Data-intensive computing systems

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Introduction - Motivation

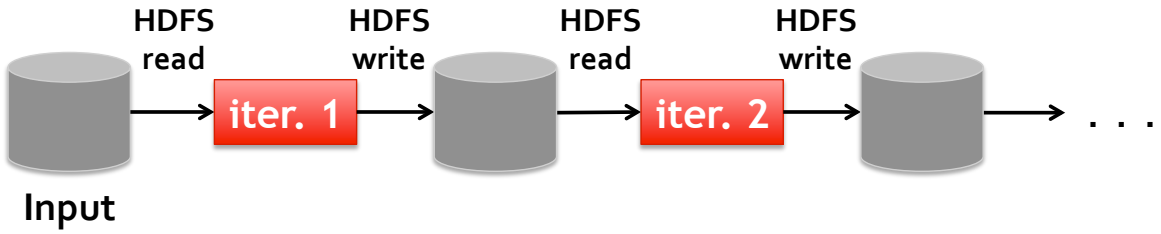
- MapReduce greatly simplified “big data” analysis on large, unreliable clusters
- But as soon as it got popular, users wanted more:
  - More complex, multi-stage applications (e.g. iterative machine learning & graph processing)
  - More interactive ad-hoc queries
- Response ➔ specialized frameworks for some of these apps
  - E.g. Pregel for graph processing

Motivation – Data point of view

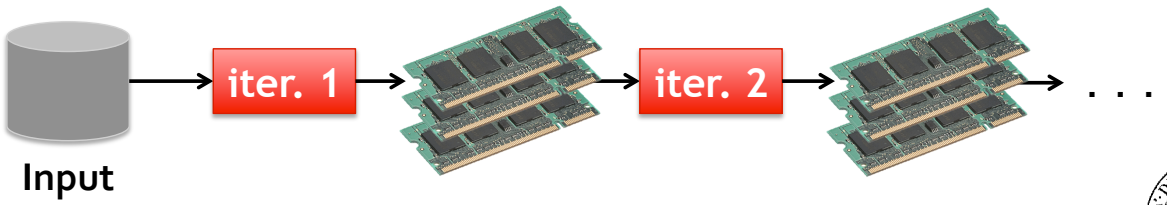
- Complex apps and interactive queries both need one thing that MapReduce lacks:
  - Efficient primitives for data sharing
- In MapReduce, the only way to share data across jobs is stable storage
  - Slow!

Goal

- From the Hadoop approach
  - Slow due to replication and disk I/O, but necessary for fault tolerance



- To an "in-memory" approach



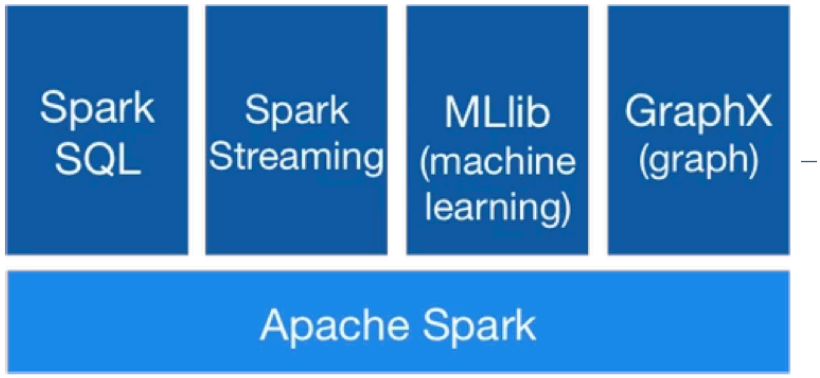
Motivation – System point of view

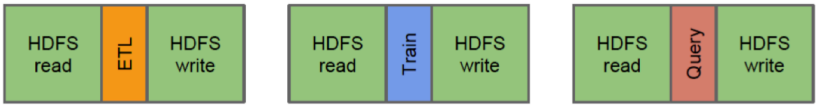
- Hadoop code base is huge
- Contributions/Extensions to Hadoop are cumbersome
- System/Framework: no unified pipeline
  - Sparse modules
  - Diversity of APIs
  - Higher operational costs

General Batching	Specialized systems			
	Streaming	Iterative	Ad-hoc / SQL	Graph
MapReduce	Storm	Mahout	Pig	Giraph
	S4		Hive	
	Samza		Drill	
			Impala	

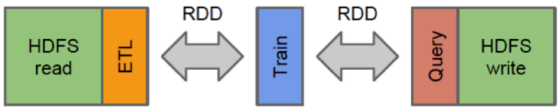
Goals

- Unified pipeline





- Simplified data flow



Summary of the challenges

- Data
  - How to design a distributed memory abstraction that is both fault-tolerant and efficient?
- System
  - Is it possible to build a unified system that includes library for the most common problems?

