Spark: Resilient Distributed Datasets as Workflow System

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CSE545

Spring 2020

Big Data Analytics, The Class

Goal: Generalizations
A *model* or *summarization* of the data.

Data Frameworks

- Hadoop File System
- Spark
- Streaming
- MapReduce
- Tensorflow

Algorithms and Analyses

- Similarity Search
- Hypothesis Testing
- Graph Analysis
- Recommendation Systems
- Deep Learning

Where is MapReduce Inefficient?

DFS ⇨ Map ⇨ LocalFS ⇨ Network ⇨ Reduce ⇨ DFS ⇨ Map ⇨ ...

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- Long pipelines sharing data
- Interactive applications
- Streaming applications
- Iterative algorithms (optimization problems)

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Resilient Distributed Datasets (RDDs) -- Read-only partitioned collection of records (like a DFS) but with a record of how the dataset was created as combination of *transformations* from other dataset(s).

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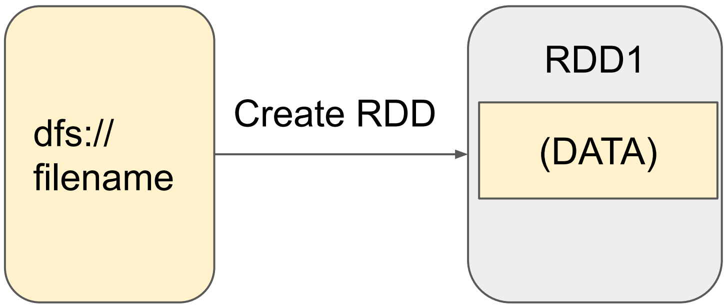

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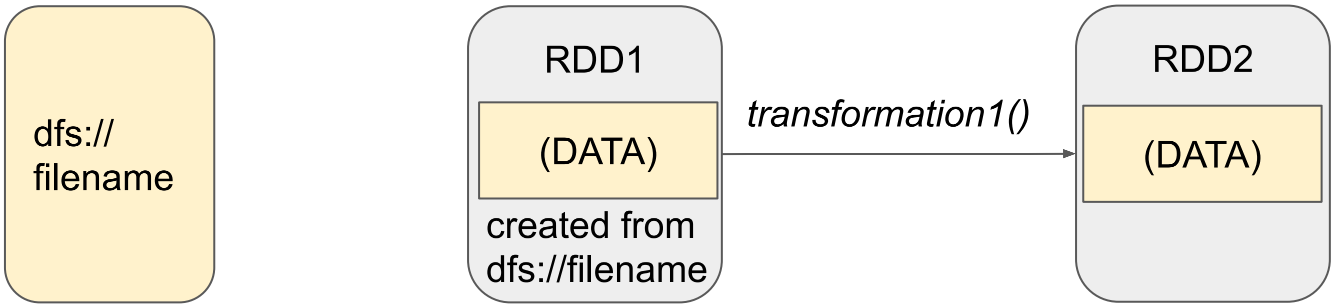

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- Enables rebuilding datasets on the fly.
- Intermediate datasets not stored on disk
  (and only in memory if needed and enough space)

⇨ Faster communication and I O

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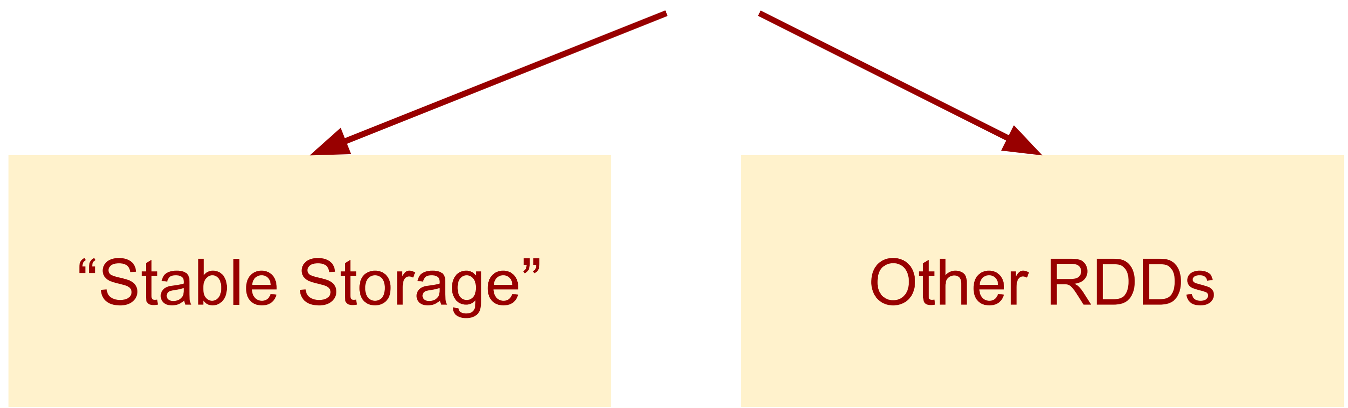

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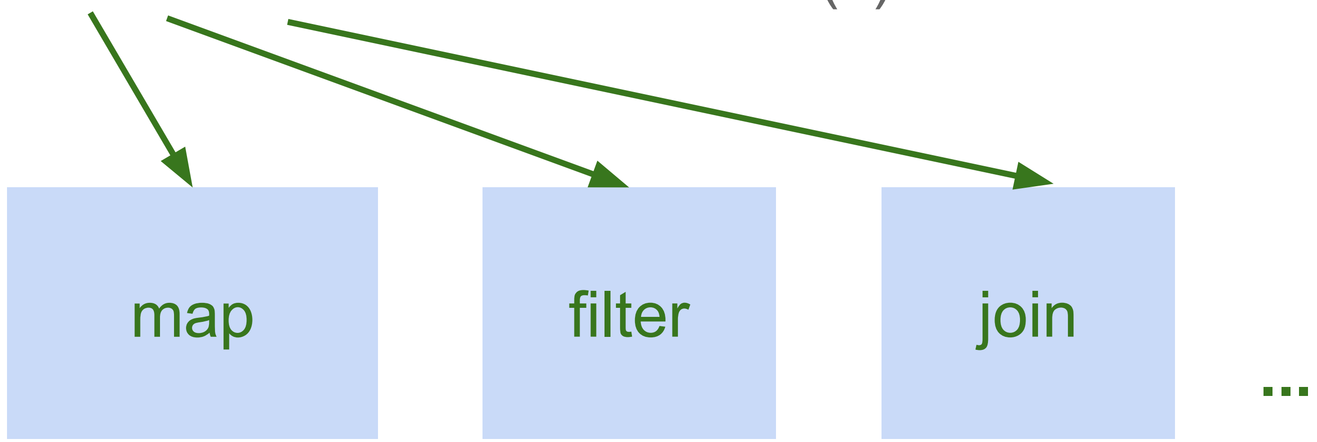

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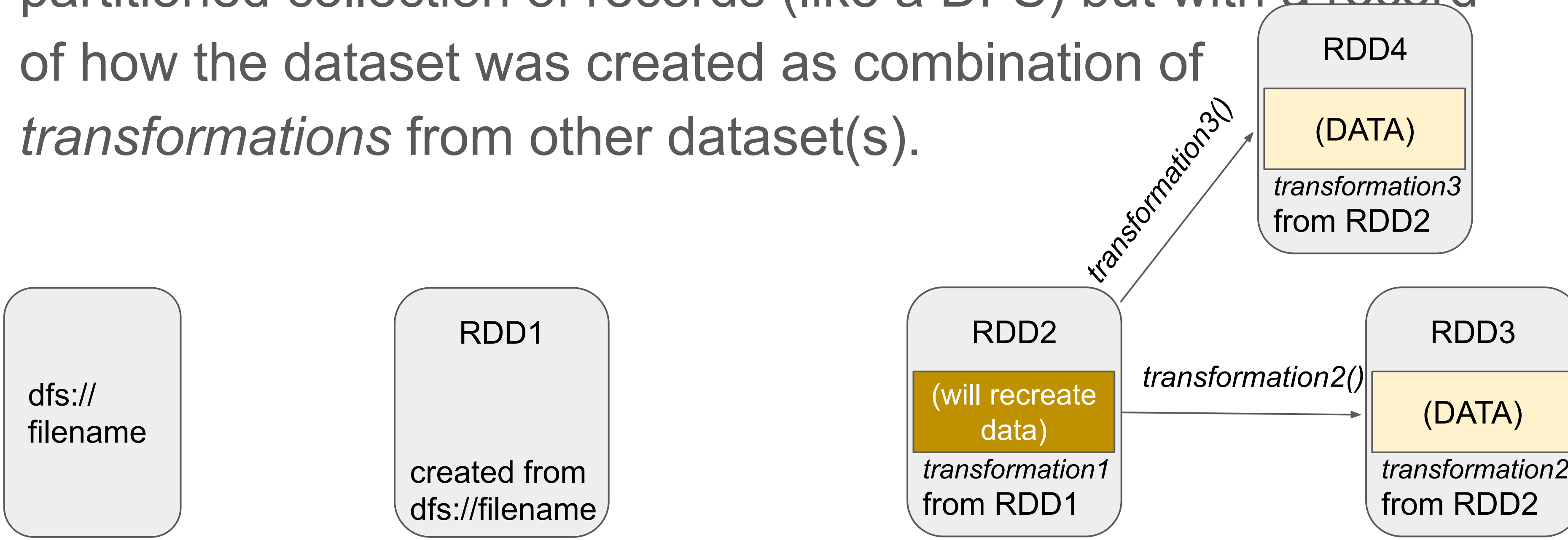

