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)

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

Spark의 Big Idea

- **Resilient Distributed Datasets(RDDs)**
  Read-only partitioned collection of records (like a DFS)
- But, 어떻게 데이터가 생성되었는지에 대한 레코드를 가짐
  - Combination of *transformations* from other dataset(s).

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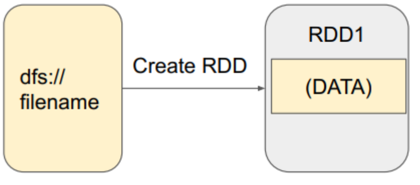

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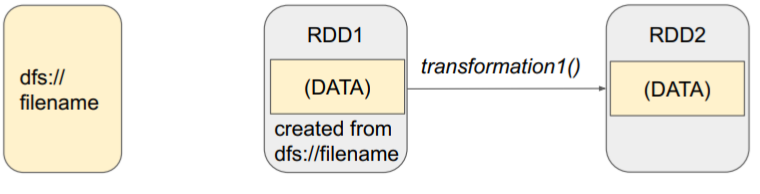

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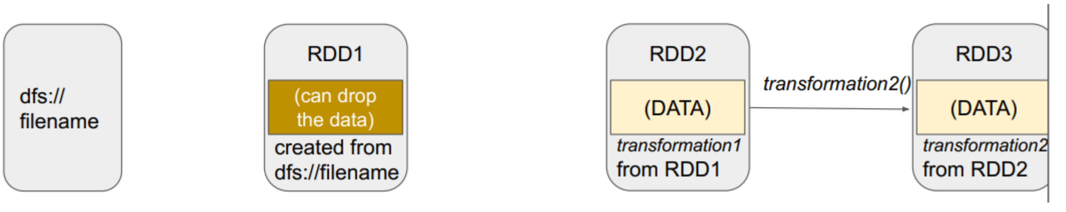

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- Faster communication and I/O
  - On-the-fly 형태로 데이터셋을 rebuilding이 가능함
  - disk에 중간 결과(Intermediate datasets)가 저장되지 않음
    - Only in-memory

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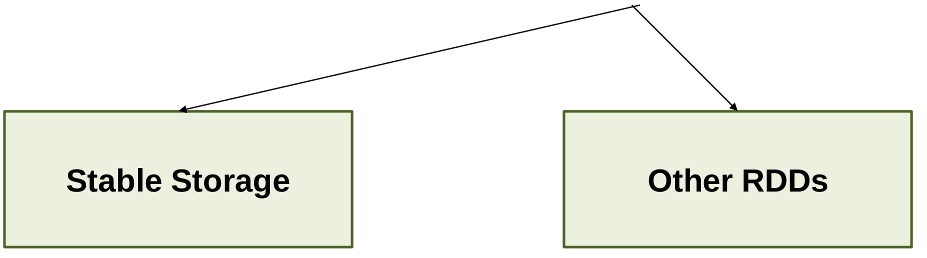

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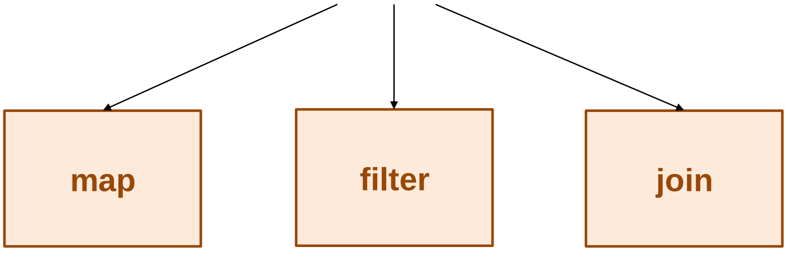

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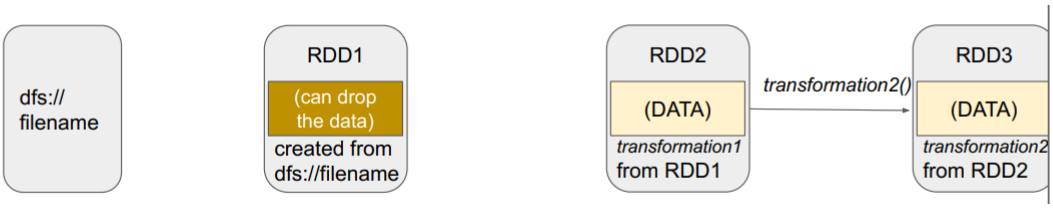

