Spark

Stony Brook University
CSE545, Spring 2019

Situations where MapReduce is not efficient

DFS → Map → LocalFS → Network → Reduce → DFS → Map → ...

Situations where MapReduce is not efficient

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

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

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

Situations where MapReduce is not efficient

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

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

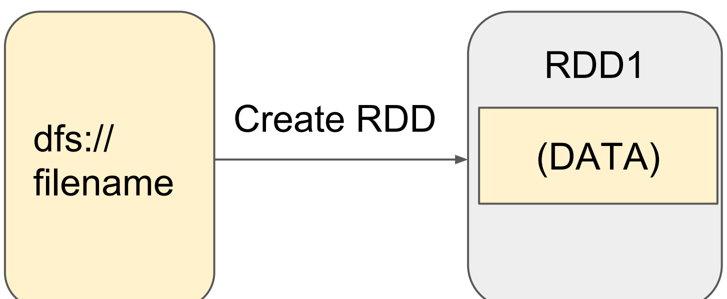
(Anytime where MapReduce would need to write and read from disk a lot).

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).

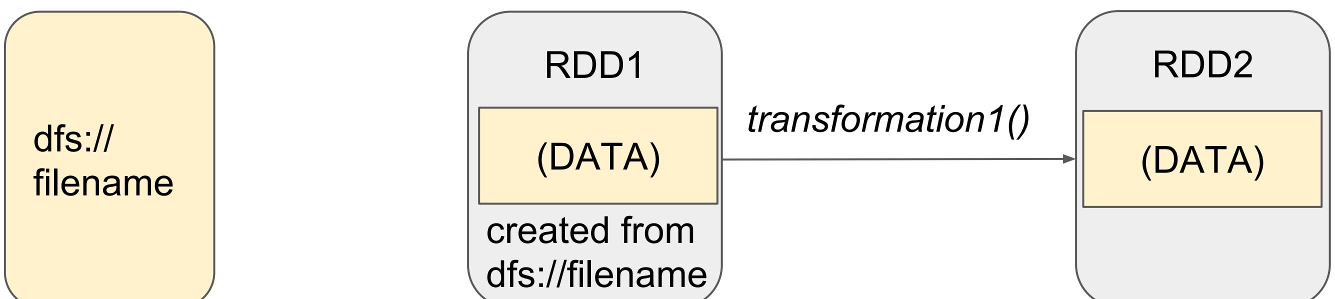
Spark's Big Idea

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).



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).



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).

Spark's Big Idea

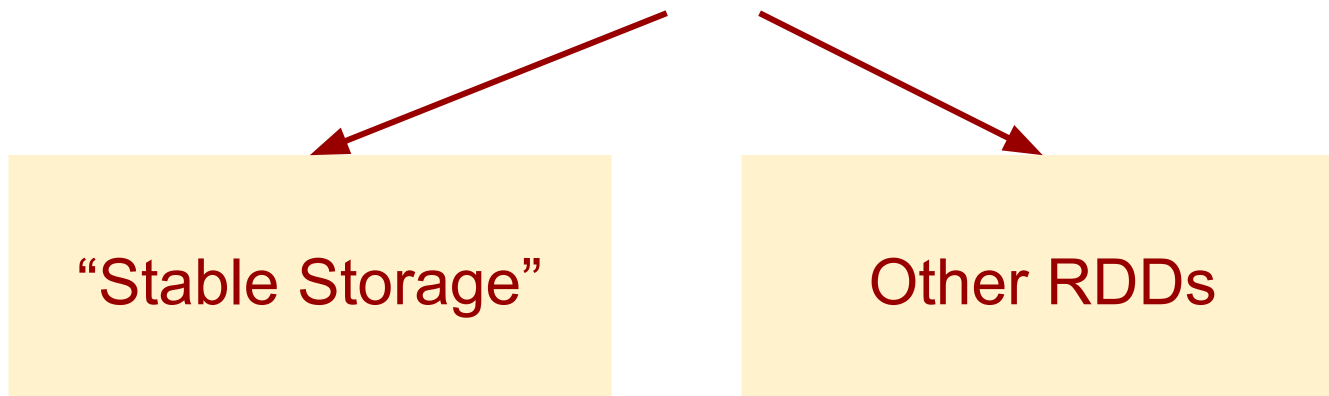
Resilient Distributed Datasets (RDDs) -- Read-only partitioned collection of records (like a DFS) but with a record of how the dataset was created as combination of *transformations* from other dataset(s).