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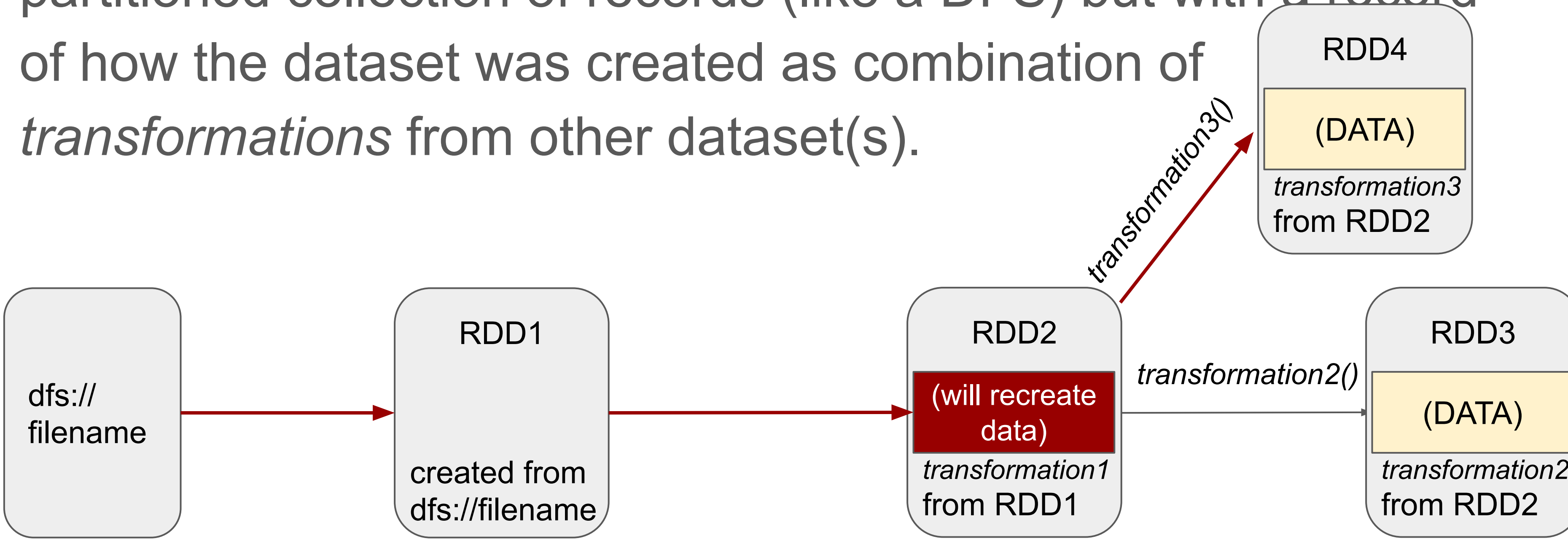

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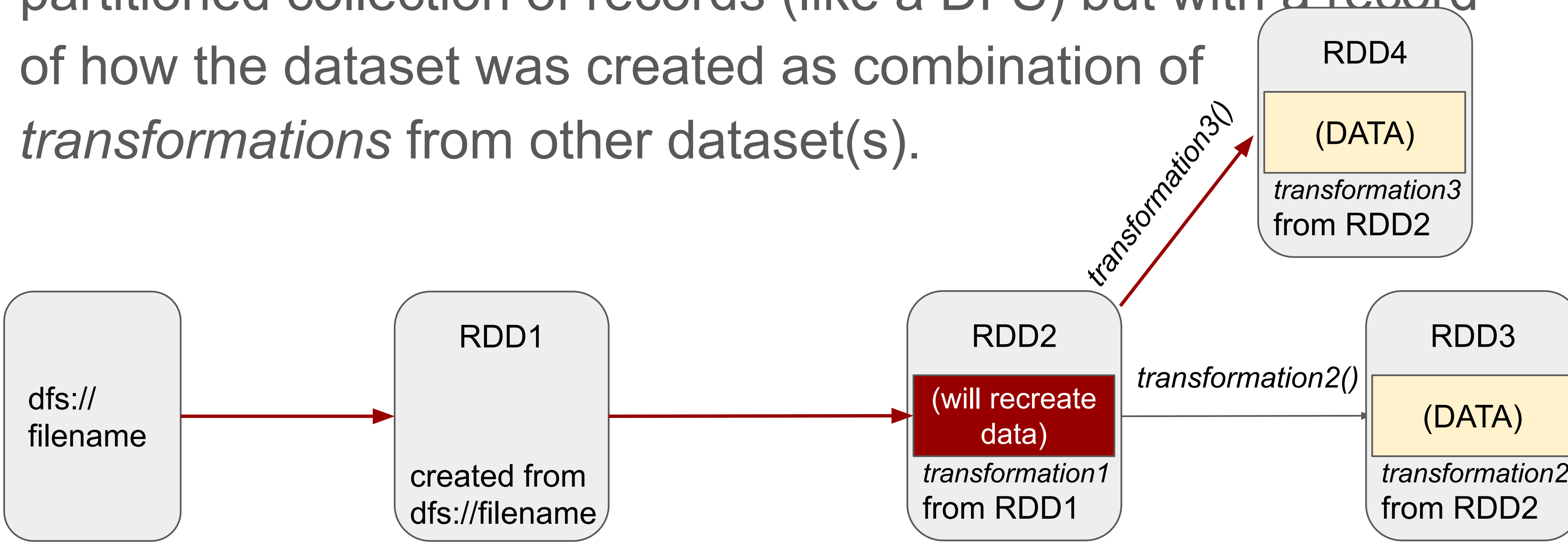

(original) *Transformations*: RDD to RDD

Transformations	$map(f: \mathrm{T} \Rightarrow \mathrm{U})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[U]}$
	$filter(f: \mathrm{T} \Rightarrow \mathrm{Bool})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[T]}$
	$flatMap(f: \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[U]}$
	$sample(fraction: \mathrm{Float})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[T]}$ (Deterministic sampling)
	$groupByKey()$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, Seq[V])]}$
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Table 2: Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

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	groupByKey()	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V])]
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(orig.) *Actions*: RDD to Value Object, or Storage

Actions	*count*()	:	RDD[T] ⇒ Long
	collect()	:	RDD[T] ⇒ Seq[T]
	reduce(*f* : (T, T) ⇒ T)	:	RDD[T] ⇒ T
	lookup(*k* : K)	:	RDD[(K, V)] ⇒ Seq[V] (On hash/range partitioned RDDs)
	save(*path* : String)	:	Outputs RDD to a storage system, *e.g.*, HDFS

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Current Transformations and Actions

http://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations

common transformations: *filter, map, flatMap, reduceByKey, groupByKey*

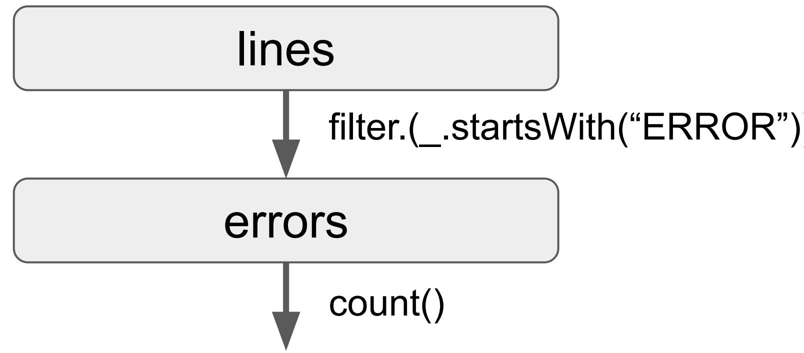
http://spark.apache.org/docs/latest/rdd-programming-guide.html#actions

common actions: *collect, count, take*

Example

Count errors in a log file:

TYPE MESSAGE TIME



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Pseudocode:

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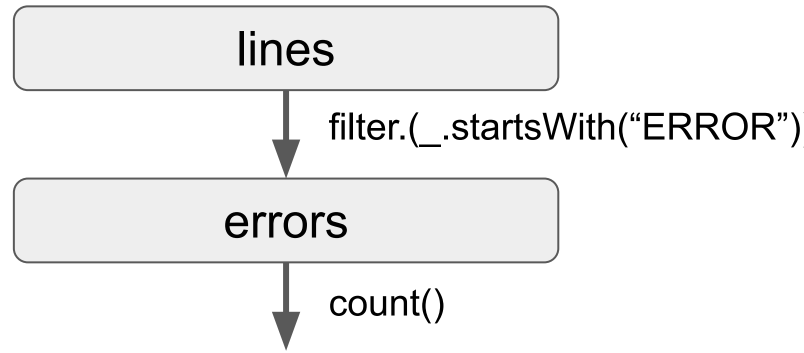

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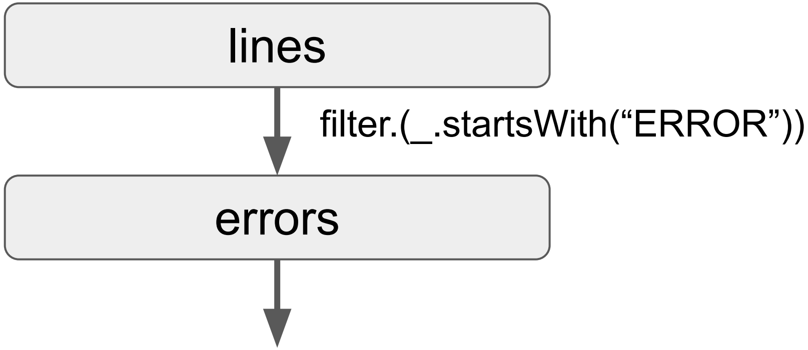
Example 2

