COMP9313: Big Data Management

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Course web site: http://www.cse.unsw.edu.au/~cs9313/

Chapter 4.2: Spark II

Part 1: Programming with RDD

SparkContext

- SparkContext is the entry point to Spark for a Spark application.
- Once a SparkContext instance is created you can use it to
  - Create RDDs
  - Create accumulators
  - Create broadcast variables
  - access Spark services and run jobs
- A Spark context is essentially a client of Spark's execution environment and acts as the *master of your Spark application*
- The first thing a Spark program must do is to create a SparkContext object, which tells Spark how to access a cluster
- In the Spark shell, a special interpreter-aware SparkContext is already created for you, in the variable called *sc*

Spark Key-Value RDDs

- Similar to Map Reduce, Spark supports Key-Value pairs
- Each element of a *Pair RDD* is a pair tuple
- Spark supports data partitioning control for pair RDDs
- Some Key-Value transformation functions:

Key-Value Transformation	Description
`reduceByKey(`*`func`*`)`	return a new distributed 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
`sortByKey()`	return a new dataset (K,V) pairs sorted by keys in ascending order
`groupByKey()`	return a new dataset of (K, Iterable<V>) pairs

Pair RDD Example (Transformation)

- Transformations on one pair RDD rdd = {(1, 2), (3, 4), (3, 6)}

Name	Purpose	Example	Result
reduceByKey(func)	Combine values with the same key	rdd.reduceByKey(lambda x, y: x+y)	[(1, 2), (3, 10)]
groupByKey()	Group values with the same key	rdd.groupByKey()	[(1, [2]), (3, [4, 6])]
mapValues(func)	Apply a function to each value of a pair RDD without changing the key	rdd.mapValues(la mbda x: x+1)	[(1, 3), (3, 5), (3, 7)]
keys()	Return an RDD of just the keys	rdd.keys()	[1, 3, 3]
values()	Return an RDD of just the values	rdd.values()	[2, 4, 6]
sortByKey()	Return an RDD sorted by the key	rdd.sortByKey()	[(1, 2), (3, 4), (3, 6)]

Pair RDD Example (Transformation)

- Transformations on two pair RDDs rdd1 = {(1, 2), (3, 4), (3, 6)} and rdd2 = {(3, 9)})

Name	Purpose	Example	Result
subtractByKey	Remove elements with a key present in the other RDD	rdd1.subtractByKey (rdd2)	[(1, 2)]
join	Perform an inner join between two RDDs	rdd1.join(rdd2)	[(3, (4, 9)), (3, (6, 9))]
cogroup	Group data from both RDDs sharing the same key	rdd1.cogroup(rdd2)	[(1,([2],[])), (3, ([4, 6],[9]))]

Pair RDD Example (Actions)

- Actions on one pair RDD rdd = ({(1, 2), (3, 4), (3, 6)})

Name	Purpose	Example	Result
countByKey()	Count the number of elements for each key	rdd.countByKey()	[(1, 1), (3, 2)]
collectAsMap()	Collect the result as a map to provide easy lookup	rdd.collectAsMap()	{1: 2, 3: 6}
lookup(key)	Return all values associated with the provided key	rdd.lookup(3)	[4, 6]

Setting the Level of Parallelism

- All the pair RDD operations take an optional second parameter for number of tasks
  - `words.reduceByKey(lambda x, y: x+y, 5)`
  - `words.groupByKey(5)`

A Few Practices on Pair RDD

```
lines = sc.parallelize(["hello world", "this is a scala program", "to create a pair RDD", "in spark"])
pairs = lines.map(lambda x: (x.split(" ")[0], x))
pairs.filter(lambda x: len(x[0])<3).collect()
```

```
>>> pairs.filter(lambda x: len(x[0])<3).collect()
[('to', 'to create a pair RDD'), ('in', 'in spark')]
```

```
pairs = sc.parallelize([(1, 2), (3, 1), (3, 6), (4,2)])
pairs1 = pairs.mapValues(lambda x: (x, 1))
pairs2 = pairs1.reduceByKey(lambda x, y: (x[0] + y[0], x[1]+y[1]))
pairs2.foreach(lambda x: print(x))
```

```
(1, (2, 1))
(3, (7, 2))
(4, (2, 1))
```

Passing Functions to RDD

- Spark's API relies heavily on passing functions in the driver program to run on the cluster.
  - Anonymous function. E.g.,
    - words = input.flatMap(lambda line: line.split(" "))
  - An explicitly defined function

Understanding Closures

- RDD operations that modify variables outside of their scope can be a frequent source of confusion.
- The result could be different when running Spark in local mode (--master = local[n]) versus deploying a Spark application to a cluster (e.g. via spark-submit to YARN):

```
counter = 0
rdd = sc.parallelize(data)
rdd.foreach(lambda x: counter += x)
print("Counter value: " + counter)
```

  - The behavior of the above code is undefined, and may not work as intended.
  - Spark sends the closure to each task containing variables must be visible to the executors. Thus “counter” in the executor is only a copy of the “counter” in the driver.

Using Local Variables

- Any external variables you use in a closure will automatically be shipped to the cluster:
  - `query = sys.stdin.readline()`
  - `pages.filter(lambda x: query in x).count()`

- Some caveats:
  - Each task gets a new copy (updates aren't sent back)
  - Variable must be Serializable

Shared Variables

- When you perform transformations and actions that use functions (e.g., map(f: T=>U)), Spark will automatically push a closure containing that function to the workers so that it can run at the workers.
- Any variable or data within a closure or data structure will be distributed to the worker nodes along with the closure
- When a function (such as map or reduce) is executed on a cluster node, it works on **separate** copies of all the variables used in it.
- Usually these variables are just constants but they cannot be shared across workers efficiently.

Shared Variables

- Consider These Use Cases
  - Iterative or single jobs with large global variables
    - Sending large read-only lookup table to workers
    - Sending large feature vector in a ML algorithm to workers
    - Problems? Inefficient to send large data to each worker with each iteration
    - Solution: Broadcast variables
  - Counting events that occur during job execution
    - How many input lines were blank?
    - How many input records were corrupt?
    - Problems? Closures are one way: driver -> worker
    - Solution: Accumulators

Broadcast Variables

- Broadcast variables allow the programmer to keep a read-only variable cached on each machine rather than shipping a copy of it with tasks.
  - For example, to give every node a copy of a large input dataset efficiently
- Spark also attempts to distribute broadcast variables using efficient broadcast algorithms to reduce communication cost
- Broadcast variables are created from a variable **v** by calling **SparkContext.broadcast(v)**. Its value can be accessed by calling the **value** method.

```
>>> broadcastVar = sc.broadcast([1, 2, 3])
<pyspark.broadcast.Broadcast object at 0x102789f10>
>>> broadcastVar.value
[1, 2, 3]
```

- The broadcast variable should be used instead of the value **v** in any functions run on the cluster, so that **v** is not shipped to the nodes more than once.

