Working With RDDs in Spark

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*Mostly based on Dr. Anthony Joseph (UC Berkeley)'s course on Apache Spark

Outline

- How do spark programs work?
- How RDDs are created from files or data in memory
- Commonly used RDD transformations
- Commonly used RDD actions
- Understand a typical lifecycle of a Spark program.

Working with RDDs in Spark

SPARK PROGRAMMING FRAMEWORK

Spark Deployment Modes

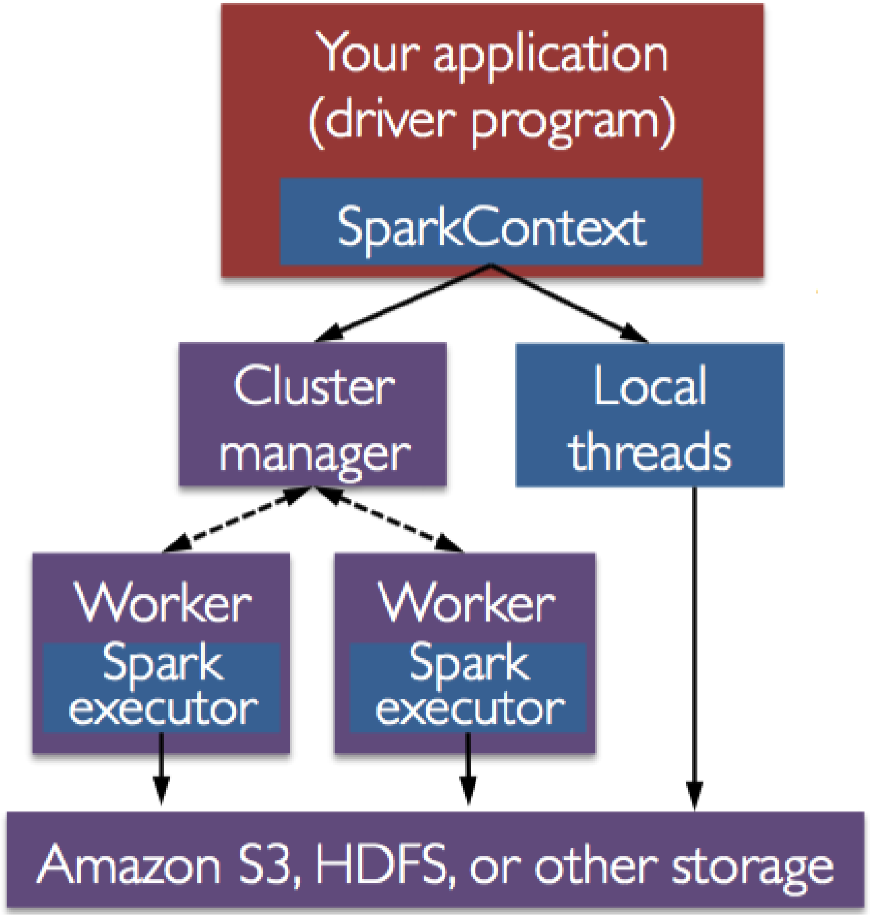
- Spark has several deployment modes
  - **Local mode**: run everything in a single JVM (java virtual machine), useful for testing or demonstration.
  - **Cluster mode:**
    - Standalone:
      - Spark manages its own cluster; simple and easy to setup
    - YARN
      - Using YARN as cluster manager
    - Mesos
      - Using Apache Mesos as cluster manager

https://techvidvan.com/tutorials/spark-modes-of-deployment/ (for additional reading)