Collect times of hdfs-related errors

TYPE MESSAGE TIME

Pseudocode:

```
lines = sc.textFile("dfs:...")
errors =
    lines.filter(_.startswith("ERROR"))
errors.persist
~~errors.count~~
...
```



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Can specify that an RDD "persists" in memory so other queries can use it.
Can specify a priority for persistance; lower priority => moves to disk, if needed, earlier

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[parameters for persist]

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Pseudocode:

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errors.filter(_.contains("HDFS"))
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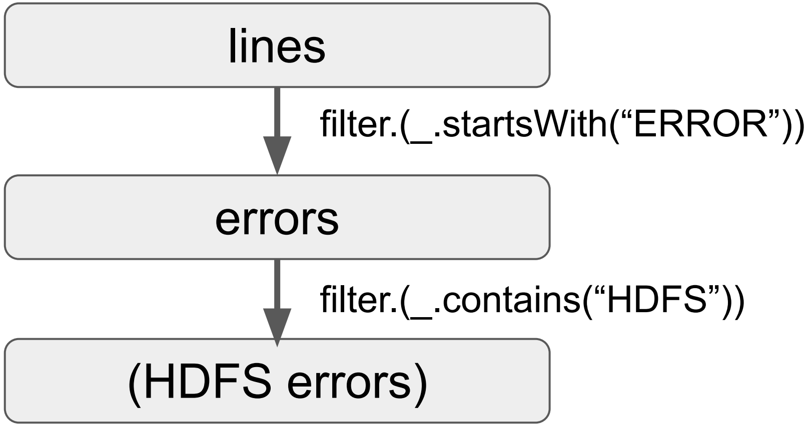

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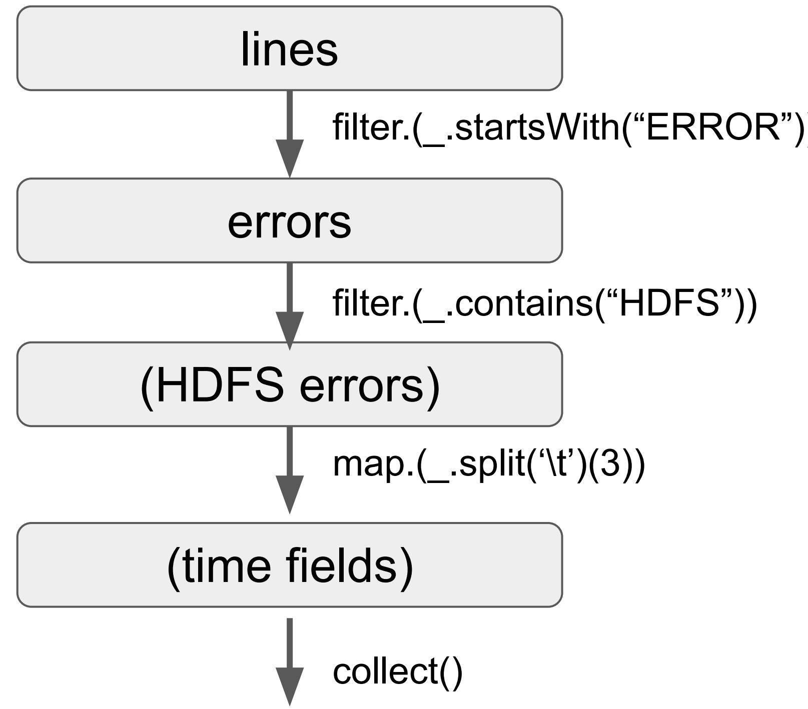

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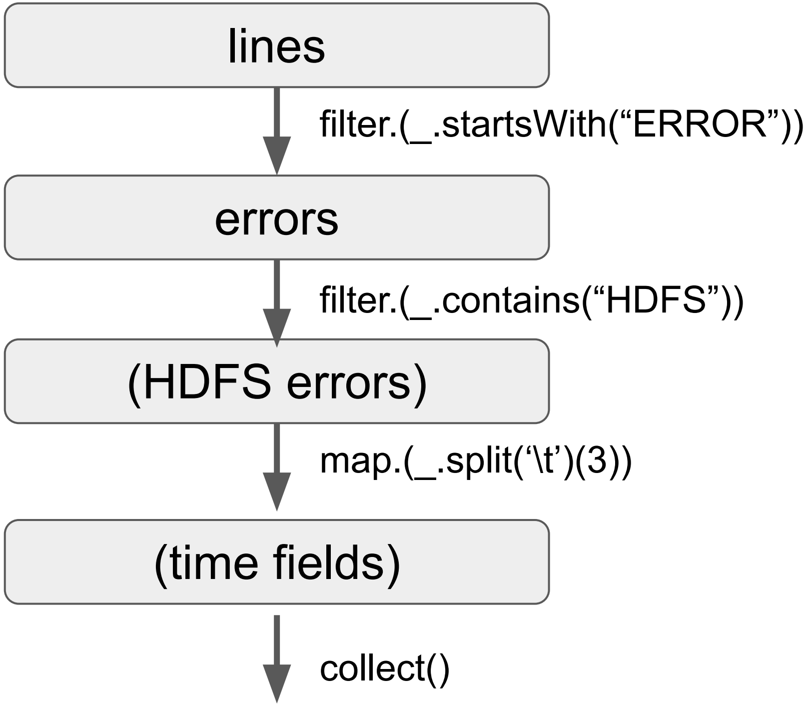
Functional Programming



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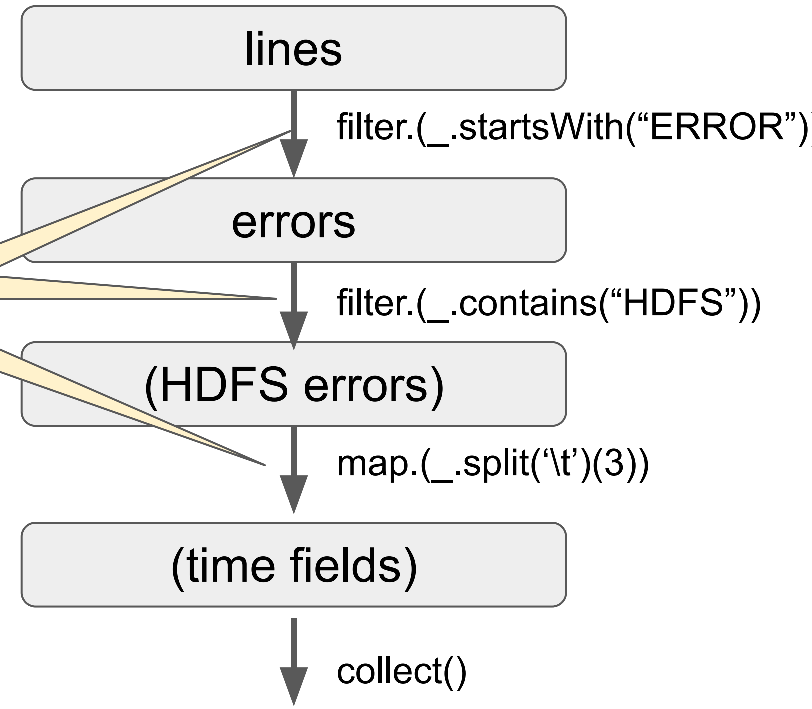

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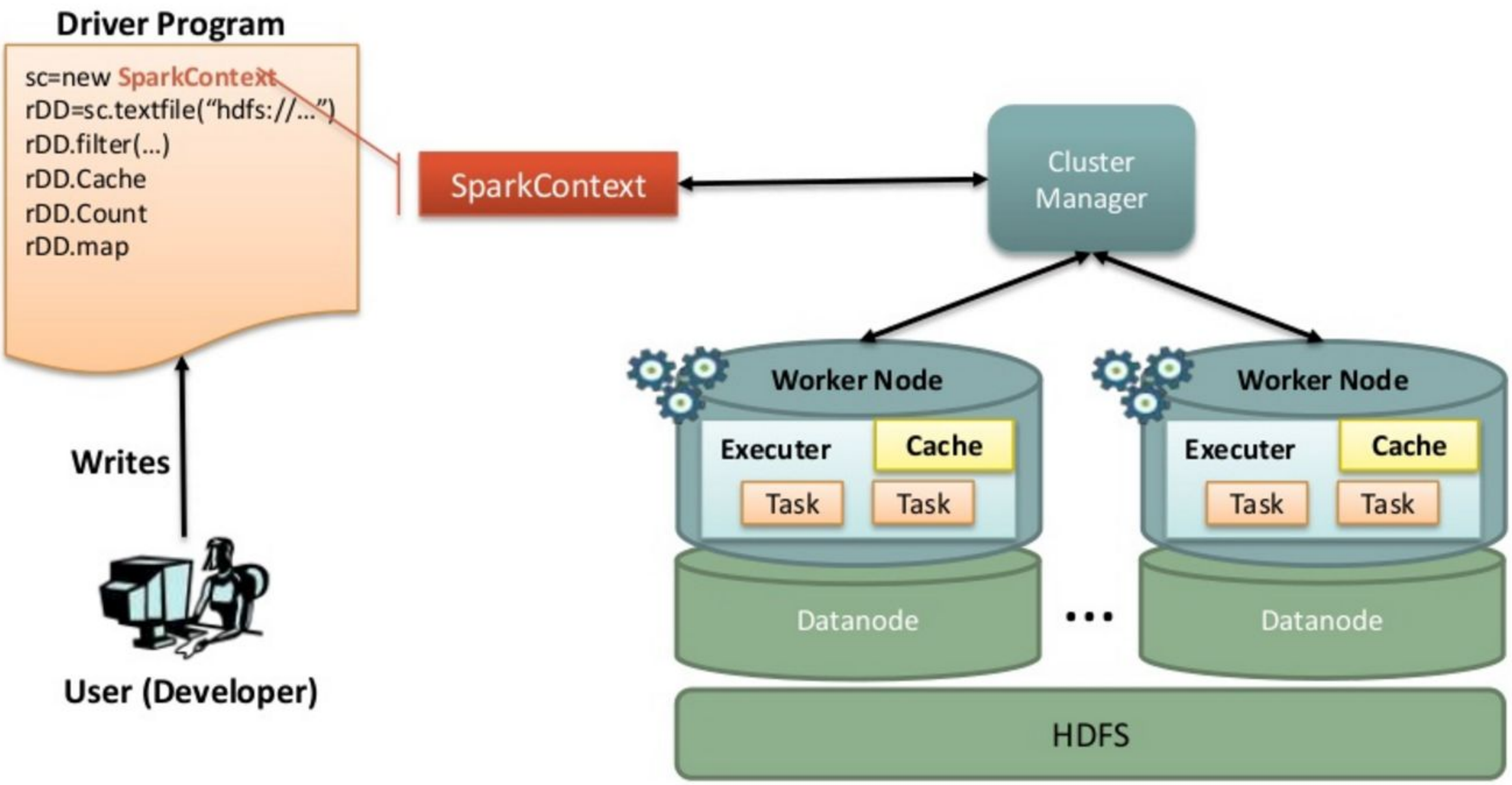
Advantages as Workflow System