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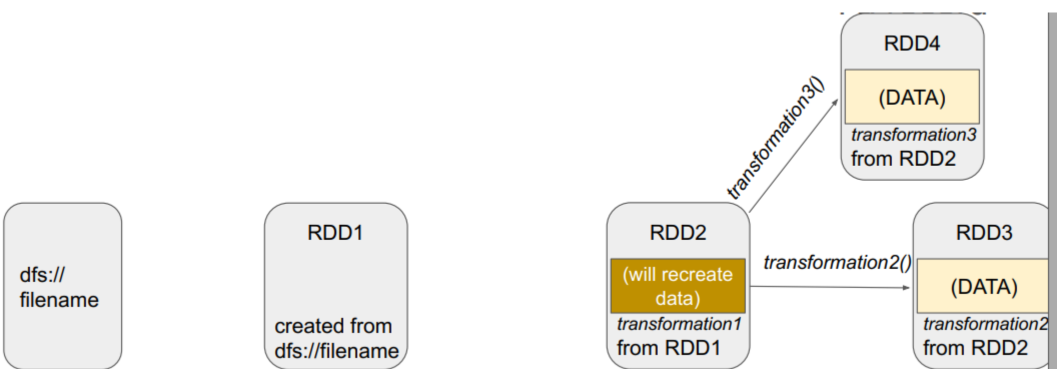

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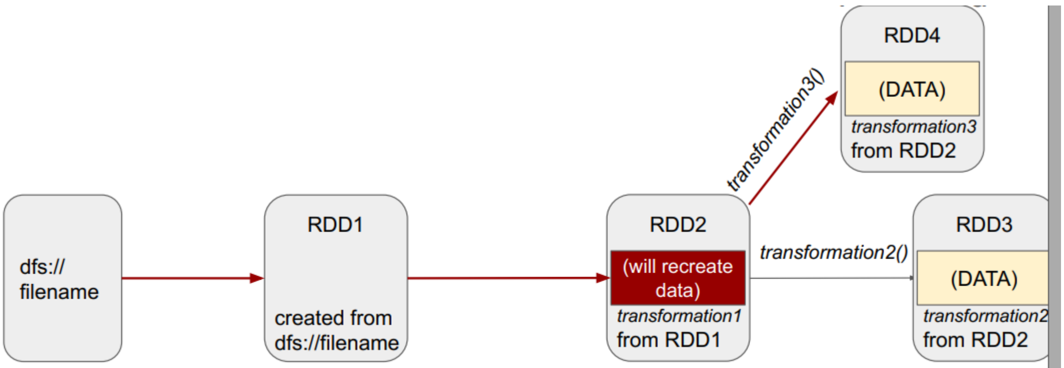


Transformations: RDD to RDD

Transformations	*map*(f : T ⇒ U)	:	RDD[T] ⇒ RDD[U]
	filter(f : T ⇒ Bool)	:	RDD[T] ⇒ RDD[T]
	flatMap(f : T ⇒ Seq[U])	:	RDD[T] ⇒ RDD[U]
	sample(*fraction* : Float)	:	RDD[T] ⇒ RDD[T] (Deterministic sampling)
	groupByKey()	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V])]
	reduceByKey(f : (V, V) ⇒ 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 : V ⇒ W)	:	RDD[(K, V)] ⇒ RDD[(K, W)] (Preserves partitioning)
	sort(c : Comparator[K])	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	partitionBy(p : Partitioner[K])	:	RDD[(K, V)] ⇒ 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

eager 와 lazy 실행의 설명

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

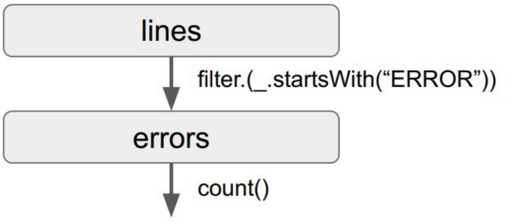
Current Transformation and Actions

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

Example

Count errors in a log file:

TYPE MESSAGE TIME



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Pseudocode:

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errors =
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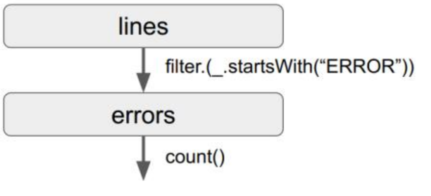
errors.count
```



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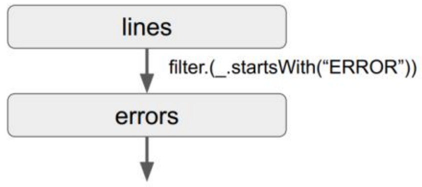
Example

Collect times of hdfs-related errors

TYPE MESSAGE TIME

Pseudocode:

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



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Persistance

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

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.

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Pseudocode:

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

lines
↓ filter.(_.startsWith("ERROR"))
errors
↓ filter.(_.contains("HDFS"))
(HDFS errors)

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errors.filter(_.contains("HDFS"))
     .map(_split('\t')(3))
     .collect()
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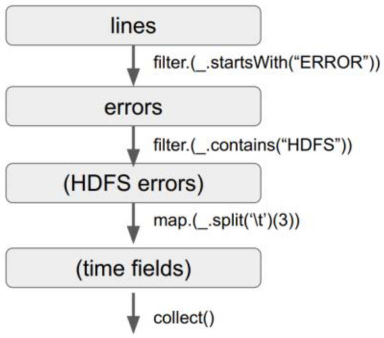

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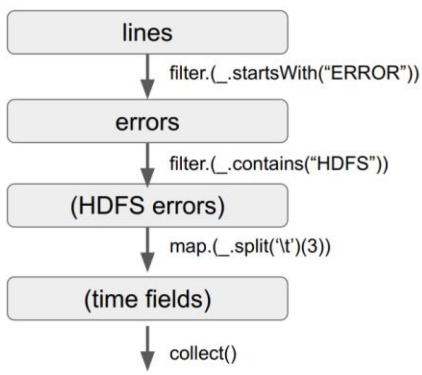

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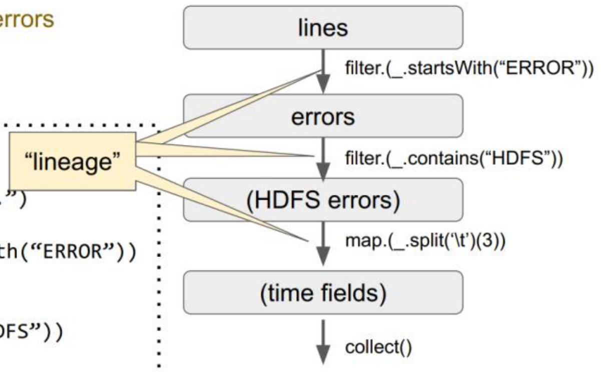

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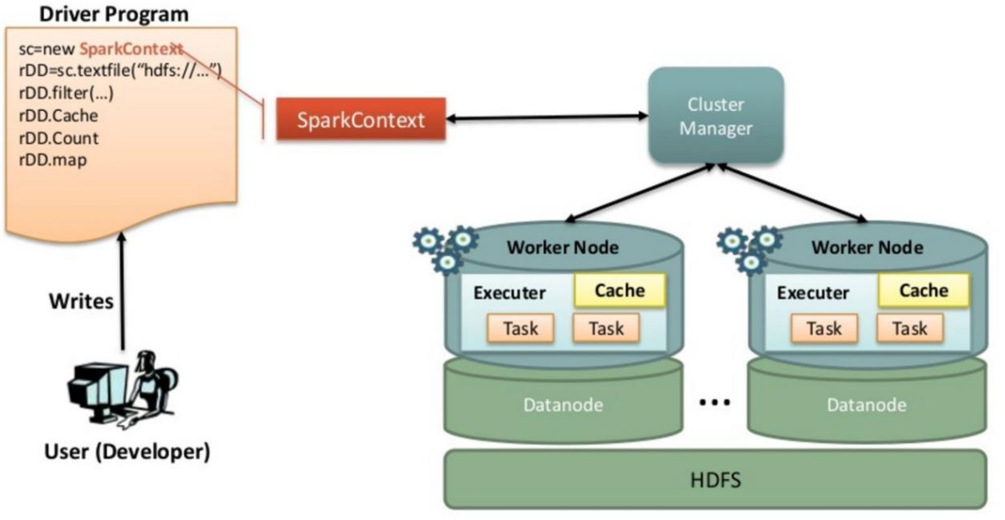
Workflow System의 장점

- 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



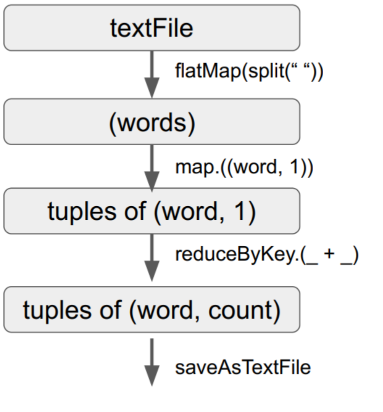
Gupta, Manish. Lightening Fast Big Data Analytics using Apache Spark. *UniCom 2014.*

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

Word Count

Python:

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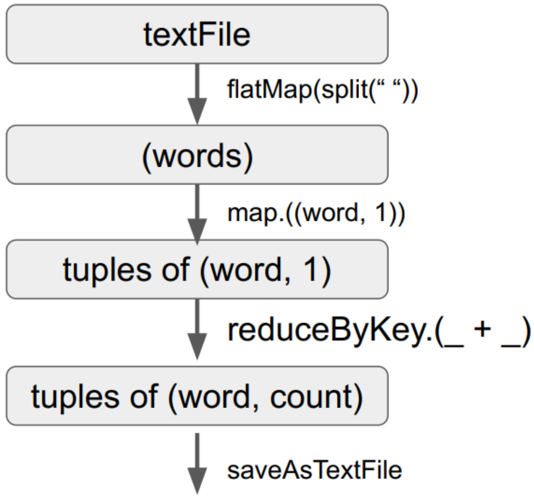

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Lazy Evaluation

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

Lazy Evaluation

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e.g. rdd(T) -> rdd(T)

```
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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Python:

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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

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Default Accumulator assumes sum function

