Spark: Resilient Distributed Datasets as Workflow System

빅데이터분석
천세진

Where is MapReduce Inefficient?

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

Where is MapReduce Inefficient?

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

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Spark의 Big Idea

- **Resilient Distributed Datasets(RDDs)**
  Read-only partitioned collection of records (like a DFS)
- But, 어떻게 데이터가 생성되었는지에 대한 레코드를 가짐
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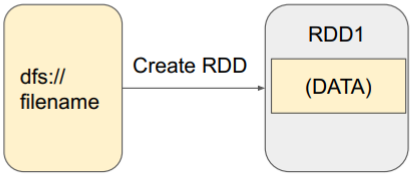

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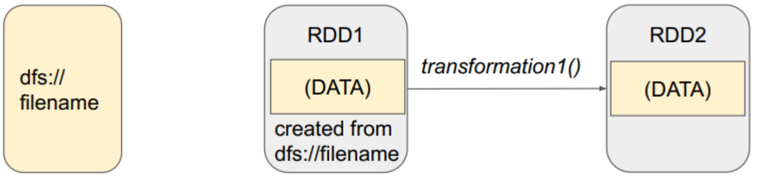

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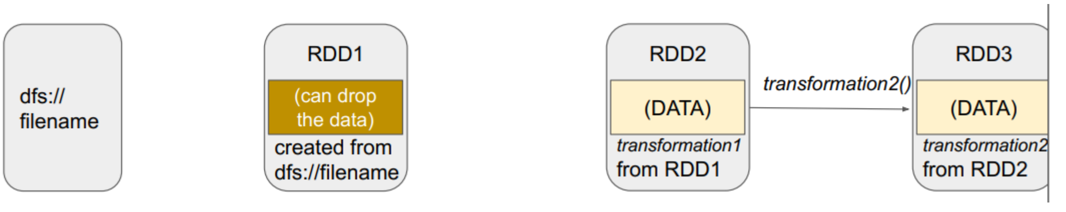

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- Faster communication and I/O
  - On-the-fly 형태로 데이터셋을 rebuilding이 가능함
  - disk에 중간 결과(Intermediate datasets)가 저장되지 않음
    - Only in-memory

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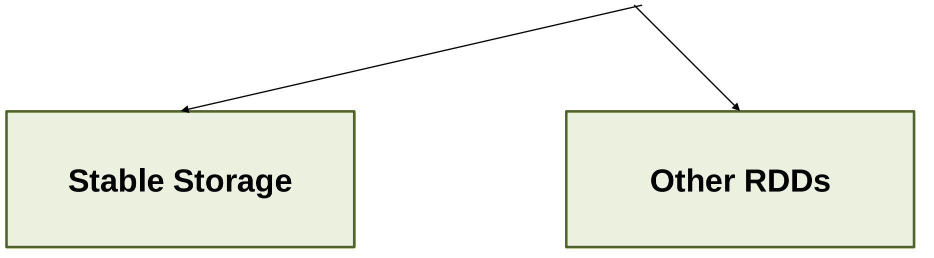

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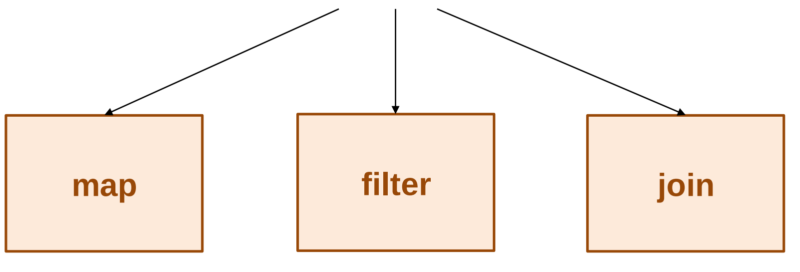

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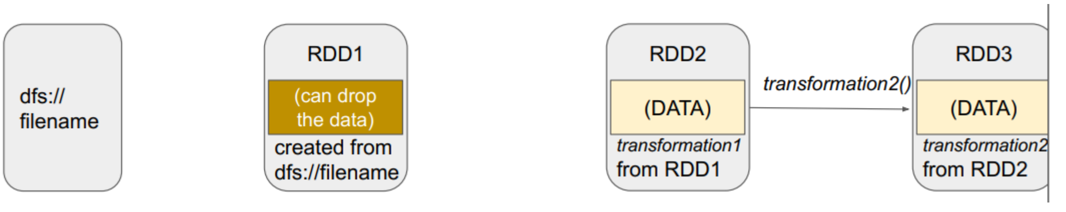