Resilient Distributed Datasets (RDD)

What is an RDD

- RDD are partitioned, locality aware, distributed collections
  - RDD are immutable
- RDD are data structures that:
  - Either point to a direct data source (e.g. HDFS)
  - Apply some transformations to its parent RDD(s) to generate new data elements
- Computations on RDDs
  - Represented by lazily evaluated lineage DAGs composed by chained RDDs

RDD Abstraction

- Overall objective
  - Support a wide array of operators (more than just Map and Reduce)
  - Allow arbitrary composition of such operators
- Simplify scheduling
  - Avoid to modify the scheduler for each operator
- The question is: How to capture dependencies in a general way?

RDD Interfaces

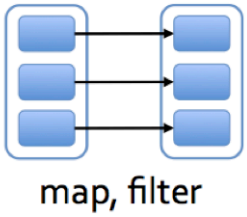
- Set of partitions ("splits")
  - Much like in Hadoop MapReduce, each RDD is associated to (input) partitions
- List of dependencies on parent RDDs
  - This is completely new w.r.t. Hadoop MapReduce
- Function to compute a partition given parents
  - This is actually the "user-defined code" we referred to when discussing about the Mapper and Reducer classes in Hadoop
- Optional preferred locations
  - This is to enforce data locality
- Optional partitioning info (Partitioner)
  - This really helps in some "advanced" scenarios in which you want to pay attention to the behavior of the shuffle mechanism

Examples of RDD

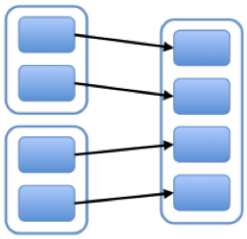
	Hadoop RDD	Filtered RDD	Joined RDD
Partitions	One per HDFS block	Same as parent RDD	One per reduce task
Dependencies	None	One-to-one on parent	Shuffle on each parent
Compute (partition)	Read corresponding block	Compute parent and filter it	Read and join shuffled data
Preferred location	HDFS block location	None (ask parent)	None
Partitioner	None	None	HashPartitioner (numTask)

Dependency types: narrow

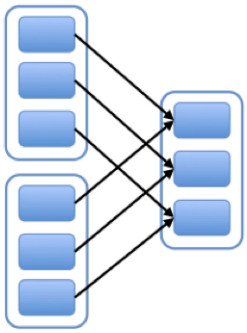
- Each partition of the parent RDD is used by at most one partition of the child RDD
- Task can be executed locally and we don't have to shuffle. (Eg: map, flatMap, filter, sample)



map, filter



union

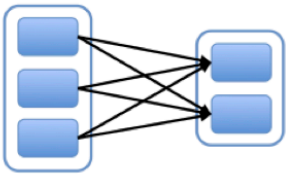


join with co-partitioned inputs

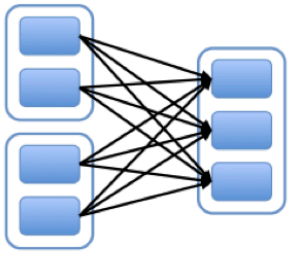
Dependency types: wide

- Multiple child partitions may depend on one partition of the parent RDD

- This means we have to shuffle data unless the parents are hash-partitioned
  - Eg: sortByKey, reduceByKey, groupByKey, cogroupByKey, join, cartesian