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

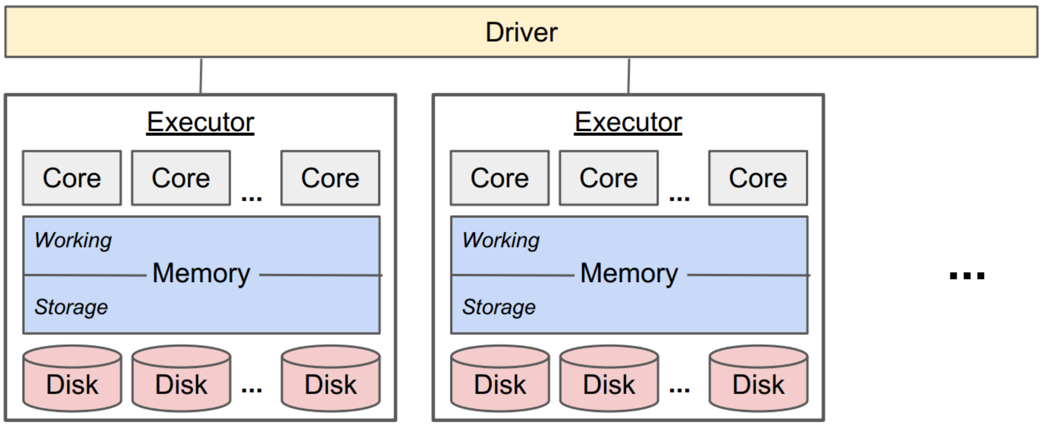
```
initialValue = 0
sumAcc = sc.accumulator(initialValue)
rdd.foreeach(lambda i: sumAcc.add(i))
print(minAcc.value)

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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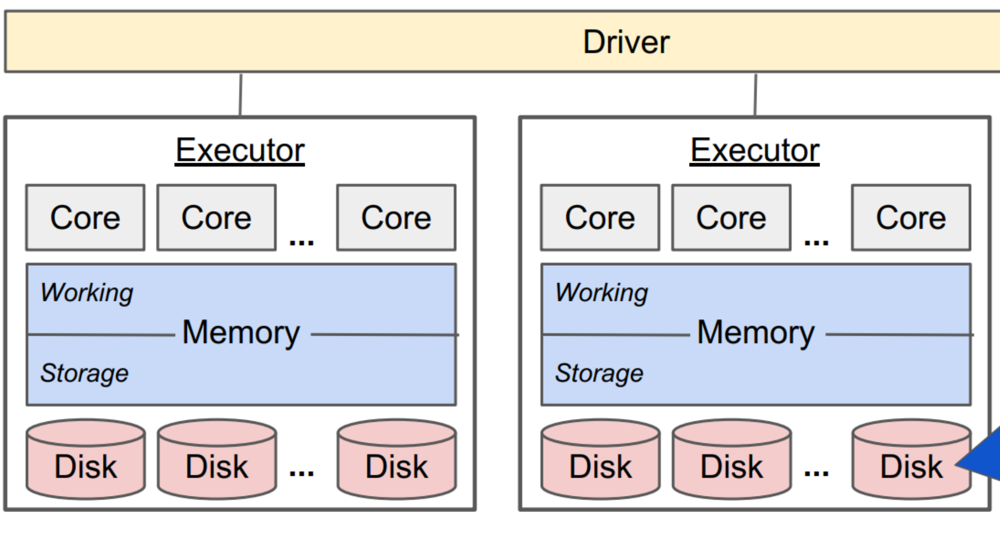