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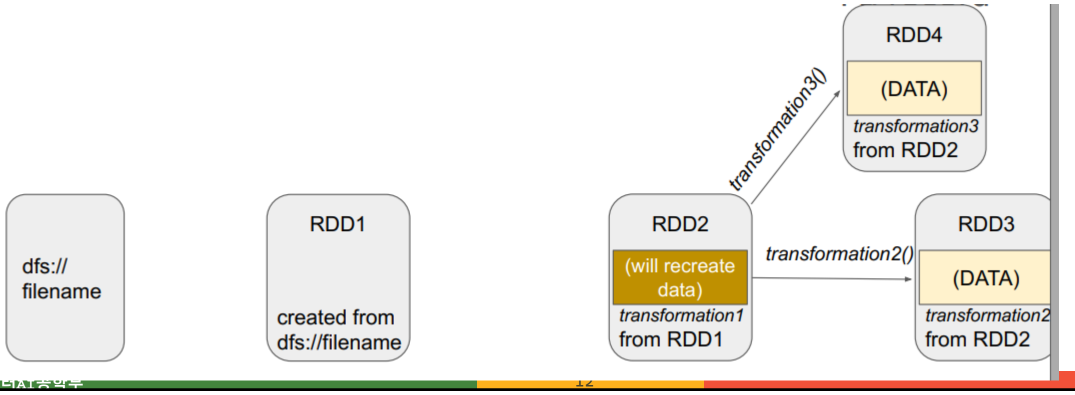

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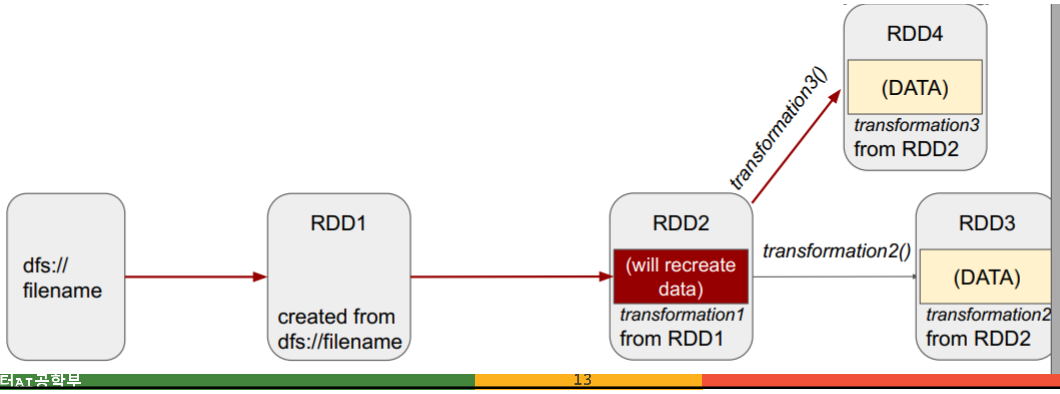


Transformations: RDD to RDD

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)
	$groupByKey()$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, Seq[V])]}$
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$union()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[T]}) \Rightarrow \mathrm{RDD[T]}$
	$join()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (V, W))]}$
	$cogroup()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (Seq[V], Seq[W]))]}$
	$crossProduct()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[U]}) \Rightarrow \mathrm{RDD[(T, U)]}$
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, W)]}$ (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$partitionBy(p : \mathrm{Partitioner[K]})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$

Table 2: Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael J. Franklin, Scott Shenker, Ion Stoica. "Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing.". *NSDI 2012.* April 2012.

Transformations: RDD to Value Object, or Storage

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

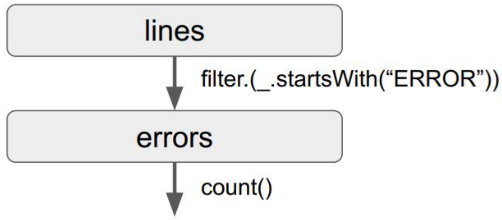
Current Transformation and Actions

- filter, map, flatMap, reduceByKey, groupByKey
- collect, count, take

Example

Count errors in a log file:

TYPE MESSAGE TIME



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errors.count
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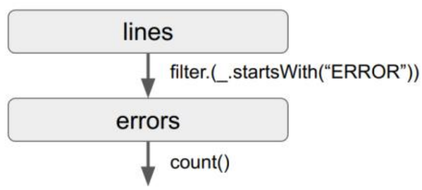

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Example

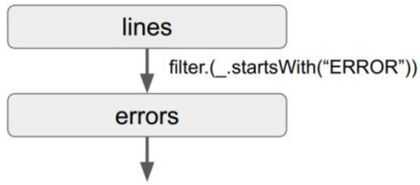
Collect times of hdfs-related errors

TYPE MESSAGE TIME

Pseudocode:

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

(`errors.count` is struck through.)