groupByKey

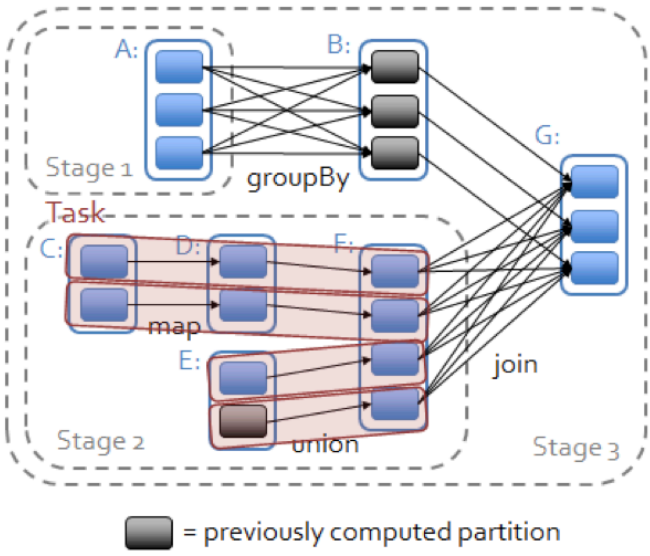


join with inputs not co-partitioned

Dependency Types: Optimizations

- Benefits of Lazy evaluation: The DAG Scheduler optimizes Stages and Tasks before submitting them to the Task Scheduler

- Examples:
  - Pipelining narrow dependencies within a Stage
  - Join plan selection based on partitioning
  - Cache reuse



Operations on RDDs: Transformations

- Transformations
  - Set of operations on a RDD that define how they should be transformed
  - As in relational algebra, the application of a transformation to an RDD yields a new RDD (because RDDs are immutable)
  - Transformations are lazily evaluated, which allow for optimizations to take place before execution
- Examples (not exhaustive)
  - map(func), flatMap(func), filter(func)
  - grouByKey()
  - reduceByKey(func), mapValues(func), distinct(), sortByKey(func)
  - join(other), union(other)
  - sample()

Operations on RDDs: Actions

- Actions
  - Apply transformation chains on RDDs, eventually performing some additional operations (e.g., counting)
  - Some actions only store data to an external data source (e.g. HDFS), others fetch data from the RDD (and its transformation chain) upon which the action is applied, and convey it to the driver
- Examples (not exhaustive)
  - reduce(func)
  - collect(), first(), take(), foreach(func)
  - count(), countByKey()
  - saveAsTextFile()

Examples

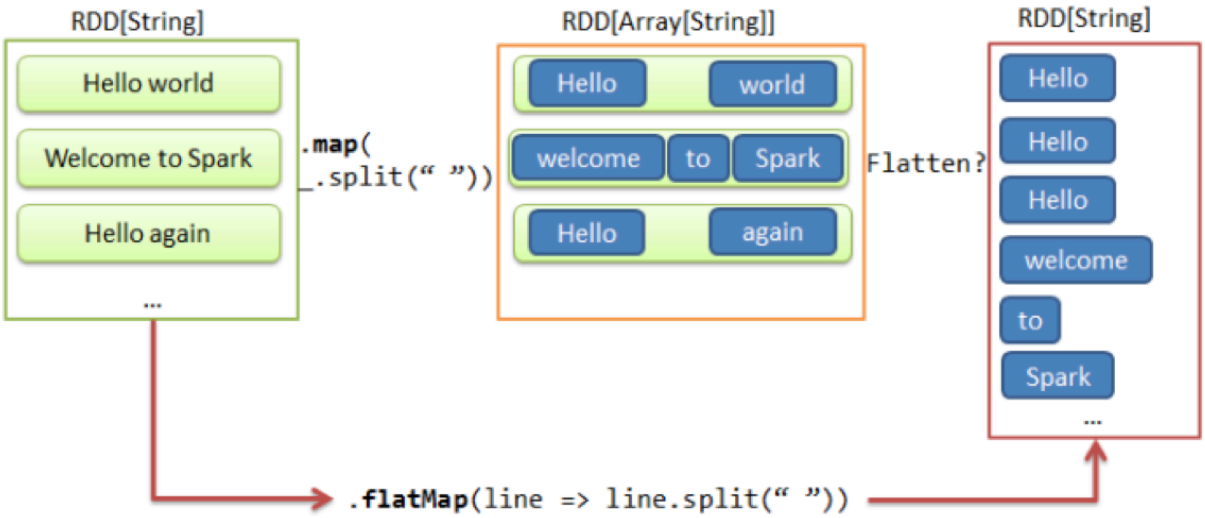
Word count

```
val textFile = sc.textFile("hdfs://...")
val counts = textFile.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey((a,b) => a + b)
counts.saveAsTextFile("hdfs://...")
```