For reading from DFS; disk persisted RDDs; extra space for shuffles

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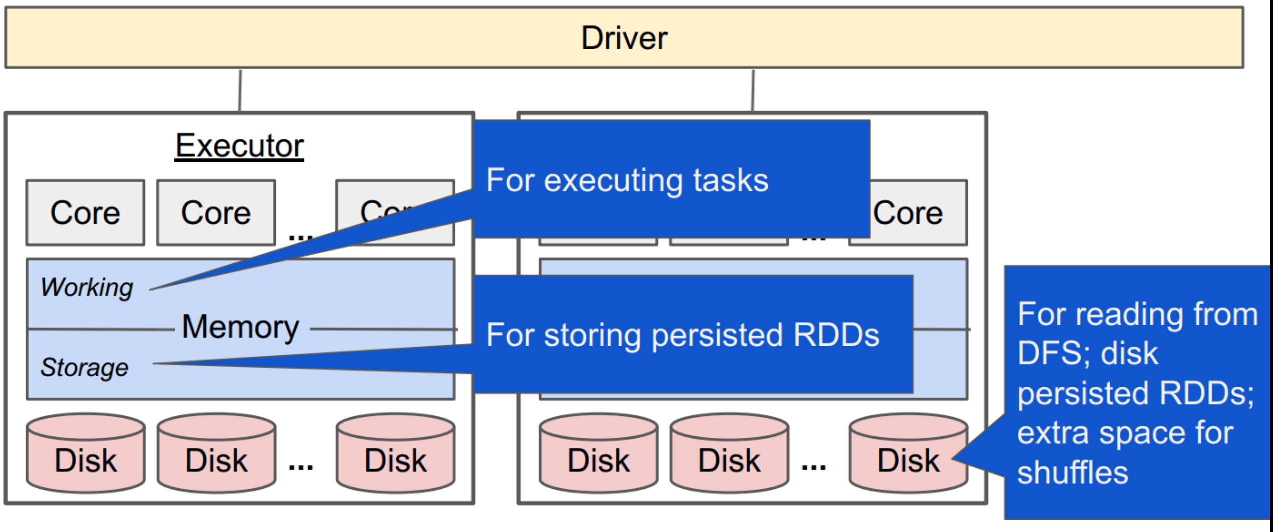

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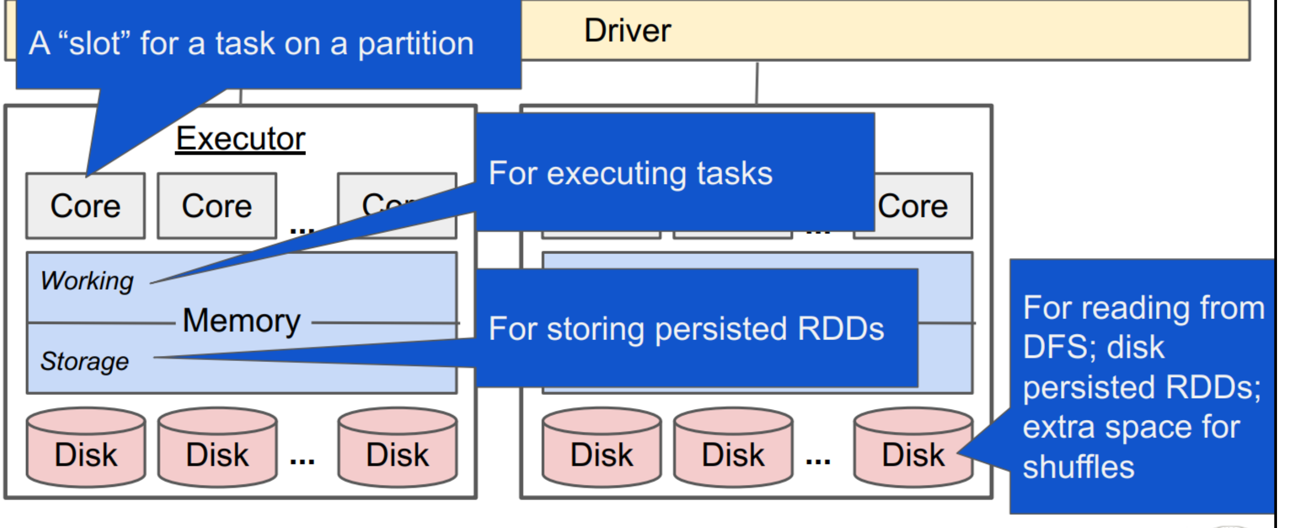

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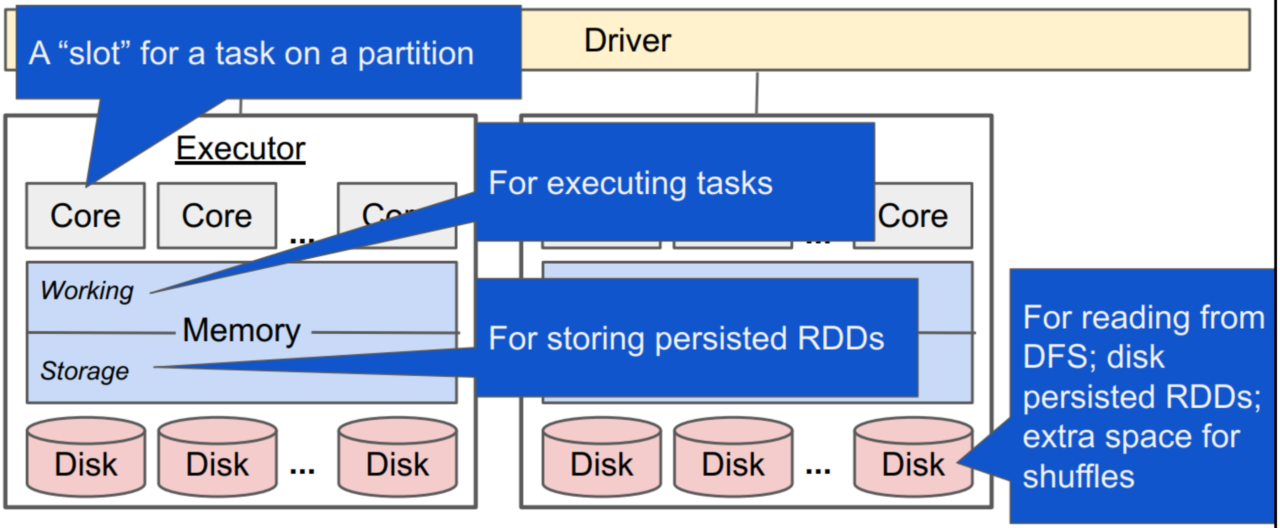