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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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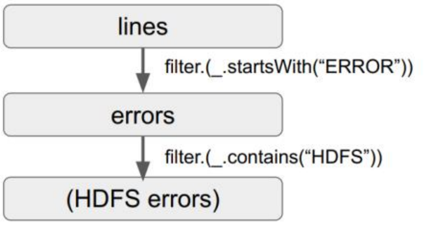

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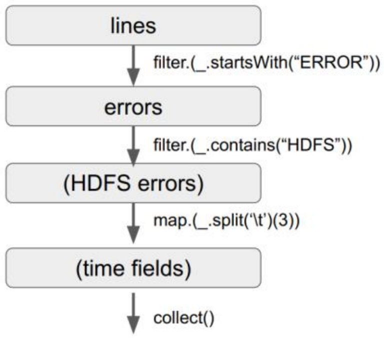

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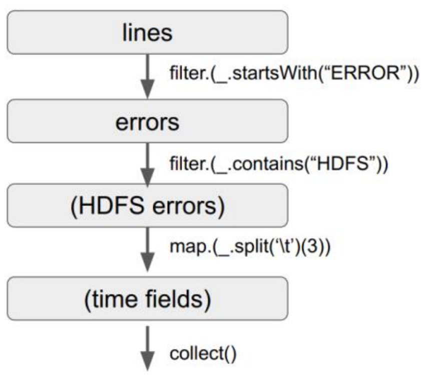

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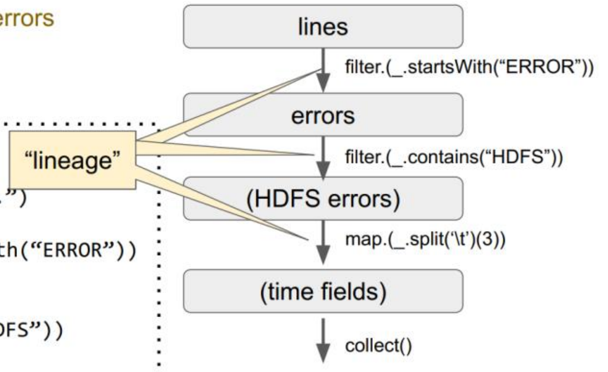

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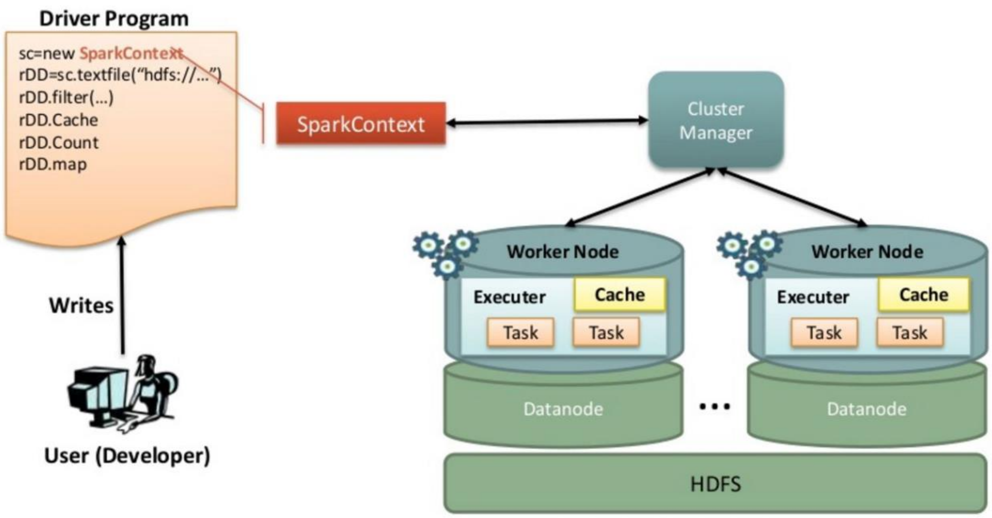
Workflow System의 장점

- More efficient failure recovery
- More efficient grouping of tasks and scheduling
- Integration of programming language features:
  - Loops (not a "cyclic" workflow system)
  - Function libraries

The Spark Programming Model



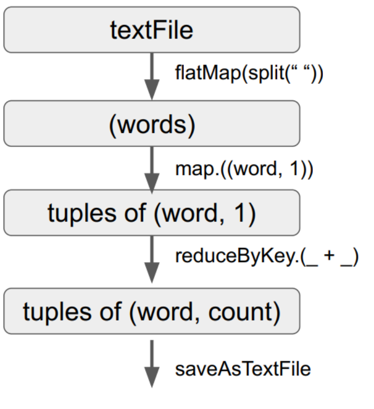
Gupta, Manish. Lightening Fast Big Data Analytics using Apache Spark. *UniCom 2014.*

The Spark Programming Model

Word Count

```
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

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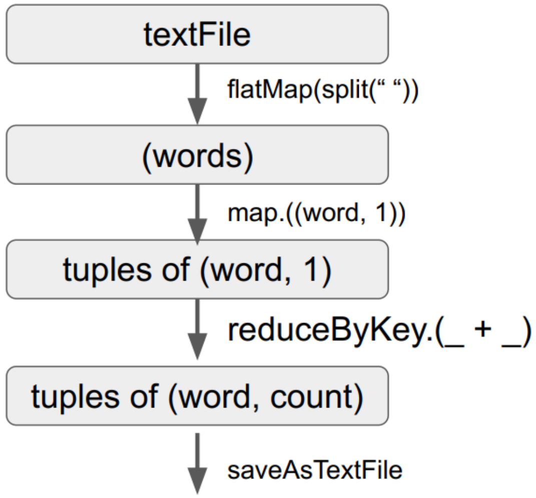

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Lazy Evaluation

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))
```