- More efficient failure recovery
- More efficient grouping of tasks and scheduling
- Integration of programming language features:
  - loops (not a “cyclic” workflow system).
  - function libraries

(MMDSv3)

The Spark Programming Model



Gupta, Manish. Lightening Fast Big Data Analytics using Apache Spark. *UniCom 2014.*

Example

Word Count

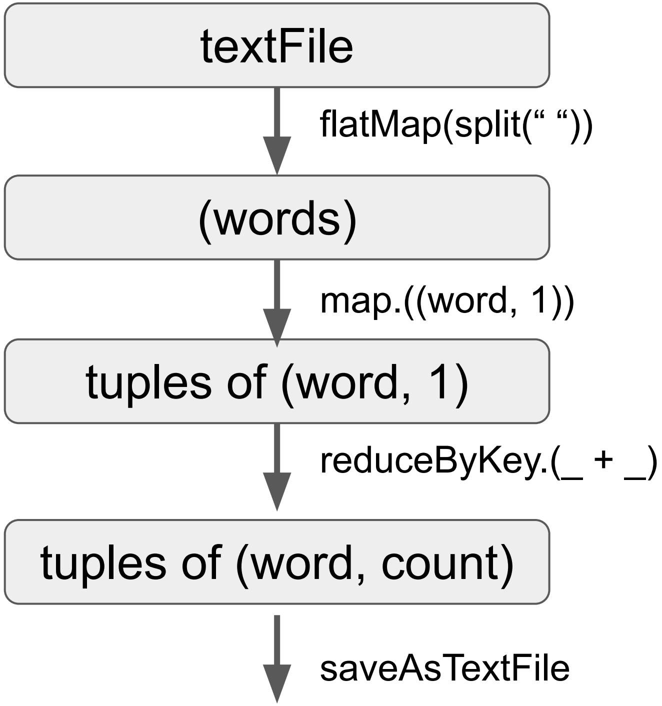
textFile

Example

Word Count

Scala:

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



Apache Spark Examples
http://spark.apache.org/examples.html

Example

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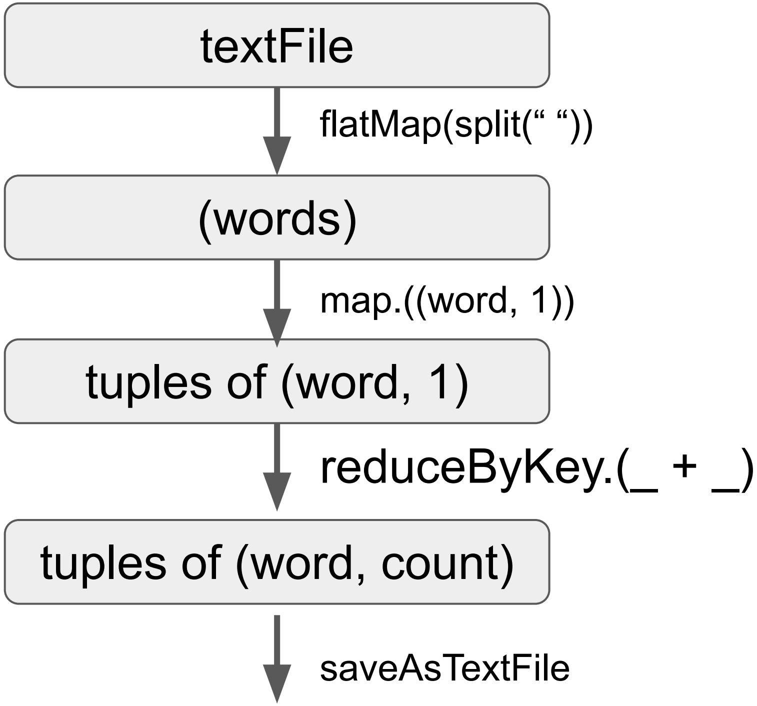

Apache Spark Examples
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PySpark Demo

https://data.worldbank.org/data-catalog/poverty-and-equity-database

Lazy Evaluation

Spark waits to **load data** and **execute transformations** until necessary -- ***lazy***
Spark tries to complete **actions** as immediately as possible -- ***eager***

Why?

- Only executes what is necessary to achieve action.
- Can optimize the complete *chain of operations* to reduce communication

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e.g.

```
rdd.map(lambda r: r[1]*r[3]).take(5)  #only executes map for five records

rdd.filter(lambda r: "ERROR" in r[0]).map(lambda r: r[1]*r[3])
                        #only passes through the data once
```

Broadcast Variables

Read-only objects can be shared across all nodes.

Broadcast variable is a wrapper: access object with .value

Python:

```
filterWords = [‘one’, ‘two’, ‘three’, ‘four’, …]
fwBC = sc.broadcast(set(filterWords))
```

Broadcast Variables

Read-only objects can be shared across all nodes.

Broadcast variable is a wrapper: access object with .value

Python:

```
filterWords = [‘one’, ‘two’, ‘three’, ‘four’, …]
fwBC = sc.broadcast(set(filterWords))

textFile = sc.textFile("hdfs:...")
counts = textFile
    .map(lambda line: line.split(" "))
    .filter(lambda words: len(set(words) and word in fwBC.value) > 0)
    .flatMap(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a + b)
counts.saveAsTextFile("hdfs:...")
```

Accumulators

Write-only objects that keep a running aggregation

- Default Accumulator assumes sum function

```
initialValue = 0
sumAcc = sc.accumulator(initialValue)
rdd.foreach(lambda i: sumAcc.add(i))
print(sumAcc.value)
```

Accumulators

Write-only objects that keep a running aggregation

Default Accumulator assumes sum function

Custom Accumulator: Inherit (AccumulatorParam) as class and override methods

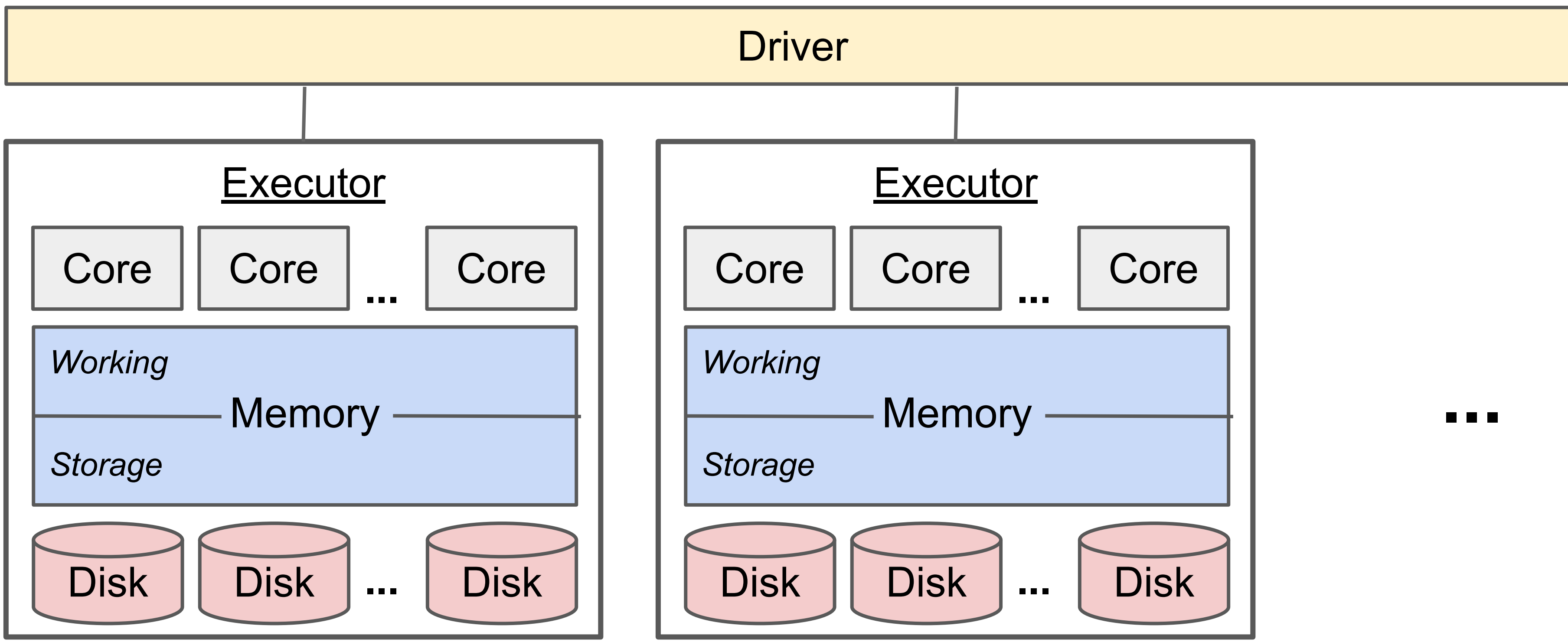
```
initialValue = 0
sumAcc = sc.accumulator(initialValue)
rdd.foreeach(lambda i: sumAcc.add(i))
print(minAcc.value)

class MinAccum(AccumulatorParam):
	def zero(self, zeroValue = np.inf):#overwrite this
		return zeroValue
	def addInPlace(self, v1, v2):#overwrite this
		return min(v1, v2)
minAcc = sc.accumulator(np.inf, minAccum())
rdd.foreeach(lambda i: minAcc.add(i))
print(minAcc.value)
```

