Introduction to Big Data with Apache Spark

Resilient Distributed Datasets

- The primary abstraction in Spark
  - Immutable once constructed
  - Track lineage information to efficiently recompute lost data
  - Enable operations on collection of elements in parallel

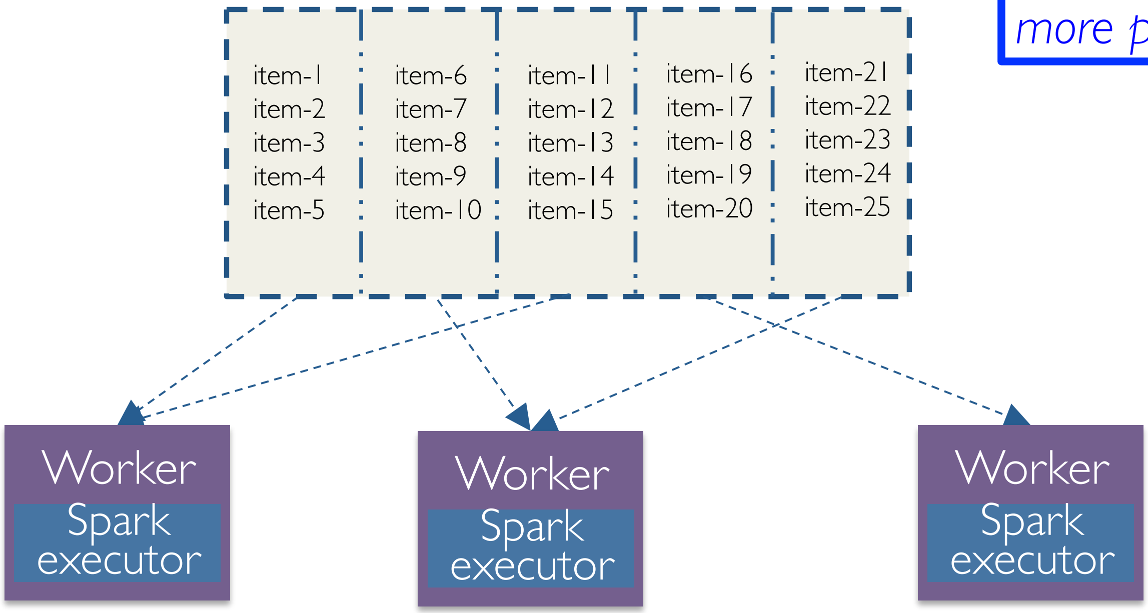
- You construct RDDs
  - by *parallelizing* existing Python collections (lists)
  - by *transforming* an existing RDDs
  - from *files* in HDFS or any other storage system

RDDs

- Programmer specifies number of partitions for an RDD

(Default value used if unspecified)

RDD split into 5 partitions

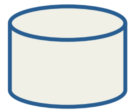


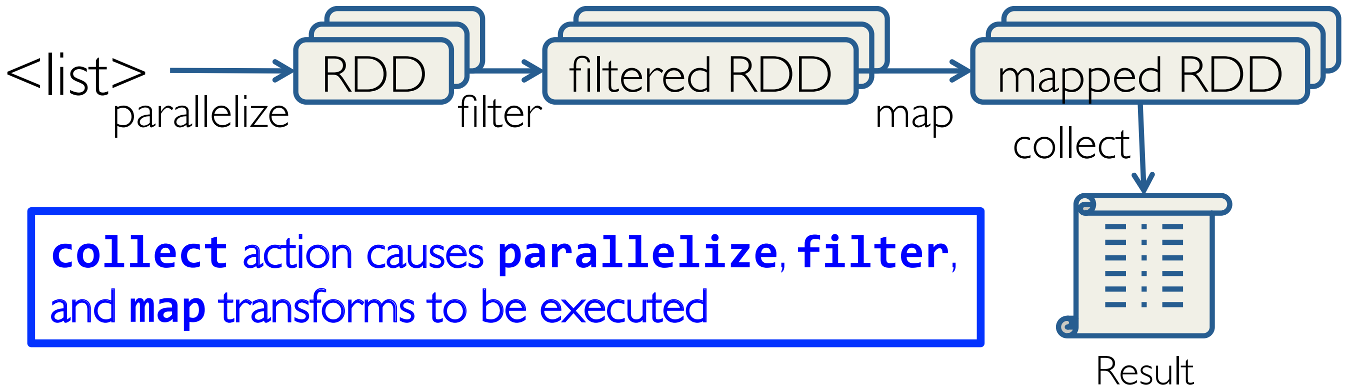
more partitions = more parallelism

RDDs

- Two types of operations: *transformations* and *actions*
- Transformations are lazy (*not computed immediately*)
- Transformed RDD is executed when action runs on it
- Persist (cache) RDDs in memory or disk