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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)
```

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

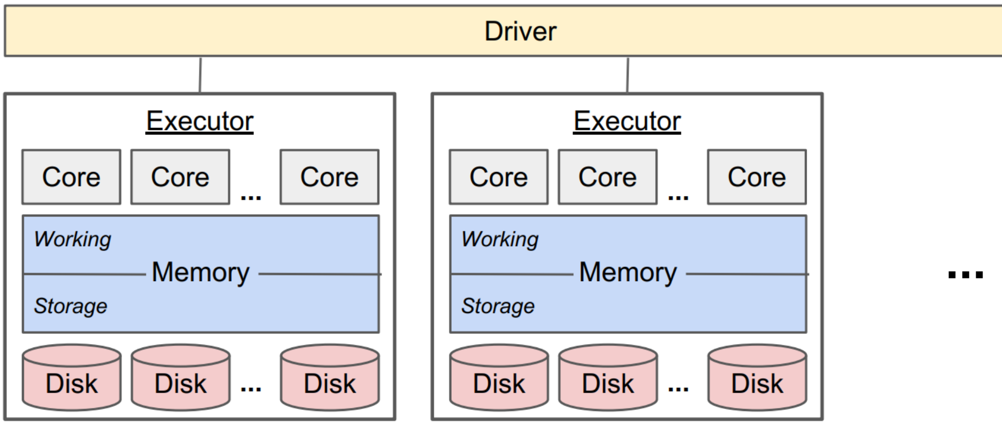
```
initialValue = 0
sumAcc = sc.accumulator(initialValue)
rdd.foreeach(lambda i: sumAcc.add(i))
print(minAcc.value)

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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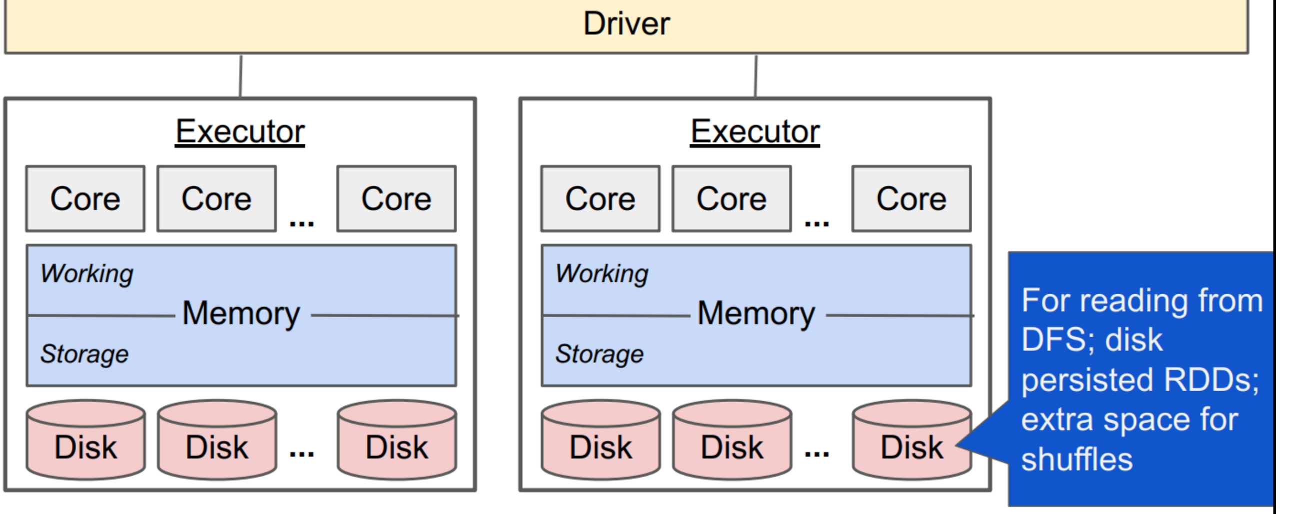

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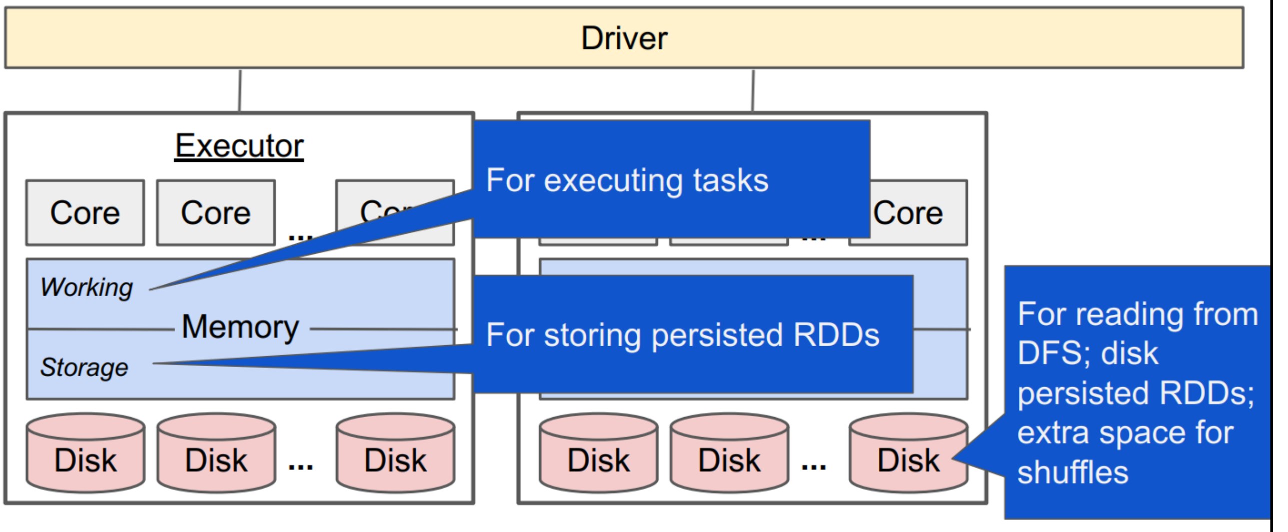