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

⇨ Faster communication and I O

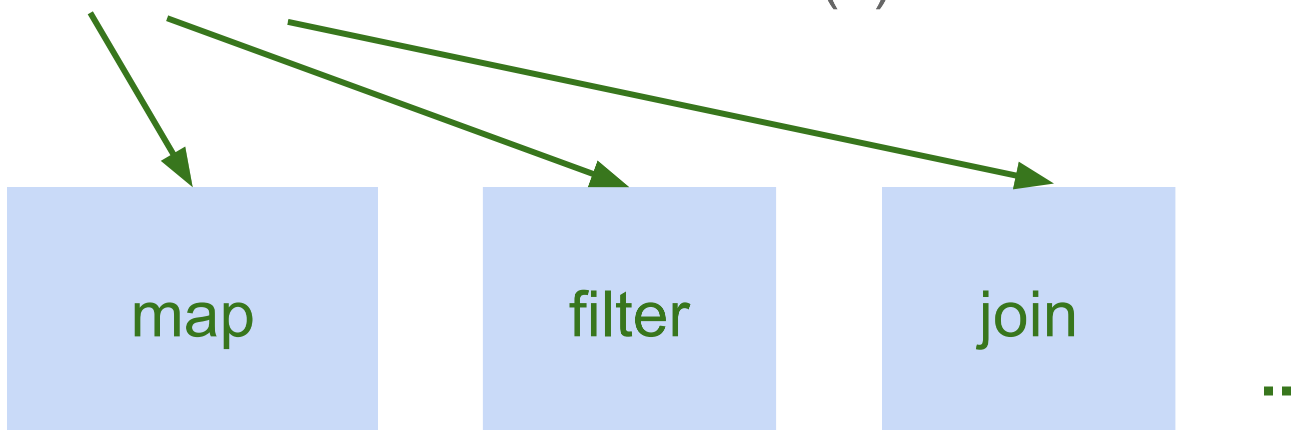
The Big Idea

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).



Spark's Big Idea

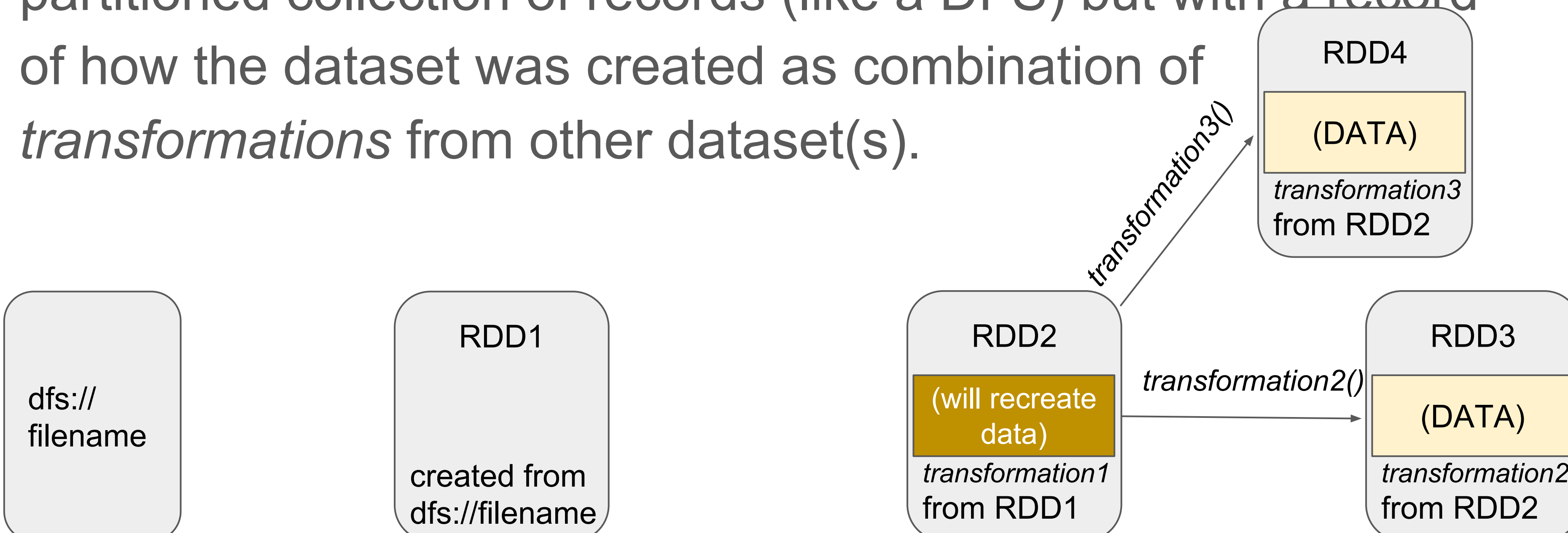
Resilient Distributed Datasets (RDDs) -- Read-only partitioned collection of records (like a DFS) but with a record of how the dataset was created as combination of *transformations* from other dataset(s).

