Introduction to Spark

Introduction to Spark
Game Plan

- Background
- Spark Versus Hadoop MapReduce
- Spark Architecture/Basics
- Introduction To Functional Programming
- Lazy Evaluation
- Persist/Cache

Introduction to Spark

Goals

- Describe the advantages/disadvantages of Spark compared to Hadoop MapReduce

- Define what an RDD is, and the difference between a transformation and action on an RDD

- Describe what persisting/caching an RDD means, and a situation in which we might want to persist or cache an RDD

Background

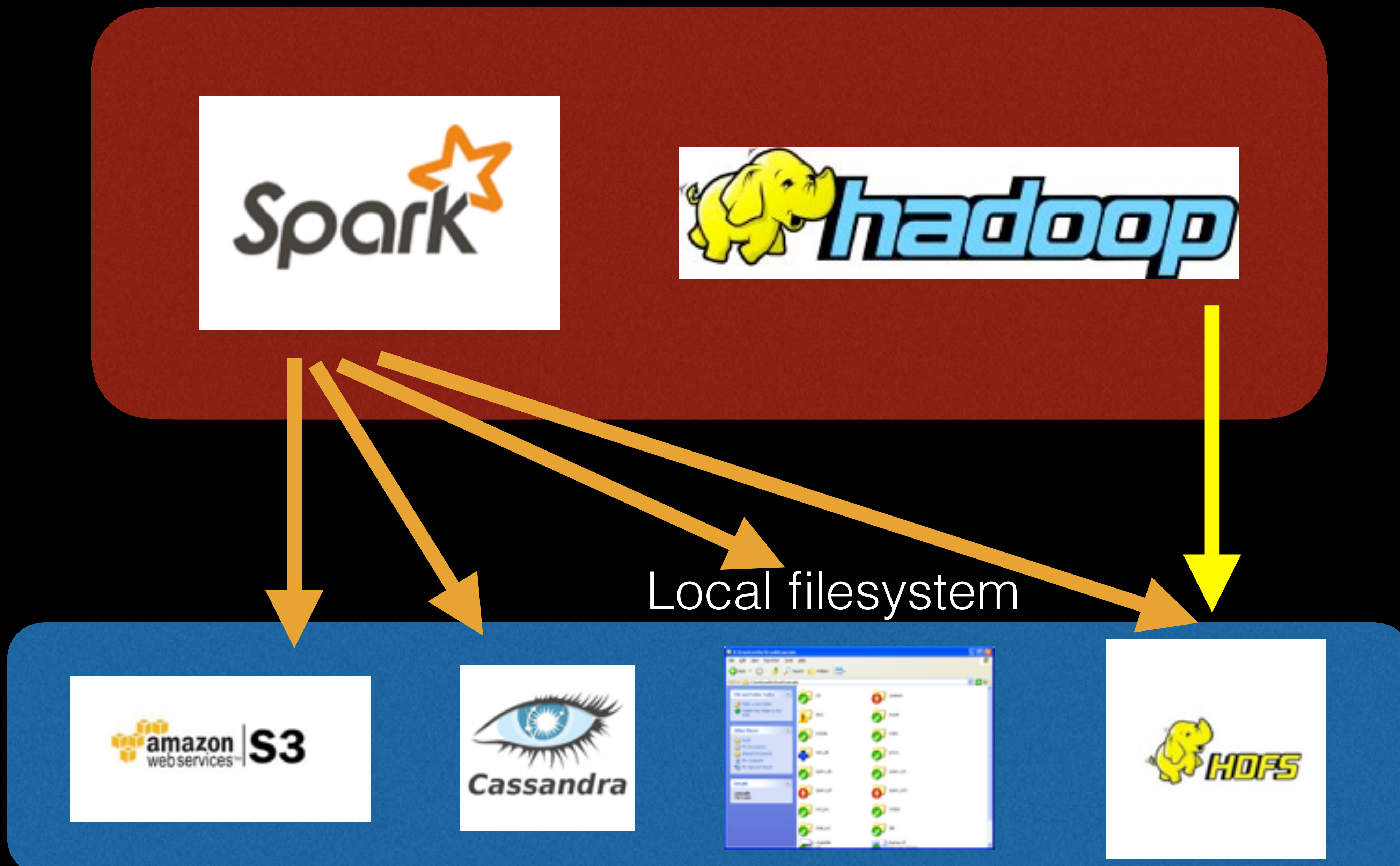
- First release: v0.7 on Feb, 2013)
- v1.3: Released April 17th, 2015