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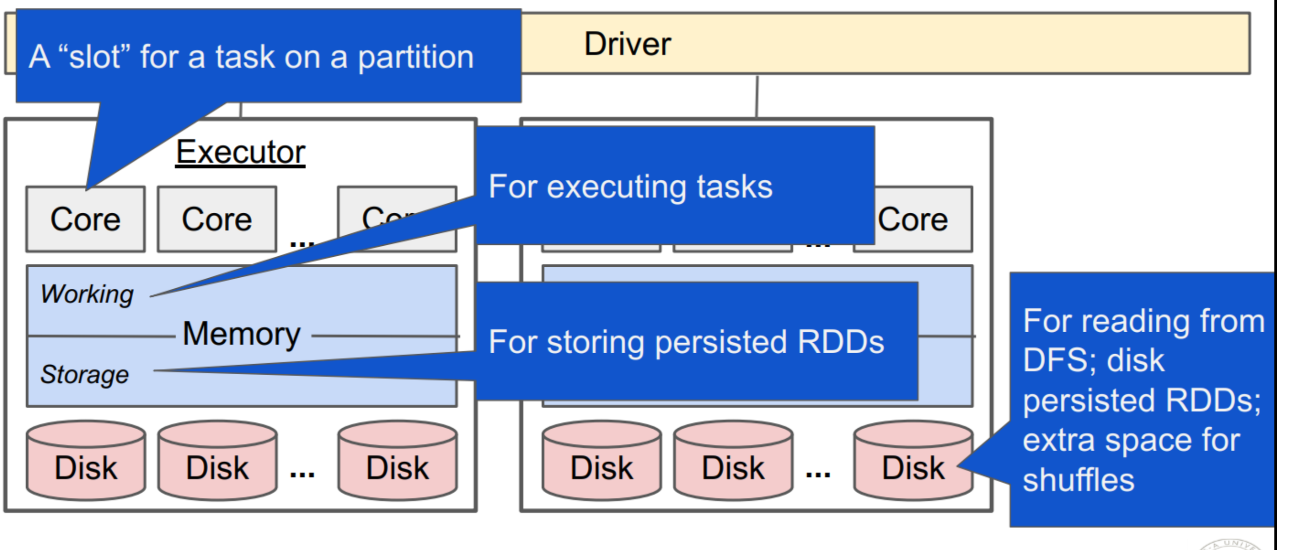

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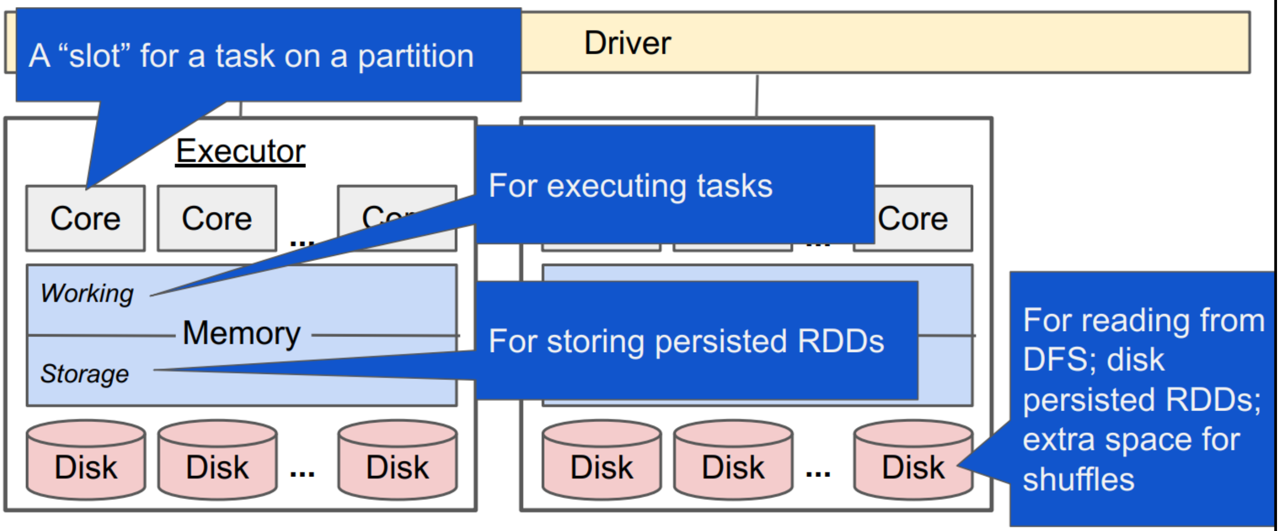