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).

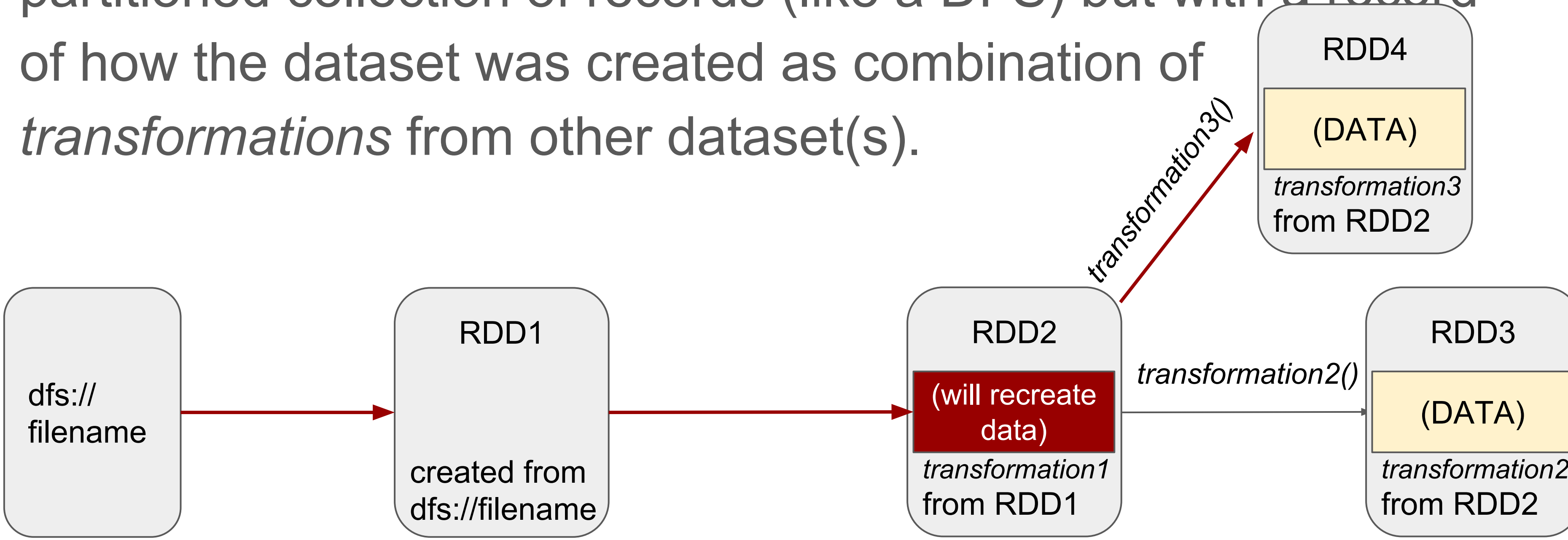
Spark's Big Idea

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).



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).



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)
	$groupByKey()$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, Seq[V])]}$
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$union()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[T]}) \Rightarrow \mathrm{RDD[T]}$
	$join()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (V, W))]}$
	$cogroup()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (Seq[V], Seq[W]))]}$
	$crossProduct()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[U]}) \Rightarrow \mathrm{RDD[(T, U)]}$
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, W)]}$ (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.

Original 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]
Multiple Records	*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.