Spark System: Review

- RDD provides full recovery by backing up transformations from stable storage rather than backing up the data itself.
- RDDs, which are immutable, can be stored in memory and thus are often much faster.
- Functional programming is used to define transformation and actions on RDDs.

Spark System: Hierarchy



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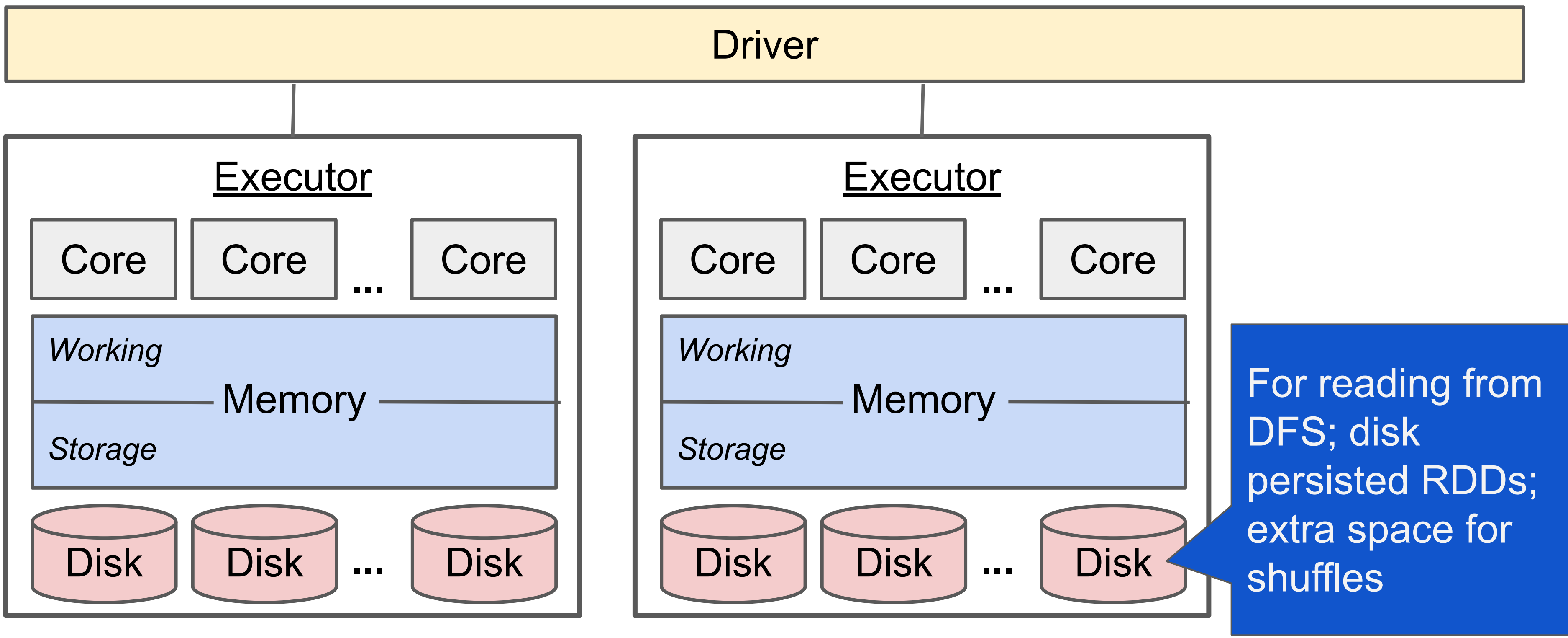

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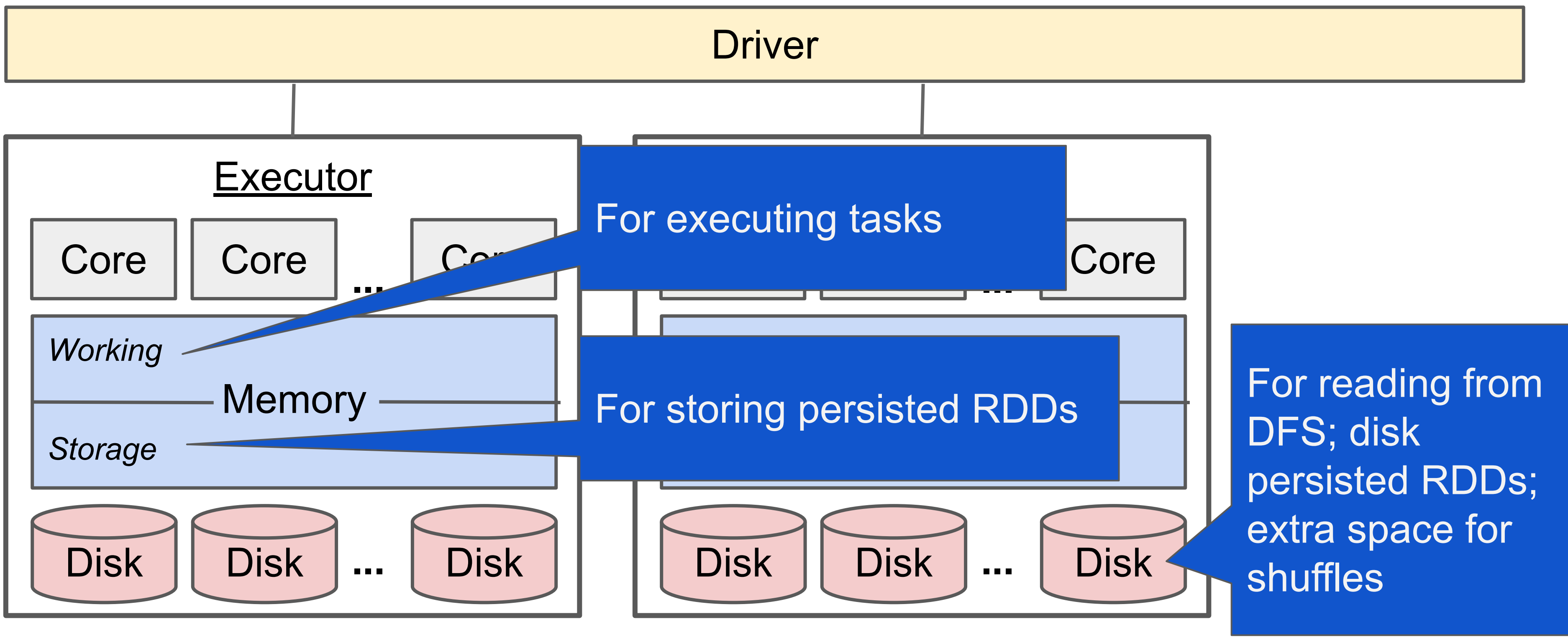

