Spark

Stony Brook University
CSE545, Fall 2016

Situations where MapReduce is not efficient

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

(Anytime where MapReduce would need to write and read from disk a lot).

Spark's Big Idea

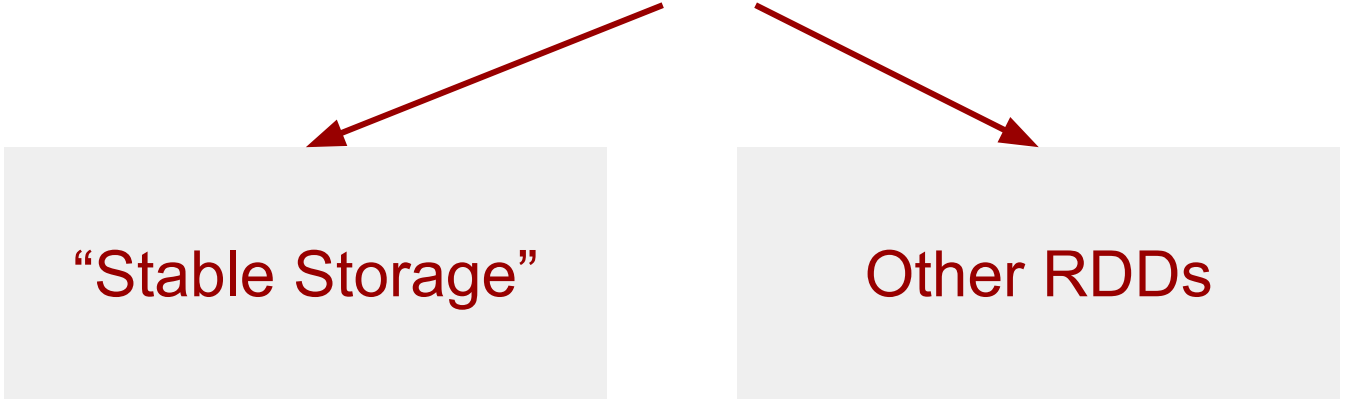
Resilient Distributed Datasets (RDDs) -- Read-only partitioned collection of records (like a DFS) but with a record of how the dataset was created as combination of *transformations* from other dataset(s).

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

⇨ Faster processing

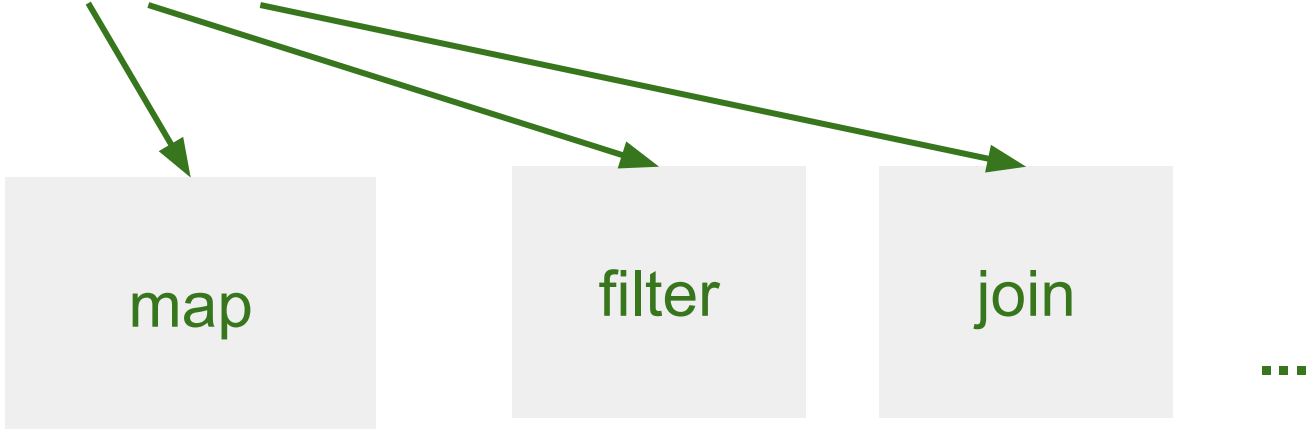
The Big Idea

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).



The Big Idea

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).



Original Transformations

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)]

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.