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)
	$groupByKey()$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, Seq[V])]}$
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$union()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[T]}) \Rightarrow \mathrm{RDD[T]}$
	$join()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (V, W))]}$
	$cogroup()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (Seq[V], Seq[W]))]}$
	$crossProduct()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[U]}) \Rightarrow \mathrm{RDD[(T, U)]}$
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, W)]}$ (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.

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

Original *Actions*: RDD to Value, Object, or Storage

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

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.

Current Transformations and Actions

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

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

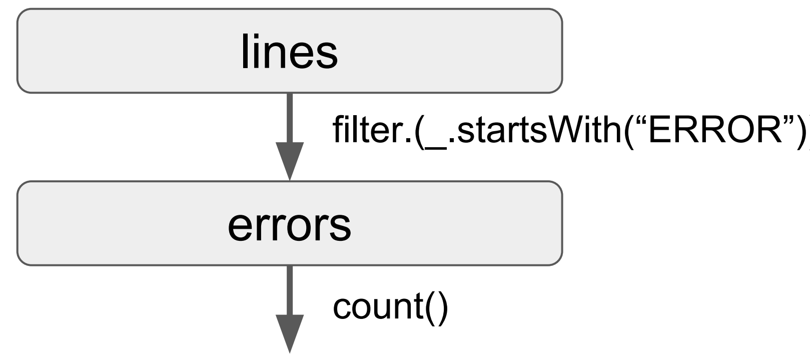
http://spark.apache.org/docs/latest/rdd-programming-guide.html#actions

common actions: *collect, count, take*

An Example

Count errors in a log file:

TYPE   MESSAGE   TIME



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.

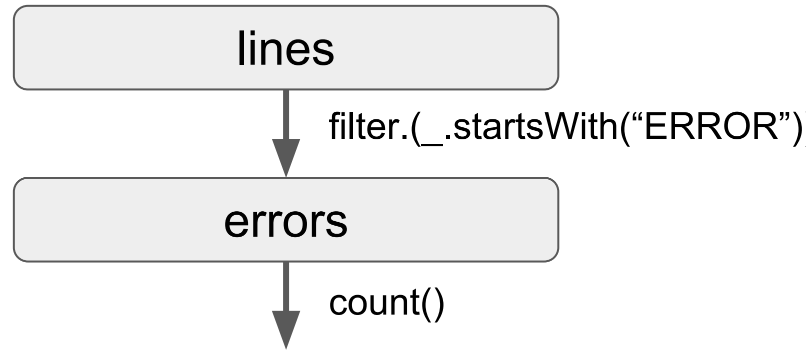
An Example

Count errors in a log file:

TYPE MESSAGE TIME

Pseudocode:

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



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.

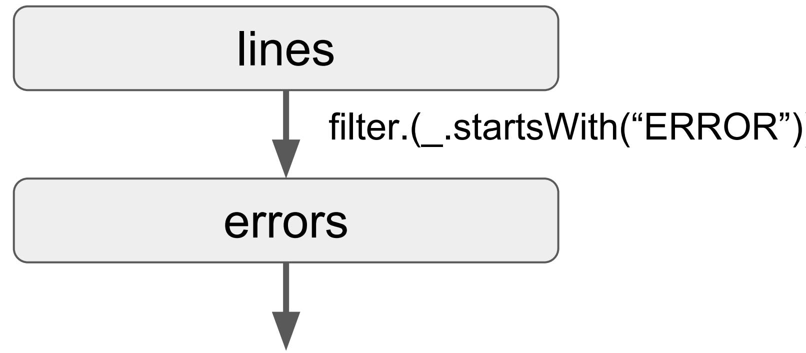
An Example

Collect times of hdfs-related errors

TYPE   MESSAGE   TIME

Pseudocode:

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



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.

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
...
```

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

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.

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~~
...
```

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

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.

