



UNIVERSITAT DE
BARCELONA

Master in Fundamental Principles of Data Science

Dr Rohit Kumar

Spark Course Outline

- Week 7: Spark Fundamentals
- Week 8: Spark SQL
- Week 9: Spark Advanced Concepts
- Week 10: Spark Streaming and Spark ML lib intro
- Week 11: Delta Lake
- Week 12: Delta Lake(Continued)



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Spark Fundamentals

Spark Intro

- Its not a replacement of Hadoop
- Its not for big data storage
- It's a *general purpose* distributed computing platform for *scalable efficient analysis* of big data.

Spark history

First
research
paper in
2010.

First stable
release in
2012.

Became the
top level
Apache
Project. In
2014*

Became the
most active
project in
Apache
foundation.
In 2015

Latest
version
Spark 3.1.1
released
(March,
2021)

*Won Gray Sort Benchmark. Sorted 100TB of data using 206 EC2 i2.8xlarge machines in 23 minutes. The previous world record was 72 minutes, set by a Hadoop MapReduce cluster of 2100 nodes.

Hadoop vs Spark

Hadoop	Spark
Disk only	Both in-memory and disk storage
Only Map and Reduce operations	Many transformations and action making it easier to write application
Batch execution	Batch, interactive and streaming execution
Java language supported	Supports Java, Scala, R and Python

Apache Spark Platform

Spark SQL
(Query
Processing)

Spark
Streaming
(Real Time
processing)

Spark MLlib,
Spark R
(Machine
Learning)

GraphX,
GraphFrames
(Graph
processing)

Spark Core API (R, Java, Scala, Python, SQL ..) and Execution Model

Cluster Resource Manager

Standalone

YARN

Mesos

Data Storage

HDFS

Amazon
S3

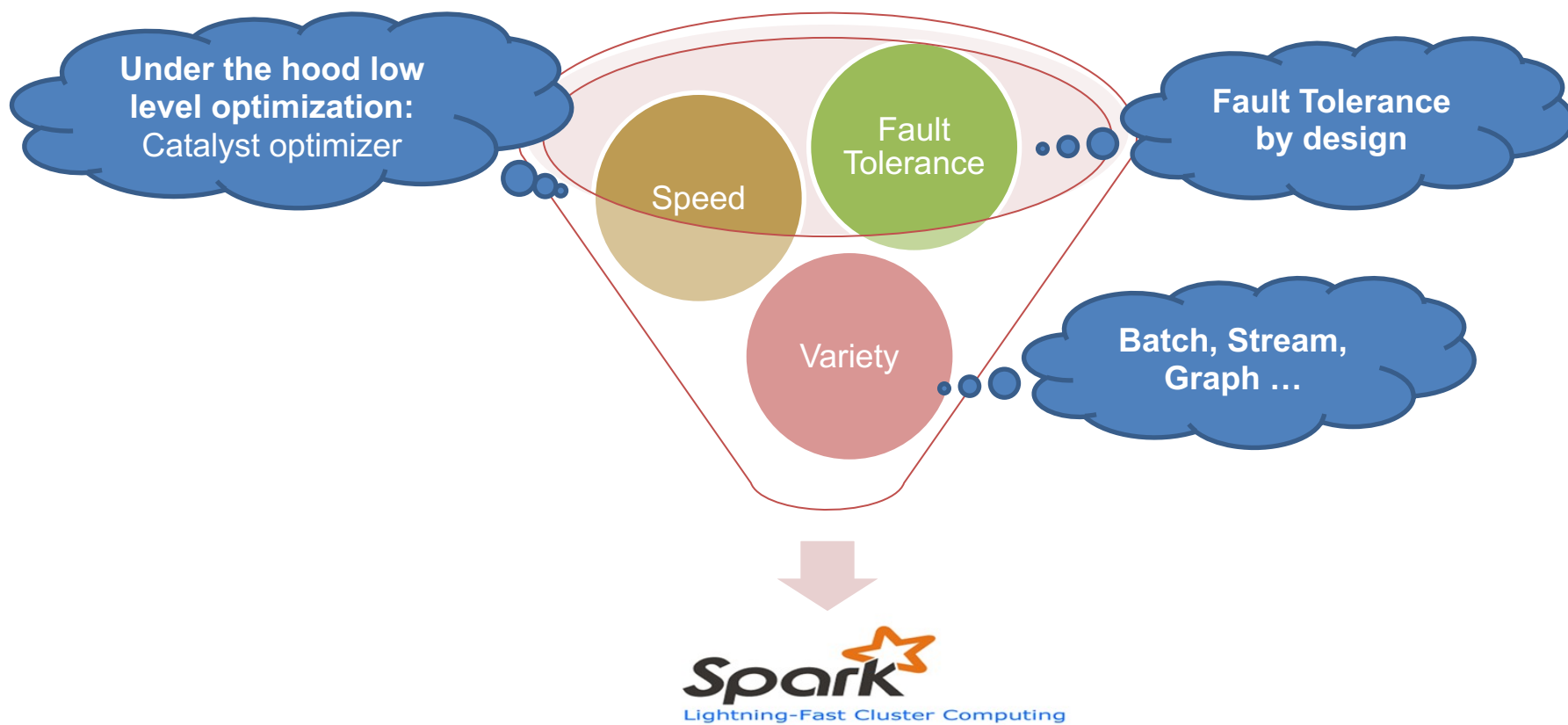
Cassandra

Spark Programming language

- Scala
- Python
- Java

Spark is built using Scala and is the best option to work on Spark as both Python and Java interface will internally convert code in Scala.

Spark Advantage

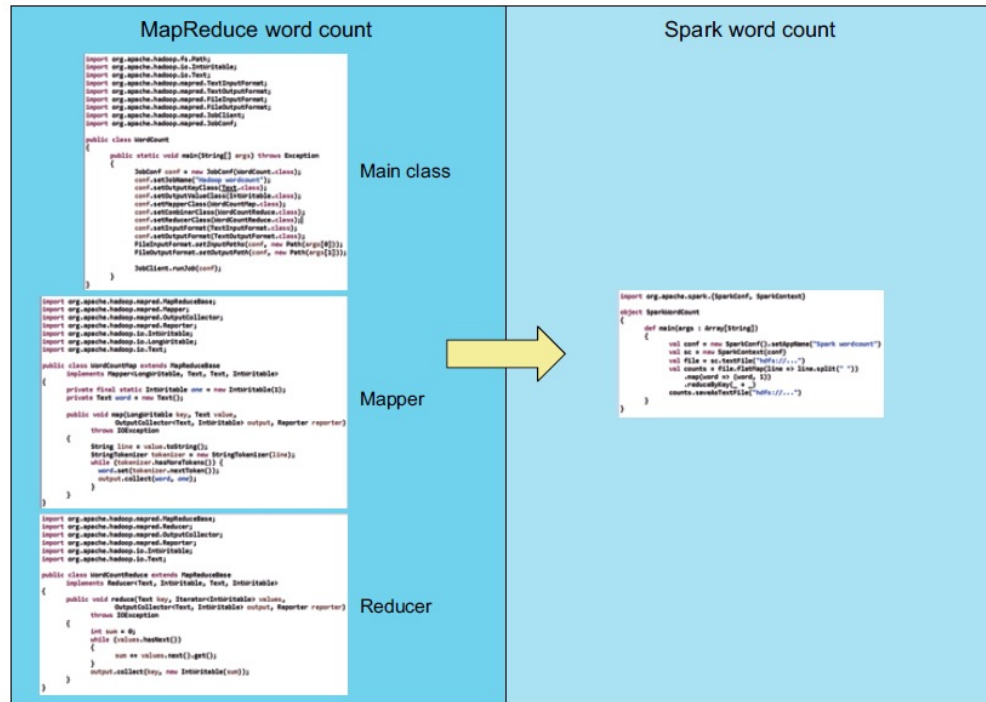


Why so popular



- **Easy to Get Started**
- **Unified Engine for Diverse Workloads:** “One of the Spark project goals was to deliver a platform that supports a very wide array of diverse workflows - not only MapReduce batch jobs (there were available in Hadoop already at that time), but also iterative computations like graph algorithms or Machine Learning.” – Matei Zaharia
- **An active community of more than 500 contributors**
- **Rich Standard Library:** MLlib, Spark-SQL, GraphX
- **Interactive Exploration / Exploratory Analytics**