Original Transformations and Actions

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)]
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

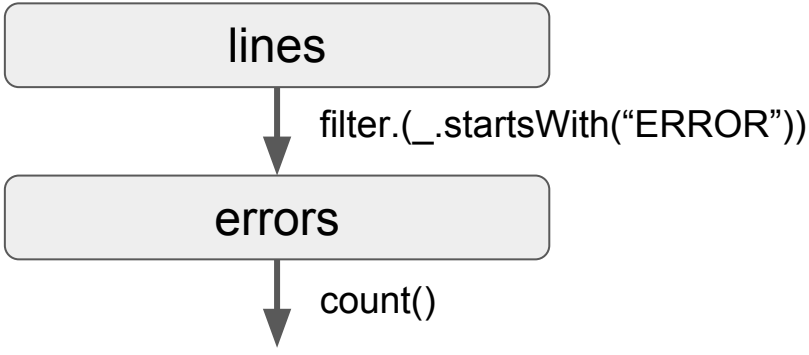
http://spark.apache.org/docs/latest/programming-guide.html#transformations

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

An Example

Count errors in a log file:

TYPE MESSAGE TIME



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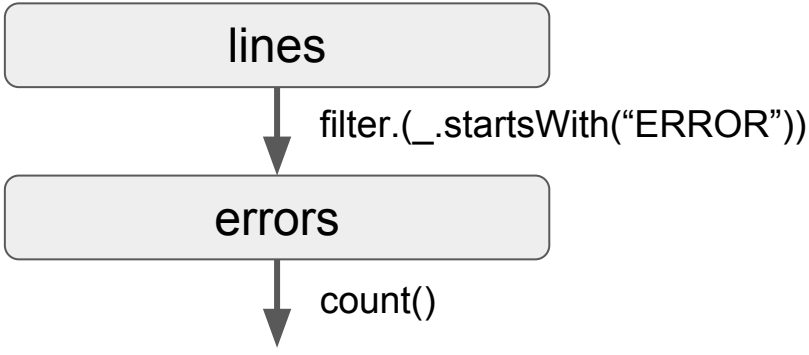
An Example

Count errors in a log file:

TYPE MESSAGE TIME

Pseudocode:

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



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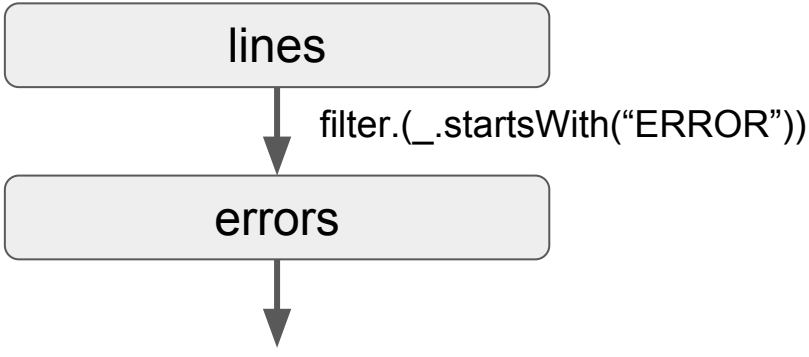
An Example

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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An Example

Collect times of hdfs-related errors

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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

Use ".cache" if wanting it to stay in memory-only.

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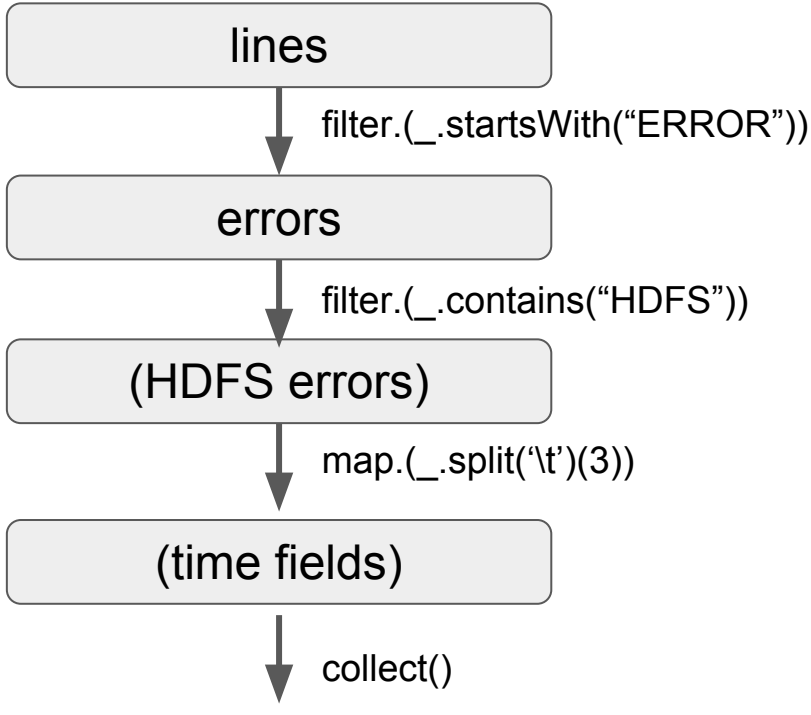
An Example