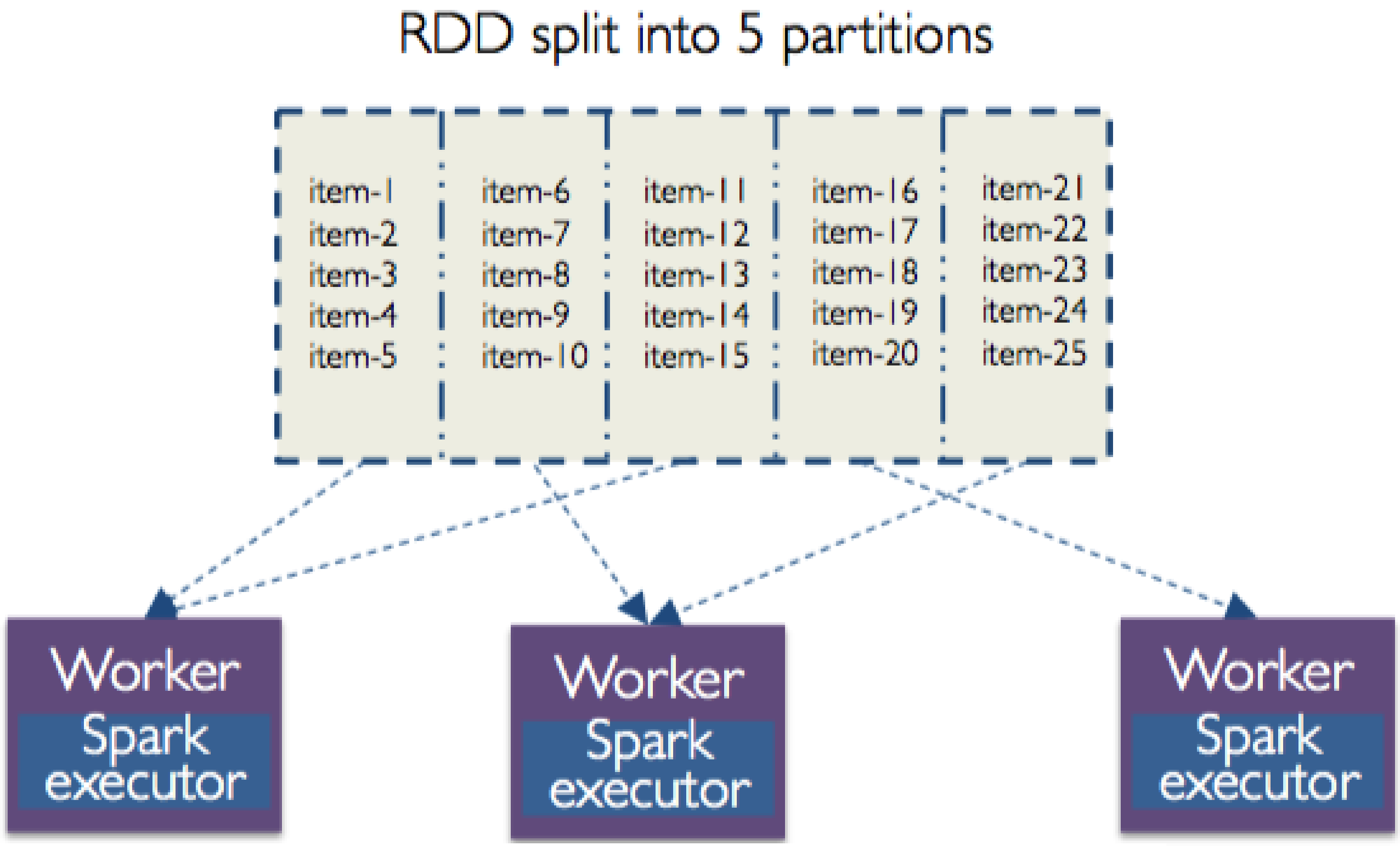
http://stackoverflow.com/questions/28664834/which-cluster-type-should-i-choose-for-spark (choosing between different cluster modes)

Anatomy of a Spark Cluster

- Each Spark application has a **driver program**, which uses **SparkContext** to communicate with **cluster manager** or **local threads**
  - The Spark program we write is the driver program.
- An **executor** is created on each worker node per application. It runs Spark tasks and interact with external storage (HDFS, S3, etc)
- RDDs are distributed among worker nodes.



Partition RDDs



More partitions = More parallelism

Each worker can work on one partition at a time
Typically you want 2-4 partitions for each CPU in your cluster (this can to be automatically set by Spark)

So, how many executors and partitions?*

- 4-6 cores per executor to maximize HDFS I/O throughput
  - Number of executors (--num-executors)
  - Cores for each executor (--executor-cores):
  - Memory for each executor (--executor-memory):
- How many partitions to have
  - Rule of thumb: ~128MB per partition
  - Don’t have too big partitions
    - your job may fail due to 2GB shuffle block limit
  - Don’t have too few partitions
    - Your job will be slow, to making use of parallelism.

*Mark Grover, Ted Malaska (2016) Top 5 Mistakes when writing spark applications, Spark SUMIT EAST.

Spark Context

- A Spark program first creates a SparkContext object that
  - Establishes a connection to the Spark's execution environment
  - tells Spark how and where to access a cluster
  - is required for every Spark application
  - is automatically created in a Spark Shell as variable `sc`.
  - is manually created in a standalone program
- Use SparkContext to create RDDs, access Spark services and run jobs.

https://jaceklaskowski.gitbooks.io/mastering-apache-spark/spark-SparkContext.html

Spark Context

Every Spark application requires a Spark Context

- The main entry point to the Spark API

Spark Shell provides a preconfigured Spark Context called `sc`

Python

```
Using Python version 2.7.8 (default, Aug 27 2015 05:23:36)
SparkContext available as sc, HiveContext available as sqlCtx.

>>> sc.appName
u'PySparkShell'
```

Scala

```
…
Spark context available as sc.
SQL context available as sqlContext.

scala> sc.appName
res0: String = Spark shell
```

Before Spark 2, separate contexts need to be created to use Spark SQL & Streaming. After Spark 2.X, a **spark session** (“spark”) is introduced to provide a single point of entry that include all of the functionality of SparkContext, plus APIs for SQL, Hive, and Streaming.

Working with RDDs in Spark

RESILIENT DISTRIBUTED DATASETS (RDDS)

Resilient Distributed Datasets

- RDDs (Resilient Distributed Dataset) are part of core Spark
  - **Resilient:** If data in memory is lost, it can be recreated
  - **Distributed**: Processed across the cluster
- Characteristics of RDDs
  - **Immutable** once constructed
  - Track lineage information to efficiently recomputed lost data
  - Unstructured
    - No schema defining columns and rows
    - Not table-like; cannot be queried using SQL-like transformations such as where and select
    - Often used to convert unstructured or semi-structured data into structured form.