Spark makes it easy

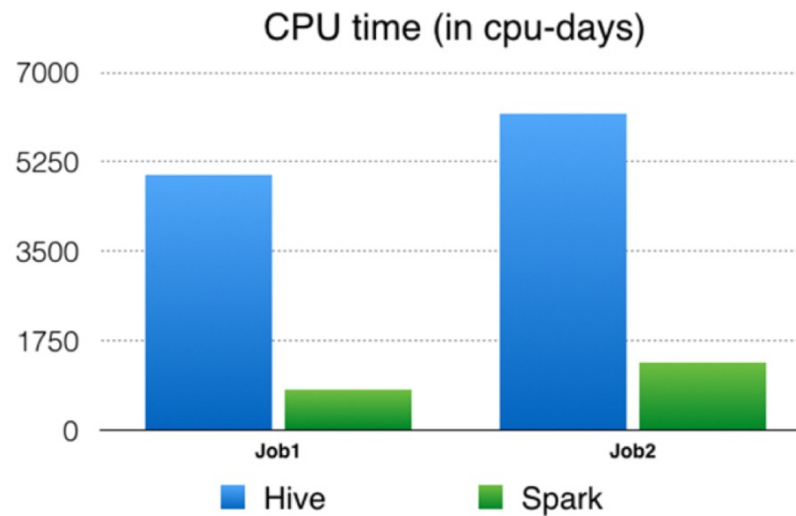


Src: Spark in Action book(page 7)

Big Users

- **Alibaba Taobao:** built one of the world's first Spark on YARN production clusters.
- **eBay Inc:** Using Spark core for log transaction aggregation and analytics.
- **TripAdvisor:** Using Apache Spark for Massively Parallel NLP.

A 60 TB+ production use case from Facebook



<https://databricks.com/blog/2016/08/31/apache-spark-scale-a-60-tb-production-use-case.html>

Spark architecture

A simple architecture diagram

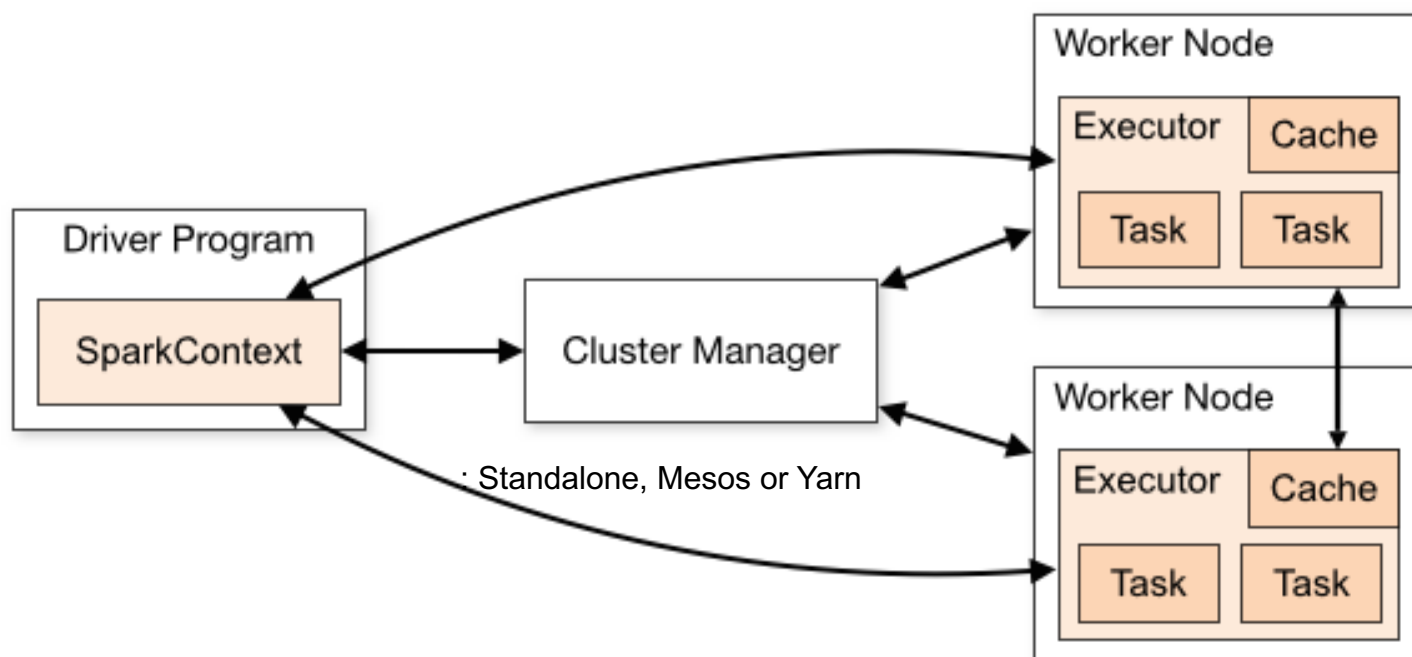


Image src: <https://spark.apache.org/docs/latest/cluster-overview.html>

Spark Driver

Master node in the Spark application.

Entry point of the Spark shell.

Runs the `main()` method of the application.

Creates and maintain the **SparkContext**.

Connects to the *cluster manager* and requests

Cluster Manager

Allocates resource on request from driver

Keep track on dead or live nodes in the cluster.

Enables the execution of jobs submitted by the driver on the worker nodes.

All driver instances talk to this one cluster manager.

Spark Worker

Executes the actual business logic submitted by the driver.

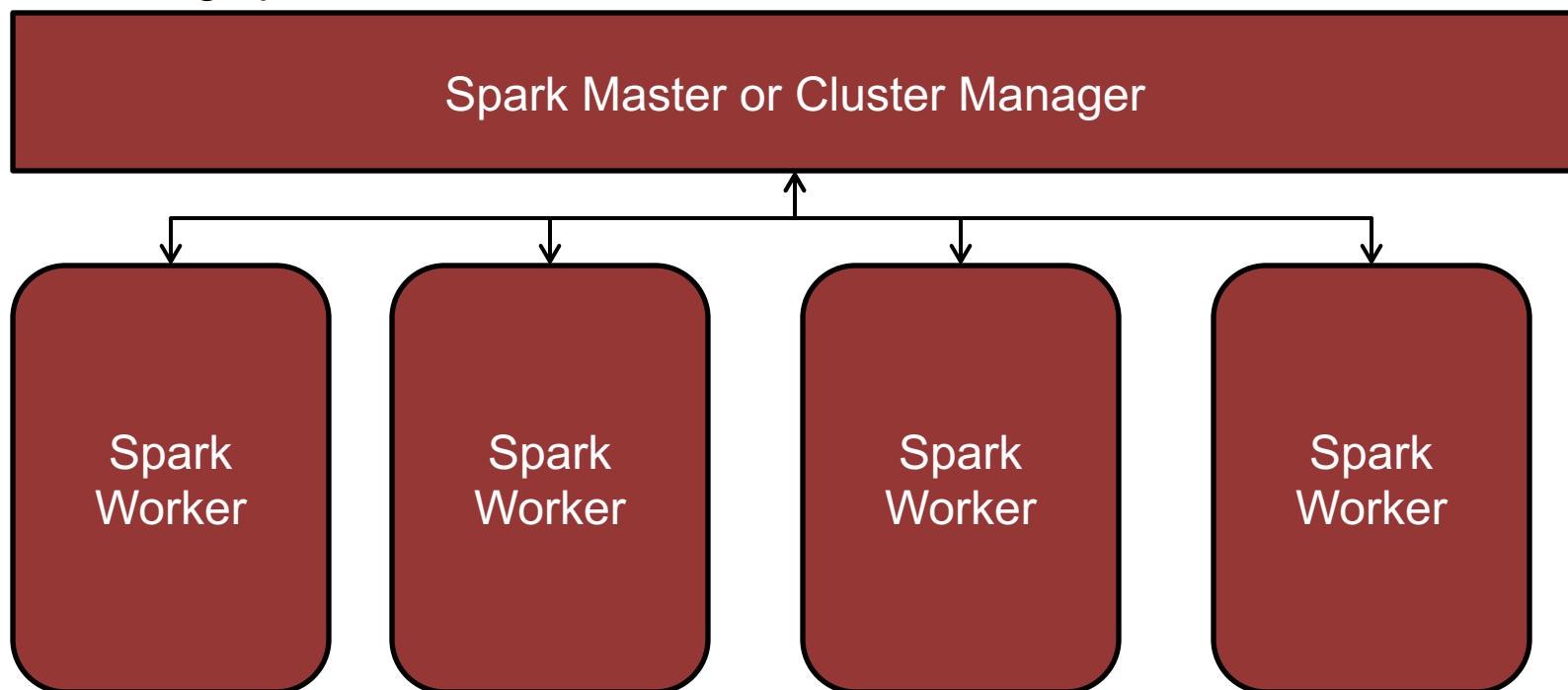
Each executor has its own JVM.