Collect times of hdfs-related errors

TYPE MESSAGE TIME

Pseudocode:

```
lines = sc.textFile(“dfs:...”)
errors =
    lines.filter(_.startswith(“ERROR”))
errors.persist
~~errors.count~~
errors.filter(_.contains(“HDFS”))
     .map(_split(‘\t’)(3))
     .collect()
```



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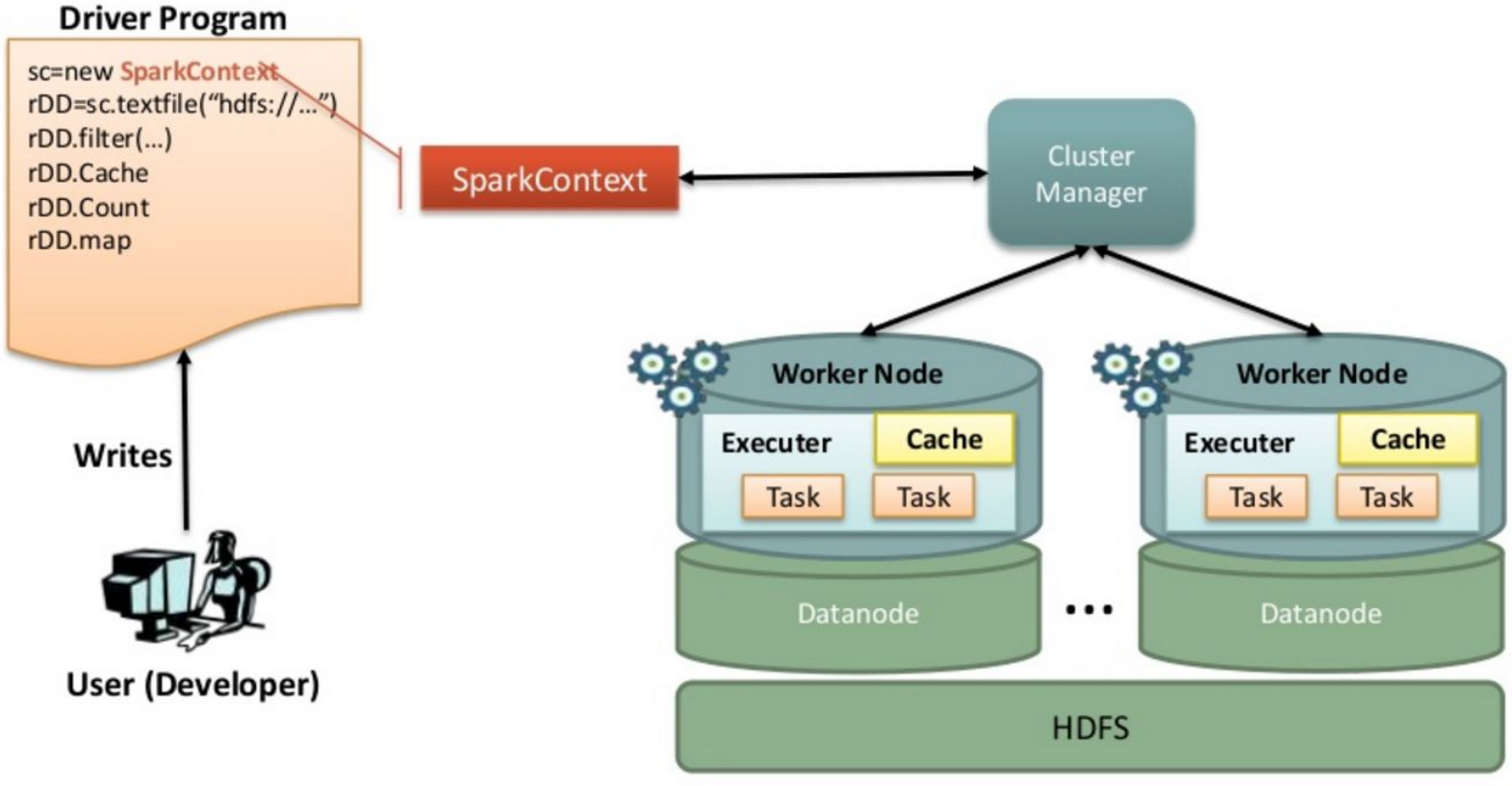
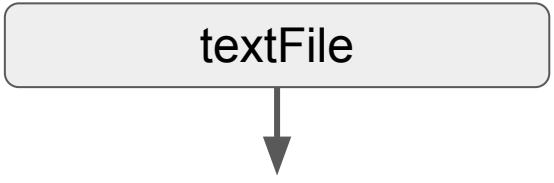
The Spark Programming Model