Content of RDDs

- RDDs can hold any serializable type of element
  - Primitive types: integers, characters, booleans etc.
  - Collections such as: strings, lists, arrays, tuples, dicts, nested collection types
  - Scala/Java objects (if serializable)
  - Mixed types

- Some types of RDDs have additional functionality
  - Pair RDDs
    - RDDs consisting of Key-Value pairs
  - Double RDDs
    - RDDs consisting of numeric data

Working with RDDs in Spark

CREATING AN RDD

RDD Data Sources

- RDDs can be constructed from
  - files in HDFS or any other storage system
  - transforming an existing RDDs
  - parallelizing existing Python collections (lists)

Creating RDDs From Collections

- You can create RDDs from collections instead of files

```
sc.parallelize(collection)
```

- Useful when
  - Testing
  - Generating data programmatically
  - Integrating

myData is a python collection on your local host

```
> myData = ["Alice","Carlos","Frank","Barbara"]
> myRdd = sc.parallelize(myData)
> myRdd.take(2)
['Alice', 'Carlos']
```

myRdd is a distributed dataset in the Spark execution environment configured by sc.

Create RDDs from Python collections

```
>>> data = [1, 2, 3, 4, 5]
>>> data
[1, 2, 3, 4, 5]
>>> rDD = sc.parallelize(data, 4)
>>> rDD
ParallelCollectionRDD[0] at parallelize at PythonRDD.scala:229
```

This argument specifies the number of partitions.

Creating RDDs from Files (1)

- For file-based RDDs, use `sc.textFile`
  - Accepts a single file, a wildcard list of files, or a comma-separated list of files, e.g.:
    - `sc.textFile("myfile.txt")`
    - `sc.textFile("mydata/*.log")`
    - `sc.textFile("myfile1.txt,myfile2.txt")`
  - Each line in the file(s) is a separate record in the RDD

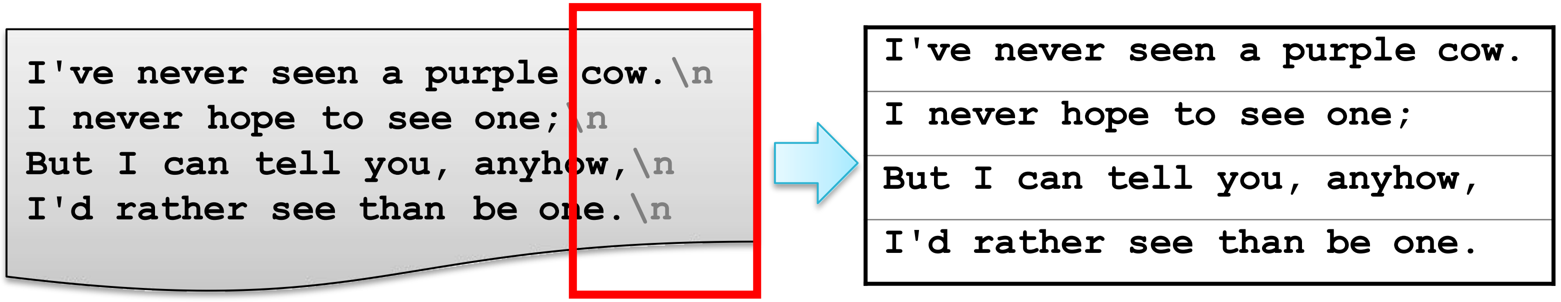
- Use `sc.hadoopFile` or `sc.newAPIHadoopFile` to read other formats

Creating RDDs from Files (cont.)

- Files are referenced by absolute or relative URI
  - Absolute URI:
    - `file:/home/training/myfile.txt` -- a file on a local host under /home/training
    - `file:///c:/Users/John/documents/myfile.txt` -- a file on C:/Users… (in windows systems)
    - `hdfs://localhost:8020/loudacre/myfile.txt` – a file on the HDFS cluster at host "localhost" at port 8020 under directory /loudacre
    - `s3n://bucket/directory/filename.ext` – reading a file on S3
  - Relative URI (assume the cluster mode):
    - `myfile.txt` – files on user's home directory on HDFS cluster (i.e. under `/user/training/`)
    - `/loudacre/weblogs/*.log` – files on spark cluster under absolute path "`/loudacre/weblogs/`"

Creating RDDs from Files (2)

- `textFile` maps each line in a file to a separate RDD element



```
I've never seen a purple cow.\n
I never hope to see one;\n
But I can tell you, anyhow,\n
I'd rather see than be one.\n
```

I've never seen a purple cow.
I never hope to see one;
But I can tell you, anyhow,
I'd rather see than be one.

- textFile only works with line-delimited text files

Create RDDs from Files

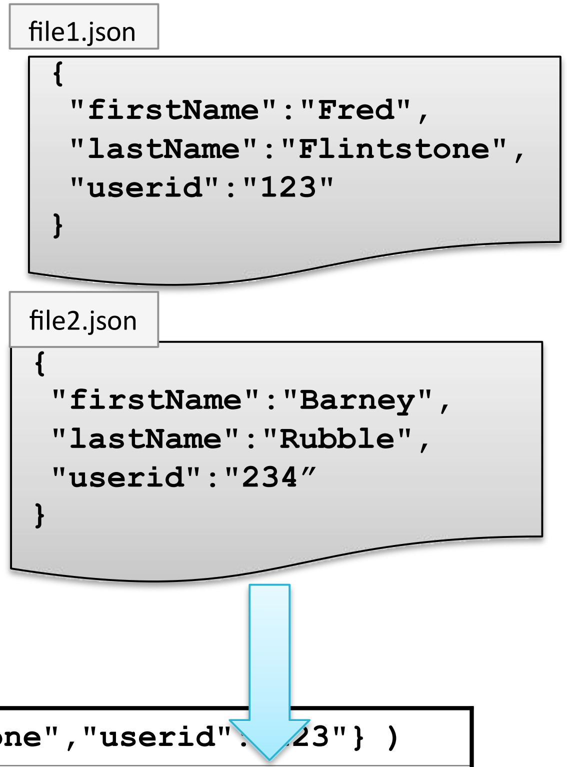
- From HDFS, text files, Hyper table, Amazon S3, Apache Hbase, SequenceFiles, any other Hadoop InputFormat, and directory or glob wildcard: /data/201404*

```
>>> distFile = sc.textFile("README.md", 4)
>>> distFile
MappedRDD[2] at textFile at
   NativeMethodAccessorImpl.java:-2
```