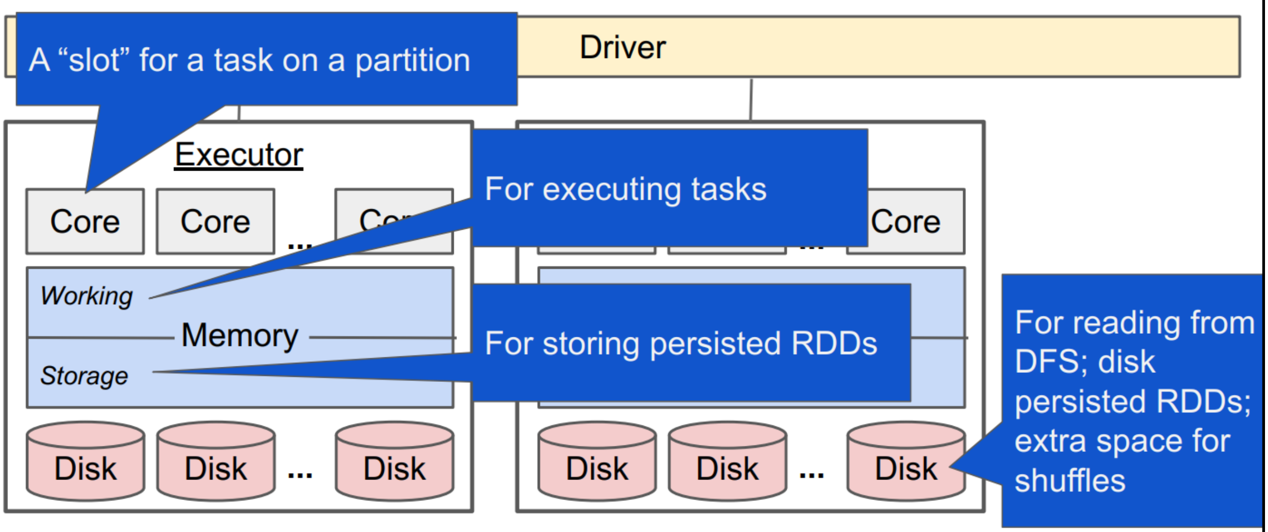


Eager *action* -> sets off (lazy) chain of *transformations*
-> launches *jobs* -> broken into *stages* -> broken into ***tasks***



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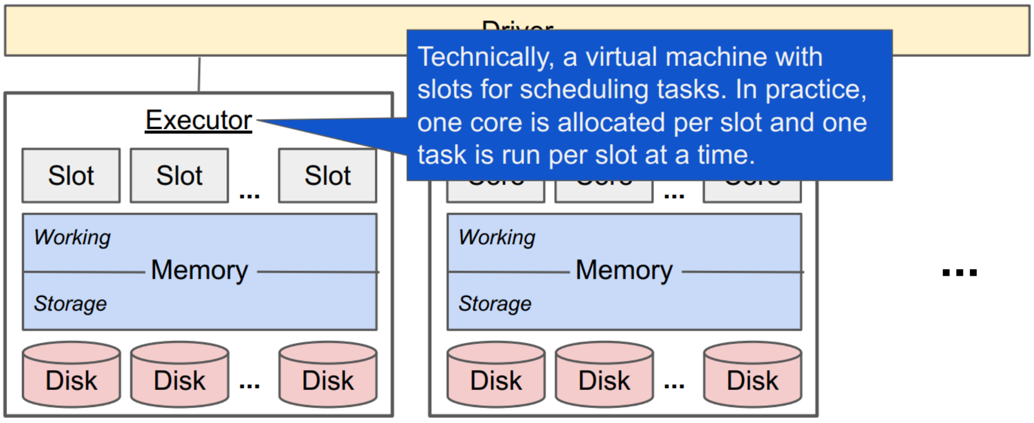