Accumulators

- Accumulators are variables that are only “added” to through an associative and commutative operation and can therefore be efficiently supported in parallel.
- They can be used to implement counters (as in MapReduce) or sums.
- Spark natively supports accumulators of numeric types, and programmers can add support for new types.
- Only driver can read an accumulator’s value, not tasks
- An accumulator is created from an initial value **v** by calling **SparkContext.accumulator(v)**.

```
>>> accum = sc.accumulator(0)
>>> accum
Accumulator<id=0, value=0>
>>> sc.parallelize([1, 2, 3, 4]).foreach(lambda x: accum.add(x))...
10/09/29 18:41:08 INFO SparkContext: Tasks finished in 0.317106 s
>>> accum.value
10
```

Accumulators Example

- Counting empty lines

```
file = sc.textFile(inputFile)
# Create Accumulator[Int] initialized to 0
blankLines = sc.accumulator(0)

def extractCallSigns(line):
        global blankLines # Make the global variable accessible
        if (line == ""):
                blankLines += 1
        return line.split(" ")

callSigns = file.flatMap(extractCallSigns)
print ("Blank lines: %d" % blankLines.value)
```

  - blankLines is created in the driver, and shared among workers
  - Each worker can access this variable

RDD Operations

Transformations	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	:	RDD[T] ⇒ RDD[U]
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	:	RDD[T] ⇒ RDD[T]
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	RDD[T] ⇒ RDD[U]
	$sample(fraction : \mathrm{Float})$	:	RDD[T] ⇒ RDD[T] (Deterministic sampling)
	$groupByKey()$	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V])]
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	$union()$	:	(RDD[T], RDD[T]) ⇒ RDD[T]
	$join()$	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (V, W))]
	$cogroup()$	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (Seq[V], Seq[W]))]
	$crossProduct()$	:	(RDD[T], RDD[U]) ⇒ RDD[(T, U)]
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	RDD[(K, V)] ⇒ RDD[(K, W)] (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	$partitionBy(p : \mathrm{Partitioner[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
Actions	$count()$	:	RDD[T] ⇒ Long
	$collect()$	:	RDD[T] ⇒ Seq[T]
	$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	:	RDD[T] ⇒ T
	$lookup(k : \mathrm{K})$	:	RDD[(K, V)] ⇒ Seq[V] (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	:	Outputs RDD to a storage system, *e.g.*, HDFS

Spark RDD API Reference（Python):
https://spark.apache.org/docs/latest/api/python/reference/api/pyspark.RDD.html?highlight=pyspark%20rdd

Spark


Steven Luscher
@steveluscher
Map/filter/reduce in a tweet:
map([🌽, 🐮, 🐔], cook)
=> [🍿, 🍔, 🍳]
filter([🍿, 🍔, 🍳], isVegetarian)
=> [🍿, 🍳]
reduce([🍿, 🍳], eat)
=> 💩
RETWEETS
6,472
LIKES
6,357

Part 2: Spark Programming Model (RDD)

How Spark Works

- User application create RDDs, transform them, and run actions.
- This results in a DAG (Directed Acyclic Graph) of operators.
- DAG is compiled into stages
- Each stage is executed as a series of Task (one Task for each Partition).

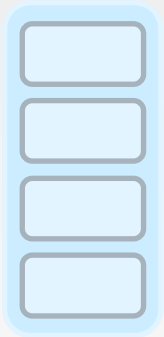
```
textfile = sc.textFile("hdfs://...", 4)

words = textfile.flatMap(lambda line: line.split(" "))
pairs = words.map(lambda word: (word, 1))
count = pairs.reduceByKey(lambda a, b: a + b)
count.collect()
```

Word Count in Spark

textfile = sc.textFile(“hdfs://…”, 4)

RDD[String]



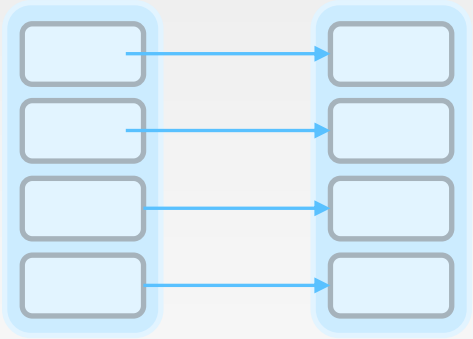
textFile

Word Count in Spark

```
textfile = sc.textFile("hdfs://…", 4)
words = text.flatMap(lambda line: line.split())
```

RDD[String]

RDD[List[String]]



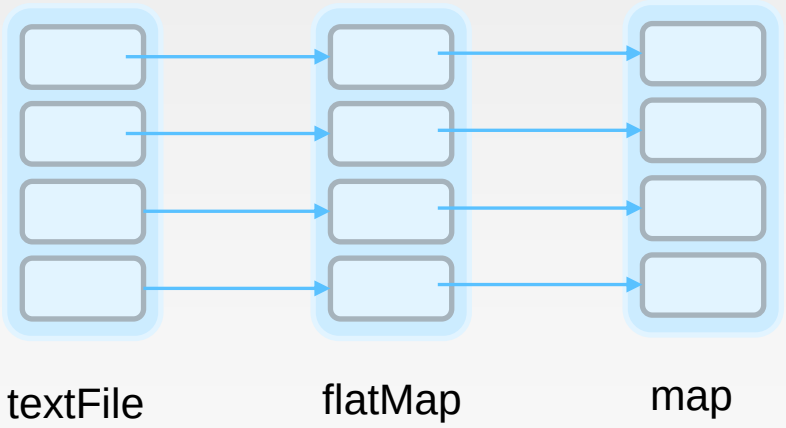
Word Count in Spark

```
textfile = sc.textFile("hdfs://…", 4)
words = text.flatMap(lambda line: line.split())
pairs = words.map(lambda word: (word, 1))
```

RDD[String]

RDD[String]

RDD[(String, Int)]