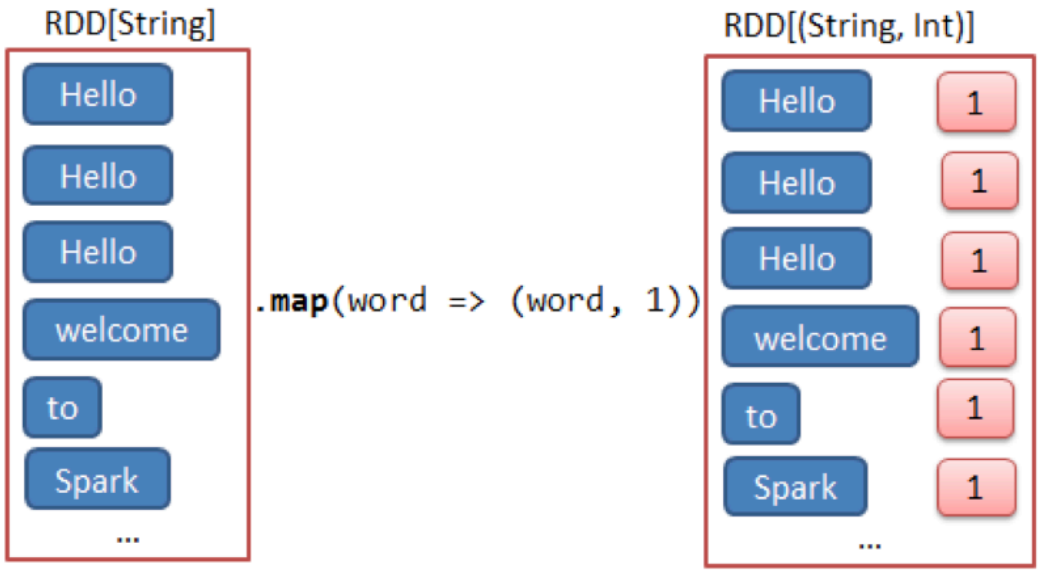
- "sc" is the SparkContext
  - A SparkContext initializes the application driver, the latter then registers the application to the cluster manager, and gets a list of executors
- Alternative version:

```
val counts = textFile.flatMap(_.split(" "))
                 .map(_ => 1))
                 .reduceByKey(_ + _)
```

Common Transformations



Common Transformations



Log mining

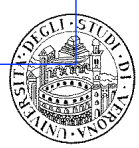
- Load error messages from a log into memory, then interactively search for various patterns

```
lines = sc.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t'))
messages.persist() // keep in memory

messages.filter(_.contains("foo")).count
messages.filter(_.contains("bar")).count
```

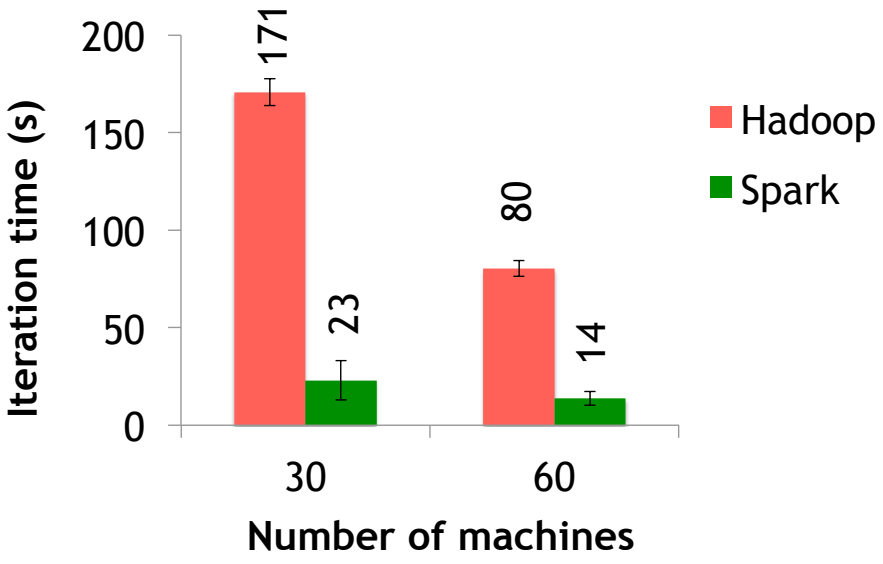
Pagerank

- Pagerank defined as usual ➔ $$P(n) = \alpha\left(\frac{1}{|G|}\right) + (1-\alpha)\sum_{m \in L(n)} \frac{P(m)}{C(m)}$$
- Simple version, with no sink nodes