The executors run separate threads to execute the code.

Do the main logic of code, read data from resource and write data.

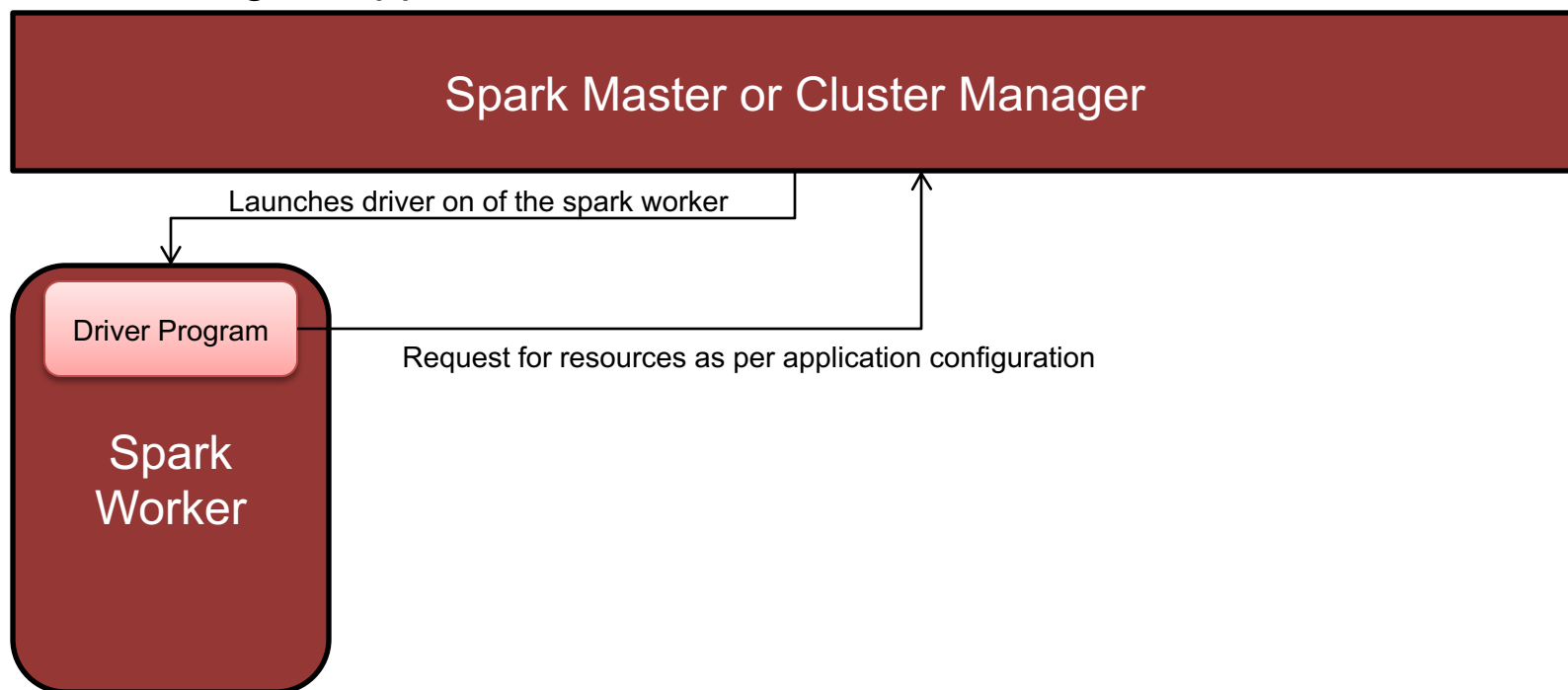
Spark application life cycle(detailed)

After starting spark cluster



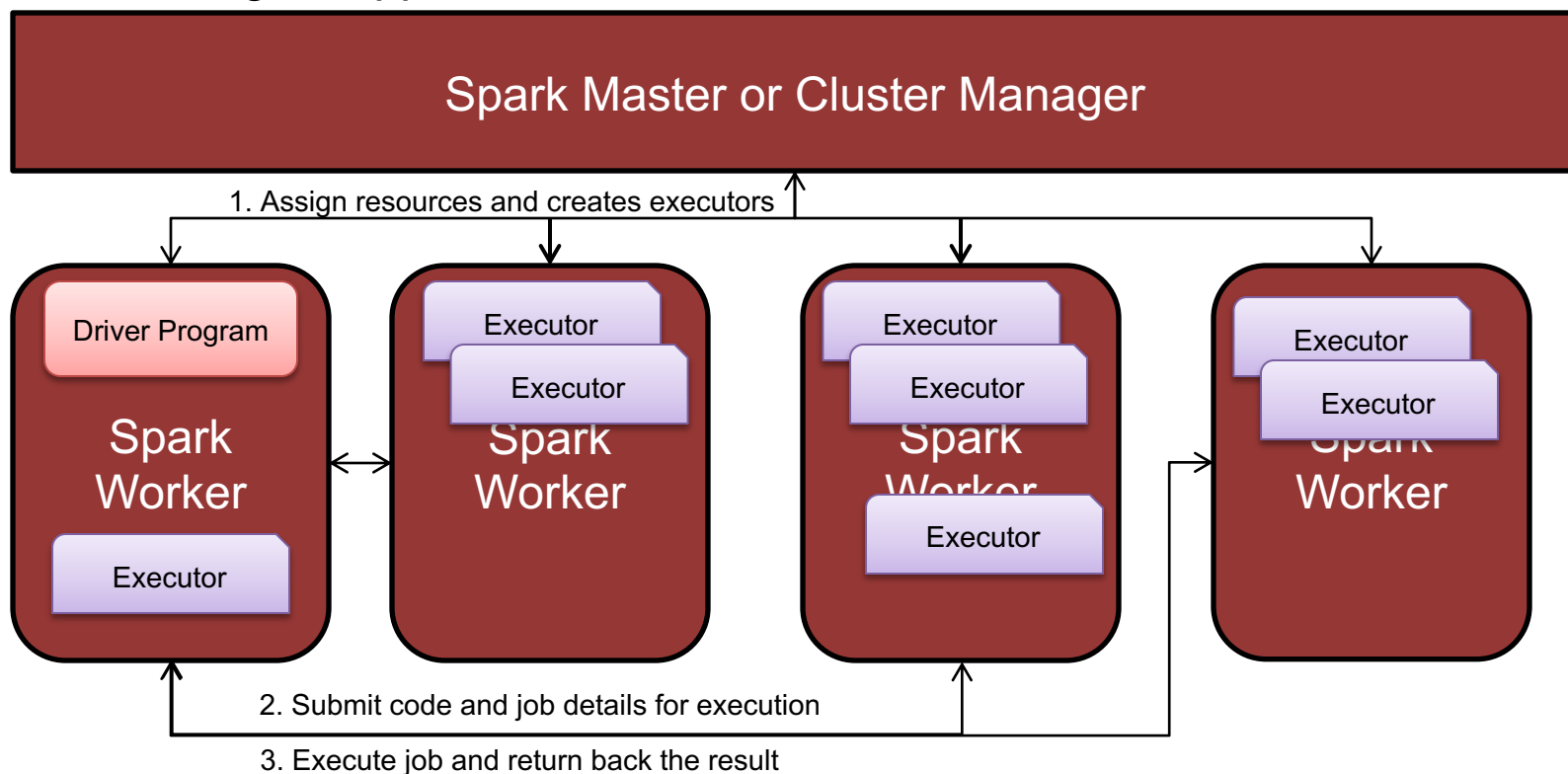
Spark application life cycle(detailed)

After launching an application



Spark application life cycle(detailed)

After launching an application



RDD intro

Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing

Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma,
Murphy McCauley, Michael J. Franklin, Scott Shenker, Ion Stoica

University of California, Berkeley

Paper published in 2012

Abstract

We present Resilient Distributed Datasets (RDDs), a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a fault-tolerant manner. RDDs are motivated by two types of applications that current computing frameworks handle inefficiently: iterative algorithms and interactive data mining tools. In both cases, keeping data in memory can improve performance by an order of magnitude. To achieve fault tolerance efficiently, RDDs provide a restricted form of shared memory, based on coarse-grained transformations rather than fine-grained updates to shared state. However, we show that RDDs are expressive enough to capture a wide class of computations, including recent specialized programming models for iterative jobs, such as Pregel, and new applications that these

tion, which can dominate application execution times.