  Added DataFrame capabilities
- v1.5.2: Released Nov. 9th, 2015

  Added/Upgraded MLlib functionality

  Upgraded Hadoop integrations
- Founded by AMPLab, UC Berkeley

Spark v. MapReduce
Round 1: Storage Compatibility



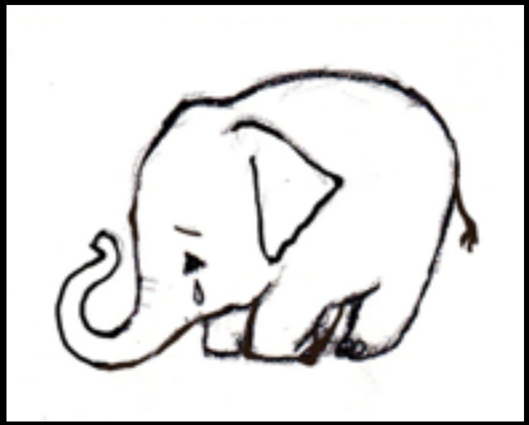
Spark v. MapReduce
Round 1: Storage Compatibility

- **Spark**

  Can be built on top of any filesystem

- **Hadoop MapReduce**

  Must be built on top of HDFS



Spark v. MapReduce
Round 2: Speed

Spark:

- Can be up to 100x faster than Hadoop MapReduce in memory, and 10x faster on disk. It does, however, use **lots** of memory. Spark keeps everything in memory when possible.

Hadoop MapReduce:

- Writes data to disk after each map step, and after each reduce step. This I/O is very costly in terms of performance, especially for iterative algorithms.

Spark v. MapReduce
Round 3: Reliability

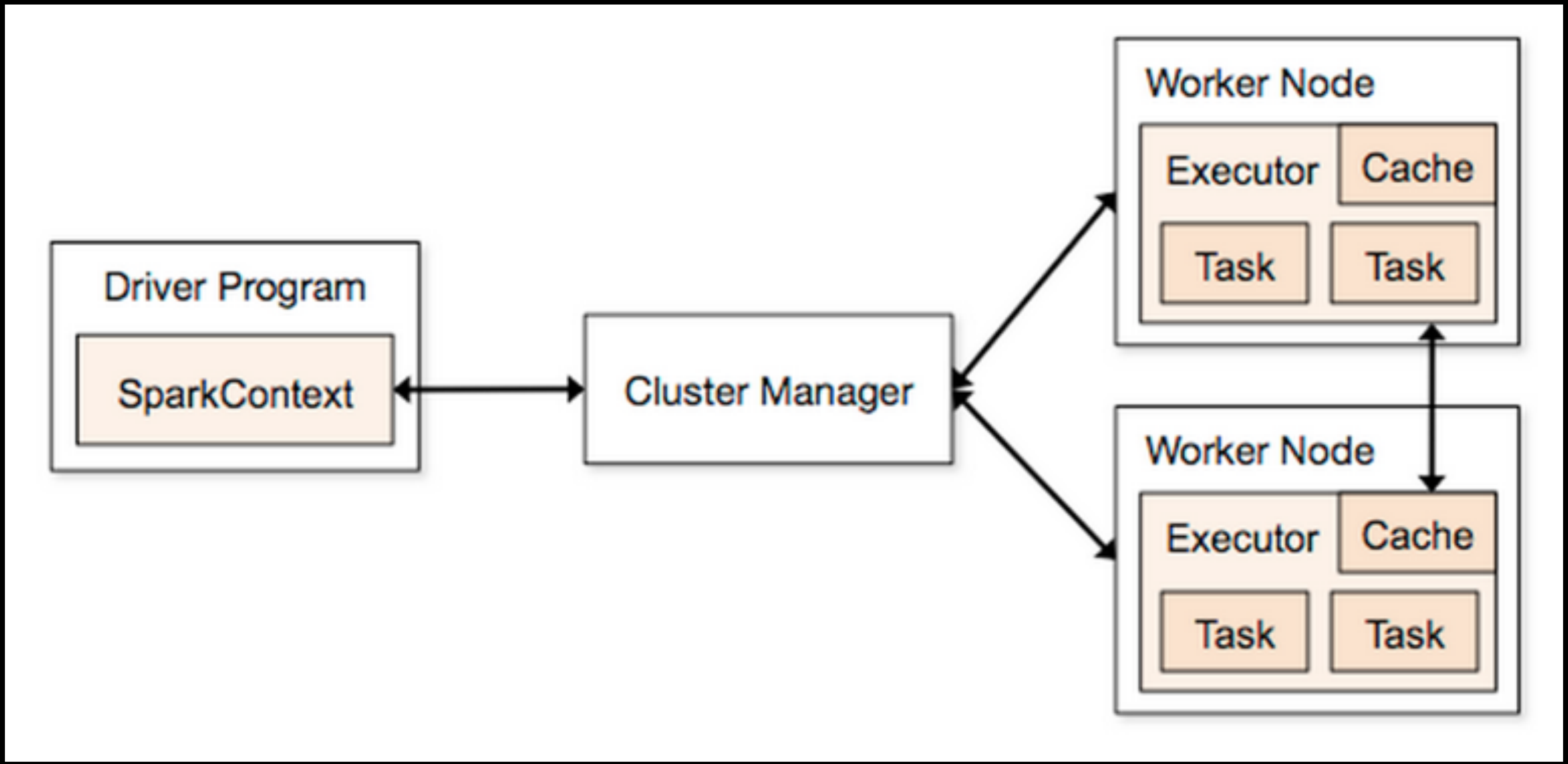
Spark:

While Spark hasn't been around as long and is still working out its bugs, it is currently one of the most actively developed projects, with ~400 active contributors.