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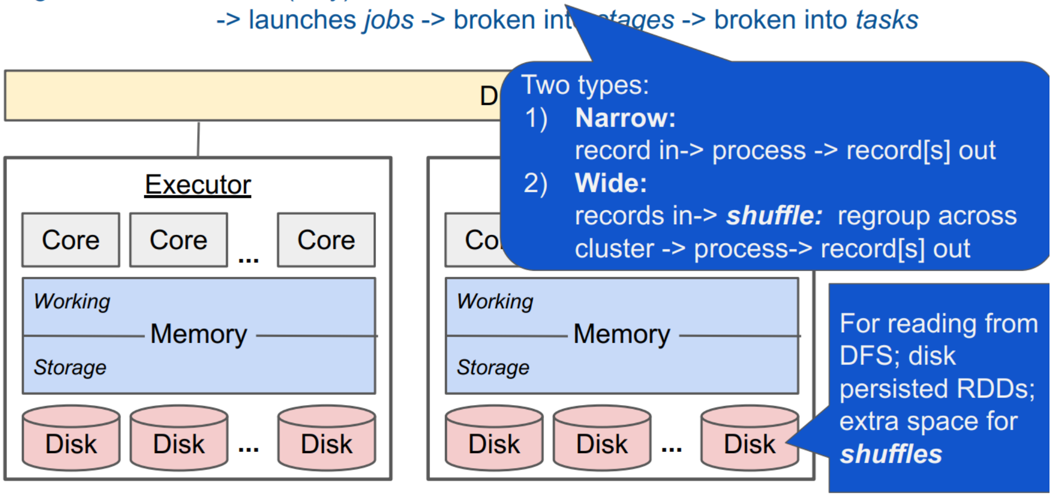

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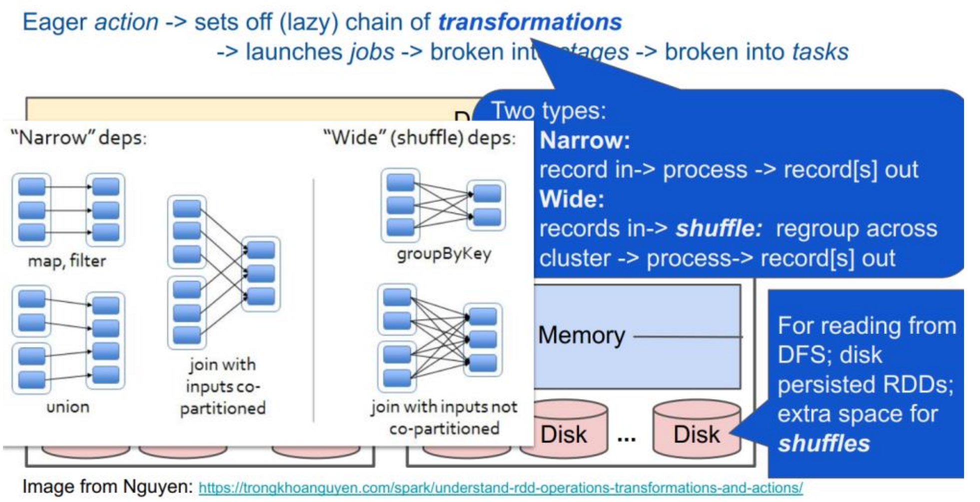

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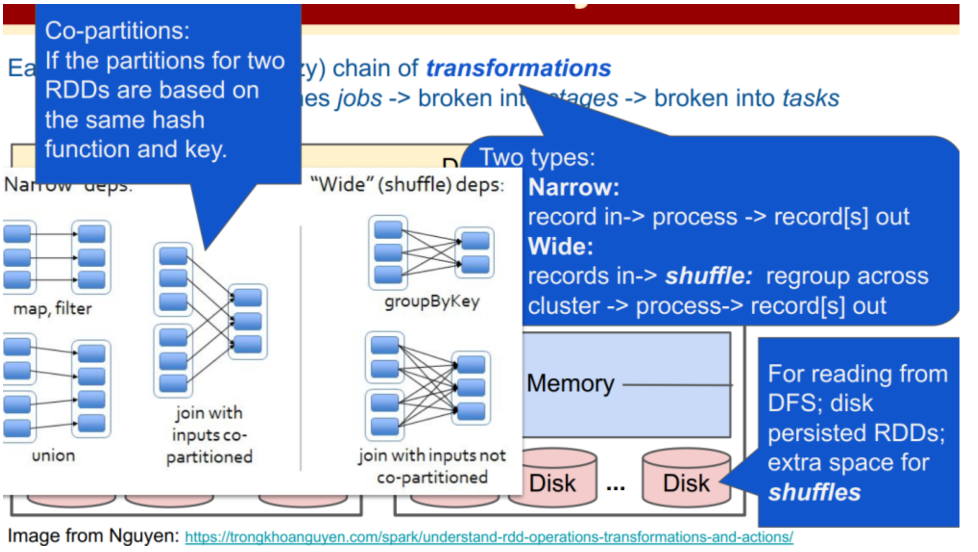

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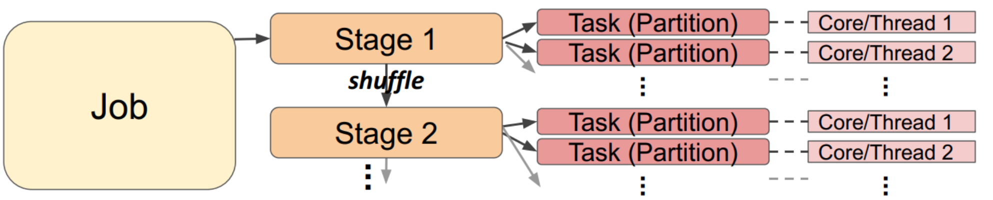