- – RDD distributed in 4 partitions
- – Elements are lines of input
- – **Lazy evaluations** – no execution happens now

Whole File--Based RDDs (1)

- `sc.textFile` maps each line in a file to a separate RDD element
  - What about files with a multi-line input format, e.g. XML or JSON?
- `sc.wholeTextFiles`(directory)
  - Maps entire contents of each file in a directory to a single RDD element
  - Works only for small files (element must fit in memory)



file1.json

```
{
 "firstName":"Fred",
 "lastName":"Flintstone",
 "userid":"123"
}
```

file2.json

```
{
 "firstName":"Barney",
 "lastName":"Rubble",
 "userid":"234″
}
```

```
(file1.json,{"firstName":"Fred","lastName":"Flintstone","userid":"123"} )
(file2.json,{"firstName":"Barney","lastName":"Rubble","userid":″234"} )
(file3.json,… )
(file4.json,… )
```

Whole File-Based RDDs (2)

```
> import json
> myrdd1 = sc.wholeTextFiles(mydir)
> myrdd2 = myrdd1
  .map(lambda (fname,s): json.loads(s))
> for record in myrdd2.take(2):
>     print record["firstName"]
```

Output:

```
Fred
Barney
```

```
> import scala.util.parsing.json.JSON
> val myrdd1 = sc.wholeTextFiles(mydir)
> val myrdd2 = myrdd1
  .map(pair => JSON.parseFull(pair._2).get.
           asInstanceOf[Map[String,String]])
> for (record <- myrdd2.take(2))
    println(record.getOrElse("firstName",null))
```

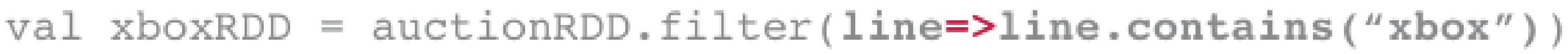
Anonymous functions

- RDD operations often involves anonymous functions
- Python: `lambda` functions
  - Restricted to a single expression, and is not re-used
  - E.g. `lambda a, b: a + b`

    `a,b` are arguments for the function

    the function returns `a + b`

- Scala: anonymous function syntax with “=>”



```
val xboxRDD = auctionRDD.filter(line=>line.contains(“xbox”))
```

  - The function accepts one argument: `line`
  - It returns a boolean value, `line.contains("xbox")`

Working with RDDs in Spark

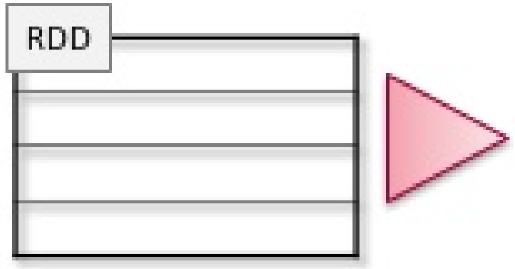
SPARK TRANSFORMATIONS AND ACTIONS

Operations on RDDs

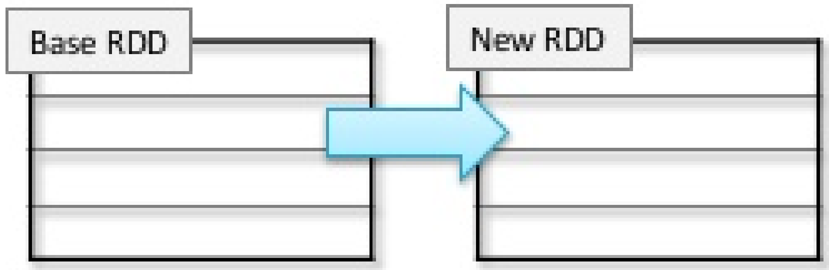
- Two types of operations: **transformations** and **actions**
- **Transformations** are lazy (not computed immediately)
- Transformed RDD is executed when action runs on it

RDD actions and transformations

- Two types of operations on RDD
  - **Actions** – returns local dataset or value (non-RDD), e.g.,
    - count
    - take(n)
    - collect()
  - **Transformations** – generate new RDDs based on the current one, e.g.
    - filter
    - map
    - reduceByKey