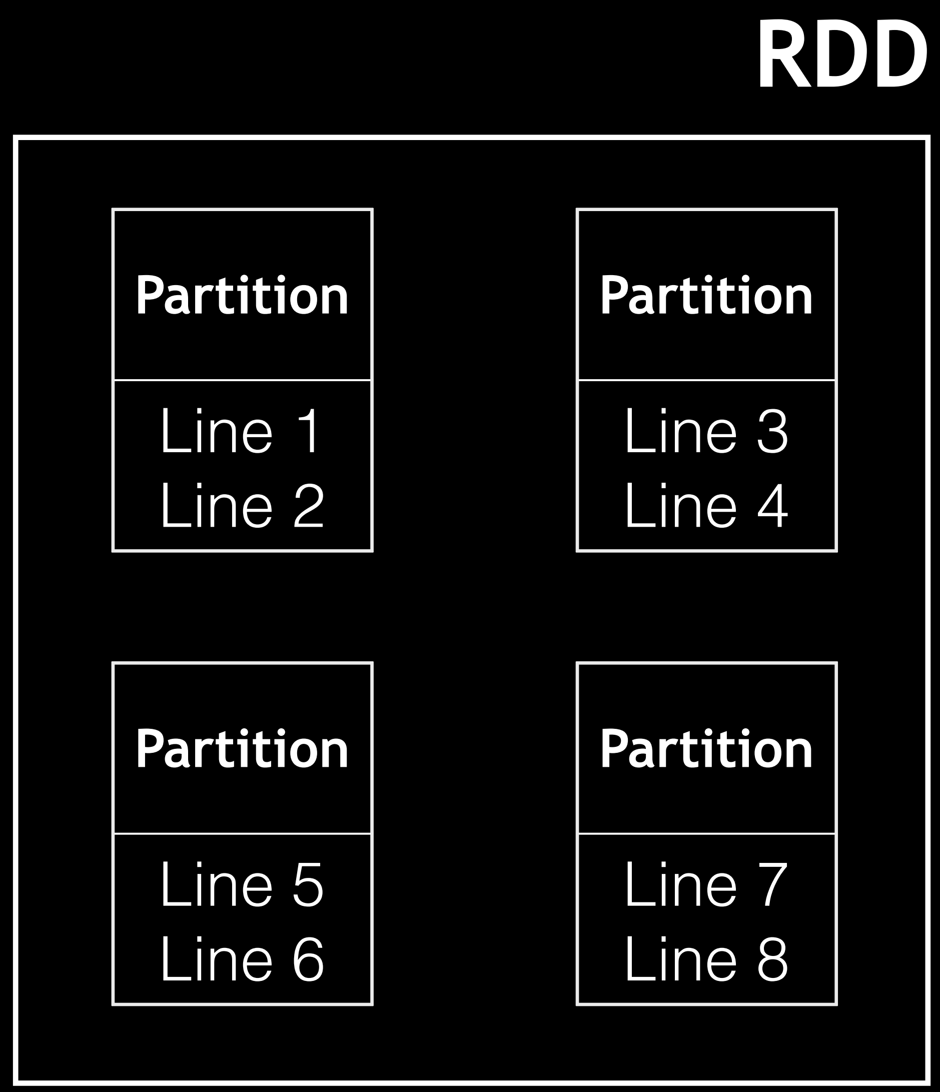
Hadoop MapReduce:

Is roughly 10 years older than Spark, and was built on the premise of scalability and reliability. A lot of tools have been built on top of the Hadoop MapReduce framework.

Spark Architecture



Spark Core:
Resilient Distributed Dataset (RDD)



Spark's RDDs will hold our data and will be what we interact with to process our data.