Recognizing this problem, researchers have developed specialized frameworks for some applications that require data reuse. For example, Pregel [22] is a system for iterative graph computations that keeps intermediate data in memory, while HaLoop [7] offers an iterative MapReduce interface. However, these frameworks only support specific computation patterns (*e.g.*, looping a series of MapReduce steps), and perform data sharing implicitly for these patterns. They do not provide abstractions for more general reuse, *e.g.*, to let a user load several datasets into memory and run ad-hoc queries across them.

In this paper, we propose a new abstraction called *resilient distributed datasets (RDDs)* that enables efficient data reuse in a broad range of applications. RDDs are fault-tolerant, parallel data structures that let users explicitly persist intermediate results in memory, control



RDD intro

RDD of Strings

Hello

World

Example

Text

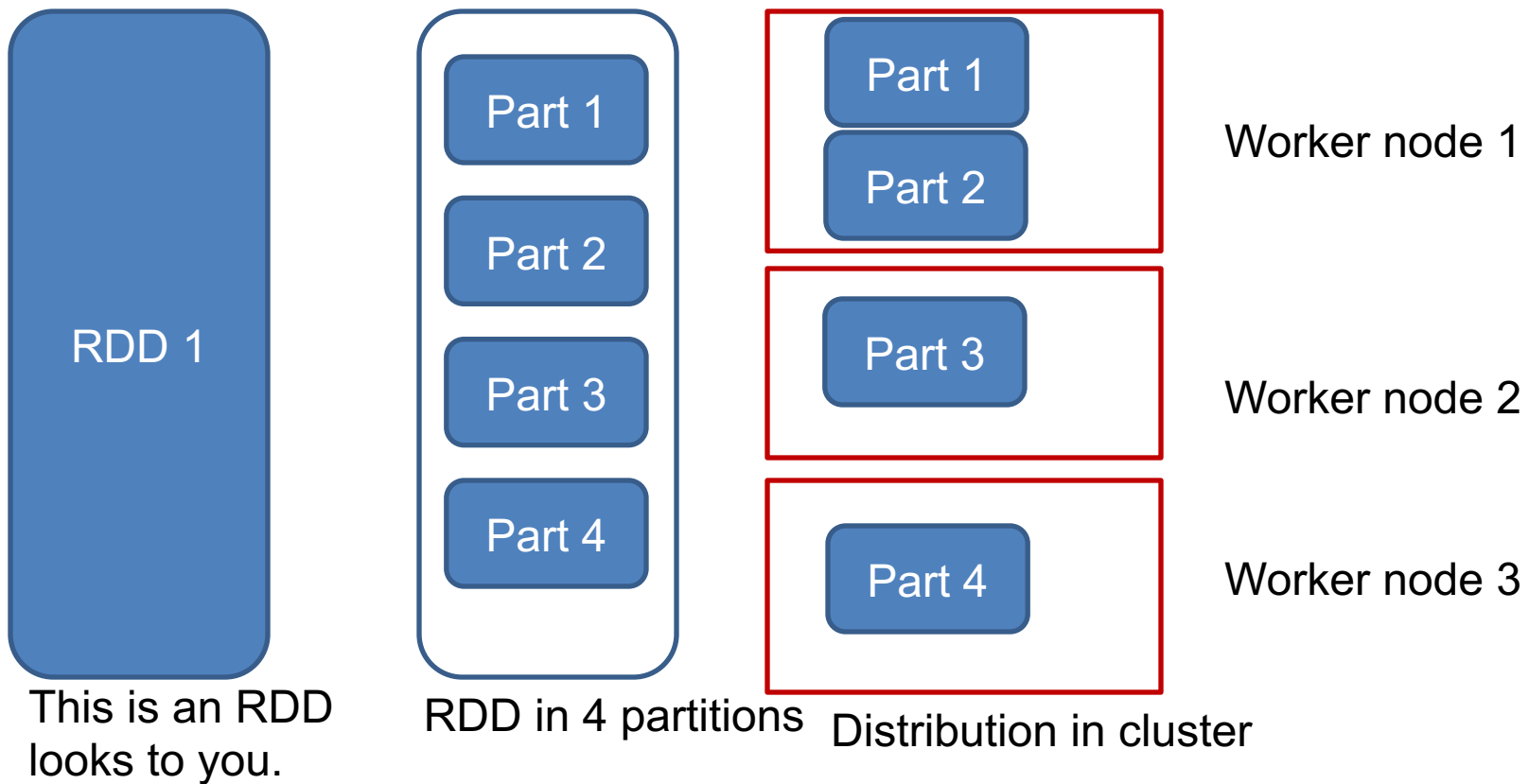
Immutable Collection of Objects

Partitioned and Distributed

Stored in Memory

Created lazily

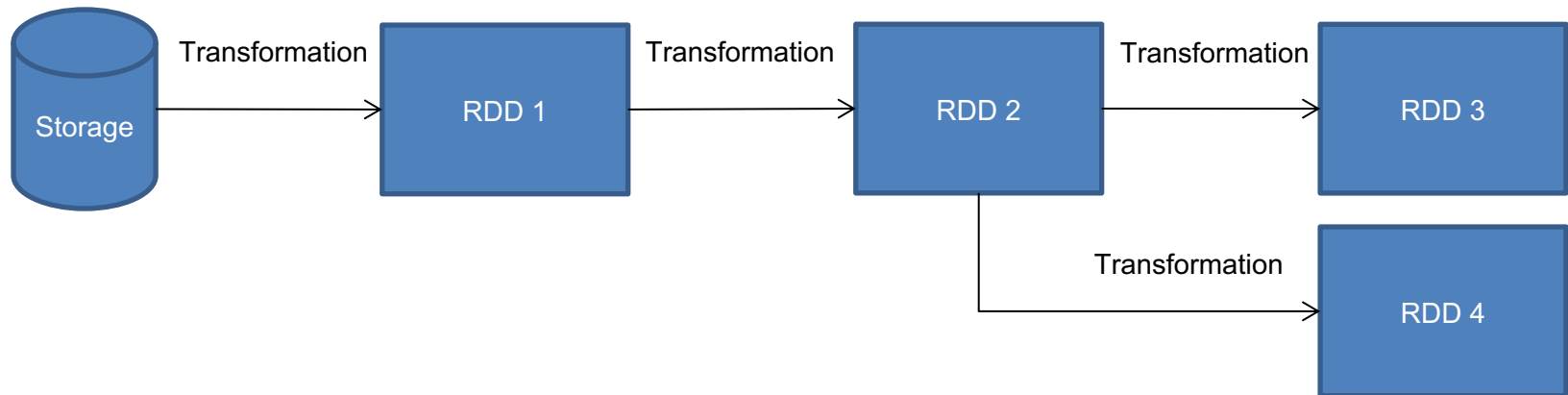
How RDD is stored as a distributed collection!



RDD intro (continued..)

- RDD can only be created through deterministic operations on either
 - data from stable storage
 - other RDDs
- RDD has enough information about how it was derived from other datasets (its lineage) to compute its partitions from data in stable storage.

Example of RDD lineage



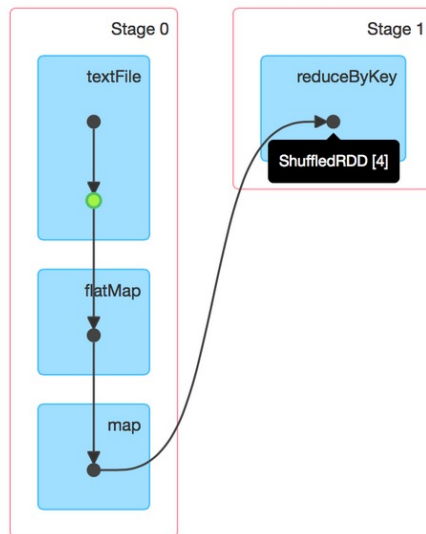
The information of the **lineage** of an RDD is saved as a **DAG** (directed acyclic graph) and used to create RDD when needed or re-create RDD partitions in case of a failure of a node.