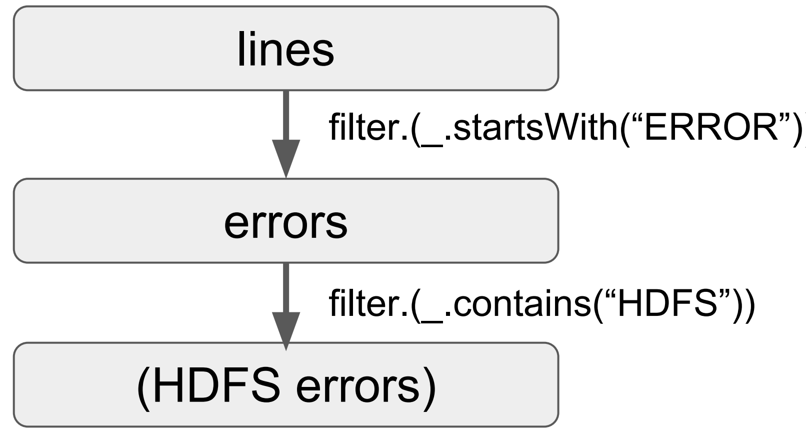
An Example

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"))
     ...
```



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.

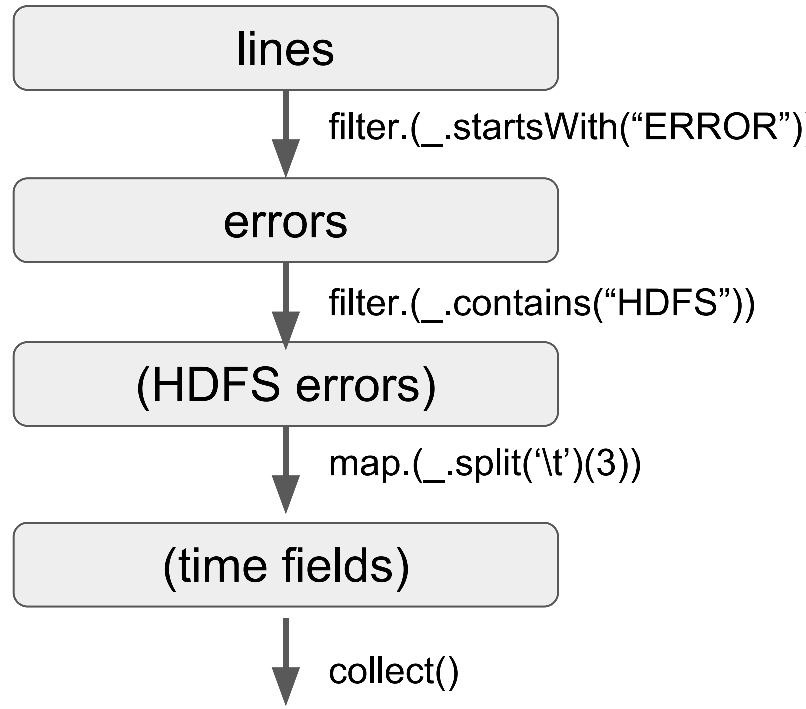
An Example

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()
```



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.

An Example

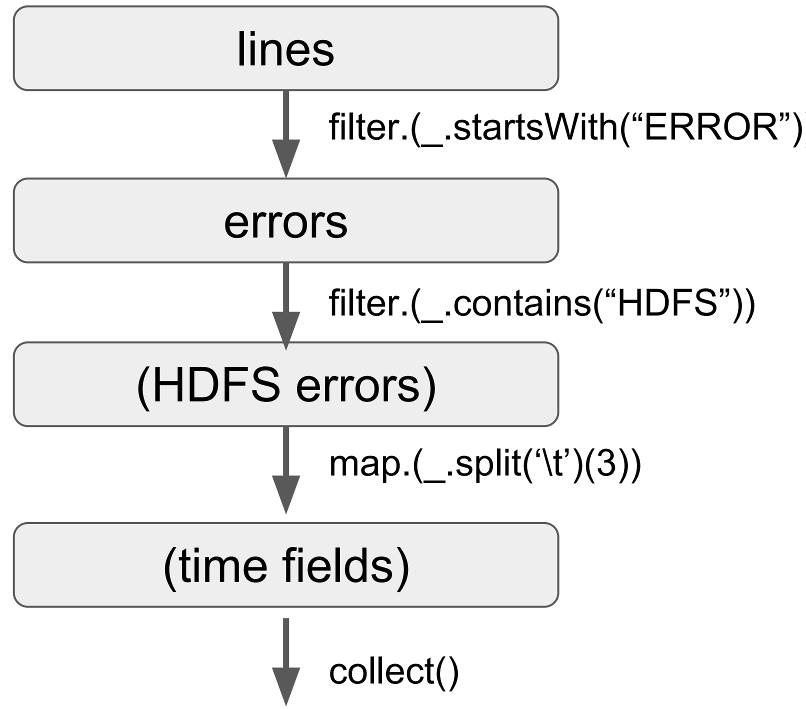
Collect times of hdfs-related errors

TYPE   MESSAGE   TIME

Pseudocode:

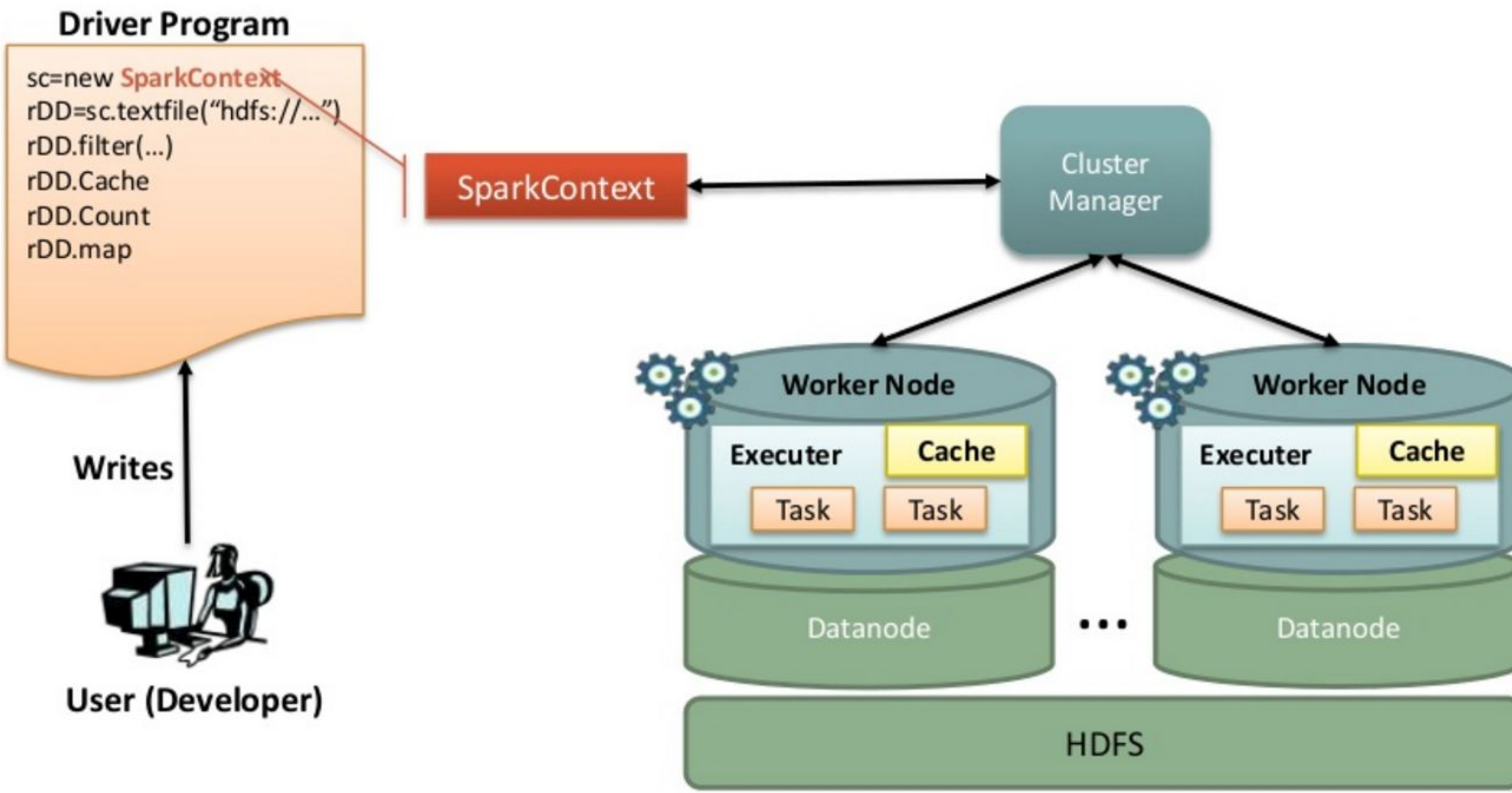
```
lines = sc.textFile(“dfs:...”)
errors =
    lines.filter(_.startswith(“ERROR”))
errors.persist
errors.count
errors.filter(_.contains(“HDFS”))
     .map(_split(‘\t’)(3))
     .collect()
```

Functional Programming



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.