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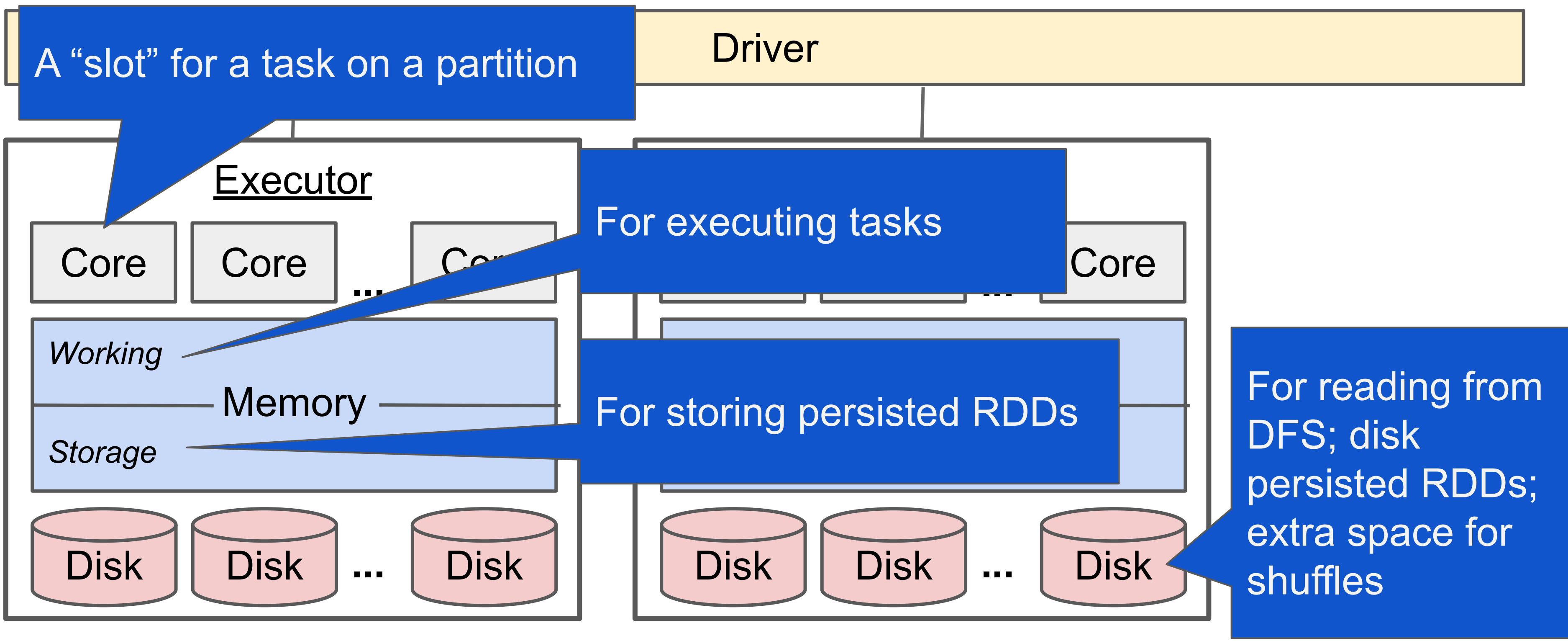
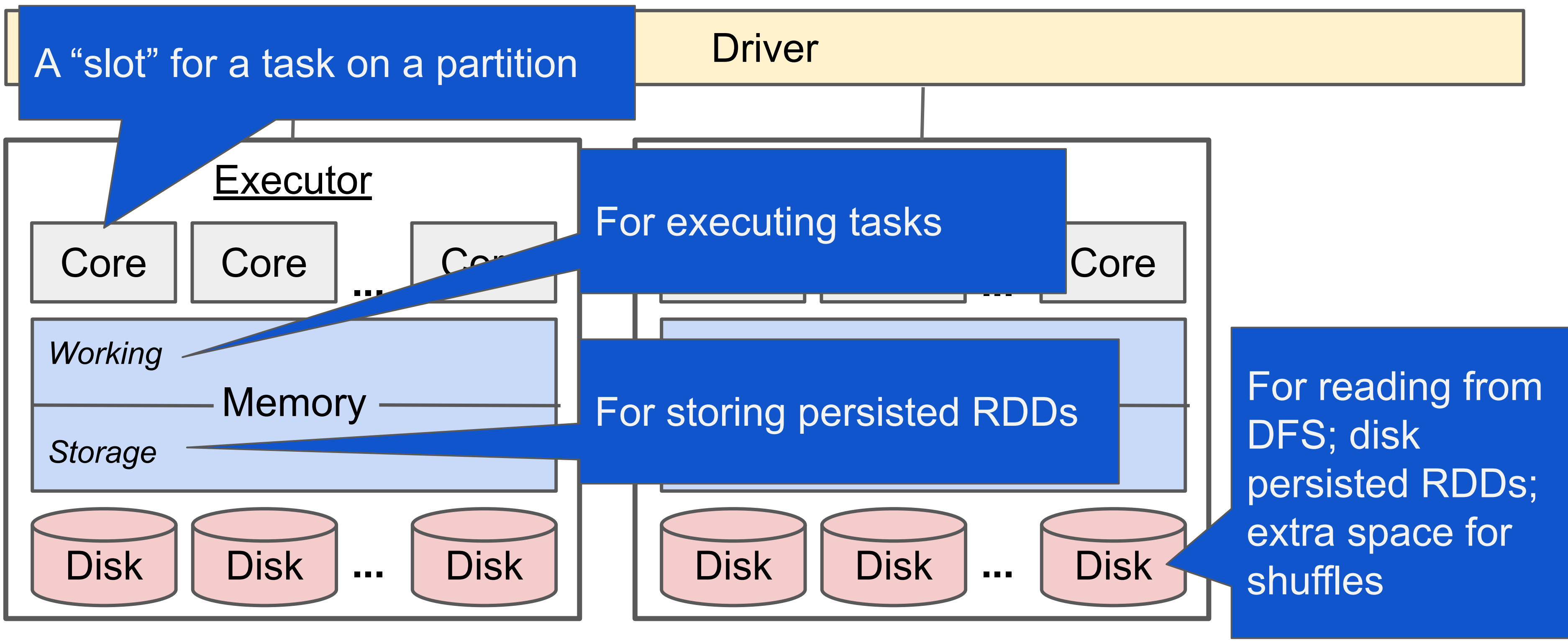


Spark System: Hierarchy

Eager *action* -> sets off (lazy) chain of *transformations*
-> launches *jobs* -> broken into *stages* -> broken into ***tasks***



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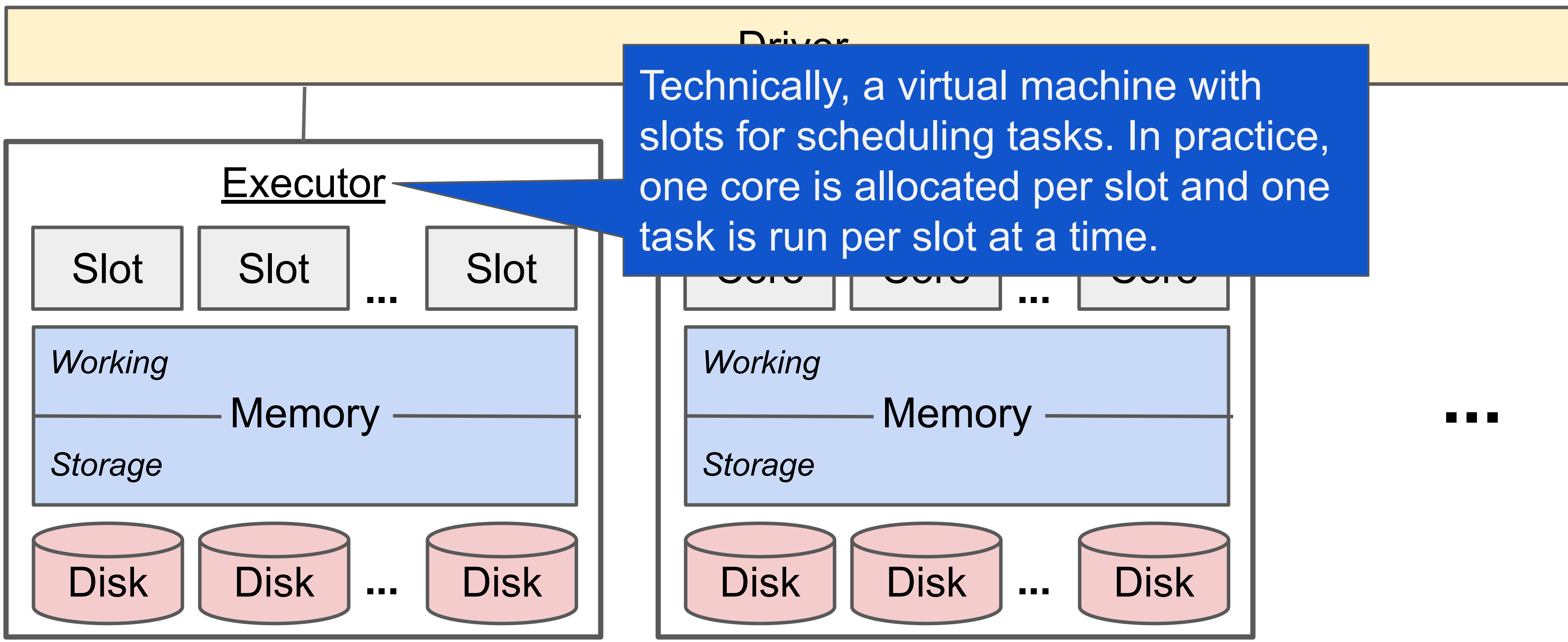