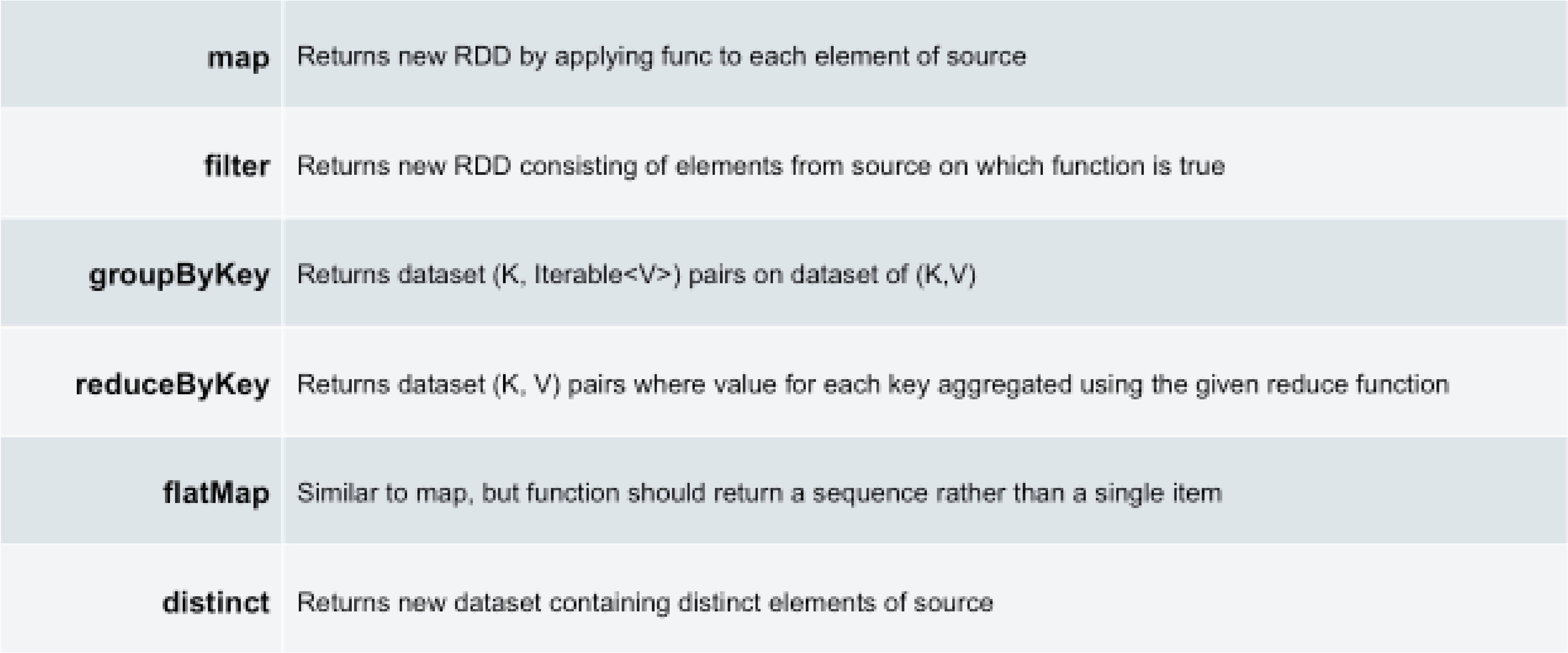


Local (non-distributed) dataset or value



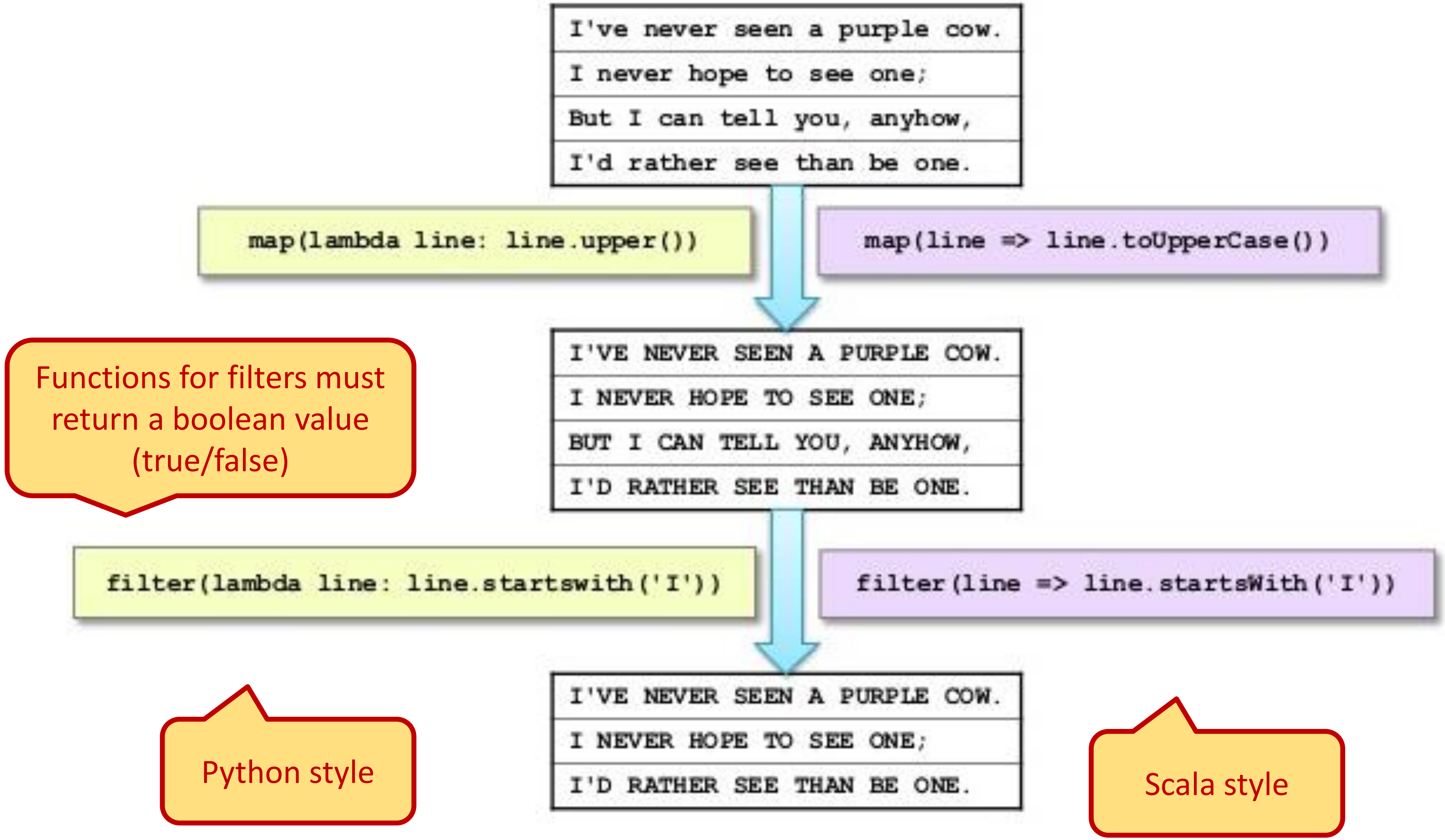
Transformations are lazy (not computed immediately) -- just like Pig is lazy