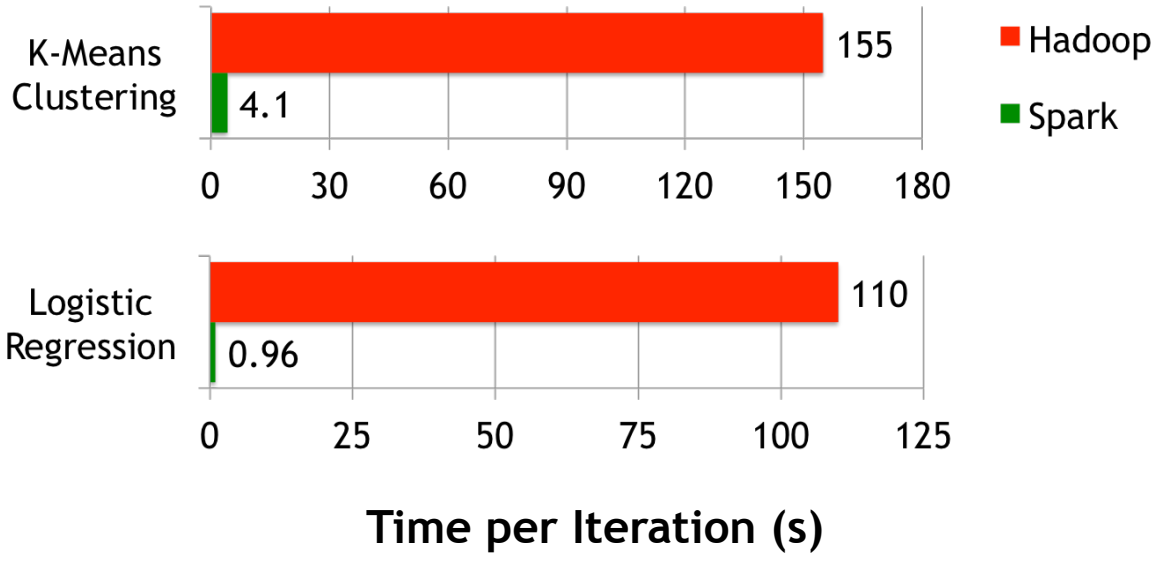
```
val links = ... // load RDD of (url, neighbors) pairs
var ranks = ... // load RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
  val contribs = links.join(ranks).flatMap {
    (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }
  ranks = contribs.reduceByKey(_ + _)
                  .mapValues(0.15/G + 0.85 * _)
}
ranks.saveAsTextFile("hdfs://...")
```