Word Count in Spark

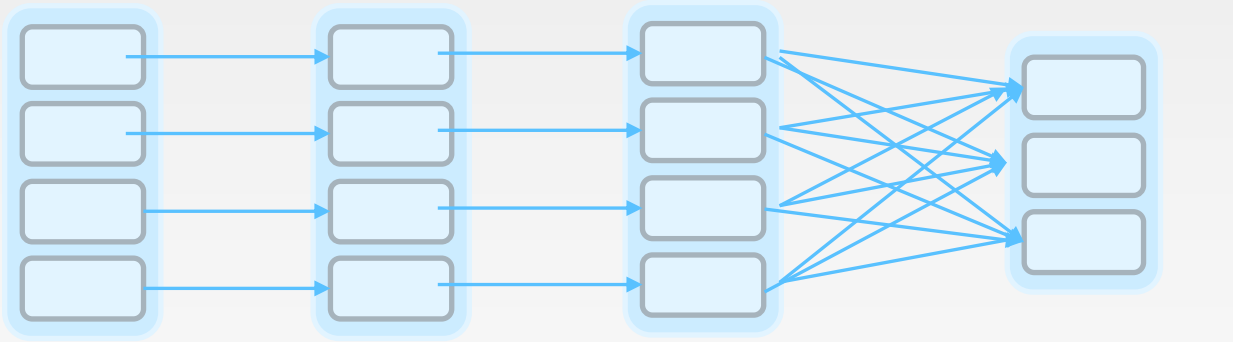
```
textfile = sc.textFile("hdfs://…", 4)
words = text.flatMap(lambda line: line.split())
pairs = words.map(lambda word: (word, 1))
count = pairs.reduceByKey(lambda a, b:
            a+b)
```

RDD[String]

RDD[String]

RDD[(String, Int)]

RDD[(String, Int)]



Word Count in Spark

```
textfile = sc.textFile("hdfs://…", 4)
words = text.flatMap(lambda line: line.split())
pairs = words.map(lambda word: (word, 1))
count = pairs.reduceByKey(lambda a, b:
            a+b)
count.collect()
```

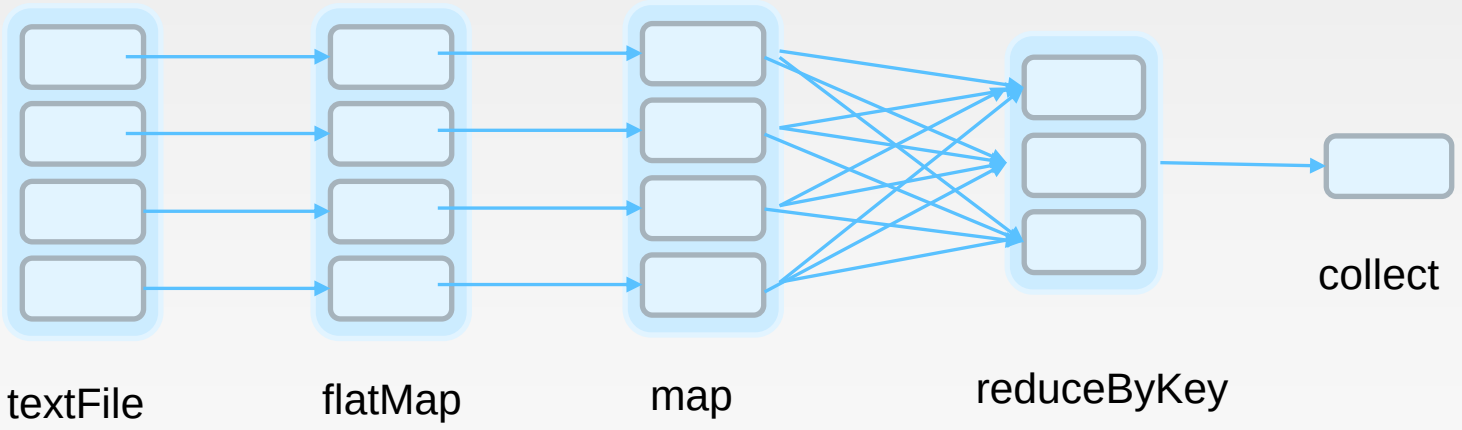
RDD[String]

RDD[String]

RDD[(String, Int)]

RDD[(String, Int)]

Array[(String, Int)]



map vs. flatMap

- Sample input file:

```
comp9313@comp9313-VirtualBox:~$ hdfs dfs -cat inputfile
This is a short sentence.
This is a second sentence.
```

```
scala> val inputfile = sc.textFile("inputfile")
inputfile: org.apache.spark.rdd.RDD[String] = inputfile MapPartitionsRDD[1] at t
extFile at <console>:24
```

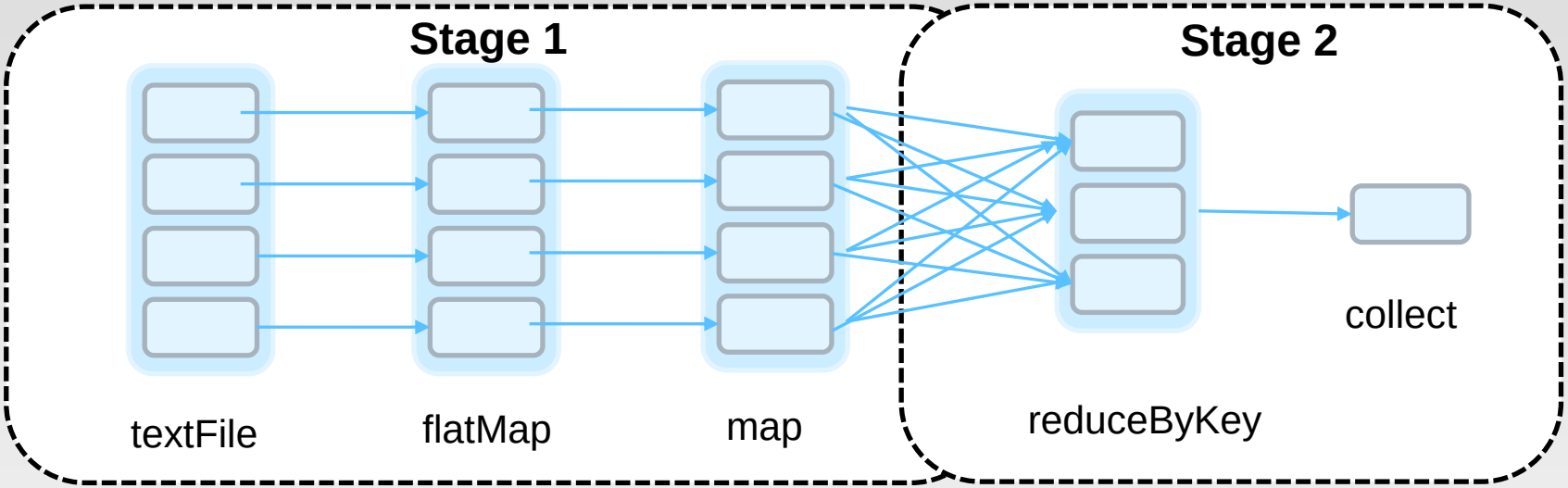
- map: Return a new distributed dataset formed by passing each element of the source through a function *func*.

```
scala> inputfile.map(x => x.split(" ")).collect()
res3: Array[Array[String]] = Array(Array(This, is, a, short, sentence.), Array(T
his, is, a, second, sentence.))
```