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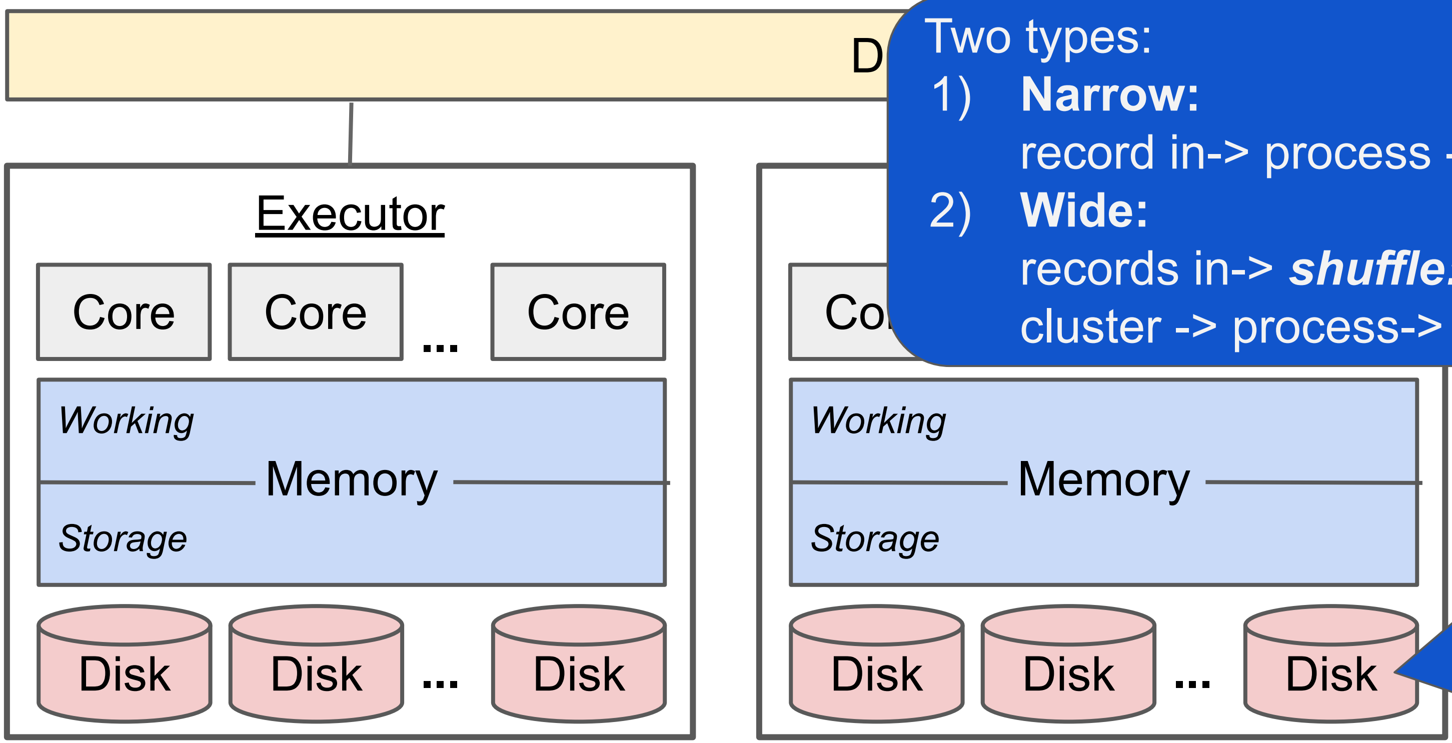

Two types:

1) **Narrow:**
record in-> process -> record[s] out
2) **Wide:**
records in-> ***shuffle:*** regroup across cluster -> process-> record[s] out

For reading from DFS; disk persisted RDDs; extra space for ***shuffles***

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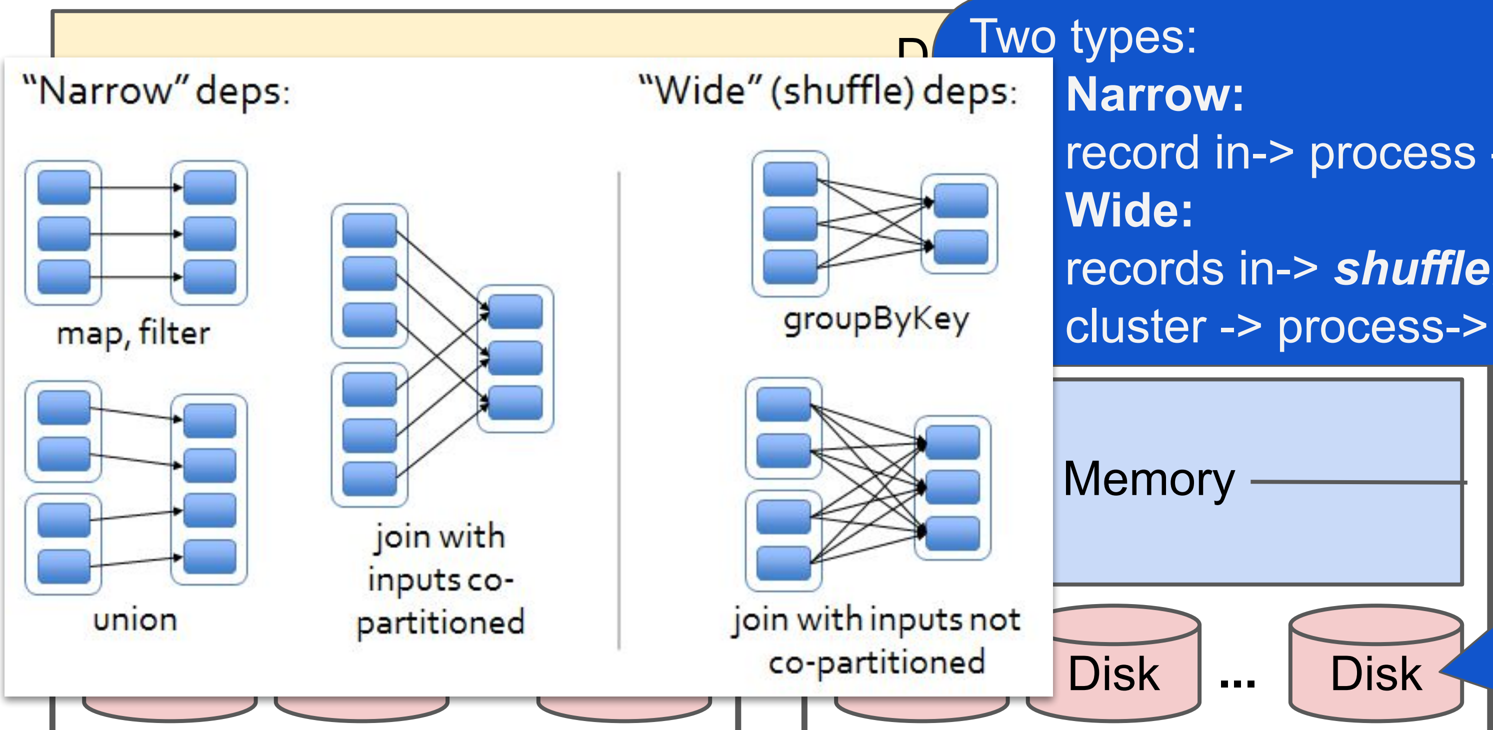

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Image from Nguyen: https://trongkhoanguyen.com/spark/understand-rdd-operations-transformations-and-actions/

Spark System: Hierarchy

Co-partitions:
If the partitions for two RDDs are based on the same hash function and key.

Ea... y) chain of ***transformations***

...es *jobs* -> broken int... *stages* -> broken into *tasks*

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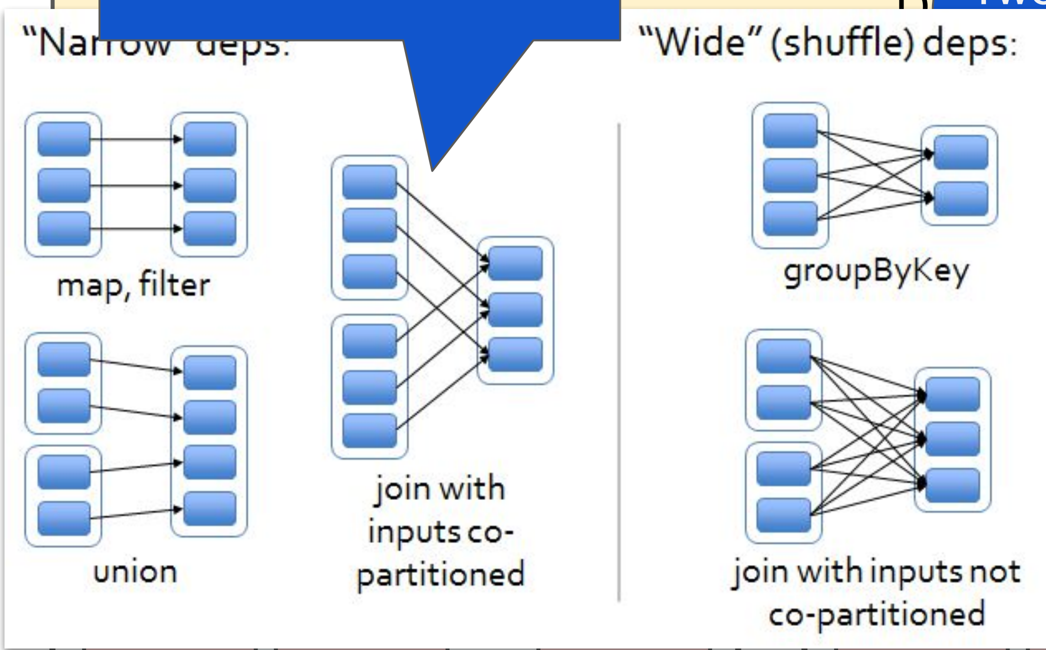