PageRank Performance



Other Iterative Algorithms



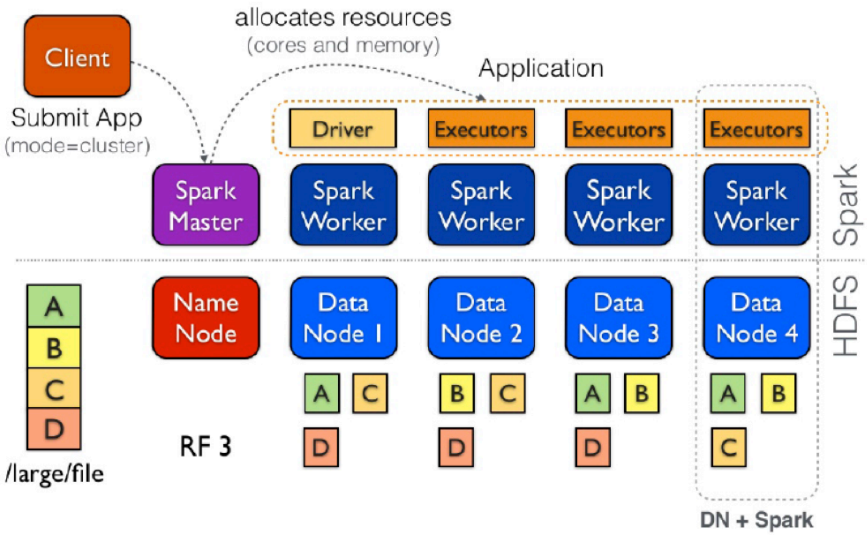
Overview of the framework

A Very Simple Application Example

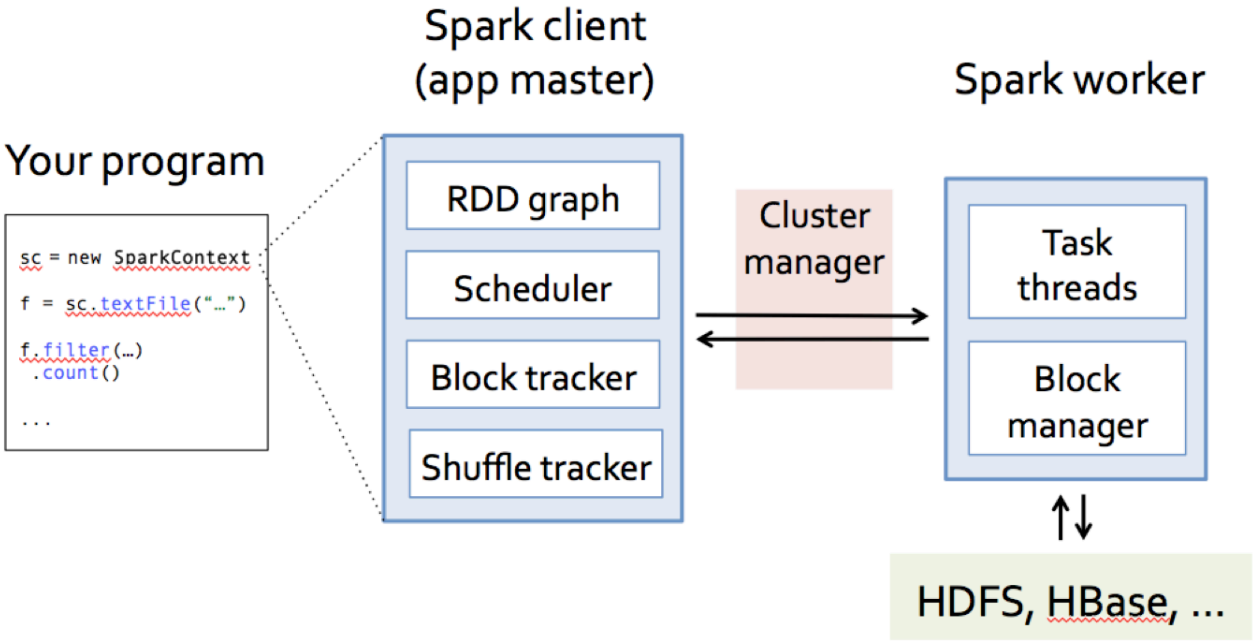
```
val sc = new SparkContext("spark://...", "MyJob", home, jars)
val file = sc.textFile("hdfs://...") // This is an RDD
val errors = file.filter(_.contains("ERROR")) // This is an RDD
errors.cache()
errors.count() // This is an action
```

Spark Applications: The Big Picture

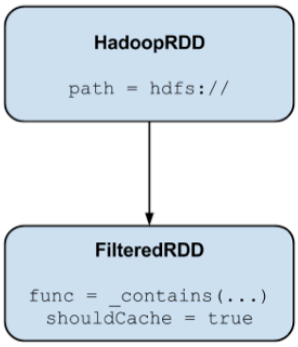
- There are two ways to manipulate data in Spark
  - Use the interactive shell
  - Write standalone applications, i.e., driver programs