DAG demystified

Details for Job 0

Status: SUCCEEDED
Completed Stages: 2

- ▶ Event Timeline
- ▼ DAG Visualization



- In theory DAG is a directed graph with no cycles.
- DAG (Directed Acyclic Graph) is a programming style for distributed systems.
- While MapReduce has two steps (map and reduce), DAG can have multiple levels that can form a tree structure.
- Apache TEZ which came after MapReduce implemented the same programming model.

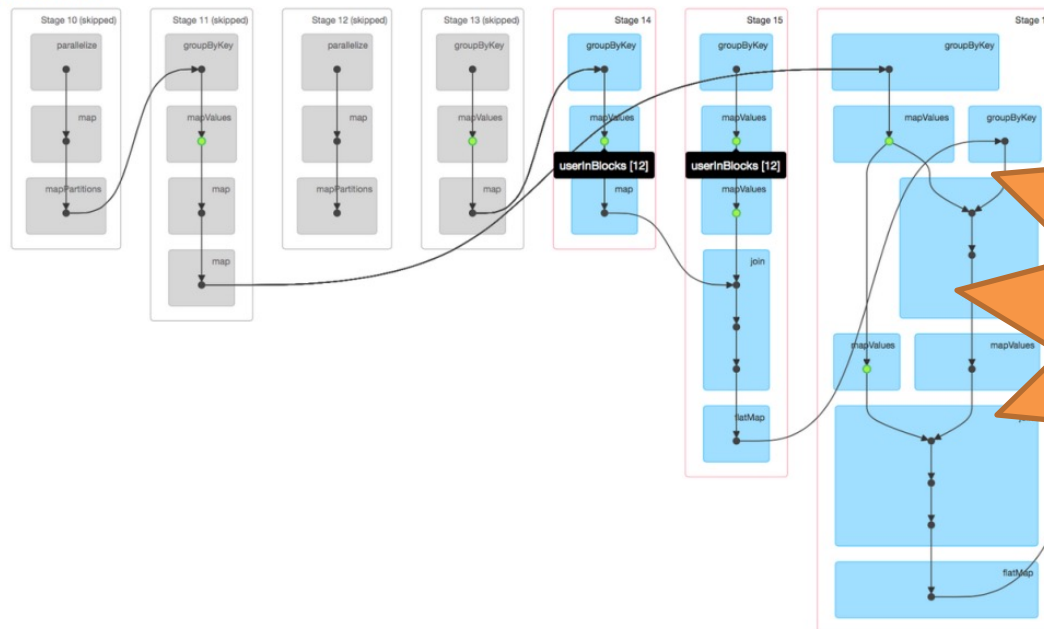


Some Complex DAGs

Details for Job 4

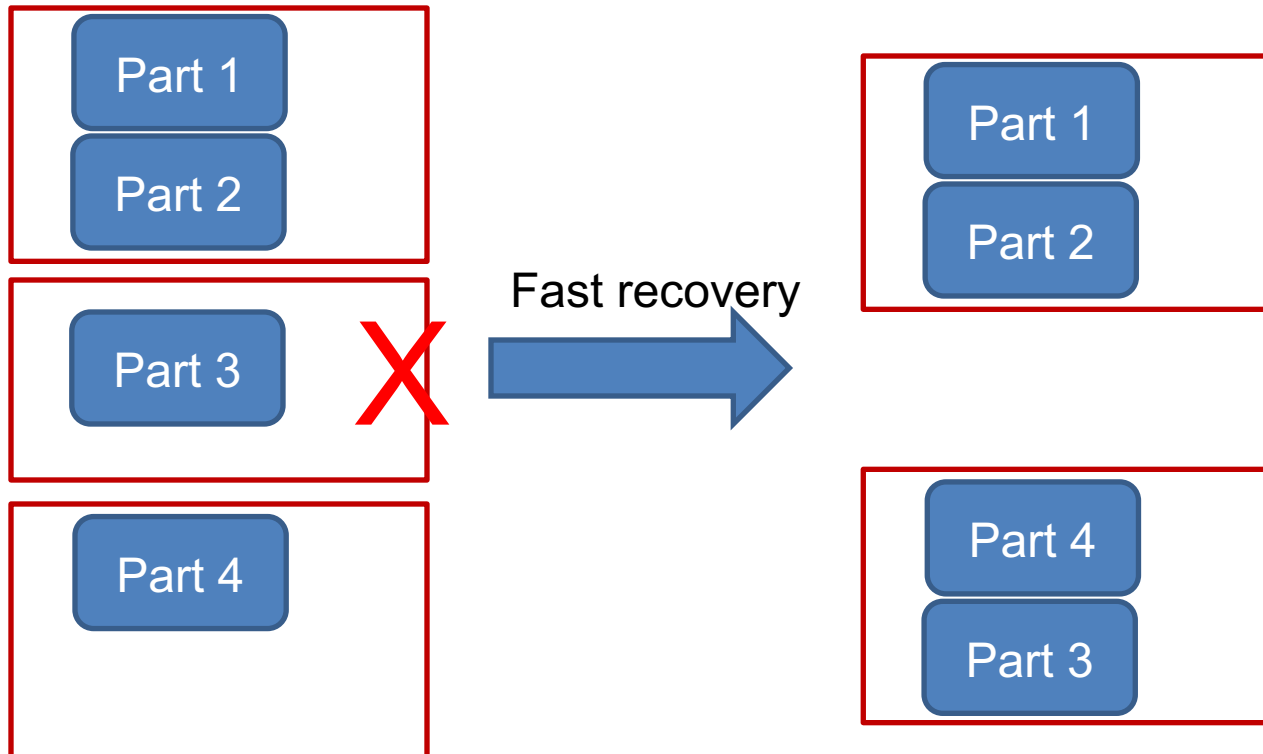
Status: SUCCEEDED
Completed Stages: 22
Skipped Stages: 4

- ▶ Event Timeline
- ▼ DAG Visualization



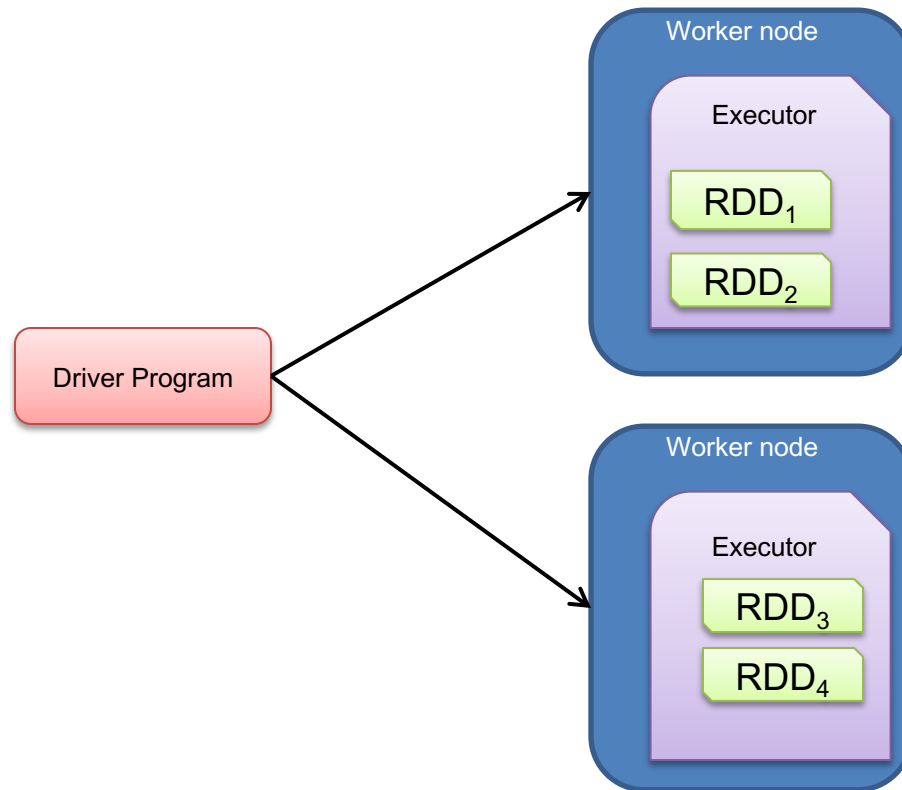
Don't Worry
SPARK
Engine takes
care of this.