- flatMap: Similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item).

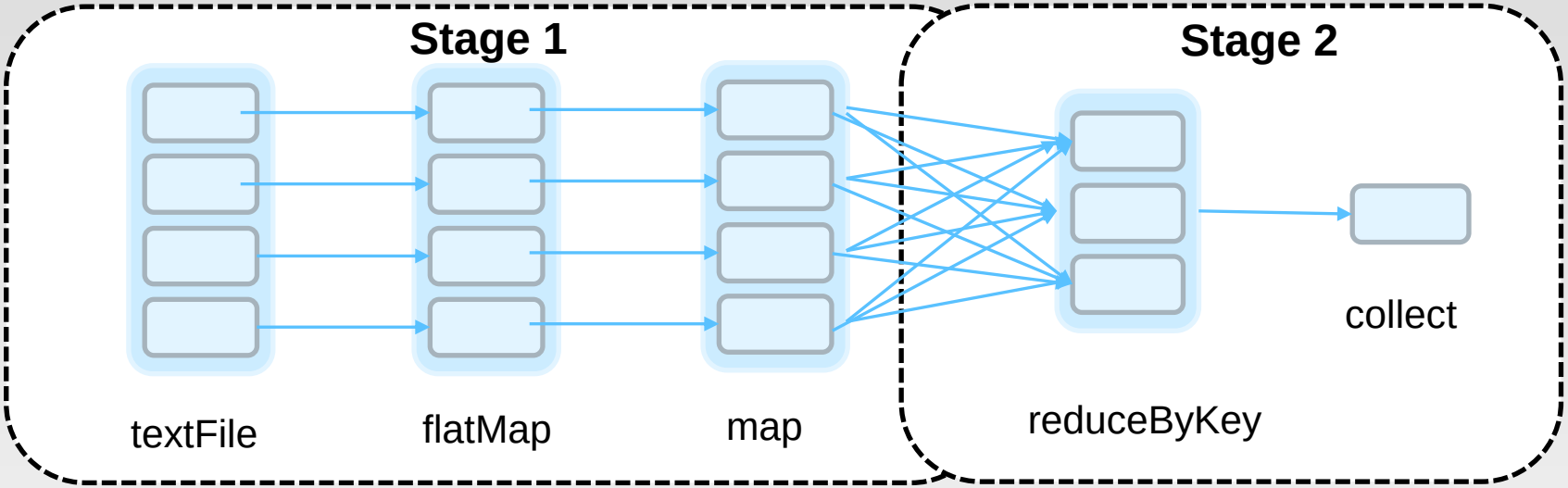
```
scala> inputfile.flatMap(x => x.split(" ")).collect()
res4: Array[String] = Array(This, is, a, short, sentence., This, is, a, second,
sentence.)
```

Execution Plan

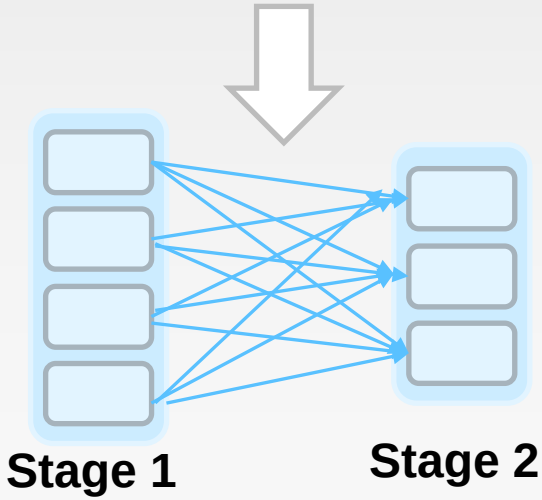


- The scheduler examines the RDD's lineage graph to build a DAG of stages.
- Stages are sequences of RDDs, that don't have a Shuffle in between
- The boundaries are the shuffle stages.

Execution Plan

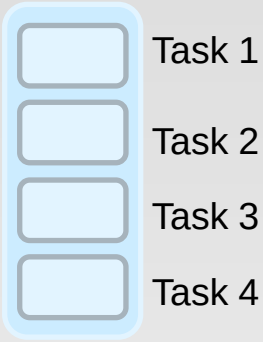


1. Read HDFS split
2. Apply both the maps
3. Start Partial reduce
4. Write shuffle data



1. Read shuffle data
2. Final reduce
3. Send result to driver program

Stage Execution



- Create a task for each Partition in the new RDD
- Serialize the Task
- Schedule and ship Tasks to Slaves