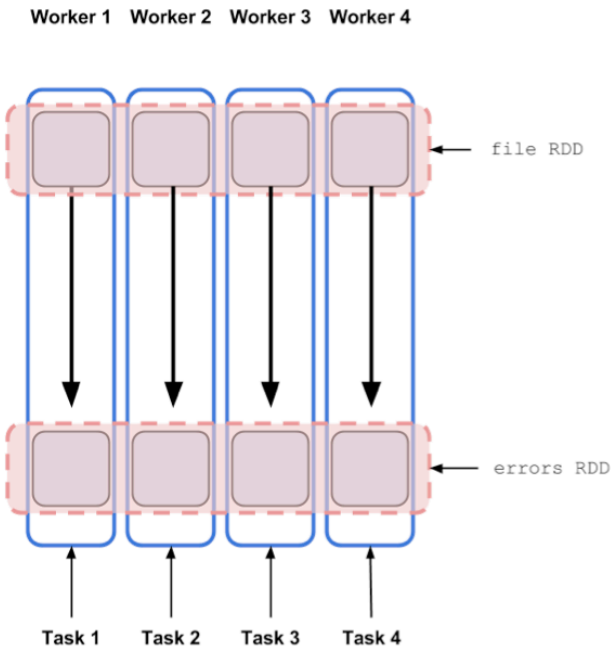


Spark Components: details



The RDD graph: dataset vs. partition views

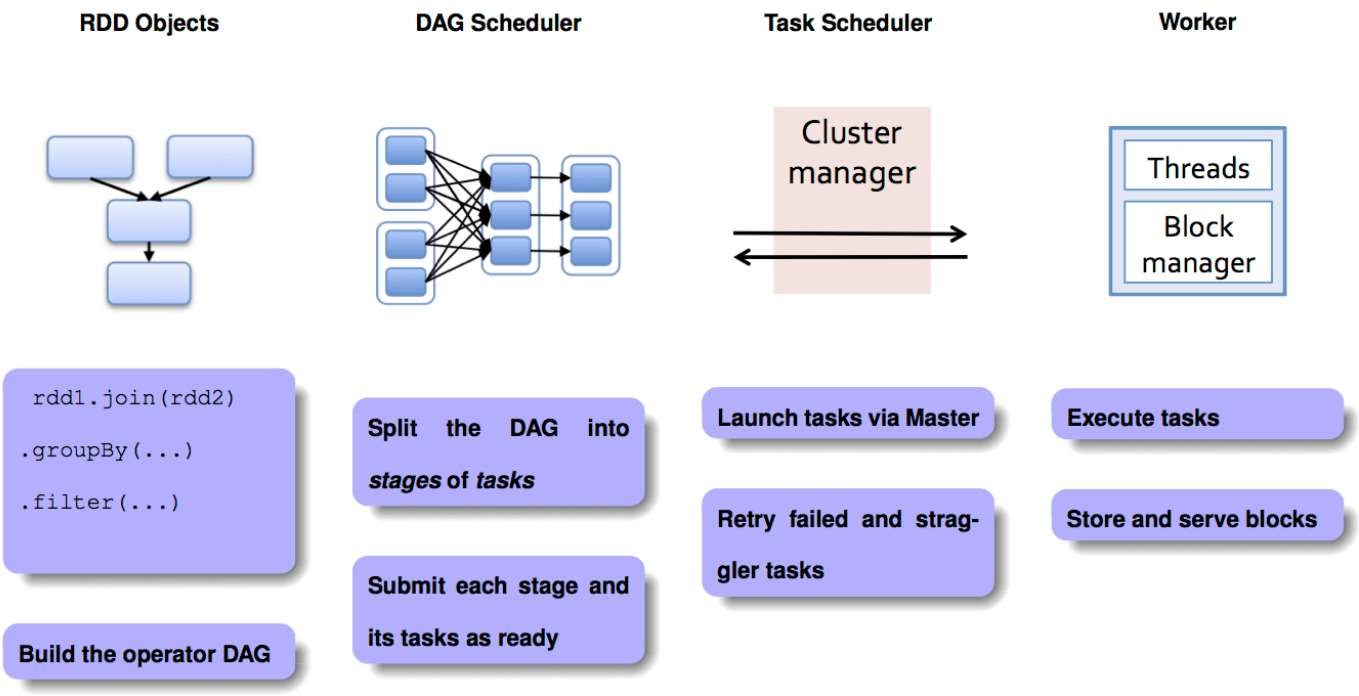




Data Locality

- Data locality principle
  - Same as for Hadoop MapReduce
  - Avoid network I/O, workers should manage local data
- Data locality and caching
  - First run: data not in cache, so use HadoopRDD's locality prefs (from HDFS)
  - Second run: FilteredRDD is in cache, so use its locations
  - If something falls out of cache, go back to HDFS

Lifetime of a Job in Spark



In Summary

- Our example Application: a jar file
  - Creates a SparkContext, which is the core component of the driver
  - Creates an input RDD, from a file in HDFS
  - Manipulates the input RDD by applying a filter transformation
  - Invokes the action count() on the transformed RDD
- The DAG Scheduler
  - Gets: RDDs, functions to run on each partition and a listener for results
  - Builds Stages of Tasks objects (code + preferred location)
  - Submits Tasks to the Task Scheduler as ready
  - Resubmits failed Stages
- The Task Scheduler
  - Launches Tasks on executors
  - Relaunches failed Tasks
  - Reports to the DAG Scheduler