RDD (fault tolerance)



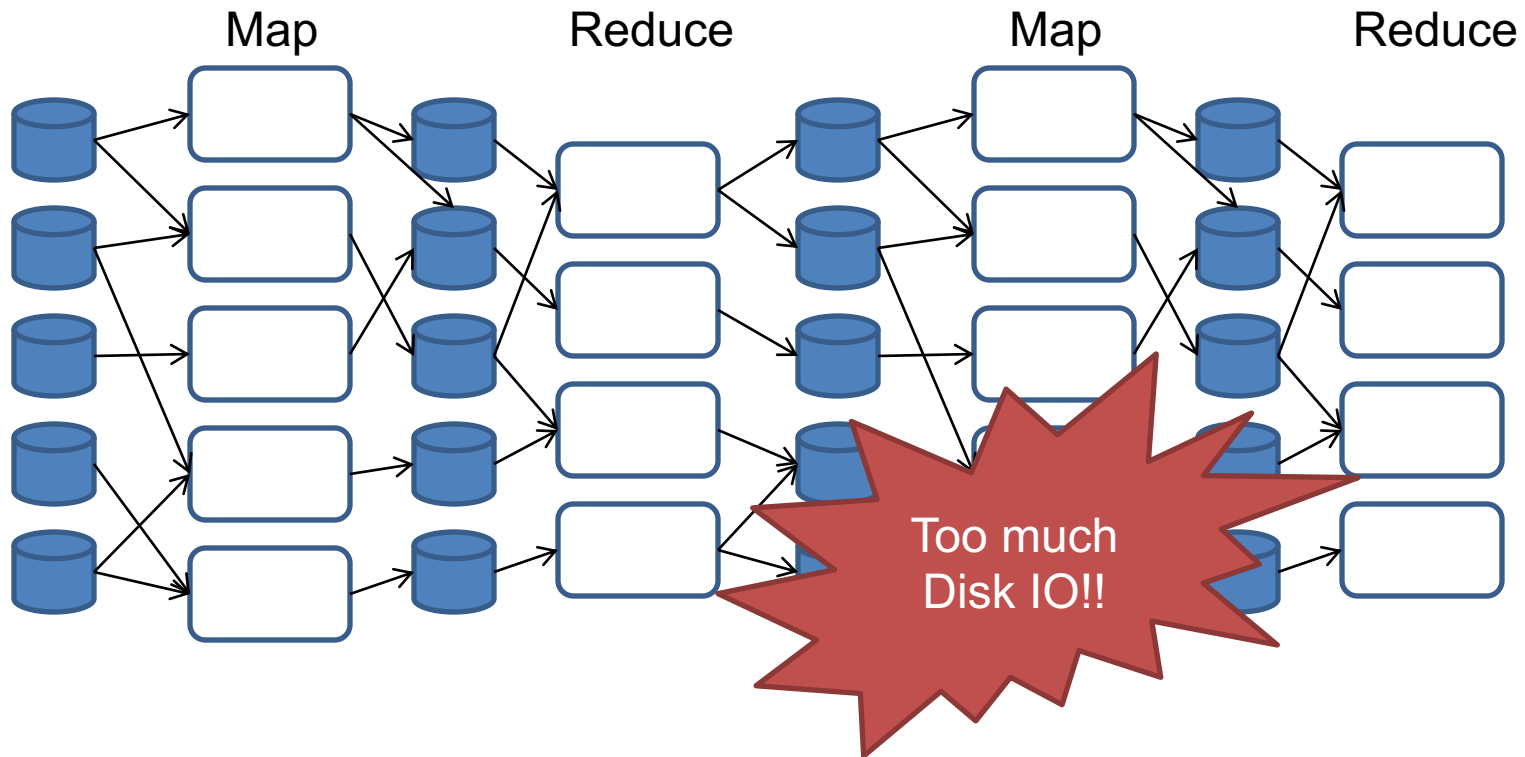
In case of failure: suppose the worker node 2 having the partition 3 crashes then only the lost RDDs partition need to be recreated and it can be easily done using the lineage information.

RDD (parallelism)

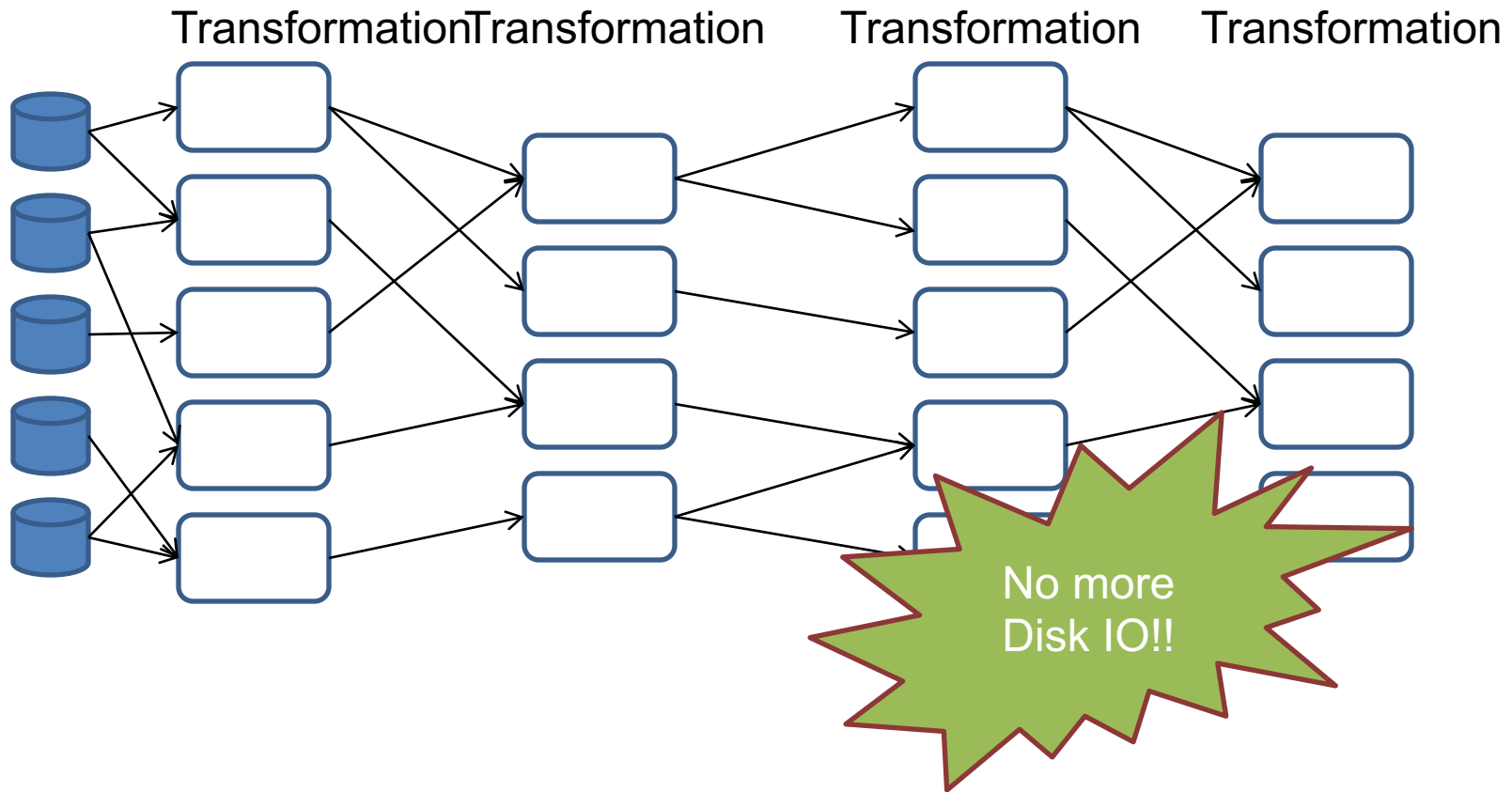


More Partition == More parallelism

Hadoop



Spark



RDD (continued..)