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

An Example

Word Count

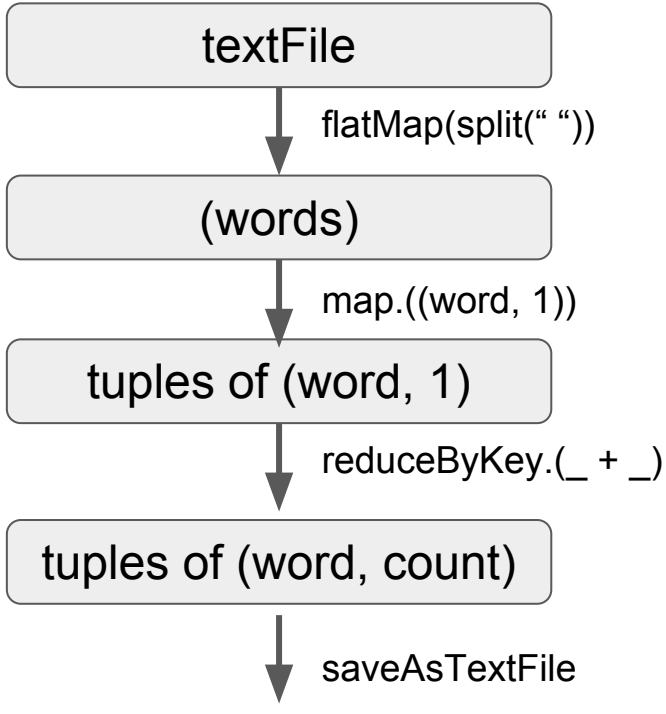


An Example

Word Count

Scala:

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



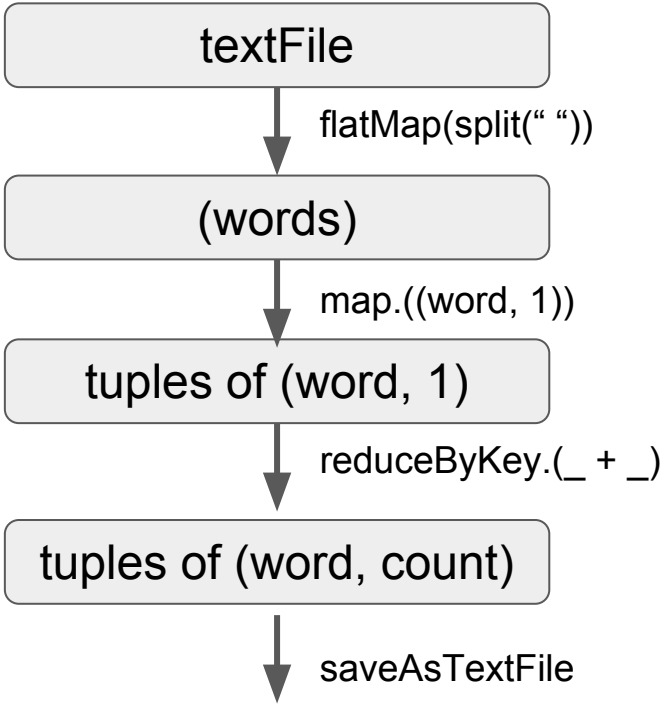
Apache Spark Examples
http://spark.apache.org/examples.html

An Example

Word Count

Python:

```
textFile = sc.textFile("hdfs://...")
counts = textFile
    .flatMap(lambda line: line.split(" "))
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a + b)
counts.saveAsTextFile("hdfs://...")
```



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

Spark Overview

- RDD provides full recovery by backing up transformations from stable storage rather than backing up the data itself.
- RDDs can be stored in memory and thus are often much faster.
- Functional programming is used to define transformation and actions on RDDs.
- 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.
    - MapReduce may still be more cost-effective for very large data that does not fit in memory.