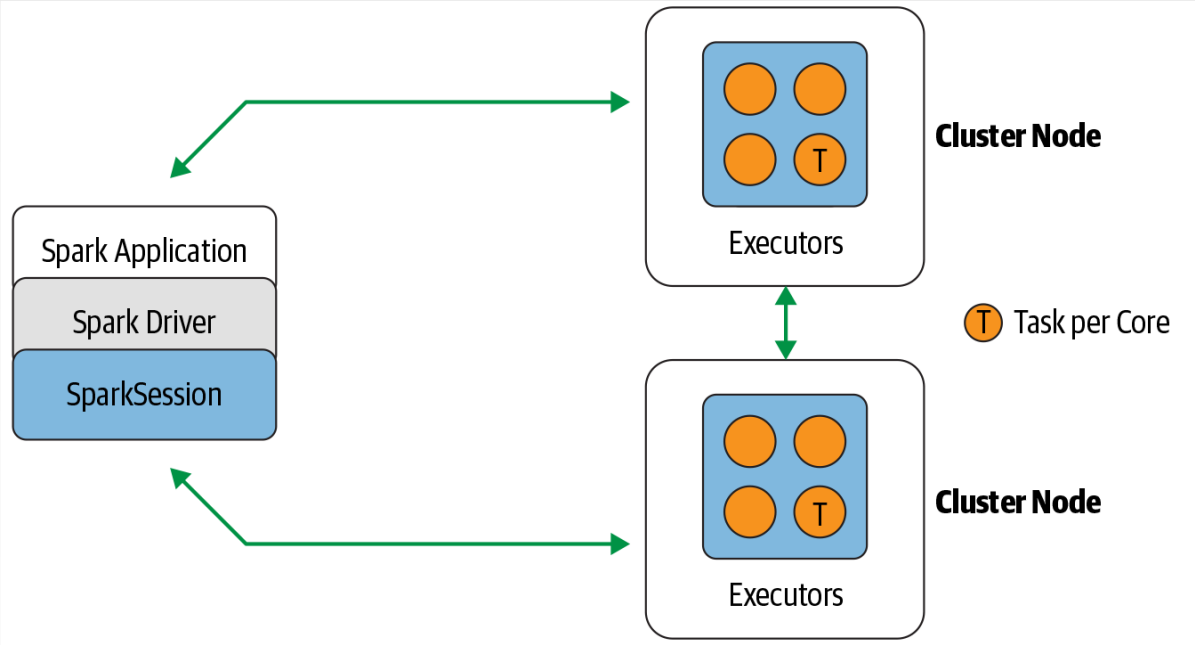
- All this happens internally

Understanding Spark Application Concepts

- Application
  - A user program built on Spark using its APIs. It consists of a driver program and executors on the cluster
- SparkContext/SparkSession
  - An object that provides a point of entry to interact with underlying Spark functionality and allows programming Spark with its APIs
- Job
  - A parallel computation consisting of multiple tasks that gets spawned in response to a Spark action (e.g., save(), collect()).
- Stage
  - Each job gets divided into smaller sets of tasks called stages that depend on each other.
- Task
  - A single unit of work or execution that will be sent to a Spark executor.

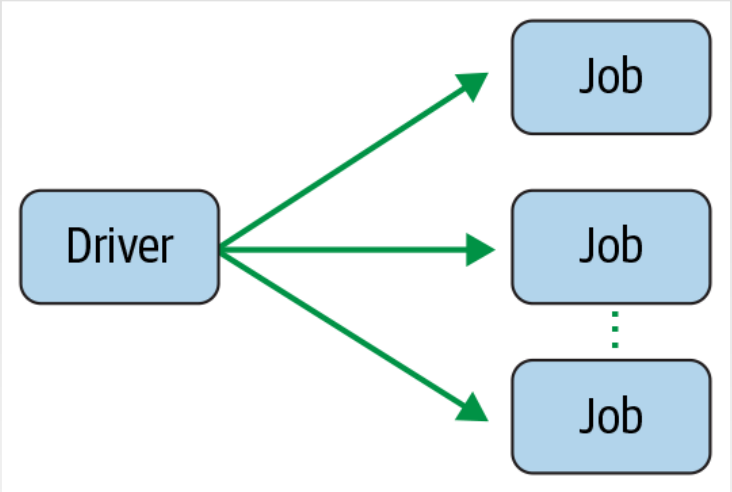
Spark Application and SparkSession

- The core of every Spark application is the Spark driver program, which creates a SparkSession (SparkContext in Spark 1.x) object.
  - When you're working with a Spark shell, the driver is part of the shell and the SparkSession/SparkContext object (accessible via the variable spark) is created for you
  - Once you have a SparkSession/ SparkContext, you can program Spark using the APIs to perform Spark operations.



Spark Jobs

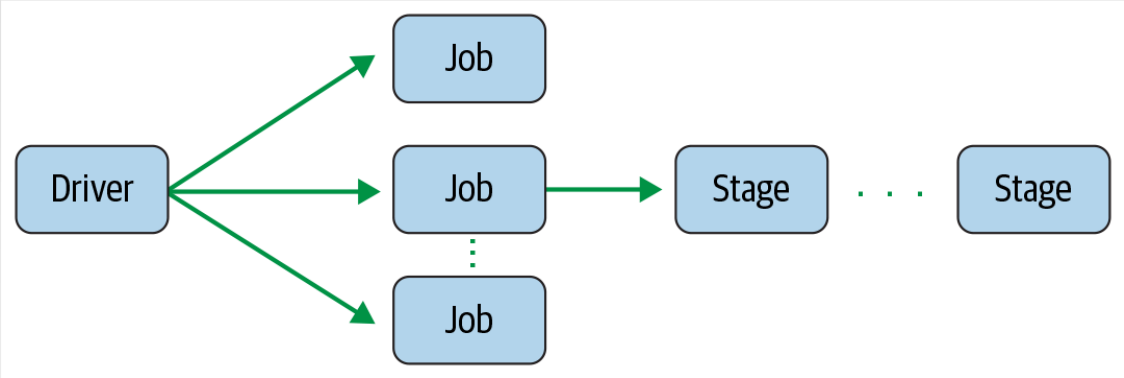
- During interactive sessions with Spark shells, the driver converts your Spark application into one or more Spark jobs



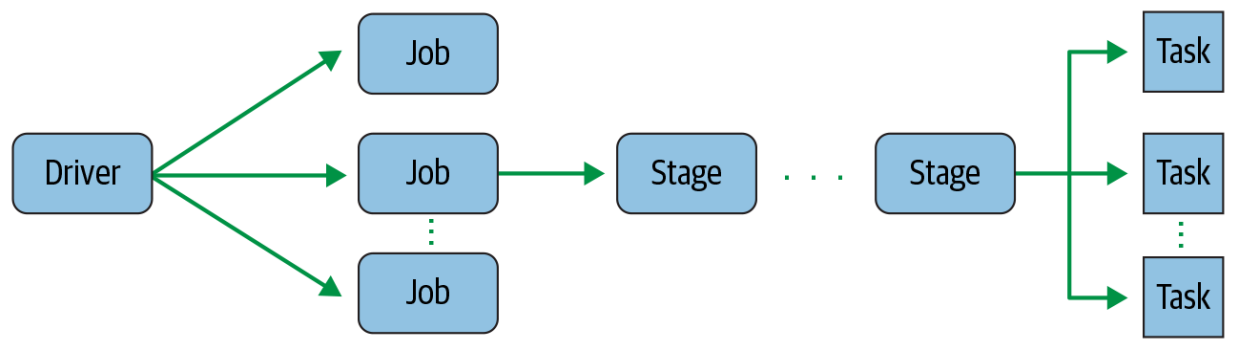
- It then transforms each job into a Spark's execution plan as a DAG, where each node within a DAG could be a single or multiple Spark stages.