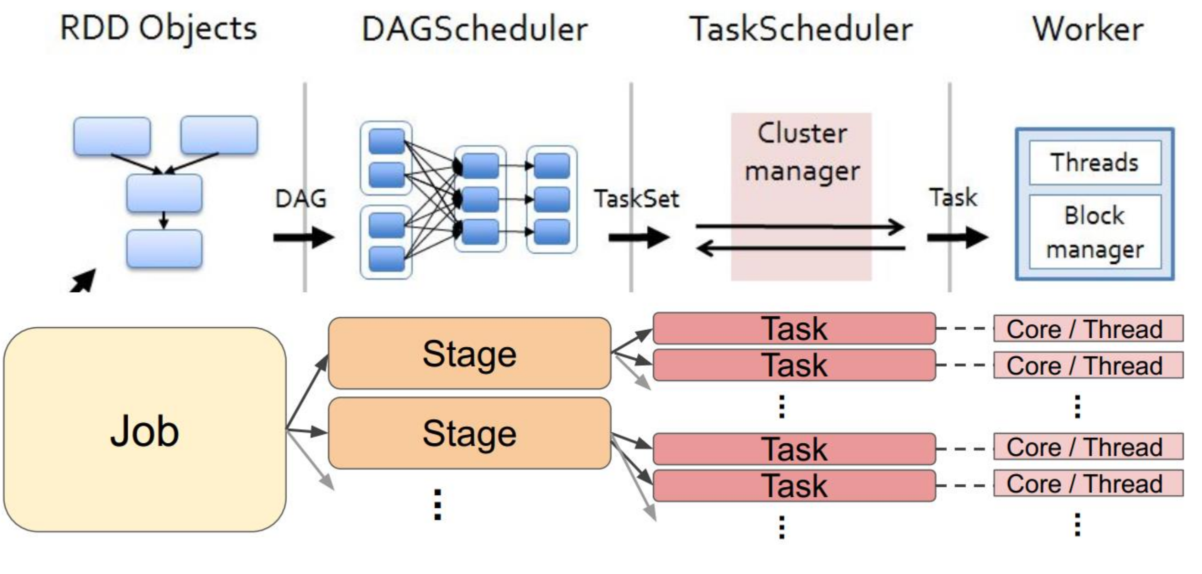
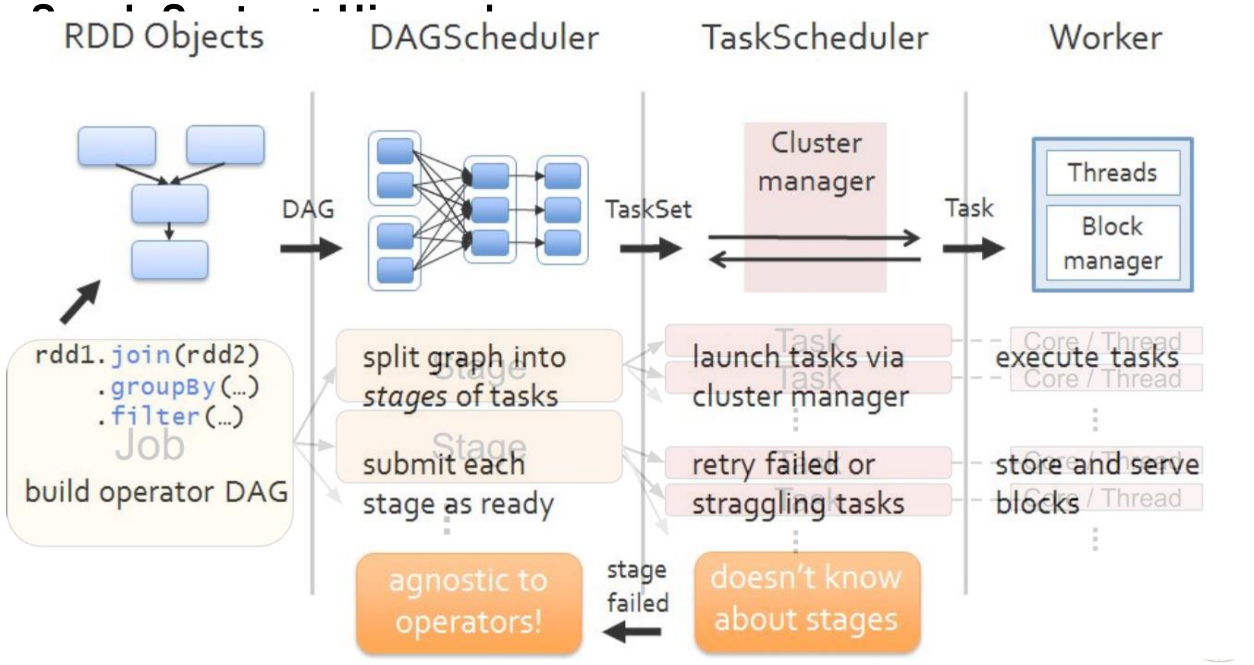
Jobs: A series of transformations (in a DAG) needed for the action
Stages: 1 or more per job -- 1 per set of operations separated by shuffle
Tasks: many per stage -- repeats exact same operation per partition



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.