Working with RDDs

- Create an RDD from a data source:  <list>
- Apply transformations to an RDD: map filter
- Apply actions to an RDD: collect count



collect action causes **parallelize**, **filter**, and **map** transforms to be executed

Spark References

- http://spark.apache.org/docs/latest/programming-guide.html
- http://spark.apache.org/docs/latest/api/python/index.html

Creating an RDD

- Create RDDs from Python collections (lists)

```
>>> 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
```

No computation occurs with **`sc.parallelize()`**

- Spark only records how to create the RDD with four partitions

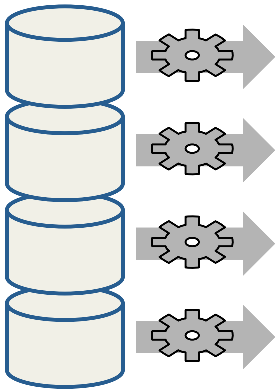
Creating RDDs

- From HDFS, text files, Hypertable, 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
```

Creating an RDD from a File

```
distFile = sc.textFile("...", 4)
```



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

Spark Transformations

- Create new datasets from an existing one
- Use *lazy evaluation*: results not computed right away – instead Spark remembers set of transformations applied to base dataset
  - » Spark optimizes the required calculations
  - » Spark recovers from failures and slow workers
- Think of this as a recipe for creating result

Some Transformations

Transformation	Description
`map(`*func*`)`	return a new distributed dataset formed by passing each element of the source through a function *func*
`filter(`*func*`)`	return a new dataset formed by selecting those elements of the source on which *func* returns true
`distinct([`*numTasks*`]))`	return a new dataset that contains the distinct elements of the source dataset
`flatMap(`*func*`)`	similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item)

Review: Python `lambda` Functions

- Small anonymous functions (not bound to a name)
  `lambda a, b: a + b`
  - » returns the sum of its two arguments
- Can use lambda functions wherever function objects are required
- Restricted to a single expression

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 workers

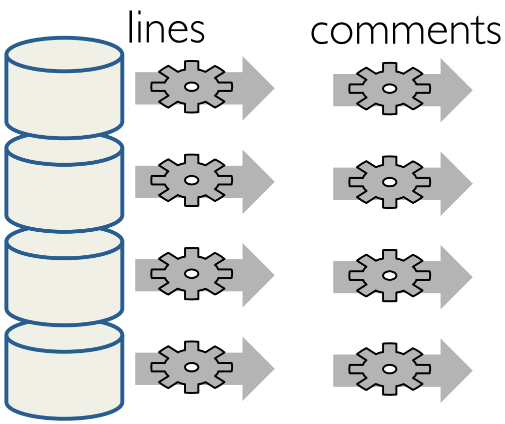
Transformations

```
>>> 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]
```

Function literals (green) are closures automatically passed to workers

Transforming an RDD

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

comments = lines.filter(isComment)
```



Lazy evaluation means nothing executes – Spark saves recipe for transforming source

Spark Actions

- Cause Spark to execute recipe to transform source
- Mechanism for getting results out of Spark

Some Actions

Action	Description
`reduce(`*`func`*`)`	aggregate dataset's elements using function *func*. *func* takes two arguments and returns one, and is commutative and associative so that it can be computed correctly in parallel
`take(`*`n`*`)`	return an array with the first *n* elements
`collect()`	return all the elements as an array WARNING: make sure will fit in driver program
`takeOrdered(`*`n, key=func`*`)`	return n elements ordered in ascending order or as specified by the optional key function