Spark Stages and Tasks

- Stages are created based on what operations can be performed serially or in parallel.

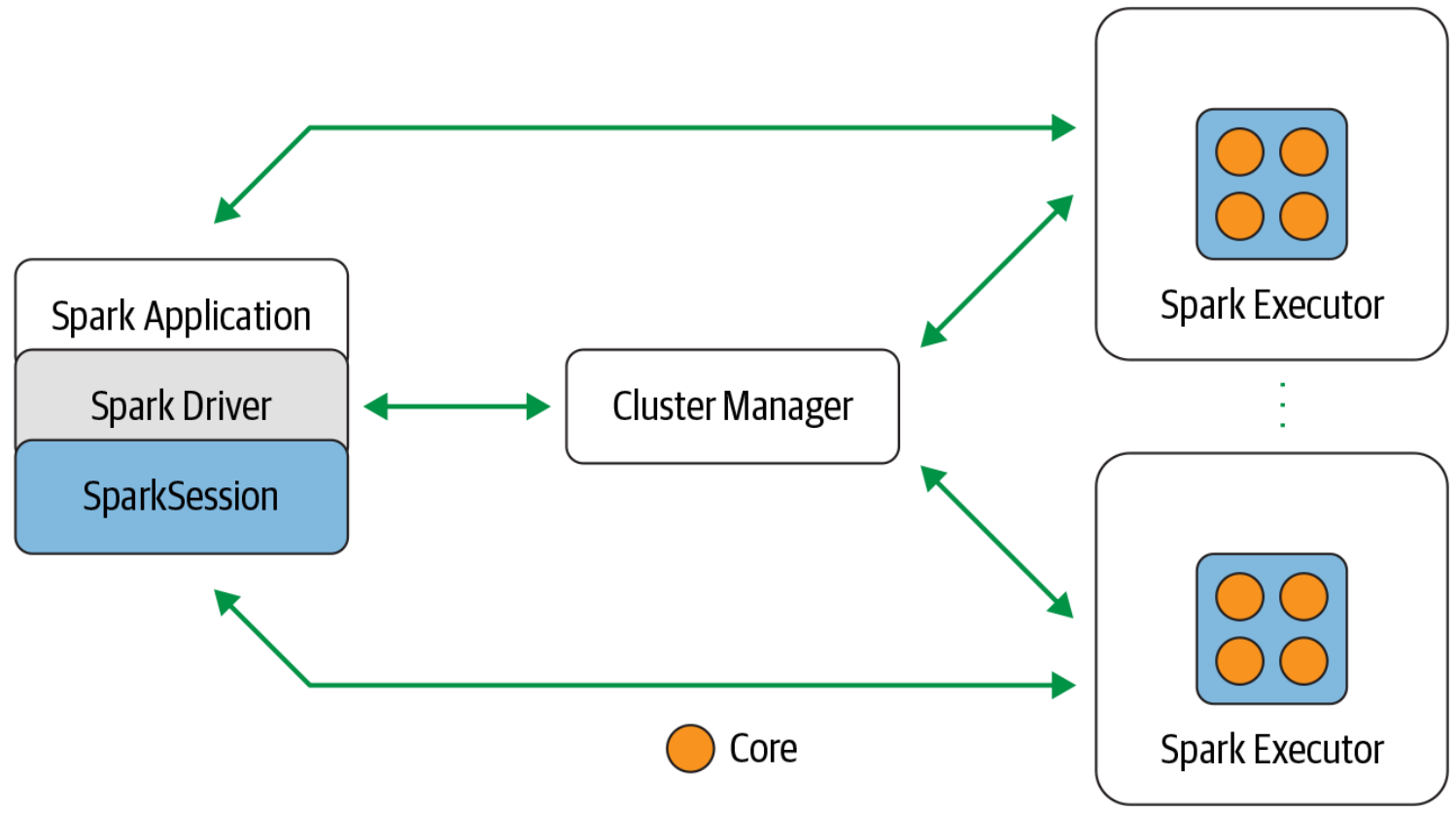


- Each stage is comprised of Spark tasks (a unit of execution), which are then federated across each Spark executor; each task maps to a single core and works on a single partition of data



Spark Architecture

- A Spark application consists of a driver program that is responsible for orchestrating parallel operations on the Spark cluster. The driver accesses the distributed components in the cluster—the Spark executors and cluster manager—through a SparkSession or SparkContext object.



Spark Components

- **Spark Driver**: part of the Spark application responsible for instantiating a SparkSession
  - Communicates with the cluster manager
  - Requests resources (CPU, memory, etc.) from the cluster manager for Spark's executors (JVMs)
  - Transforms all the Spark operations into DAG computations, schedules them, and distributes their execution as tasks across the Spark executors
  - Once the resources are allocated, it communicates directly with the executors.