Commonly Used Transformations



map	Returns new RDD by applying func to each element of source
filter	Returns new RDD consisting of elements from source on which function is true
groupByKey	Returns dataset (K, Iterable<V>) pairs on dataset of (K,V)
reduceByKey	Returns dataset (K, V) pairs where value for each key aggregated using the given reduce function
flatMap	Similar to map, but function should return a sequence rather than a single item
distinct	Returns new dataset containing distinct elements of source

Example: map and filter transformations



```
I've never seen a purple cow.
I never hope to see one;
But I can tell you, anyhow,
I'd rather see than be one.
```

```
map(lambda line: line.upper())
```

```
map(line => line.toUpperCase())
```

```
I'VE NEVER SEEN A PURPLE COW.
I NEVER HOPE TO SEE ONE;
BUT I CAN TELL YOU, ANYHOW,
I'D RATHER SEE THAN BE ONE.
```

```
filter(lambda line: line.startswith('I'))
```

```
filter(line => line.startsWith('I'))
```

```
I'VE NEVER SEEN A PURPLE COW.
I NEVER HOPE TO SEE ONE;
I'D RATHER SEE THAN BE ONE.
```

Functions for filters must return a boolean value (true/false)

Python style

Scala style

Example: **flatMap** and **distinct**

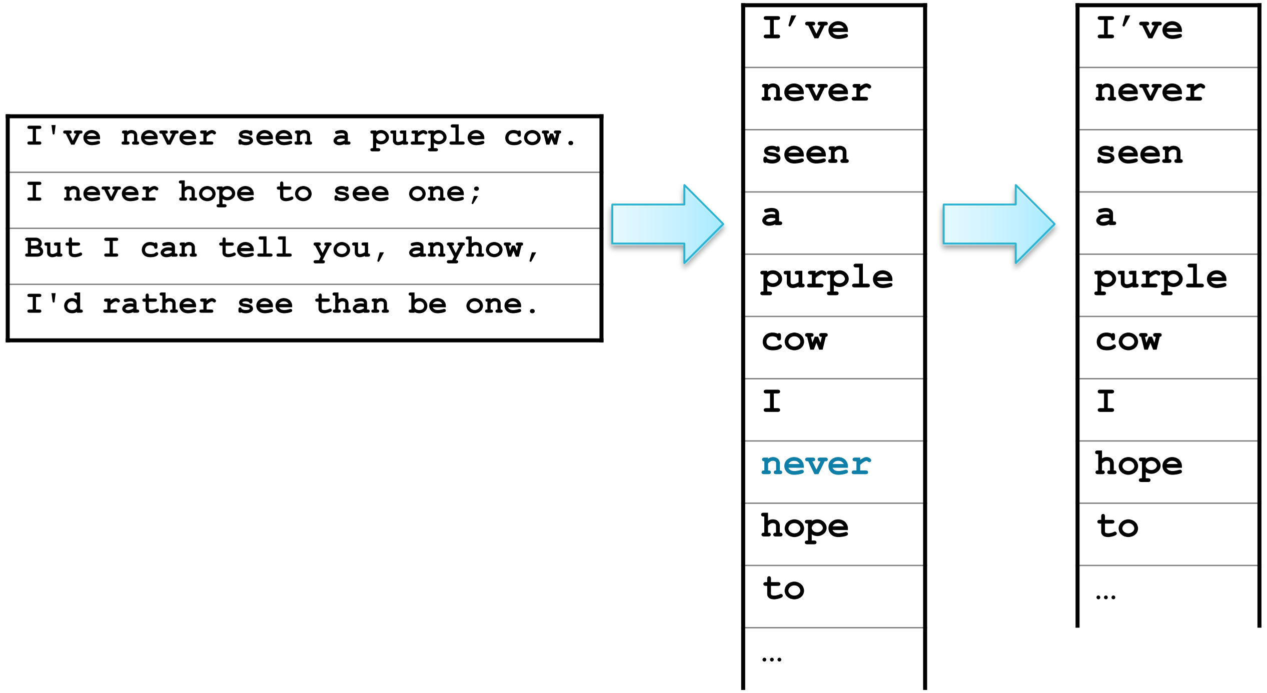
Python

```
> sc.textFile(file) \
   .flatMap(lambda line: line.split()) \
   .distinct()
```