Getting Data Out of RDDs

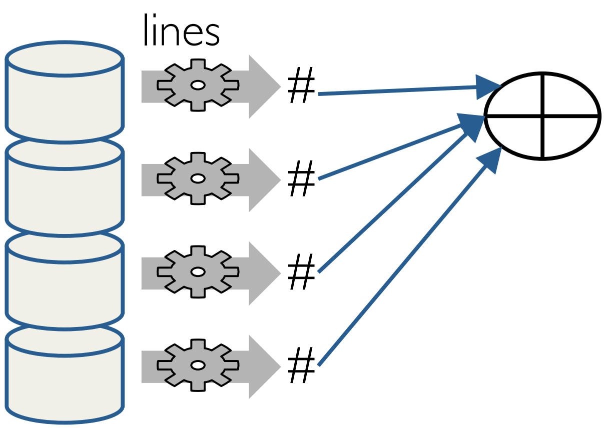
```
>>> rdd = sc.parallelize([1, 2, 3])
>>> rdd.reduce(lambda a, b: a * b)
Value: 6

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

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

Getting Data Out of RDDs

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

Spark Programming Model

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

print lines.count()
```

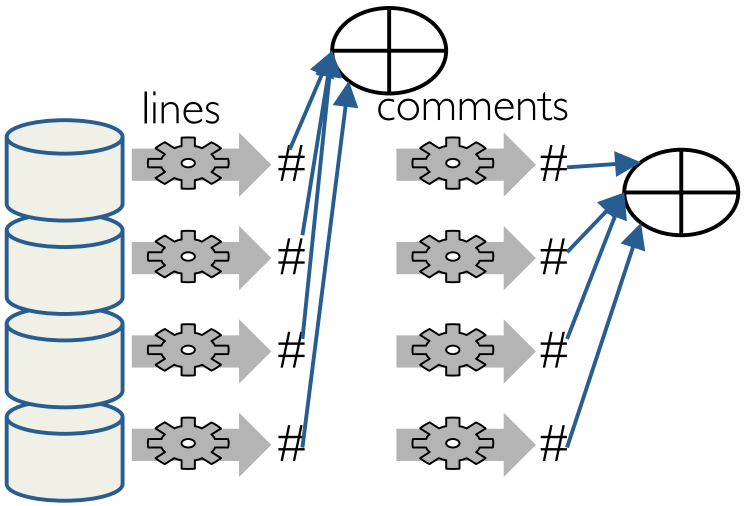


`count()` causes Spark to:

- read data
- sum within partitions
- combine sums in driver

Spark Programming Model

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

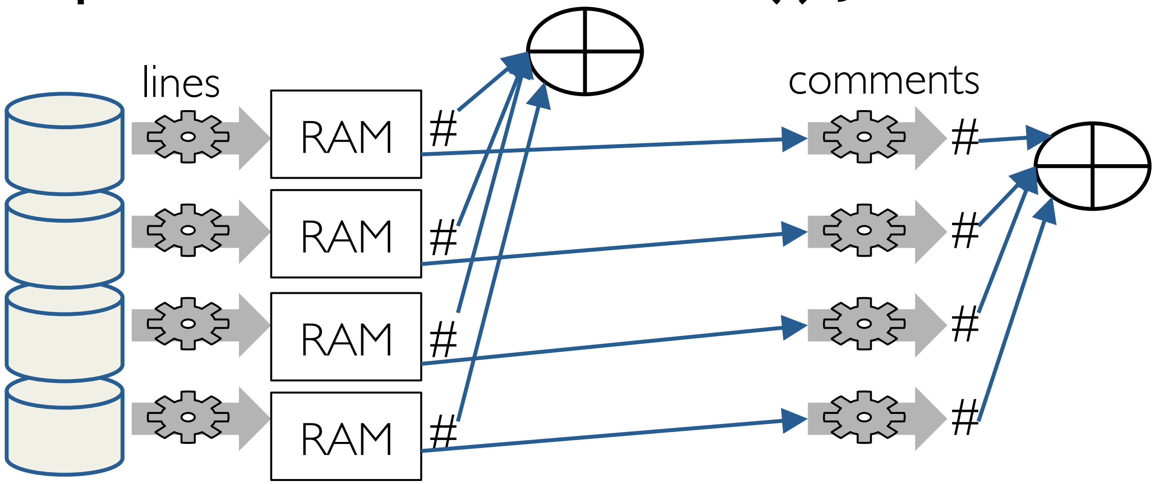


Spark recomputes **lines**:

- read data (again)
- sum within partitions
- combine sums in driver

Caching RDDs

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



Spark Program Lifecycle

1. Create RDDs from external data or parallelize a collection in your driver program
2. Lazily transform them into new RDDs
3. **`cache()`** some RDDs for reuse
4. Perform actions to execute parallel computation and produce results

Spark Key-Value RDDs

- Similar to Map Reduce, Spark supports Key-Value pairs
- Each element of a Pair RDD is a pair tuple

```
>>> rdd = sc.parallelize([(1, 2), (3, 4)])
RDD: [(1, 2), (3, 4)]
```

Some Key-Value Transformations

Key-Value Transformation	Description
`reduceByKey(`*`func`*`)`	return a new distributed dataset of (K,V) pairs where the values for each key are aggregated using the given reduce function *func*, which must be of type (V,V) ➔ V
`sortByKey()`	return a new dataset (K,V) pairs sorted by keys in ascending order
`groupByKey()`	return a new dataset of (K, Iterable<V>) pairs

Key-Value Transformations

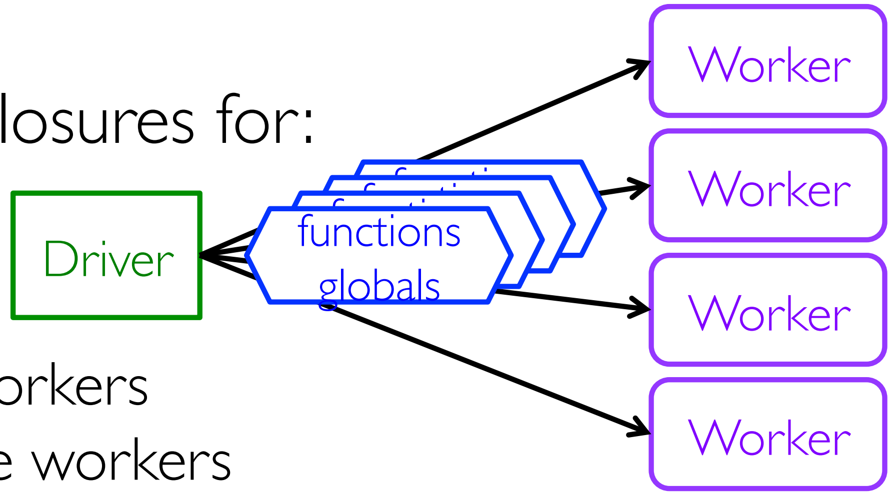
```
>>> rdd = sc.parallelize([(1,2), (3,4), (3,6)])
>>> rdd.reduceByKey(lambda a, b: a + b)
RDD: [(1,2), (3,4), (3,6)] → [(1,2), (3,10)]

>>> rdd2 = sc.parallelize([(1,'a'), (2,'c'), (1,'b')])
>>> rdd2.sortByKey()
RDD: [(1,'a'), (2,'c'), (1,'b')] →
             [(1,'a'), (1,'b'), (2,'c')]
```

Key-Value Transformations

```
>>> rdd2 = sc.parallelize([(1,'a'), (2,'c'), (1,'b')])
>>> rdd2.groupByKey()
RDD: [(1,'a'), (1,'b'), (2,'c')] →
               [(1,['a','b']), (2,['c'])]
```

Be careful using **`groupByKey()`** as it can cause a lot of data movement across the network and create large Iterables at workers

pySpark Closures



- Spark automatically creates closures for:
  - » Functions that run on RDDs at workers
  - » Any global variables used by those workers

- One closure per worker
  - » Sent for ***every*** task
  - » No communication between workers
  - » Changes to global variables at workers are not sent to driver

Consider These Use Cases

- Iterative or single jobs with large global variables
  - » Sending large read-only lookup table to workers
  - » Sending large feature vector in a ML algorithm to workers

- Counting events that occur during job execution
  - » How many input lines were blank?
  - » How many input records were corrupt?