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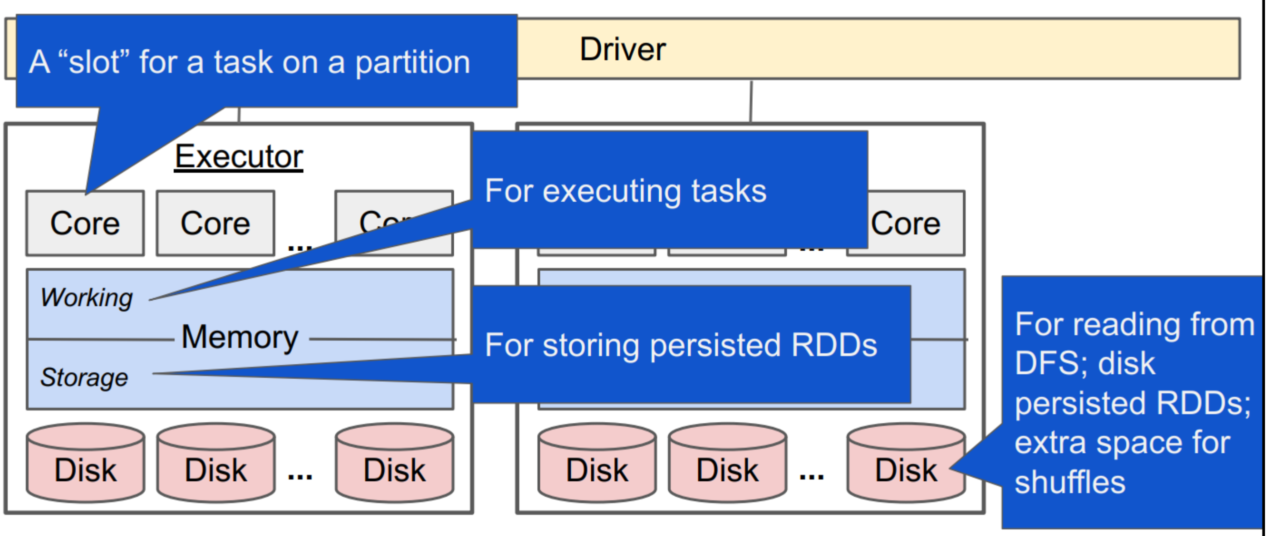
-> launches *jobs* -> broken into *stages* -> broken into ***tasks***



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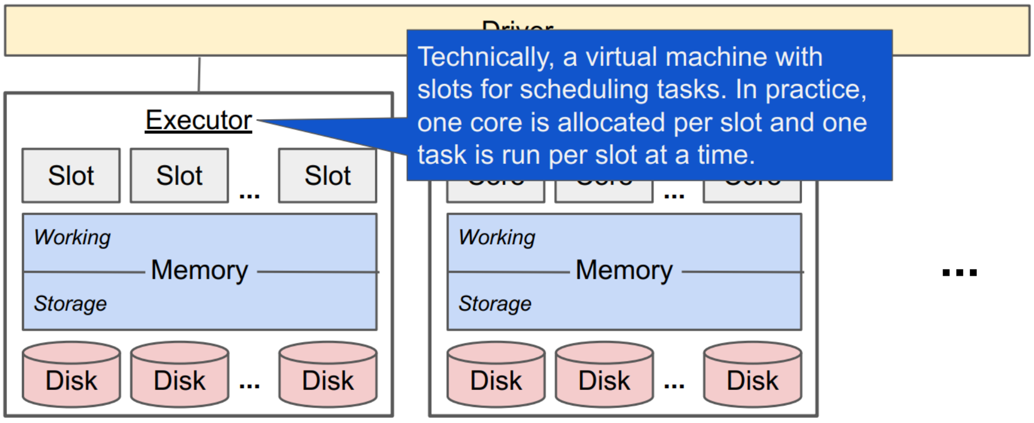