Scala

```
> sc.textFile(file).
    flatMap(line => line.split(' ')).
    distinct()
```

Each function returns a list; the collection of lists are then “flattened”



```
I've never seen a purple cow.
I never hope to see one;
But I can tell you, anyhow,
I'd rather see than be one.
```

```
I’ve
never
seen
a
purple
cow
I
never
hope
to
…
```

```
I’ve
never
seen
a
purple
cow
I
hope
to
…
```

RDD Transformations

- `map`, `filter`, and `distinct` transformations

```
>>>    rdd   =  sc.parallelize([1,2, 3, 4])
>>>    rdd.map(lambda x: x  *  2)
RDD:   [1, 2, 3, 4]   -> [2, 4, 6, 8]
>>>    rdd.filter(lambda x: x  %  2  == 0)
RDD:   [1,2, 3, 4] -> [2, 4]
>>>    rdd2  =  sc.parallelize([1, 4, 2, 2, 3])
>>>    rdd2.distinct()
RDD:   [1, 4, 2, 2, 3]   -> [1, 4, 2, 3]
```

Function literals (green) are *closures* automatically passed to Spark workers

RDD Transformations

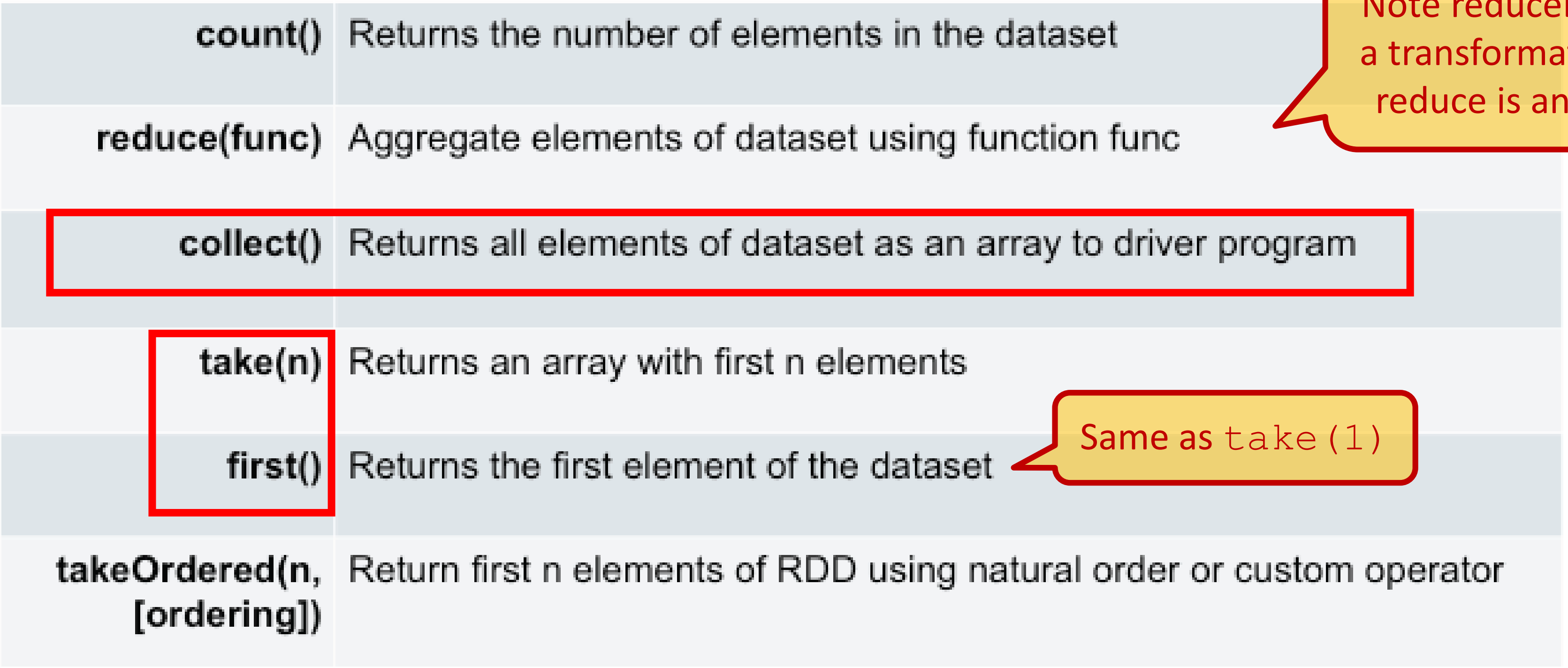
- map and flatMap

```
>>> rdd = sc.parallelize([1, 2, 3])
>>> rdd.map(lambda x: [x, x+5])
RDD: [1, 2, 3] -> [[1, 6], [2, 7], [3, 8]]

>>> rdd.flatMap(lambda x: [x, x+5])
RDD: [1, 2, 3] -> [1, 6, 2, 7, 3, 8]
```

flatMap merges the results into a single sequence

Commonly Used Actions



count()	Returns the number of elements in the dataset
reduce(func)	Aggregate elements of dataset using function func
collect()	Returns all elements of dataset as an array to driver program
take(n)	Returns an array with first n elements
first()	Returns the first element of the dataset
takeOrdered(n, [ordering])	Return first n elements of RDD using natural order or custom operator