Spark Client / Spark Context

- We need some way to interact with Spark…

  IPython / IPython Notebook can be a **client** to **interact with the master**

- The client will have a SparkContext that…

  1.) Acts as a gateway between the client and Spark master

  2.) Sends code/data from IPython to the master (who then sends it to the workers)

Starting a cluster Locally

- The following starts a cluster with only the driver, using all 4 cores (similar to multiprocessing)

```
import pyspark as ps
sc = ps.SparkContext('local[4]')
```

- Simplest way to start a cluster - can be useful to test code really quickly and work out kinks

Starting a cluster Locally

- Start a master node:

```
${SPARK_HOME}/bin/spark-class \
org.apache.spark.deploy.master.Master \
-h 127.0.0.1 \
-p 7077 \
—webui-port 8080
```

Domain to run master on

Port to run master on

Port to run web UI on

- Start a worker node:

```
${SPARK_HOME}/bin/spark-class \
org.apache.spark.deploy.worker.Worker \
-c 1 \
-m 1G \
spark://127.0.0.1:7077
```

Worker assigned 1 core

Worker assigned 1G RAM

Master URI to link to

- Useful for testing on a realistic cluster, before deploying and using valuable resources

Create an RDD

- Created from a SparkContext (sc) in one of two ways:

```
1.) Parallelize an existing collection
of objects in your program:

   rdd = sc.parallelize([1, 3, 4, 5,6])


2.) Read in an external data set:

   rdd = sc.textFile('path/to/file')
```

Functional Programming

- Spark's RDD's operate within a functional programming paradigm…

  This means that RDDs are immutable, and that when we apply a function to an RDD, it will create a new RDD and return that to us (rather than modifying the RDD in place).

- How do functions get applied to the RDD?

  Functions are passed from the client to the master, who then distributes them to workers, who apply them across their partitions of the RDD.

Two types of functions

1.) Transformations:

Return a new RDD

2.) Actions:

Return a final value or collection of values

Two types of functions

1.) Transformations:

```
map()           groupByKey()
flatMap()       filter()
sortBy()        reduceByKey()
join()
```

2.) Actions:

```
first()         countByKey()
take()          collect()
count()         saveAsTextFile()
reduce()
```

Lazy Evaluation

Very Important

- **Transformations are not run** when you run the command
- **Only actions** will cause transformations to be run (all transformations prior to that action will be run)

Persisting/Caching

- **Explicitly keep an RDD in memory**

- Used if you have an RDD that is or will be used for different operations many times

Persisting/Caching

rdd.setName(name)
rdd.persist()

OR

rdd.setName(name)
rdd.cache()

- .cache() uses the default storage level MEMORY_ONLY, while .persist() gives you the option to specify the storage level

Types of Caching

```
from pyspark.storagelevel import StorageLevel

rdd.setName(name)
rdd.persist(StorageLevel.MEMORY_ONLY)
```

Storage Level	Meaning
MEMORY_ONLY	Store RDD as deserialized Java objects in the JVM. If the RDD does not fit in memory, some partitions will not be cached and will be recomputed on the fly each time they're needed. This is the default level.
MEMORY_AND_DISK	Store RDD as deserialized Java objects in the JVM. If the RDD does not fit in memory, store the partitions that don't fit on disk, and read them from there when they're needed.
MEMORY_ONLY_SER	Store RDD as *serialized* Java objects (one byte array per partition). This is generally more space-efficient than deserialized objects, especially when using a fast serializer, but more CPU-intensive to read.
MEMORY_AND_DISK_SER	Similar to MEMORY_ONLY_SER, but spill partitions that don't fit in memory to disk instead of recomputing them on the fly each time they're needed.
DISK_ONLY	Store the RDD partitions only on disk.

Persisting/Caching

- Caching will only take place **when an action is performed**

- Can also do **rdd.unpersist()** to free memory

Spark In Practice

- Set up master / workers
- Open up UI at **domain:8080** (e.g. **localhost:8080**)
- Attach IPython client to master
- Load data in and start data manipulation
- Track UI as you execute your commands

Spark In Practice

Spark 1.3.1 Jobs Stages Storage Environment Executors PySparkShell a

Details for Stage 1

Total task time across all tasks: 5 s
Input Size / Records: 75.4 MB / 5904

▸ **Show additional metrics**

Summary Metrics for 4 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	0.5 s	0.8 s	0.8 s	3 s	3 s
GC Time	0 ms	0 ms	0 ms	0.1 s	0.1 s
Input Size / Records	139.0 B / 1	24.2 MB / 1957	25.2 MB / 1962	26.0 MB / 1984	26.0 MB / 1984

Aggregated Metrics by Executor

Executor ID	Address	Task Time	Total Tasks	Failed Tasks	Succeeded Tasks	Input Size / Records
0	10.3.35.25:58445	3 s	1	0	1	26.0 MB / 1957
1	10.3.35.25:58444	2 s	3	0	3	49.4 MB / 3947

Tasks

Index	ID	Attempt	Status	Locality Level	Executor ID / Host	Launch Time	Duration	GC Time	Input Size / Records
0	1	0	SUCCESS	PROCESS_LOCAL	1 / 10.3.35.25	2015/06/03 19:37:31	0.8 s		25.2 MB (hadoop) / 1984