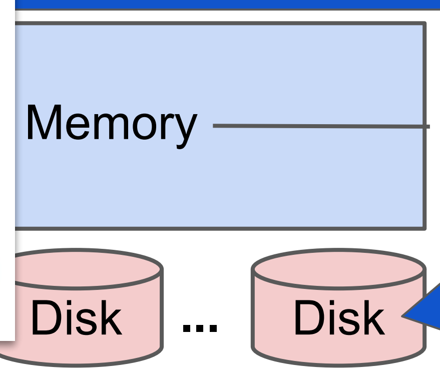

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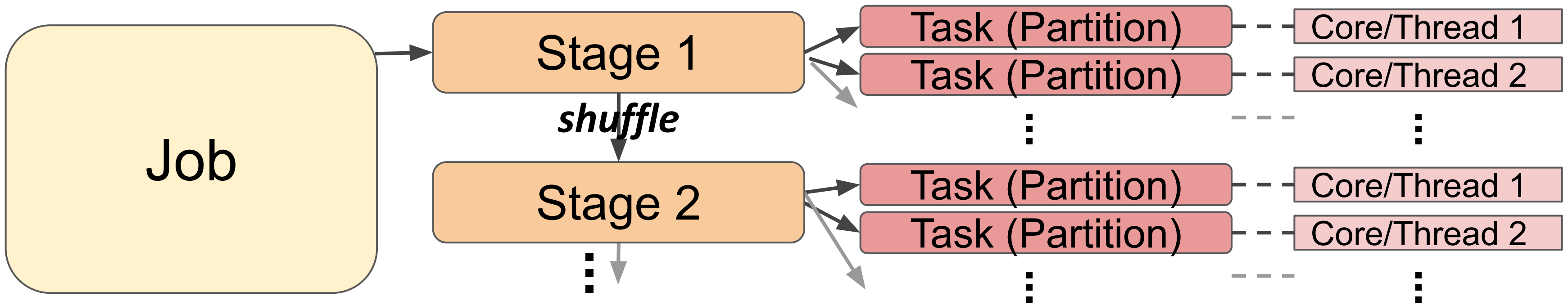
Spark System: Scheduling

Eager *action* -> sets off (lazy) chain of *transformations*
-> launches *jobs* -> broken into *stages* -> broken into *tasks*

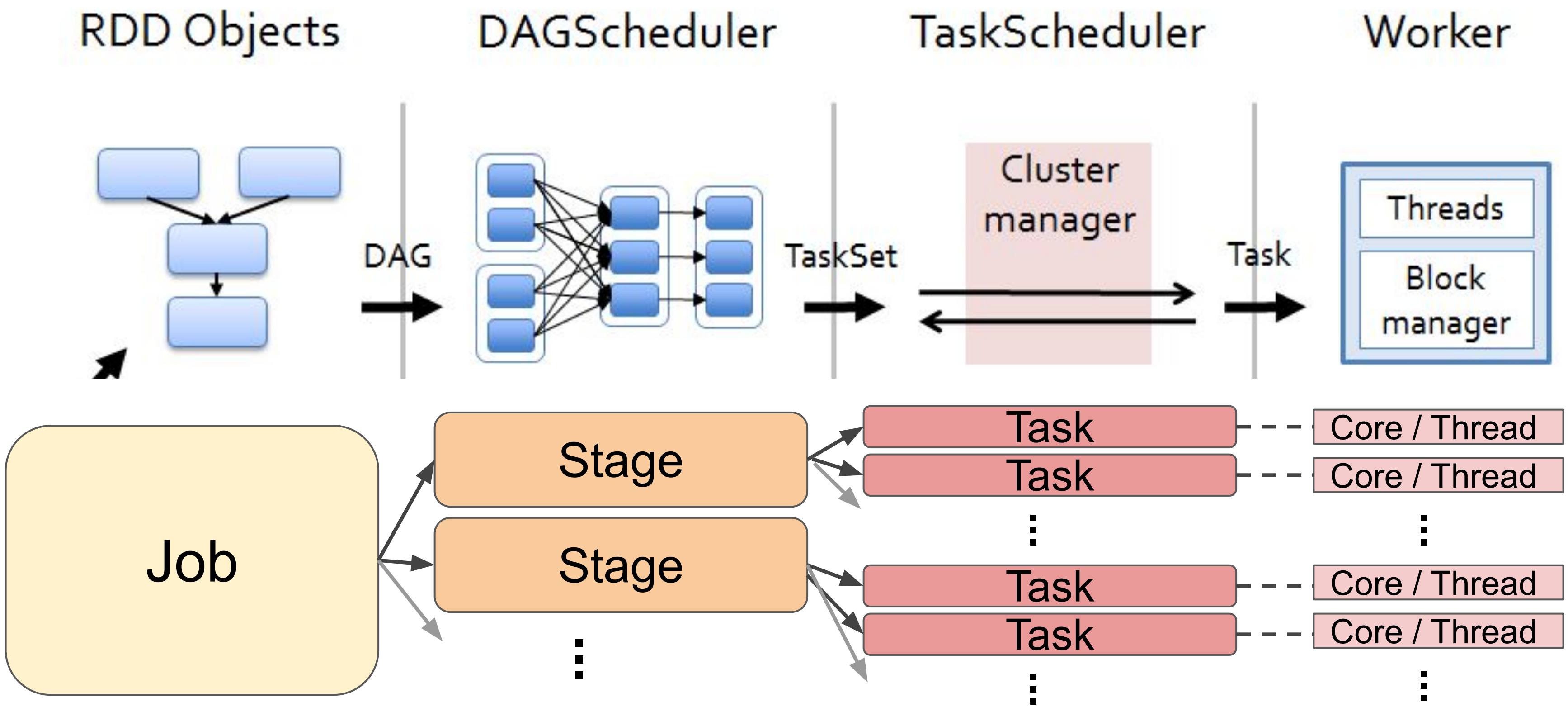
Jobs: A series of transformations (in a DAG) needed for the action

Stages: 1 or more per job -- 1 per set of operations separated by shuffle

Tasks: many per stage -- repeats exact same operation per partition



Spark System: Scheduling



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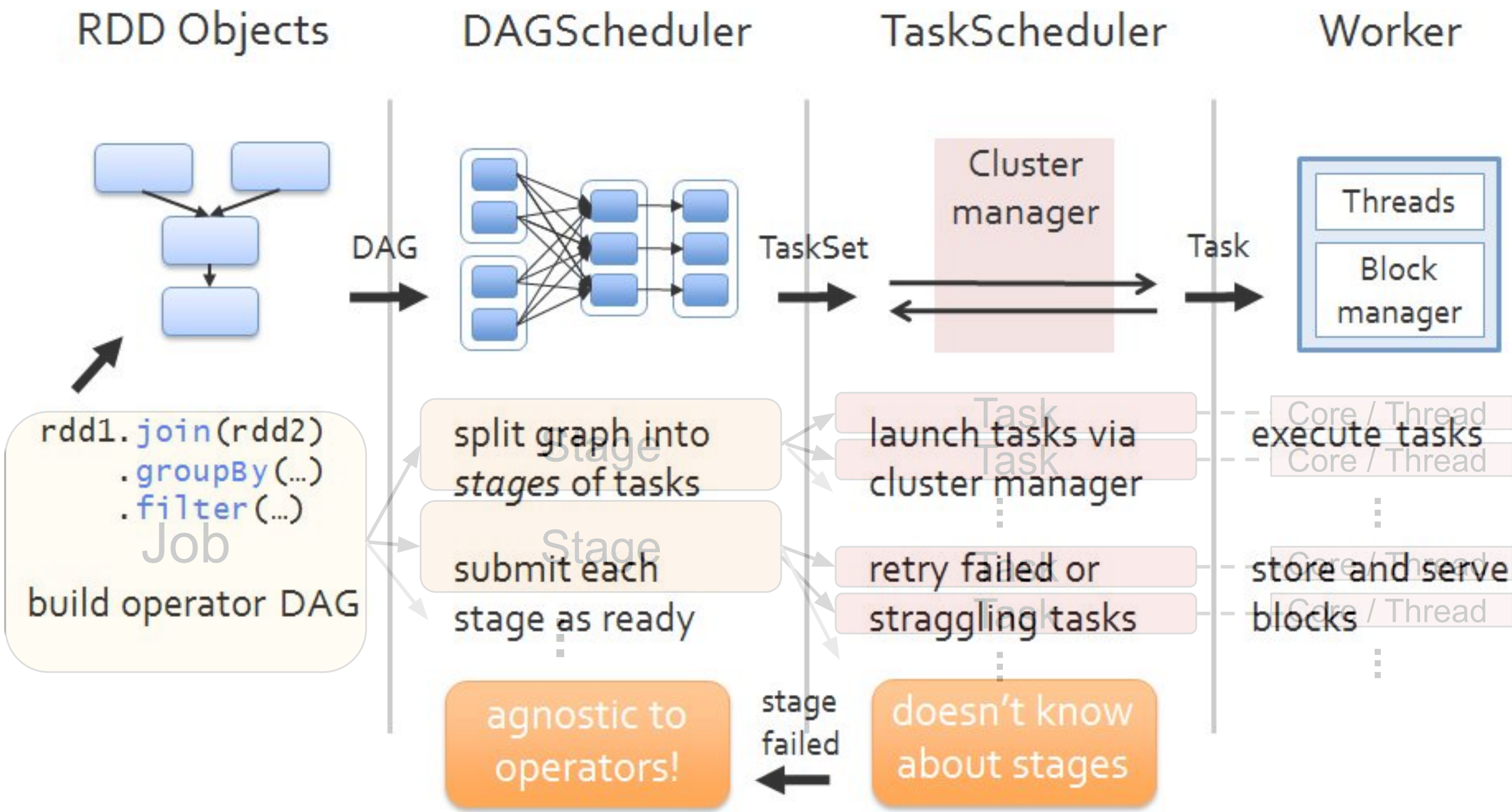

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MapReduce or Spark?

- Spark is typically faster
  - RDDs in memory
  - Lazy evaluation enables optimizing chain of operations.
- Spark is typically more flexible (custom chains of transformations)

MapReduce or Spark?

- Spark is typically faster
  - RDDs in memory
  - Lazy evaluation enables optimizing chain of operations.
- Spark is typically more flexible (custom chains of transformations)

However:

- Still need Hadoop (or some DFS) to hold original or resulting data efficiently and reliably.
- Memory across Spark cluster should be large enough to hold entire dataset to fully leverage speed.

Thus, MapReduce may sometimes be more cost-effective for very large data that does not fit in memory.