Note reduceByKey is a transformation but reduce is an action

Same as `take(1)`

- An action on an RDD returns values to the driver program, after running the computation on the dataset.
- As mentioned earlier, transformations are lazy. They are only computed when an action requires a result to be returned to the Driver program.

reduce, take, and collect

- Getting data out of RDDs

```
>>> rdd = sc.parallelize([1, 2, 3])
>>> rdd.reduce(lambda a, b: a * b)
Value: 6

>>> rdd.take(2)
Value: [1,2] # the first two as list


>>> rdd.collect()
Value: [1,2,3] # the entire collection as list
```

The reducer is applied recursively to produce a single result. The function must be commutative and associative.

takeOrdered and count:

Indicating a descending order of values

```
>>> rdd = sc.parallelize([5,3,1,2])
>>> rdd.takeOrdered(3, lambda s: -1 * s)
Value: [5,3,2] # as list

lines = sc.textFile("...", 4)
print lines.count()
```

Sort by values (descending):

lines.count() causes Spark to:
- read data
- sum within partitions
- combine sums in driver

Other General RDD Operations

- **Other RDD actions**
  - **`first`** – return the first element of the RDD
  - **`foreach`** – apply a function to each element in an RDD
  - **`top(`*`n`*`)`** – return the largest *n* elements using natural ordering
- **Sampling**
  - **`sample`** – create a new RDD with a sampling of elements [transformation]
  - **`takeSample`** – return an array of sampled elements [action]
- **Double RDD operations – operate on double RDDs only**
  - Statistical functions, e.g., **`mean`**, **`sum`**, **`variance`**, **`stdev`**

Documentation and more examples: https://data-flair.training/blogs/spark-rdd-operations-transformations-actions/

Working with RDDs in Spark

LAZY EXECUTION & CACHING

Lazy Execution

- Consider a the following

```
RDD = sc.textFile(…)
newRDD = RDD.filter(….)
newRDD.count()
```

- What will happen after each line?

After this line:

```
RDD = sc.textFile(…)
newRDD = RDD.filter(….)
newRDD.count()
```

No computation has happened yet

After this line:

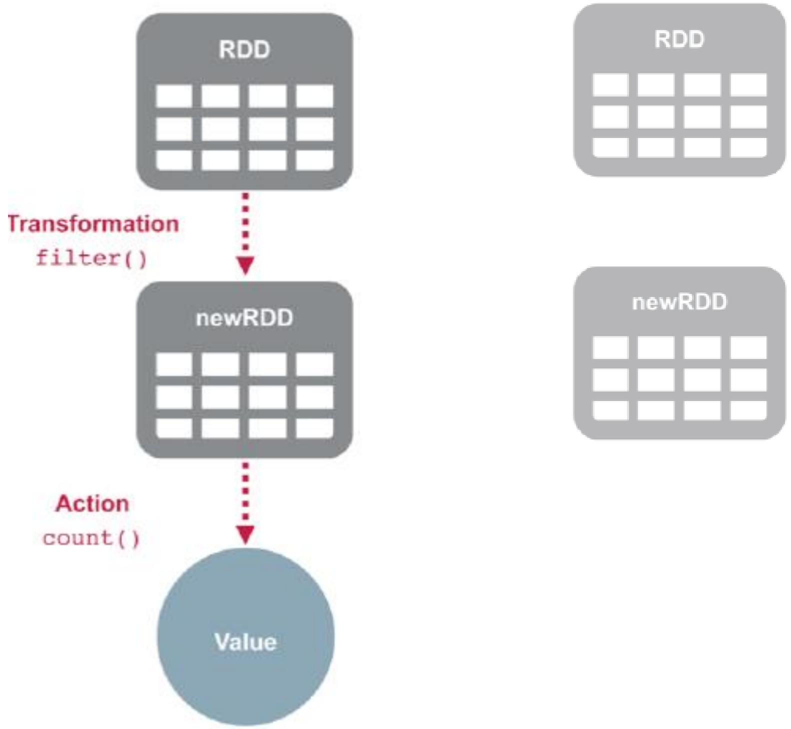
```
RDD = sc.textFile(…)
newRDD = RDD.filter(….)
newRDD.count()
```

No computation has happened yet

After this line:

```
RDD = sc.textFile(…)
newRDD = RDD.filter(….)
newRDD.count()
```

Data will be read into memory. RDD and newRDD will be created. After getting the result - count, the RDDs are no longer in memory.



Caching

```
lines = sc.textFile("...", 4)
comments = lines.filter(isComment)
print lines.count(), comments.count()
```

- Spark will read the source data twice
  - 1st time – `lines.count()`
    - read data, sum within partitions, combine sums in driver
  - 2nd time – `comments.count()`
    - Read data (again), filter & sum within partition, combine sums in driver

Caching

```
lines = sc.textFile("...", 4)
lines.cache() # save, don't recompute!
comments = lines.filter(isComment)
print lines.count(),comments.count()
```

- Reading is a common step in two processes. Use `cache()` to avoid re-computing.