Spark Components

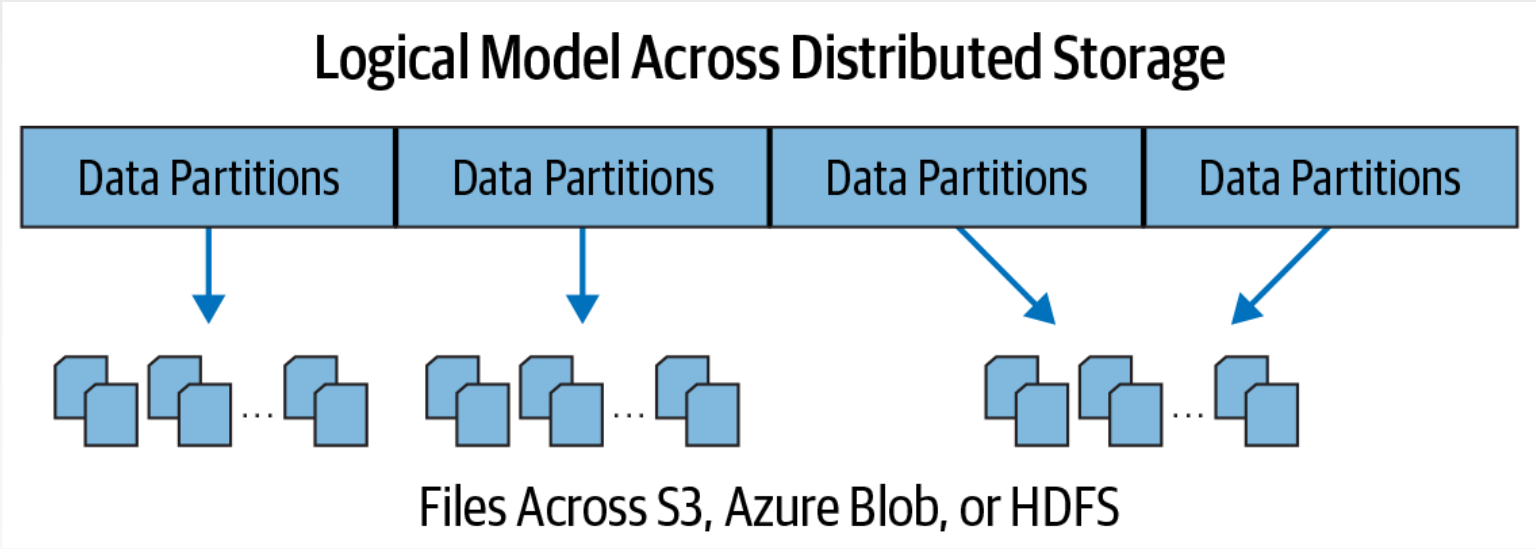
- Since Spark 2.x, the **SparkSession** became a unified conduit to all Spark operations and data (it subsumes previous entry points to Spark like the SparkContext)
- SparkSession provides a single unified entry point to all of Spark's functionality
  - Create JVM runtime parameters
  - Define DataFrames and Datasets
  - Read from Data Sources
  - Access catalog metadata
  - Issue Spark SQL queries

Spark Components

- Cluster manager
  - Responsible for managing and allocating resources for the cluster of nodes on which your Spark application runs.
  - Support four cluster managers: the built-in standalone cluster manager, Apache Hadoop YARN, Apache Mesos, and Kubernetes.
- Spark executor
  - Runs on each worker node in the cluster.
  - Communicate with the driver program and is responsible for executing tasks on the workers.
  - In most deployments modes, only a single executor runs per node.

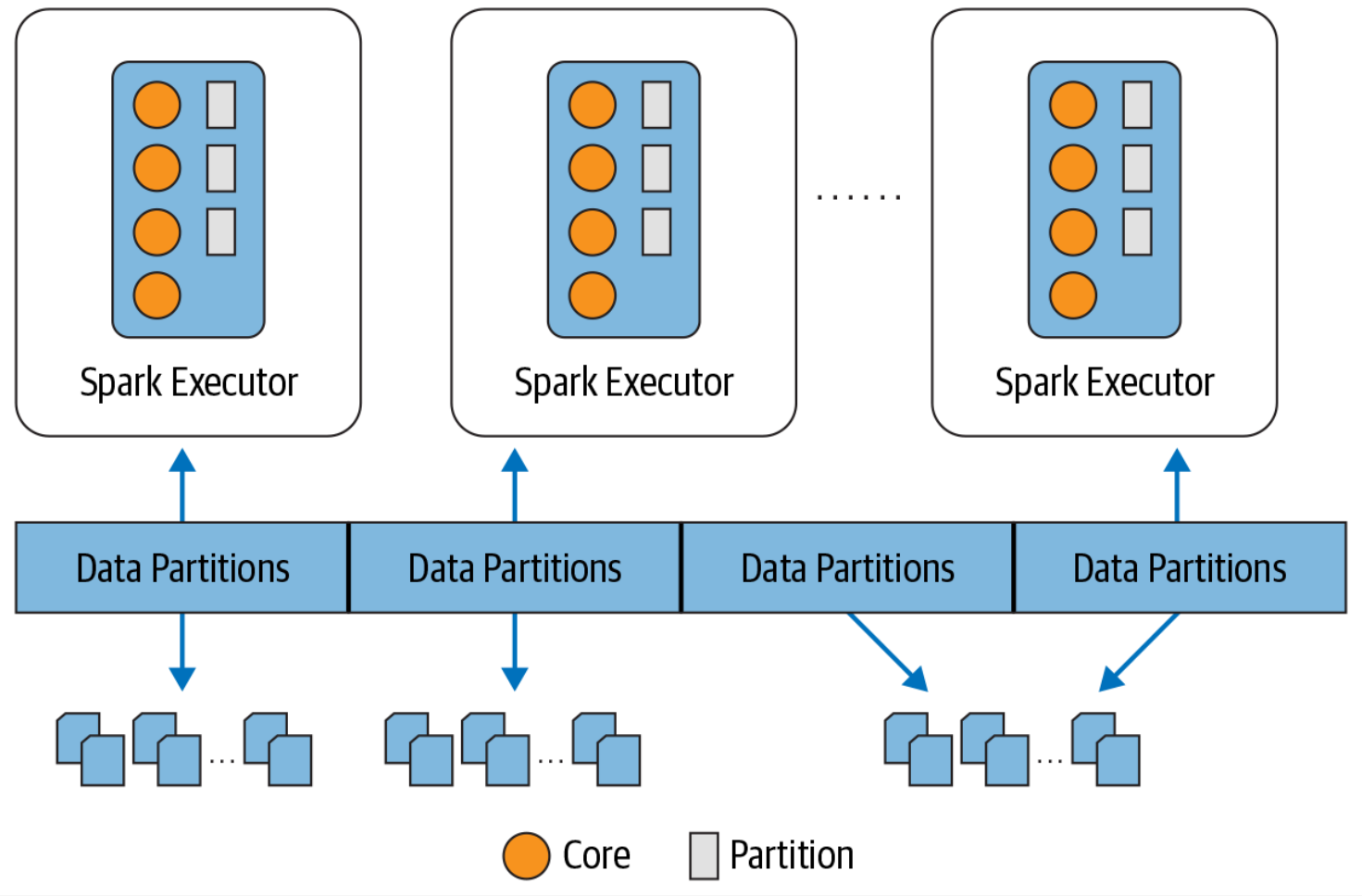
Distributed Data and Partitions

- Actual physical data is distributed across storage as partitions residing in either HDFS or other cloud storage.
- The data is distributed as partitions across the physical cluster
- Spark treats each partition as a high-level logical data abstraction in memory.
- Each Spark executor is preferably allocated a task that requires it to read the partition closest to it in the network, observing data locality.