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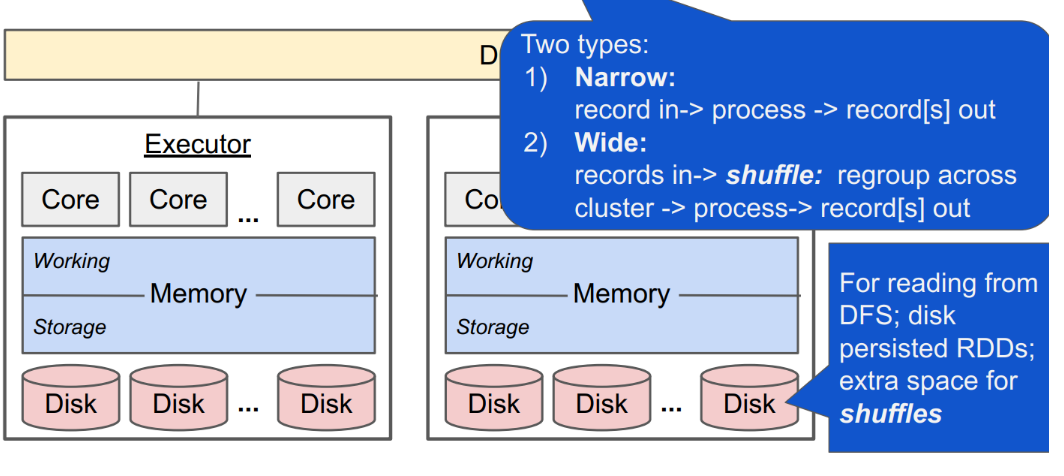

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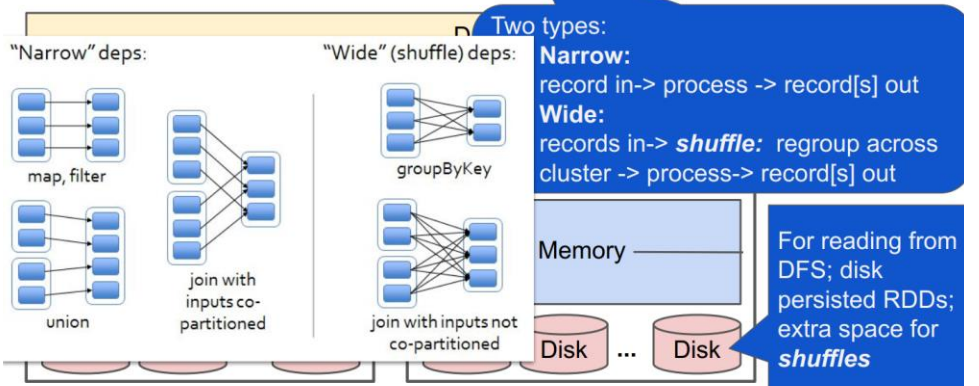


Image from Nguyen: https://trongkhoanguyen.com/spark/understand-rdd-operations-transformations-and-actions/

Spark System: Hierarchy

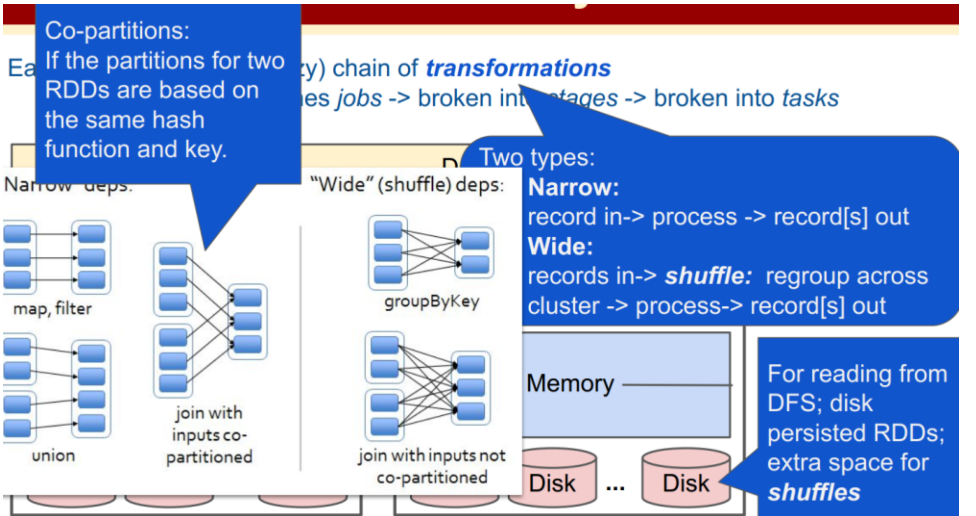
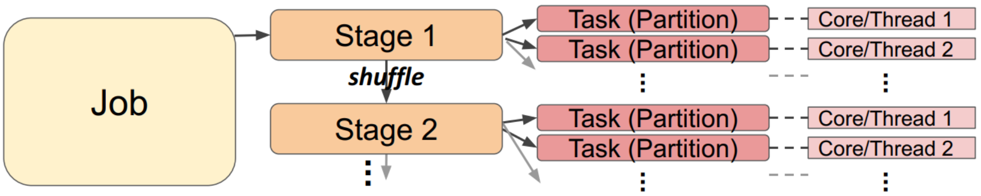


Image from Nguyen: https://trongkhoanguyen.com/spark/understand-rdd-operations-transformations-and-actions/