An RDD can be created by 2 ways

- I. Parallelize a collection
- II. Read data from external source

Parallelize

- Take an existing in-memory collection and pass it to Spark Context's `parallelize` method.
- The in-memory collection is created at the driver program and then the data is partitioned and shipped to the executors in the worker node.
- Used mostly for prototyping and not in production.
- Example: `fruitRDD= sc.parallelize(["apple", "banana", "mango"])`

External data source

- Read from a textFile
 - `localRDD= sc.textFile("/path_to_file")`
 - `hdfsRDD = sc.textFile("hdfs://...")`
- Specific APIs for different data source has been developed.

Types of RDD

There are many types of RDDs:

- `ParallelCollectionRDD`: is the result of `SparkContext.parallelize`
- `HadoopRDD`: is an RDD that provides core functionality for reading data stored in HDFS using the older MapReduce API. The most notable use case is the return RDD of `SparkContext.textFile`.
- `MapPartitionsRDD`: a result of calling operations like `map`, `flatMap`, `filter`, `mapPartitions`, etc.
- `CoalescedRDD`: a result of repartition or coalesce transformations.
- `ShuffledRDD`: a result of shuffling, e.g. after repartition or coalesce transformations.
- `PairRDD` (implicit conversion by `PairRDDFunctions`) that is an RDD of key-value pairs that is a result of `groupByKey` and `join` operations.
- ..

RDD interface

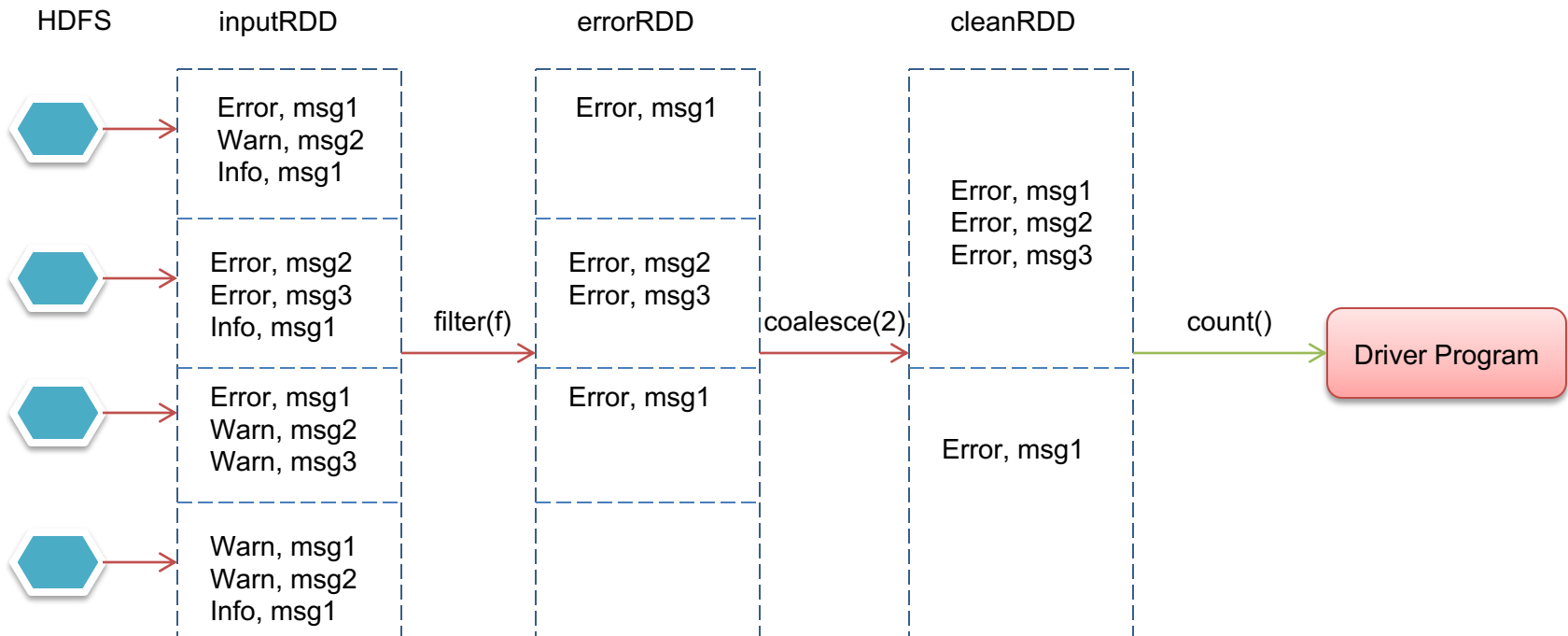
An RDD has 5 main attributes:

1. Set of partitions: Atomic pieces of data
2. List of dependencies on parent RDDs
3. Function to compute a partition given parents
4. Preferred location (optional metadata)
5. Partitioning information.

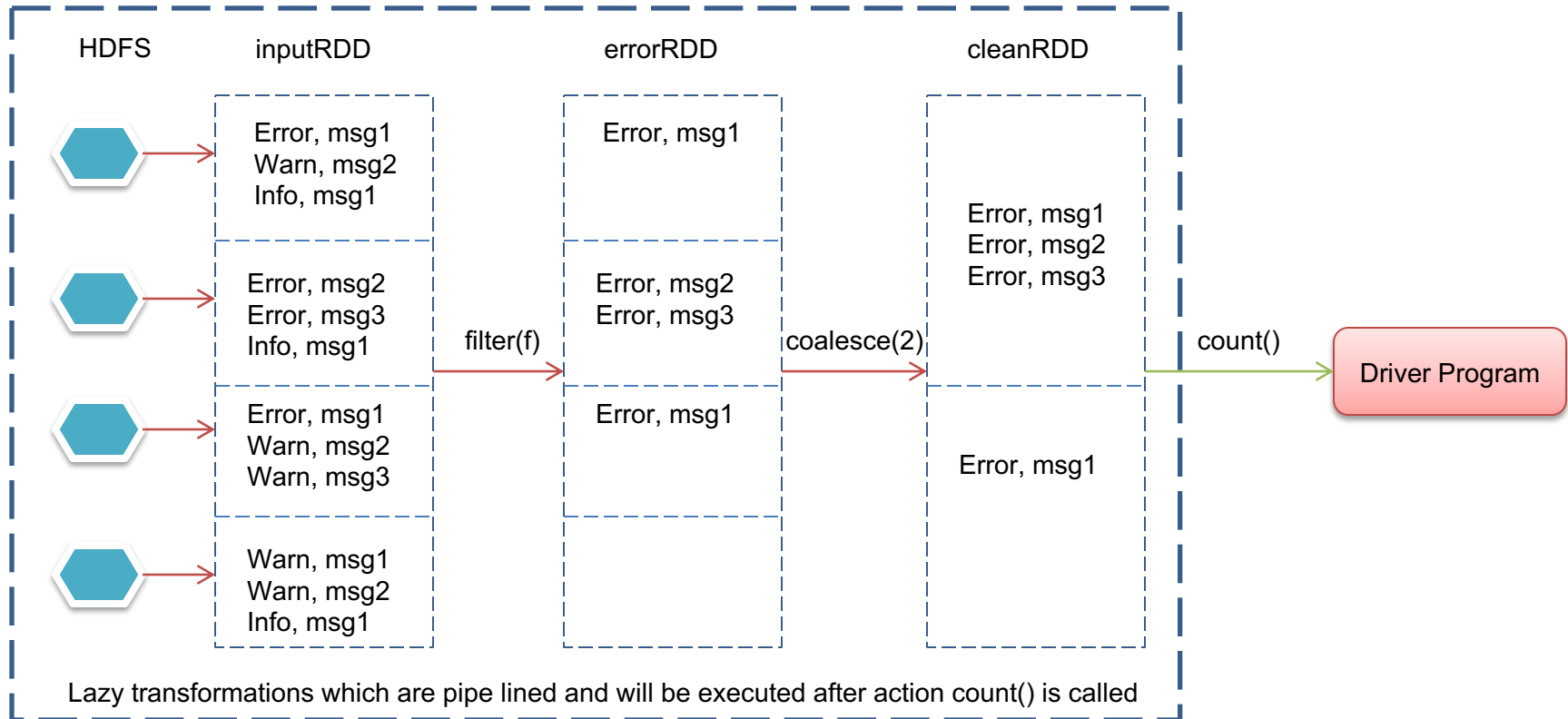
RDD transformations

- RDD transformations are **lazy** i.e. when a transformation happens only the lineage is updated and no physical execution happens.
- Only after an **action** is called the whole thing plays out.