Distributed Data and Partitions

- Each executor's core is assigned its own data partition to work on



Word Count in Spark (As a Whole View)

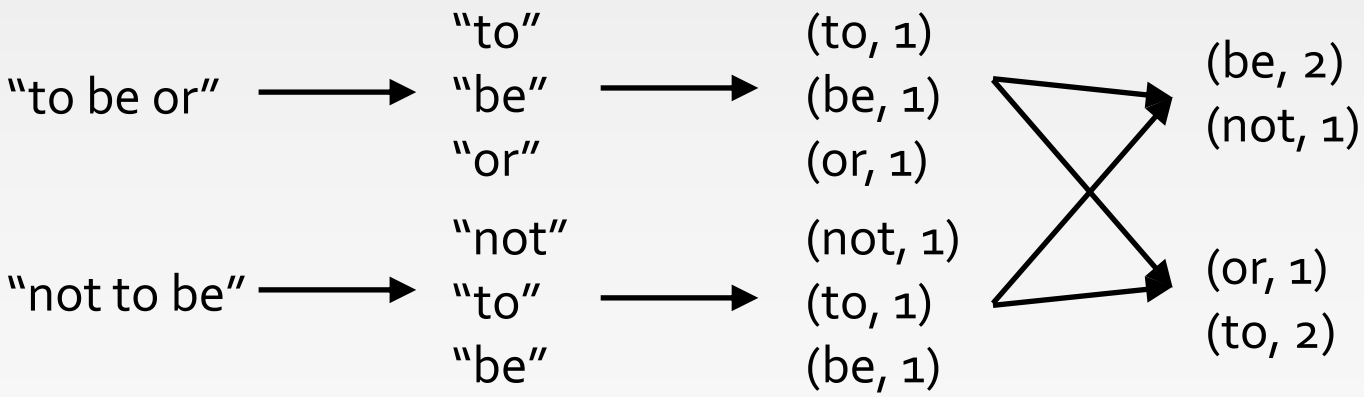
- Word Count using Scala in Spark

```
textfile = sc.textFile("hdfs://...", 4)

words = textfile.flatMap(lambda line: line.split(" "))
pairs = words.map(lambda word: (word, 1))
count = pairs.reduceByKey(lambda a, b: a + b)
count.collect()
```

Transformation

Action

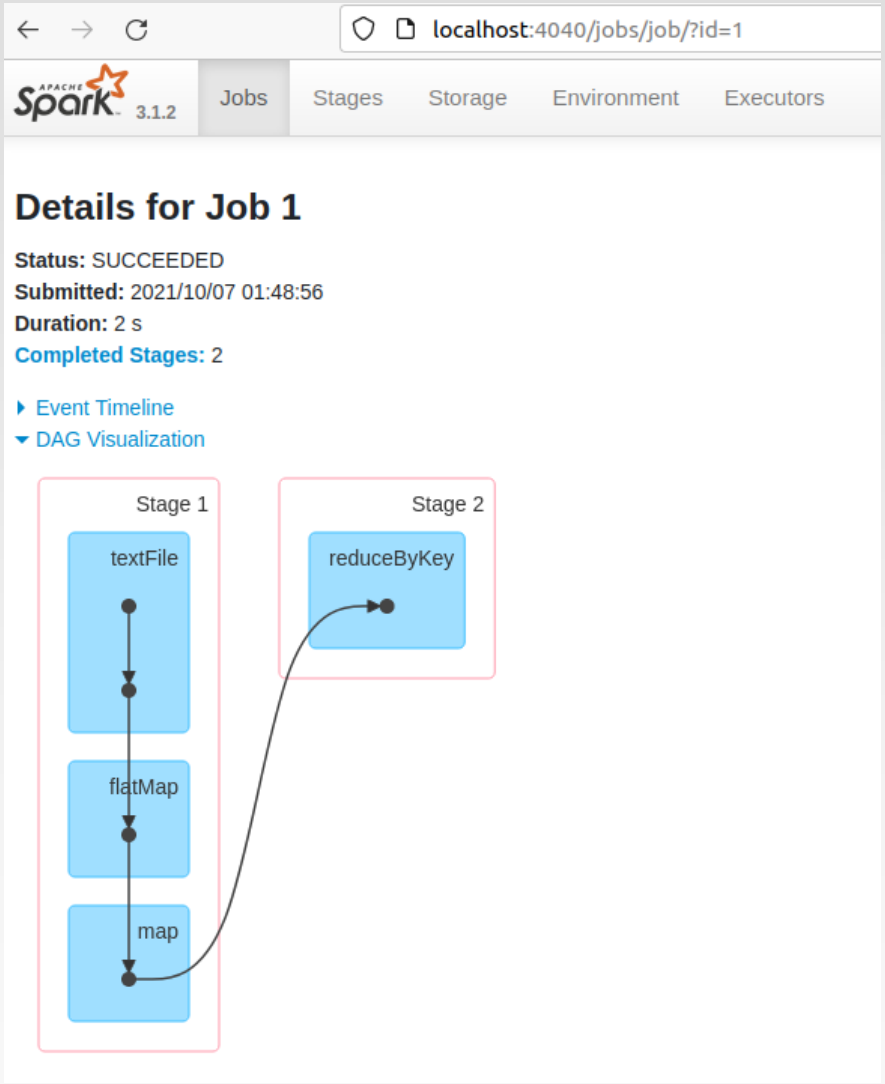


The Spark UI

- Spark includes a graphical user interface that you can use to inspect or monitor Spark applications in their various stages of decomposition—that is jobs, stages, and tasks.
- The driver launches a web UI, running by default on port 4040, where you can view metrics and details such as:
  - A list of scheduler stages and tasks
  - A summary of RDD sizes and memory usage
  - Information about the environment
  - Information about the running executors
  - All the Spark SQL queries
- In local mode, you can access this interface at http://localhost:4040 in a web browser.

Spark Web Console

- You can browse the web interface for the information of Spark Jobs, storage, etc. at: **http://localhost:4040**



References

- http://spark.apache.org/docs/latest/index.html
- Learning Spark. 1st edition

End of Chapter 4.2