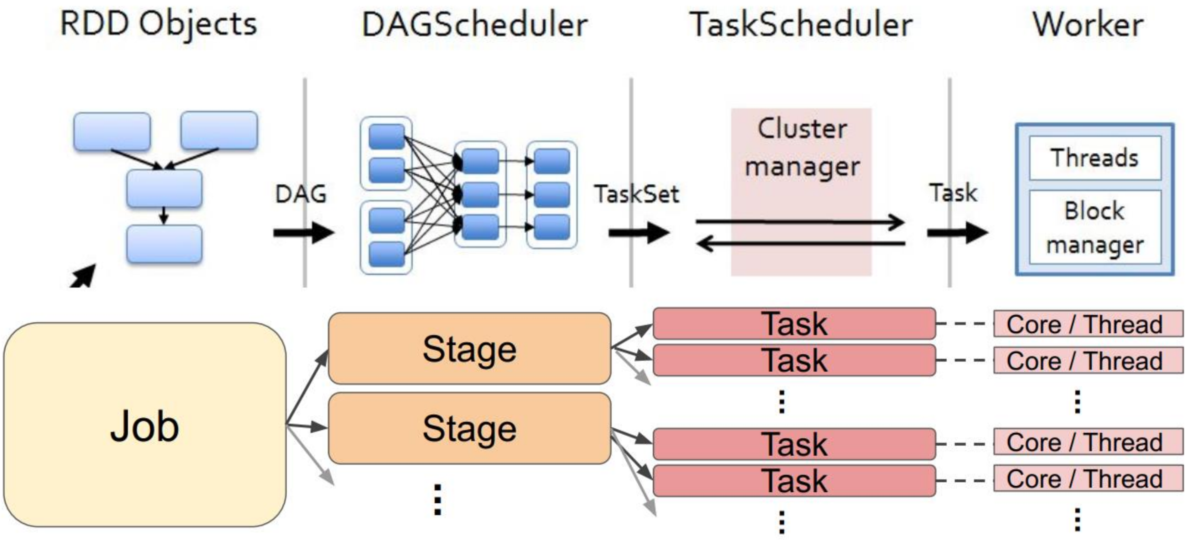
Spark System: Hierarchy

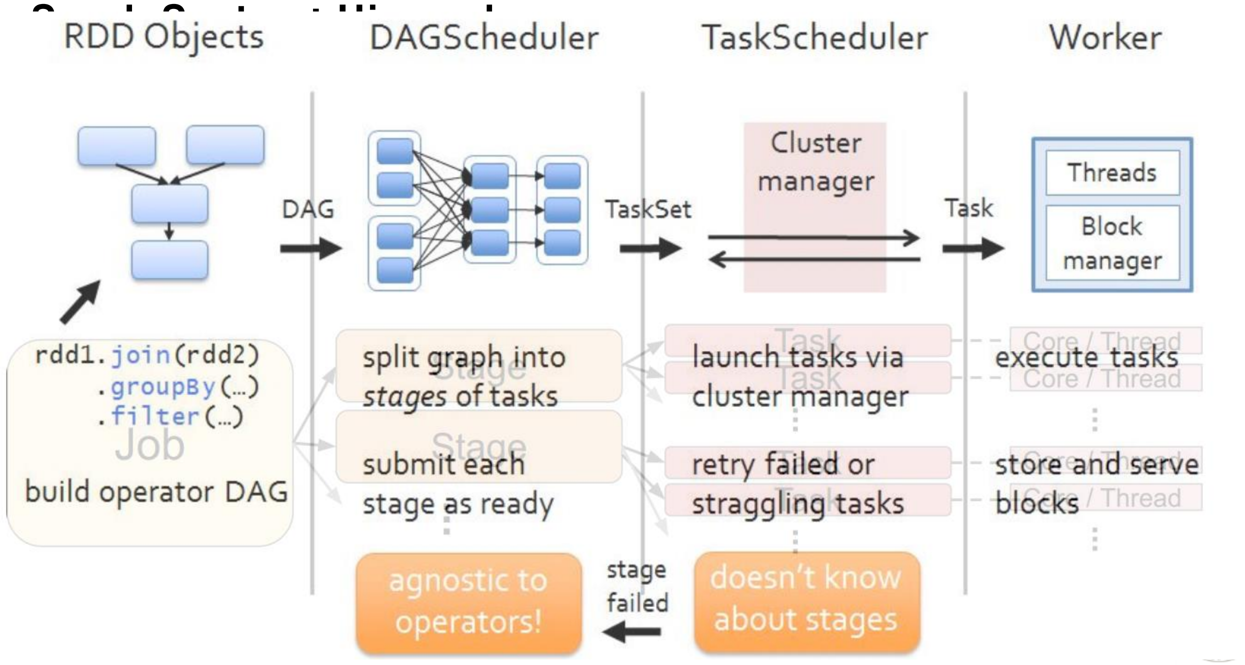
Eager *action* -> sets off (lazy) chain of *transformations*
-> launches *jobs* -> broken into *stages* -> broken into *tasks*

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: Hierarchy





MapReduce or Spark?

- Spark is typically faster
  - RDDs in memory
  - Lazy evaluation enables optimizing chain of operations.
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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.