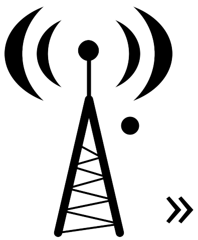
Consider These Use Cases

- Iterative or single jobs with large global variables
  - » Sending large read-only lookup table to workers
  - » Sending large feature vector in a ML algorithm to workers

- Counting events that occur during job execution
  - » How many input lines were blank?
  - » How many input records were corrupt?

Problems:
- Closures are (re-)sent with ***every*** job
- Inefficient to send large data to each worker
- Closures are one way: driver ➔ worker

pySpark Shared Variables

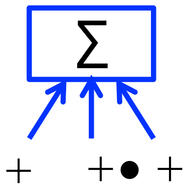


Broadcast Variables

» Efficiently send large, ***read-only*** value to all workers

» Saved at workers for use in one or more Spark operations

» Like sending a large, read-only lookup table to all the nodes



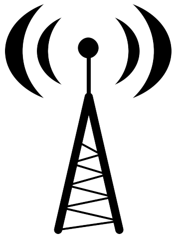
Accumulators

» Aggregate values from workers back to driver

» Only driver can access value of accumulator

» For tasks, accumulators are write-only

» Use to count errors seen in RDD across workers



Broadcast Variables

- Keep ***read-only*** variable cached on workers
  - » Ship to each worker only once instead of with each task
- Example: efficiently give every worker a large dataset
- Usually distributed using efficient broadcast algorithms

```
At the driver:
>>> broadcastVar = sc.broadcast([1, 2, 3])

At a worker (in code passed via a closure)
>>> broadcastVar.value
[1, 2, 3]
```

Broadcast Variables Example

- Country code lookup for HAM radio call signs

```python
# Lookup the locations of the call signs on the
# RDD contactCounts. We load a list of call sign
# prefixes to country code to support this lookup
signPrefixes = loadCallSignTable()

def processSignCount(sign_count, signPrefixes):
    country = lookupCountry(sign_count[0], signPrefixes)
    count = sign_count[1]
    return (country, count)

countryContactCounts = (contactCounts
                        .map(processSignCount)
                        .reduceByKey((lambda x, y: x+ y)))
```

Expensive to send large table
(Re-)sent for every processed file

From: http://shop.oreilly.com/product/0636920028512.do

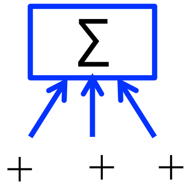
Broadcast Variables Example

Country code lookup for HAM radio call signs

```
# Lookup the locations of the call signs on the
# RDD contactCounts. We load a list of call sign
# prefixes to country code to support this lookup
signPrefixes = sc.broadcast(loadCallSignTable())

def processSignCount(sign_count, signPrefixes):
    country = lookupCountry(sign_count[0], signPrefixes.value)
    count = sign_count[1]
    return (country, count)

countryContactCounts = (contactCounts
                        .map(processSignCount)
                        .reduceByKey((lambda x, y: x+ y)))
```

Efficiently sent once to workers

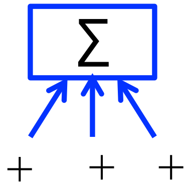
From: http://shop.oreilly.com/product/0636920028512.do



Accumulators

- Variables that can only be "added" to by associative op
- Used to efficiently implement parallel counters and sums
- Only driver can read an accumulator's value, not tasks

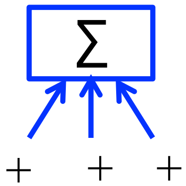
```
>>> accum = sc.accumulator(0)
>>> rdd = sc.parallelize([1, 2, 3, 4])
>>> def f(x):
>>>   global accum
>>>   accum += x

>>> rdd.foreach(f)
>>> accum.value
Value: 10
```