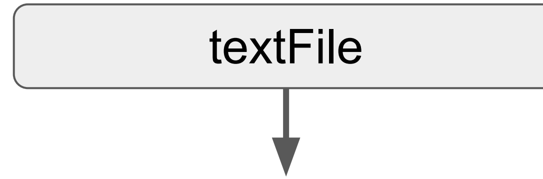
The Spark Programming Model



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

An Example

Word Count

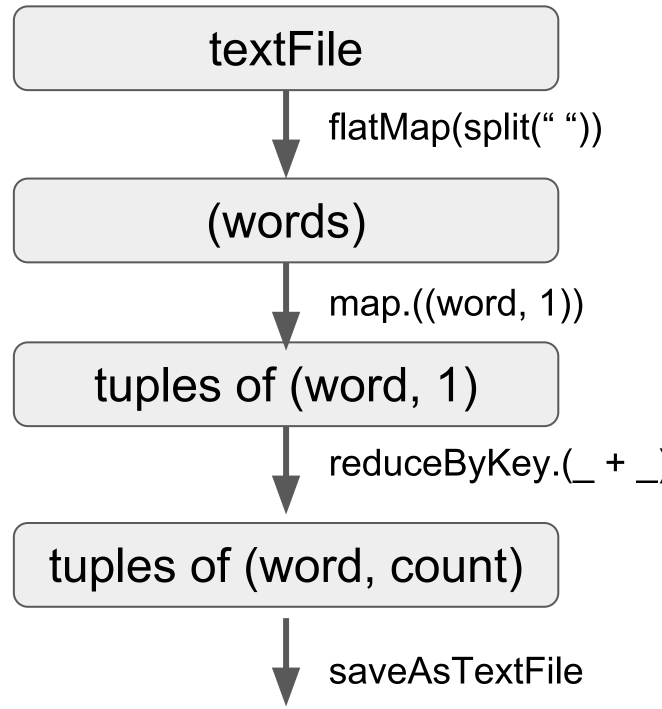


An Example

Word Count

Scala:

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



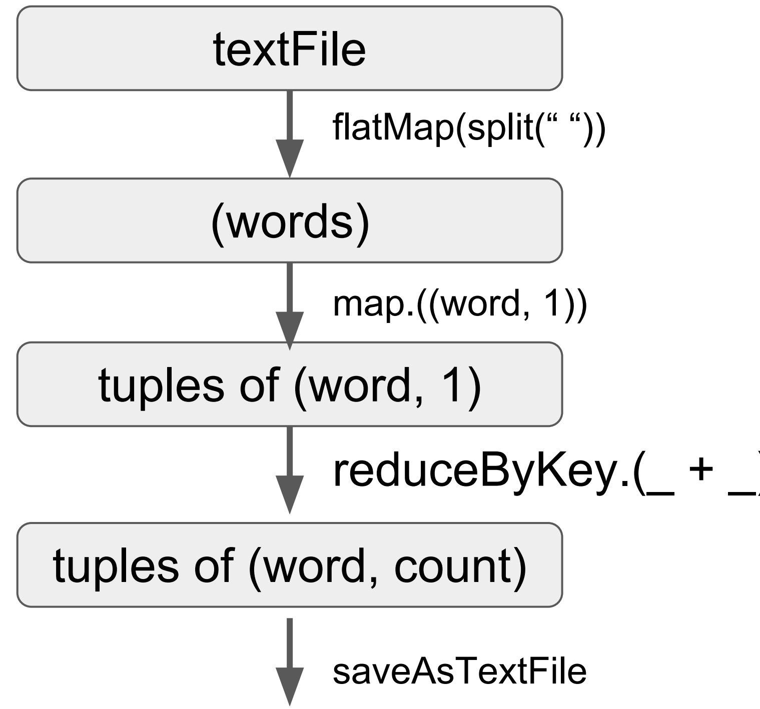
Apache Spark Examples
http://spark.apache.org/examples.html

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

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

Lazy Evaluation

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

Why?

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

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 Overview

- 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 Overview

- 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.
- Still need Hadoop (or some DFS) to hold original or resulting data efficiently and reliably.
- Lazy evaluation enables optimizing chain of operations.
- 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.