> a + b),  
 ["is", [1,1,1]].reduce((a,b) -> a + b),  
 ["a", [1]].reduce((a,b) -> a + b),  
 ["line", [1,1,1]].reduce((a,b) -> a + b),  
 ["another", [1,1]].reduce((a,b) -> a + b),  
 ["yet", [1]].reduce((a,b) -> a + b))]
```



# Word Count in Apache Spark

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```
[["this", [1,1,1]].reduce((a,b) -> a + b),  
 ["is", [1,1,1]].reduce((a,b) -> a + b),  
 ["a", [1]].reduce((a,b) -> a + b),  
 ["line", [1,1,1]].reduce((a,b) -> a + b),  
 ["another", [1,1]].reduce((a,b) -> a + b),  
 ["yet", [1]].reduce((a,b) -> a + b))]
```

—>

```
[["this", 3], ["is", 3], ["a", 1],  
 ["line", 3], ["another", 2], ["yet", 1]]
```