Accumulators Example

- Counting empty lines

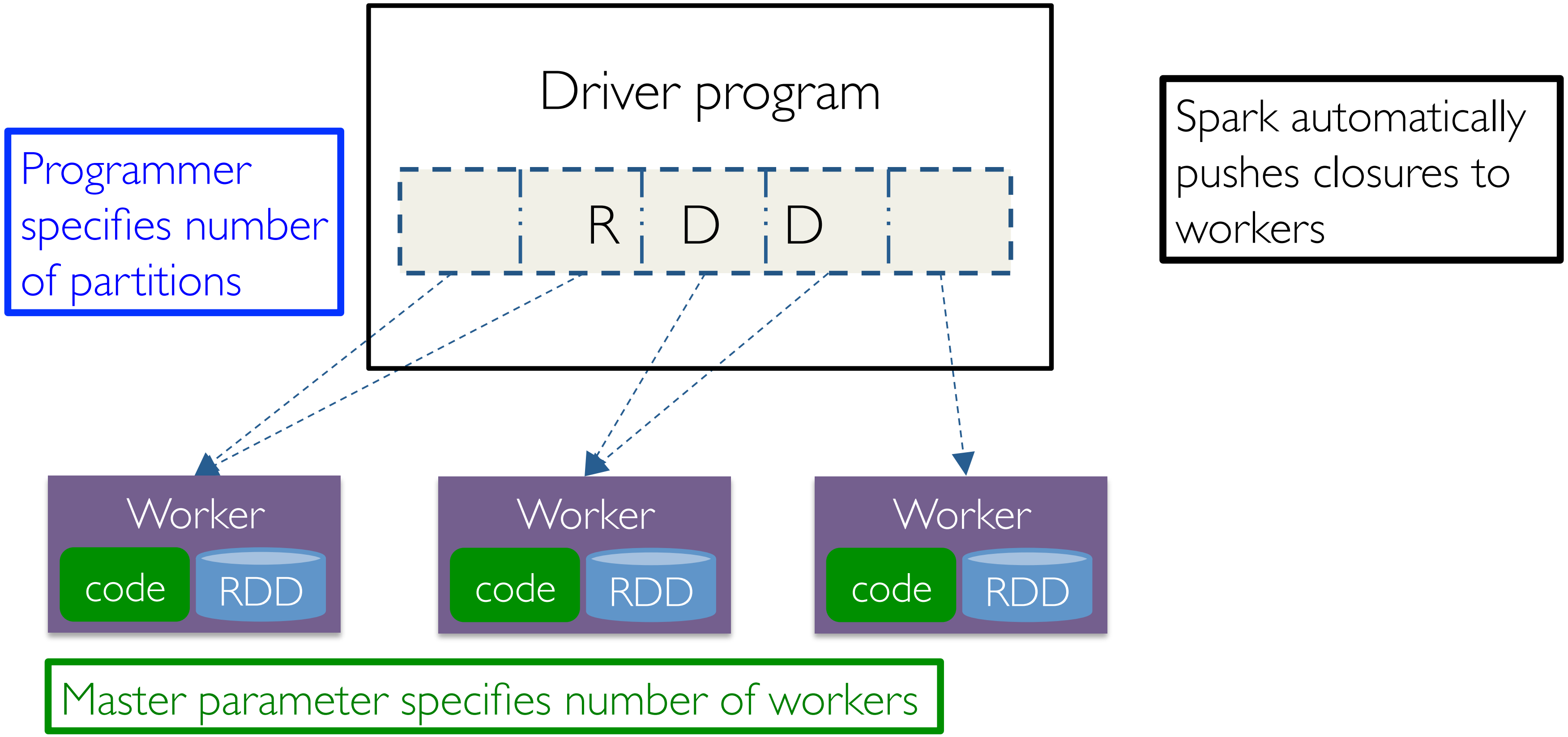
```
file = sc.textFile(inputFile)
# Create Accumulator[Int] initialized to 0
blankLines = sc.accumulator(0)

def extractCallSigns(line):
    global blankLines # Make the global variable accessible
    if (line == ""):
        blankLines += 1
    return line.split(" ")

callSigns = file.flatMap(extractCallSigns)
print "Blank lines: %d" % blankLines.value
```



Accumulators

- Tasks at workers cannot access accumulator's values
- Tasks see accumulators as write-only variables
- Accumulators can be used in actions or transformations:
  - » Actions: each task's update to accumulator is *applied only once*
  - » Transformations: *no guarantees* (use only for debugging)
- Types: integers, double, long, float
  - » See lab for example of custom type

Summary



Driver program
R
D
D
Programmer specifies number of partitions
Spark automatically pushes closures to workers
Worker
code
RDD
Worker
code
RDD
Worker
code
RDD
Master parameter specifies number of workers