RDD transformations



RDD transformations





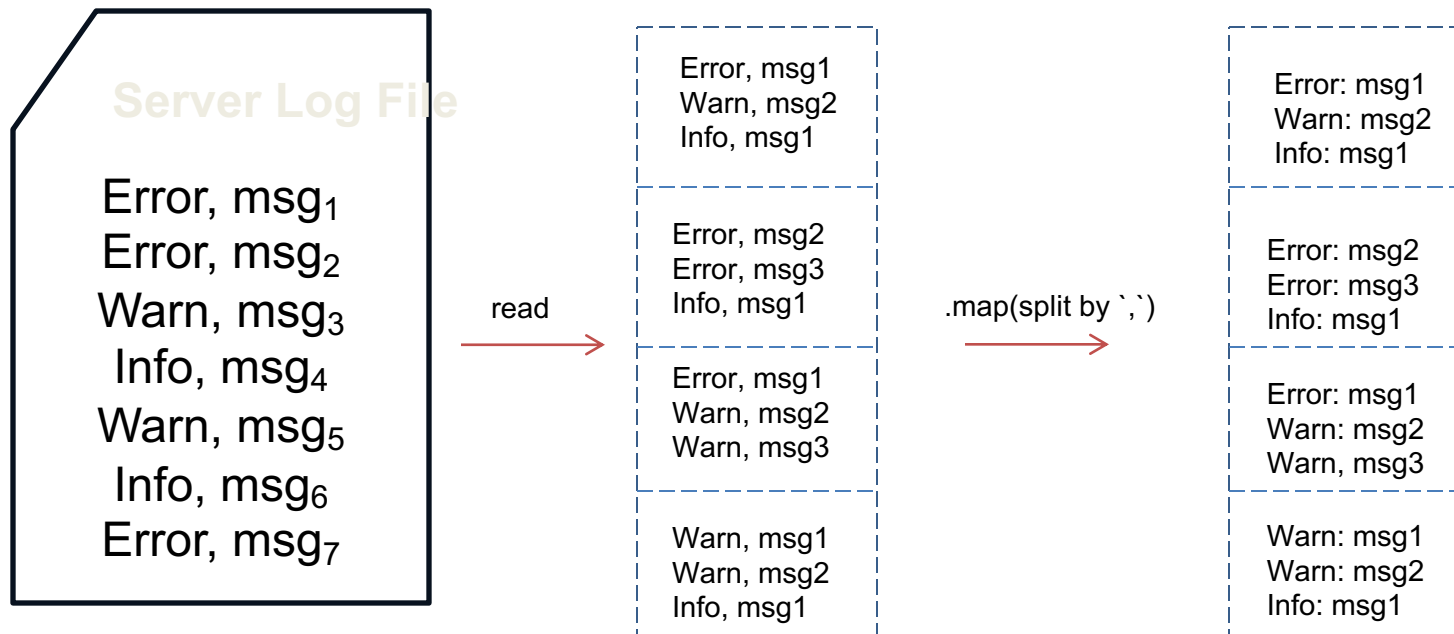
Simple RDD transformations

Transformation	Meaning
<code>map(func)</code>	Return a new distributed dataset formed by passing each element of the source through a function <code>func</code> .
<code>filter(func)</code>	Return a new dataset formed by selecting those elements of the source on which <code>func</code> returns true.
<code>flatMap(func)</code>	Similar to <code>map</code> , but each input item can be mapped to 0 or more output items (so <code>func</code> should return a <code>Seq</code> rather than a single item).
<code>mapPartitions(func)</code>	Similar to <code>map</code> , but runs separately on each partition (block) of the RDD, so <code>func</code> must be of type <code>Iterator<T> => Iterator<U></code> when running on an RDD of type <code>T</code> .
<code>sample(withReplacement, fraction, seed)</code>	Sample a fraction of the data, with or without replacement, using a given random number generator <code>seed</code> .
<code>union(otherDataset)</code>	Return a new dataset that contains the union of the elements in the source dataset and the argument.
<code>intersection(otherDataset)</code>	Return a new RDD that contains the intersection of elements in the source dataset and the argument.
<code>distinct([numTasks])</code>	Return a new dataset that contains the distinct elements of the source dataset.

Key Value : pairRDD

“Spark provides special type of operations on RDDs containing key/value pairs. These RDDs are called pair RDDs. Pair RDDs are very useful in data analytical tasks, as they provide operations that allows to act on each key operations in parallel or regroup data across the network.”

Key Value : pairRDD



Transformations on pairRDD

Transformation	Meaning
<code>groupByKey([numTasks])</code>	When called on a dataset of (K, V) pairs, returns a dataset of (K, Iterable<V>) pairs.
<code>reduceByKey(func, [numTasks])</code>	When called on a dataset of (K, V) pairs, returns a 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. Like in <code>groupByKey</code> , the number of reduce tasks is configurable through an optional second argument.
<code>aggregateByKey(zeroValue)(seqOp, combOp, [numTasks])</code>	When called on a dataset of (K, V) pairs, returns a dataset of (K, U) pairs where the values for each key are aggregated using the given combine functions and a neutral "zero" value. Allows an aggregated value type that is different than the input value type, while avoiding unnecessary allocations. Like in <code>groupByKey</code> , the number of reduce tasks is configurable through an optional second argument.
<code>sortByKey([ascending], [numTasks])</code>	When called on a dataset of (K, V) pairs where K implements Ordered, returns a dataset of (K, V) pairs sorted by keys in ascending or descending order, as specified in the boolean ascending argument.
<code>join(otherDataset, [numTasks])</code>	When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key. Outer joins are supported through <code>leftOuterJoin</code> , <code>rightOuterJoin</code> , and <code>fullOuterJoin</code> .
<code>cogroup(otherDataset, [numTasks])</code>	When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (Iterable<V>, Iterable<W>)) tuples. This operation is also called <code>groupWith</code> .



Transformation leading to repartition of data

Transformation	Meaning
<code>coalesce(numPartitions)</code>	Decrease the number of partitions in the RDD to numPartitions. Useful for running operations more efficiently after filtering down a large dataset.
<code>repartition(numPartitions)</code>	Reshuffle the data in the RDD randomly to create either more or fewer partitions and balance it across them. This always shuffles all data over the network.

Note: Repartitioning is necessary some time for better performance but should be carefully used.



RDD Actions

Transformation	Meaning
<code>reduce(func)</code>	Aggregate the elements of the dataset using a function <code>func</code> (which takes two arguments and returns one). The function should be commutative and associative so that it can be computed correctly in parallel.
<code>collect()</code>	Return all the elements of the dataset as an array at the driver program. This is usually useful after a filter or other operation that returns a sufficiently small subset of the data.
<code>count()</code>	Return the number of elements in the dataset.
<code>first()</code>	Return the first element of the dataset (similar to <code>take(1)</code>).
<code>take(n)</code>	Return an array with the first <code>n</code> elements of the dataset.
<code>takeSample(withReplacement, num, [seed])</code>	Return an array with a random sample of <code>num</code> elements of the dataset, with or without replacement, optionally pre-specifying a random number generator seed.
<code>takeOrdered(n, [ordering])</code>	Return the first <code>n</code> elements of the RDD using either their natural order or a custom comparator.

RDD Actions

Transformation	Meaning
<code>saveAsTextFile(path)</code>	Write the elements of the dataset as a text file (or set of text files) in a given directory in the local filesystem, HDFS or any other Hadoop-supported file system. Spark will call <code>toString</code> on each element to convert it to a line of text in the file.
<code>countByKey()</code>	Only available on RDDs of type (K, V). Returns a hashmap of (K, Int) pairs with the count of each key.
<code>foreach(func)</code>	Run a function <code>func</code> on each element of the dataset. This is usually done for side effects such as updating an Accumulator or interacting with external storage systems.



IPython Notebook

- Run the spark jupyter notebook using the image
jupyter/all-spark-notebook
- Try the notebook Lab1

References

- Spark in Action
- <https://spark.apache.org/docs/latest/programming-guide.html>
- <https://spark.apache.org/docs/latest/cluster-overview.html>
- Spark: Cluster Computing with Working Sets
- Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing