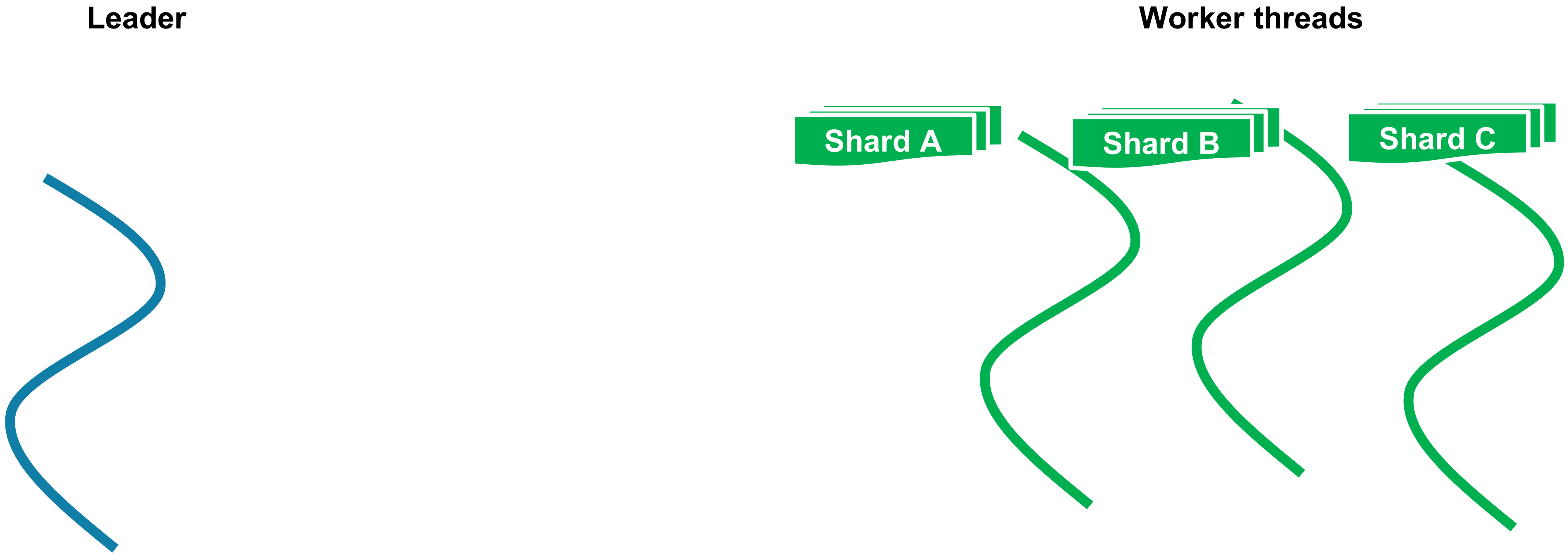
CS5412 / Lecture 21
MapReduce, Spark and RDDs

Big Data Tools in the Cloud

MapReduce pattern: Sharded data set



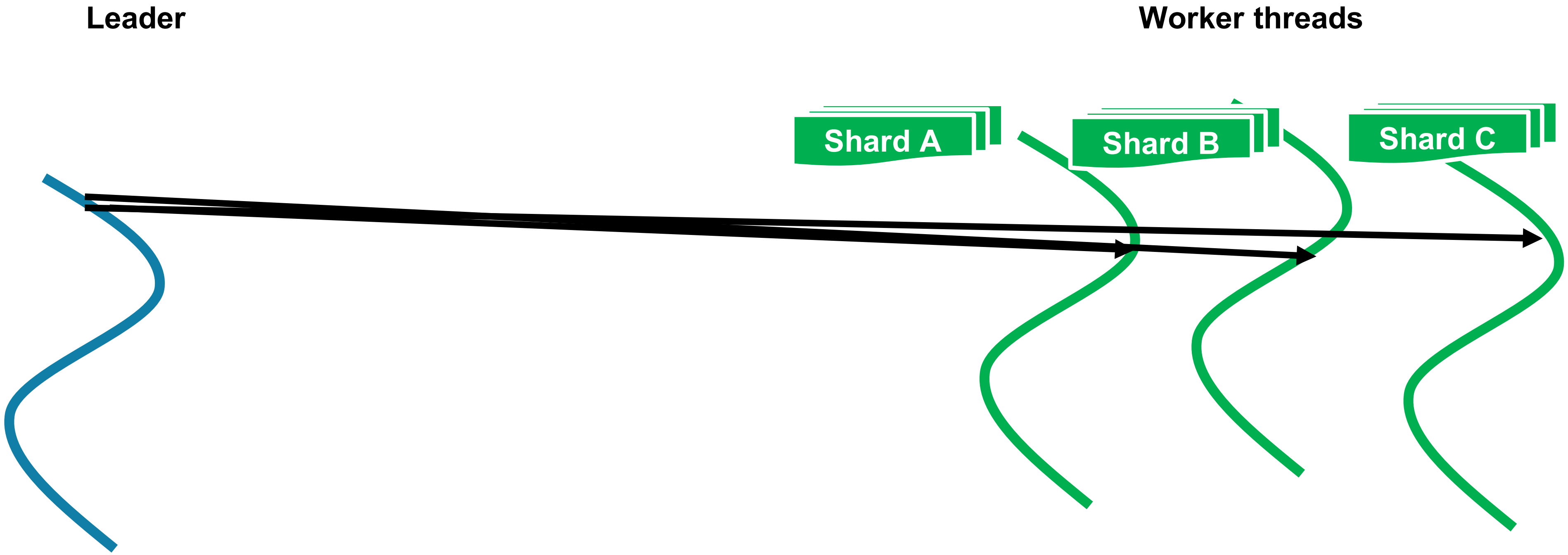
MapReduce: Map step

The leader **maps** some task over the n workers. This can be done in any way that makes sense for the application.

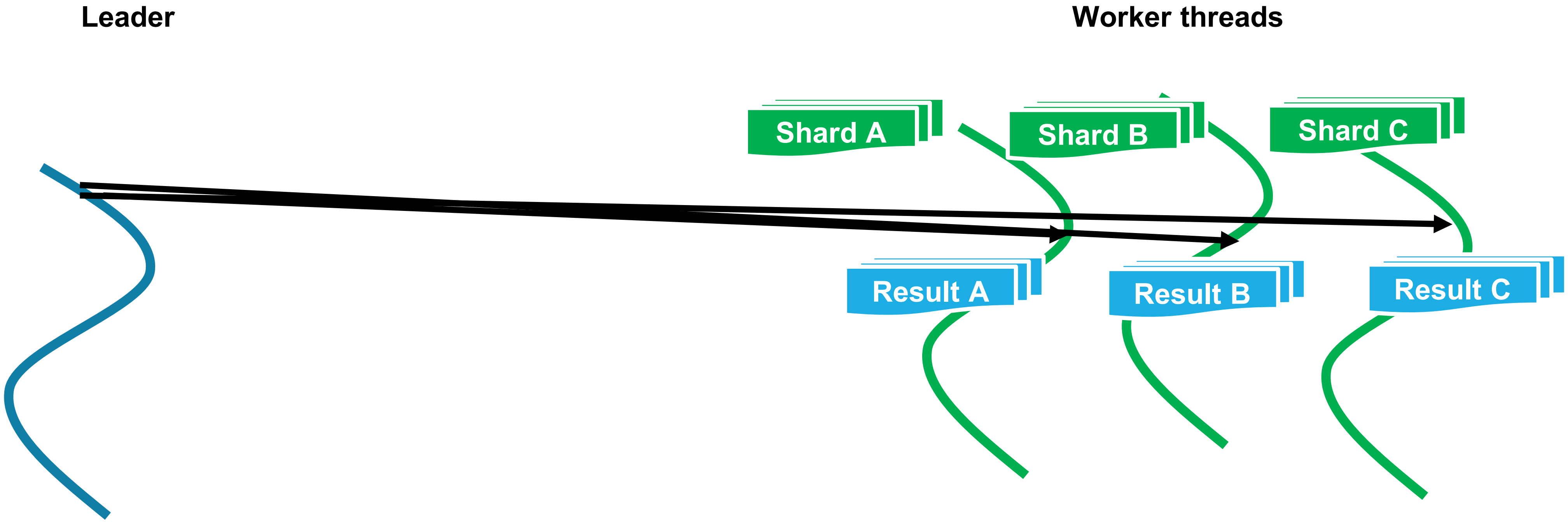
Each worker performs its share of the work by applying the requested function to the data in its shard.

When finished, each worker will have a list of new (key,value) pairs as its share of the result.

MapReduce pattern: Sharded data set



MapReduce pattern: Map (first step)



MapReduce: Shuffle exchange

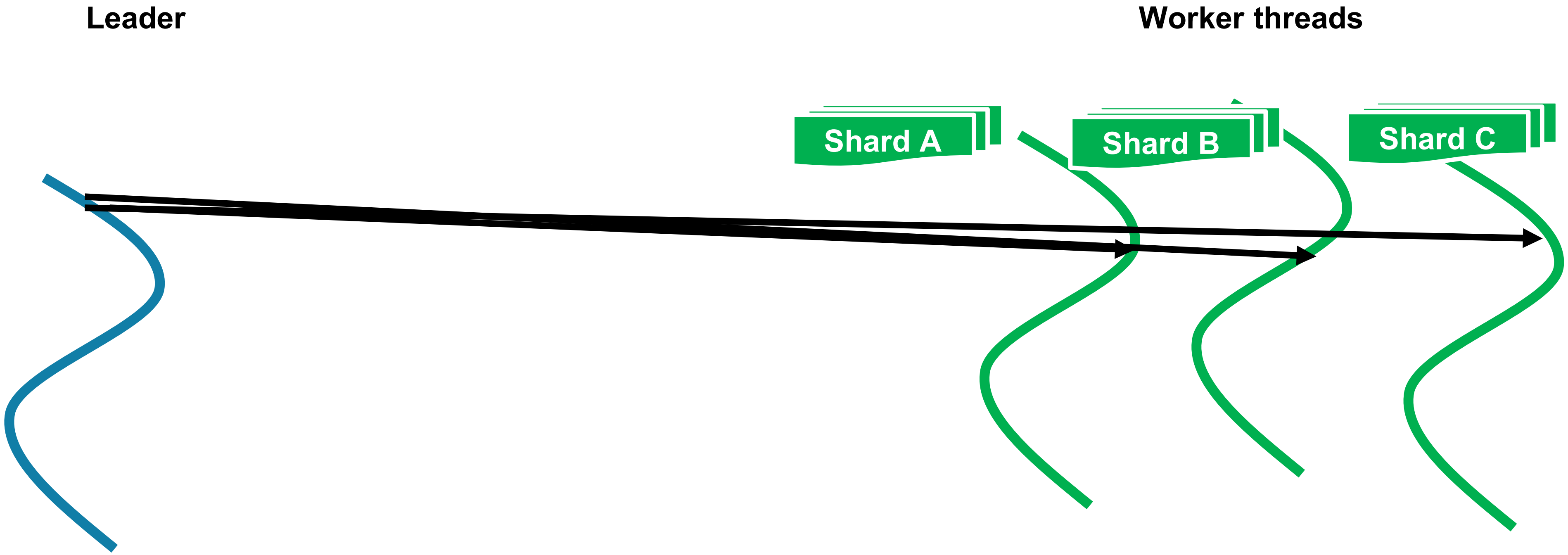
Each worker breaks its key-value result set into n parts by applying the sharding rule to the keys.

- Uses GroupBy to group the key-value results (one subset per shard)
- Recall that one member was picked to be responsible for each shard
- So, each worker sends each of its subsets to the responsible worker for that subset.

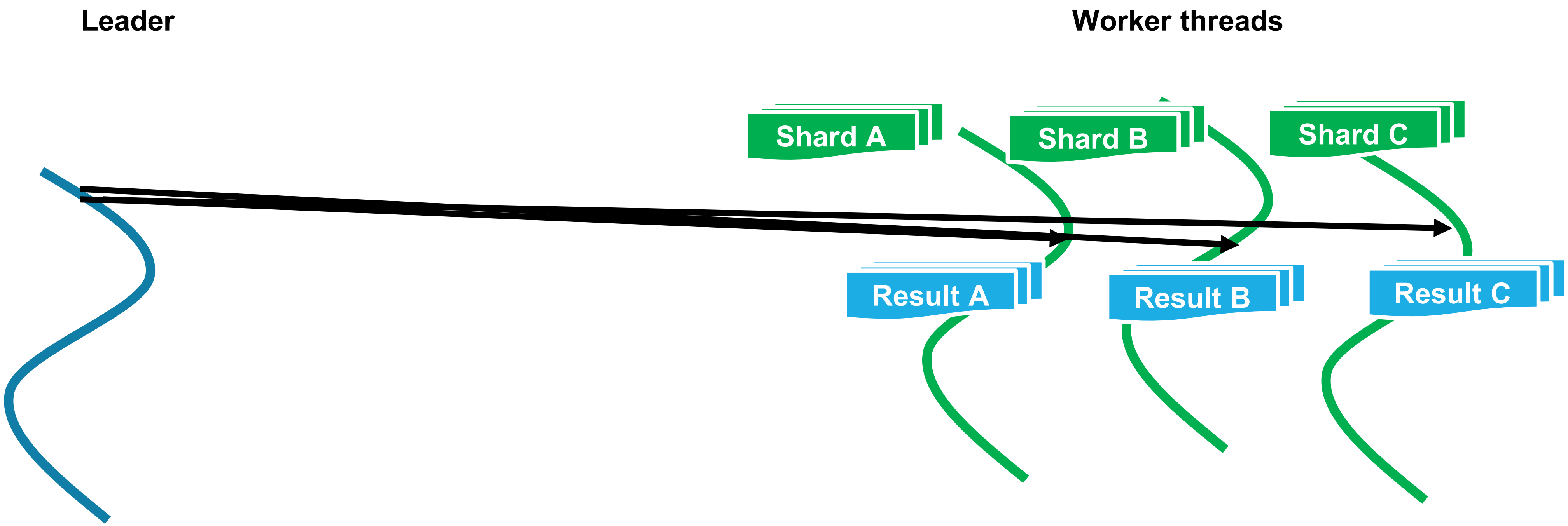
Every worker waits until it has its one message from each worker. Now it runs GroupBy a second time. This time, we group subresults that had the same key.

It now has a list of (key, {set-of-values}) tuples. It calls reduce to end up with (key, result) pairs

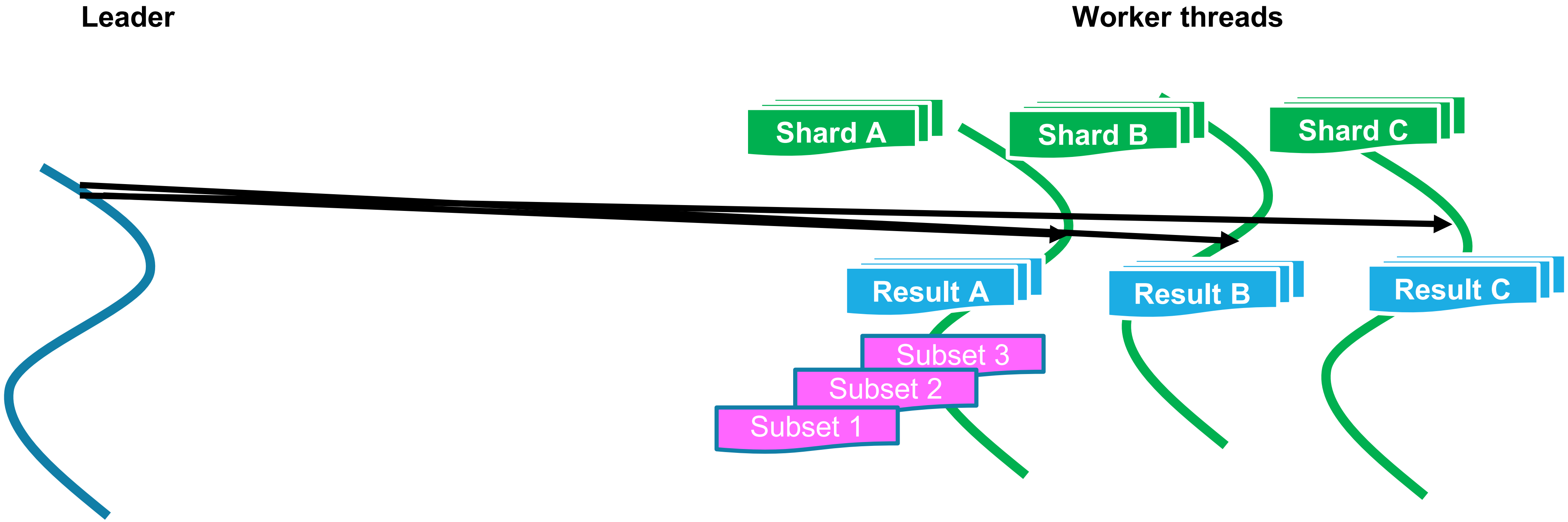
MapReduce pattern: Map (first step)



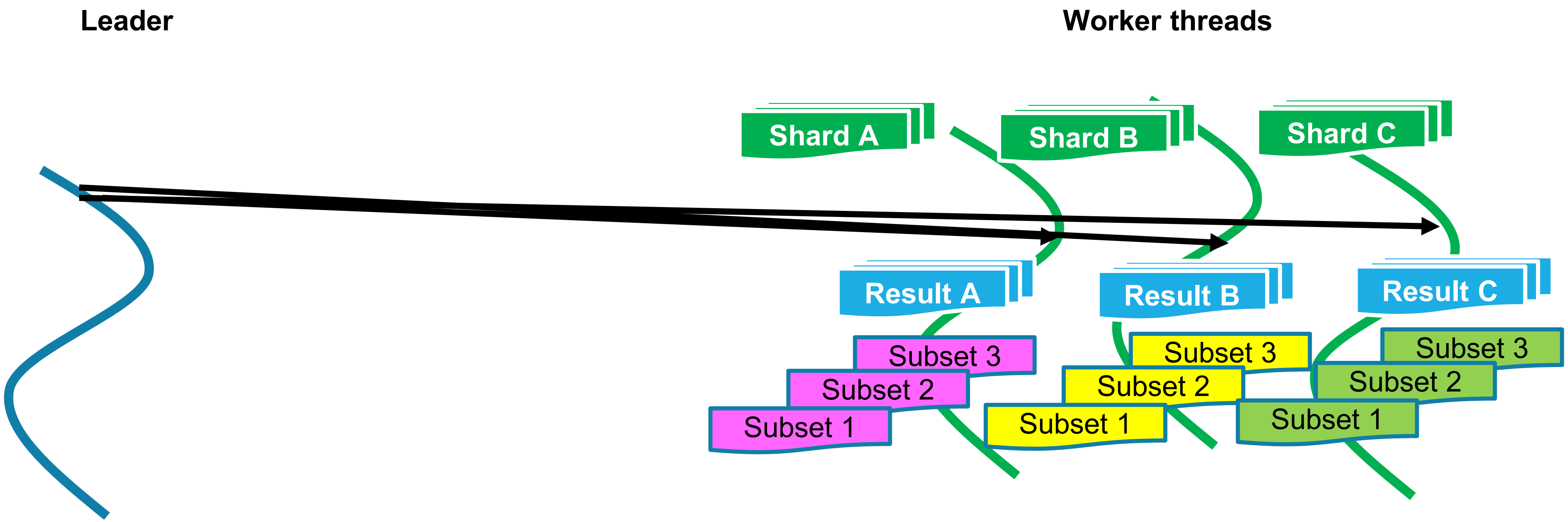
MapReduce pattern: Map (first step)



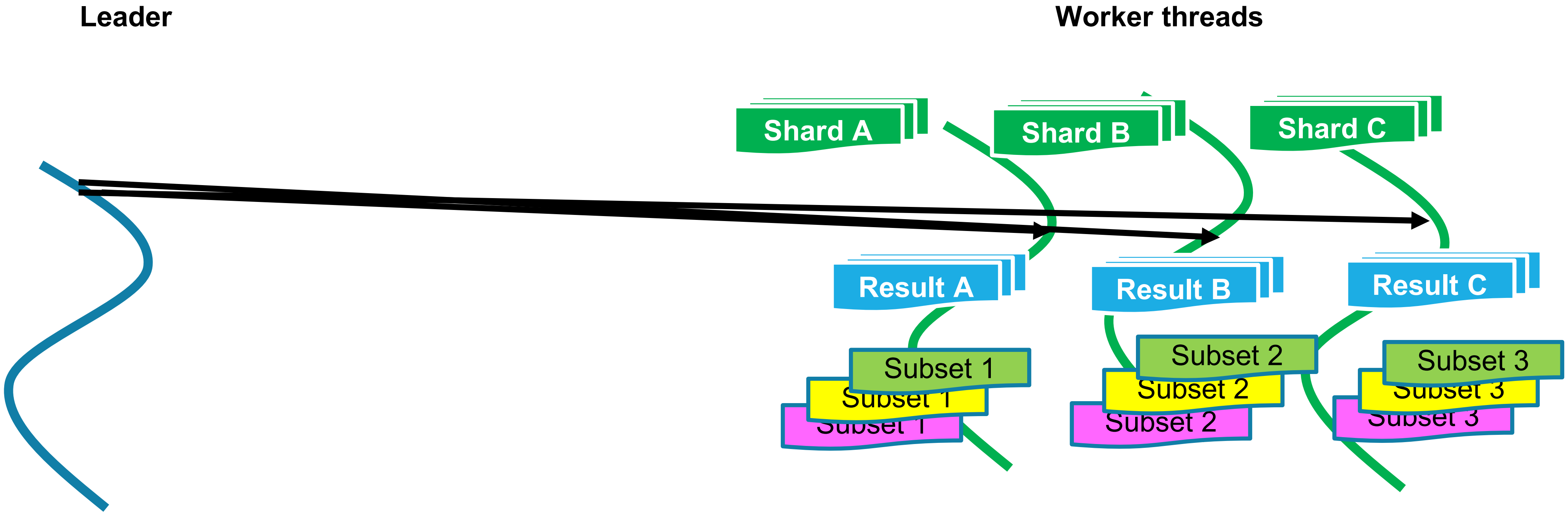
MapReduce pattern: Map (first step)



MapReduce pattern: Shuffle

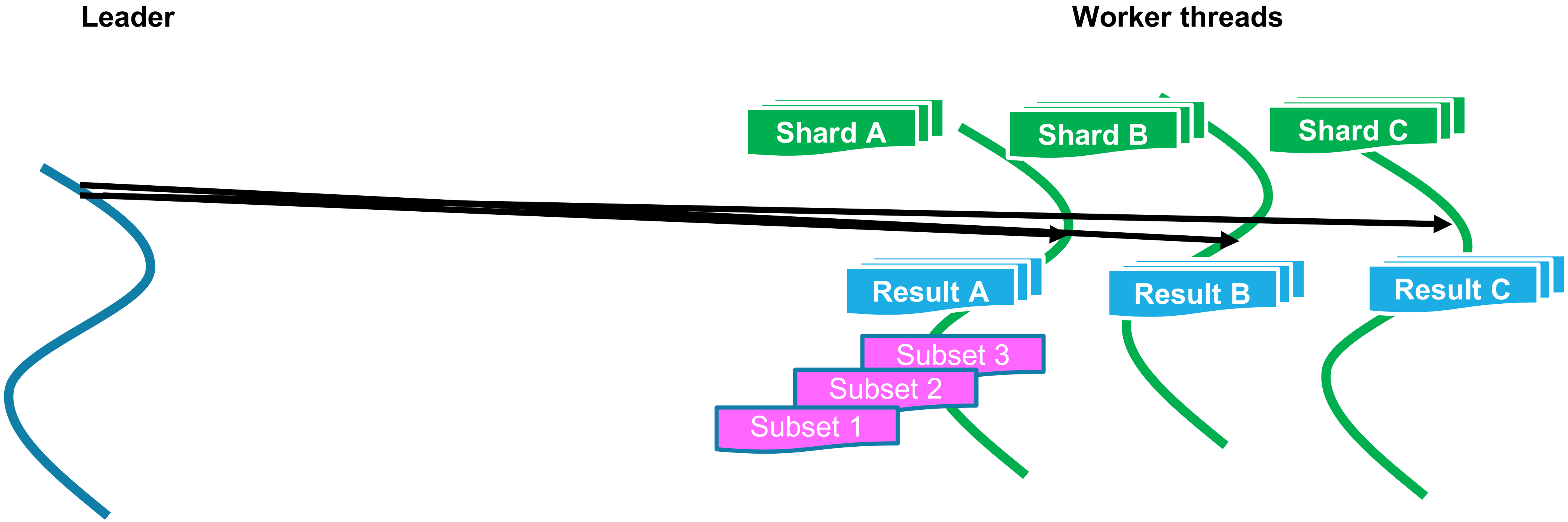


MapReduce pattern: Sort

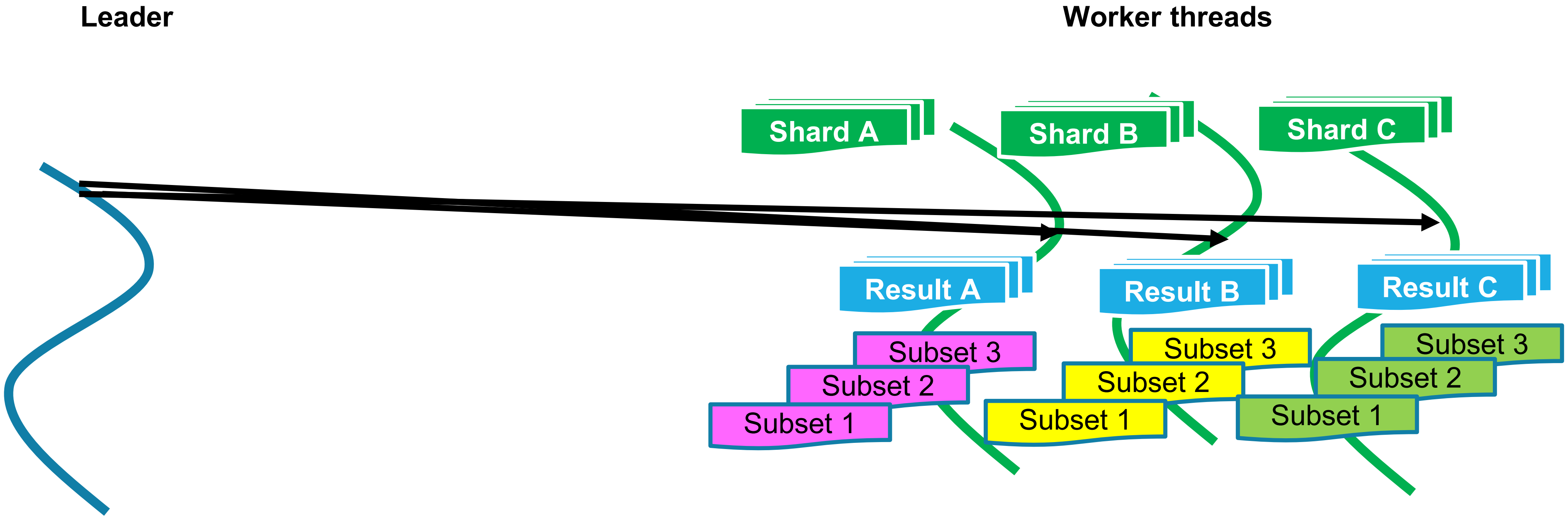


Not shown: There are additional messages being sent from A to B and C, from B to A and C, and from C to A and B. This “shuffles” the data

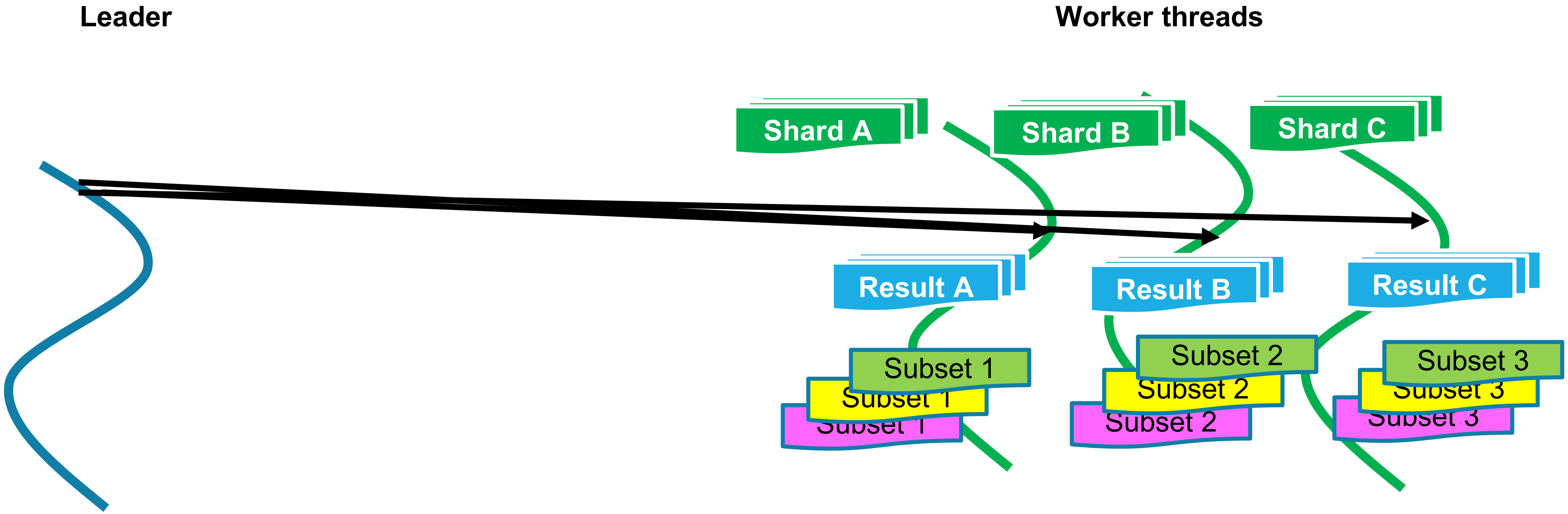
MapReduce pattern: Map (first step)



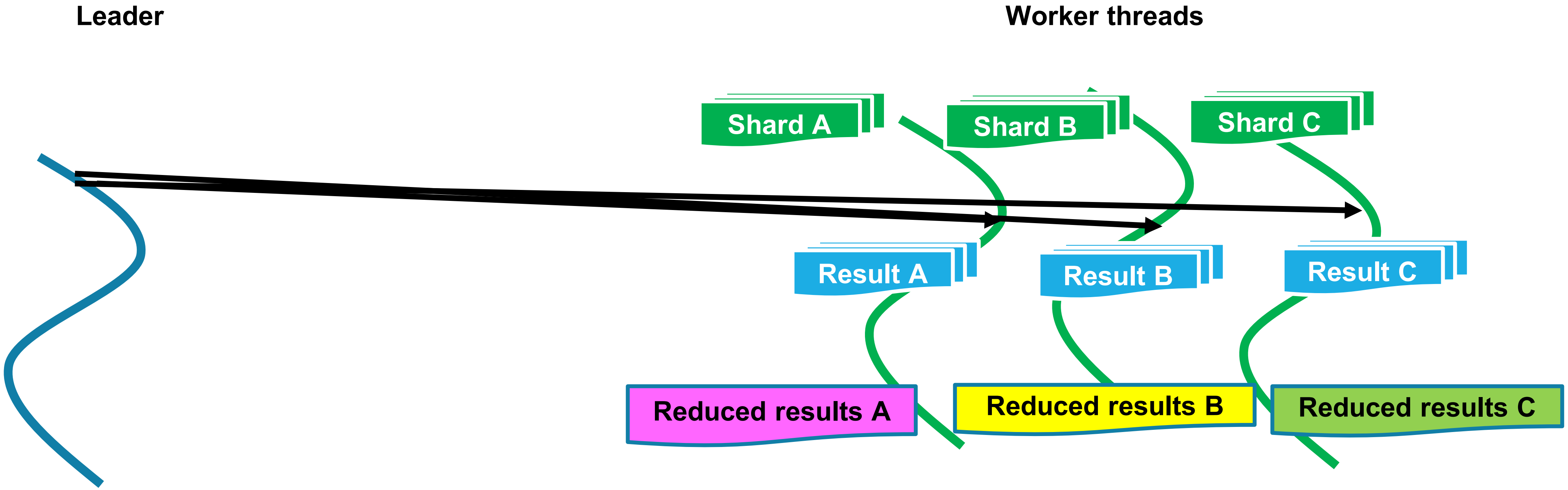
MapReduce pattern: Shuffle



MapReduce pattern: Sort



MapReduce pattern: reduce



Example: Word Count

The use case scenario: Start with standard WC for one file.

We have a large file of documents (the input elements)

Documents are words separated by whitespace.

Count the number of times each distinct word appears in the file.

… with MapReduce we can extend this concept to huge numbers of files.

Example: Word Count

Why Do We Care About Counting Words?

NLP systems train on n-grams: counts of n-word sequences

Word or n-gram count is challenging over massive amounts of data

- Using a single compute node would be too time-consuming
- Using distributed nodes requires moving data
- Number of unique words can easily exceed available memory -- would need to store to disk

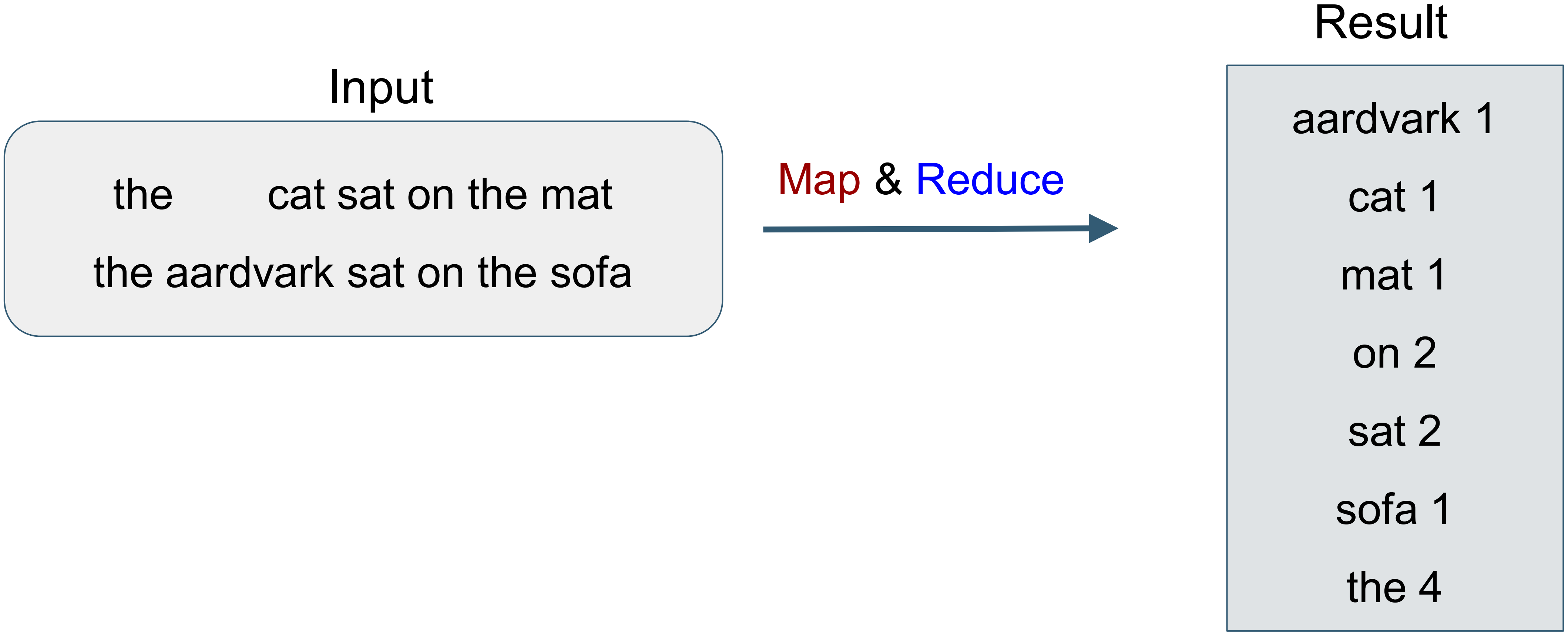
Many common tasks are very similar to word count, e.g., log file analysis where we might look for the storage devices with the highest error rates, to service the ones that are most likely to fail soon

Word Count Using MapReduce

```
map(key, value):
// key: document ID; value: text of document
    for (each word w in value)
        emit(w, 1);
```

```
reduce(key, value-list):
// key: a word; value-list: a list of integers
    result = 0;
    for (each integer v on value-list)
        result += v;
    emit(key, result);
```

Word Count Using MapReduce



Input

the cat sat on the mat

the aardvark sat on the sofa

Map & Reduce

Result

aardvark 1

cat 1

mat 1

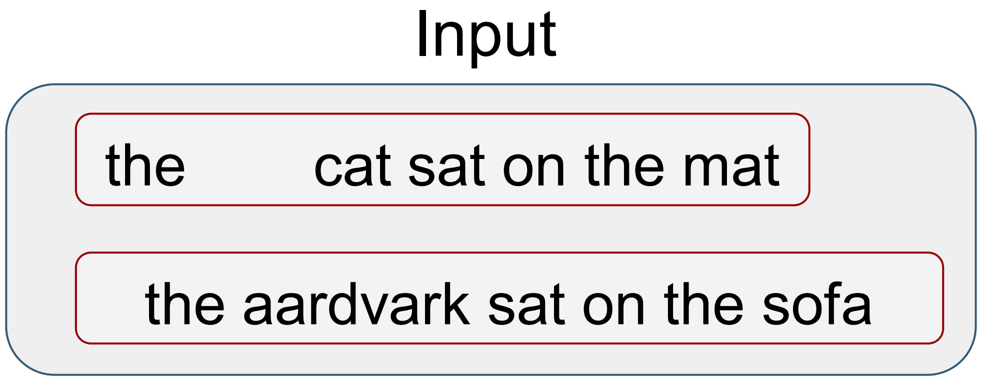
on 2

sat 2

sofa 1

the 4

Sharded Word Count: Map



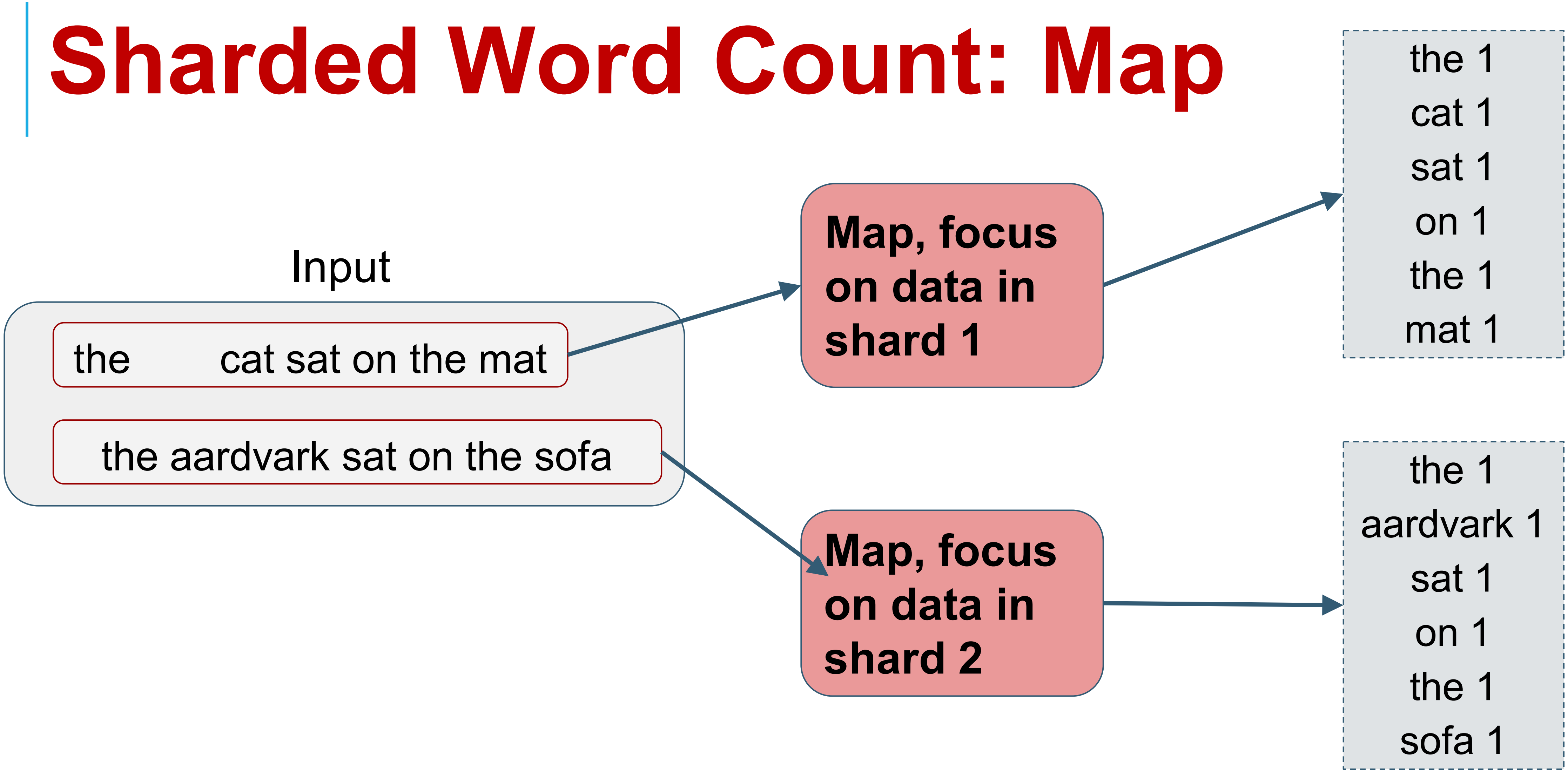
We sharded the data when it was first stored.

MapReduce uses Zookeeper to look up the sharding pattern.

This lets it run compute tasks in a pattern matched to the shard pattern.

The machines on which it runs probably won't be the ones holding the data, but each task focuses on a distinct portion of the data set.

Sharded Word Count: Map



Input

the cat sat on the mat

the aardvark sat on the sofa

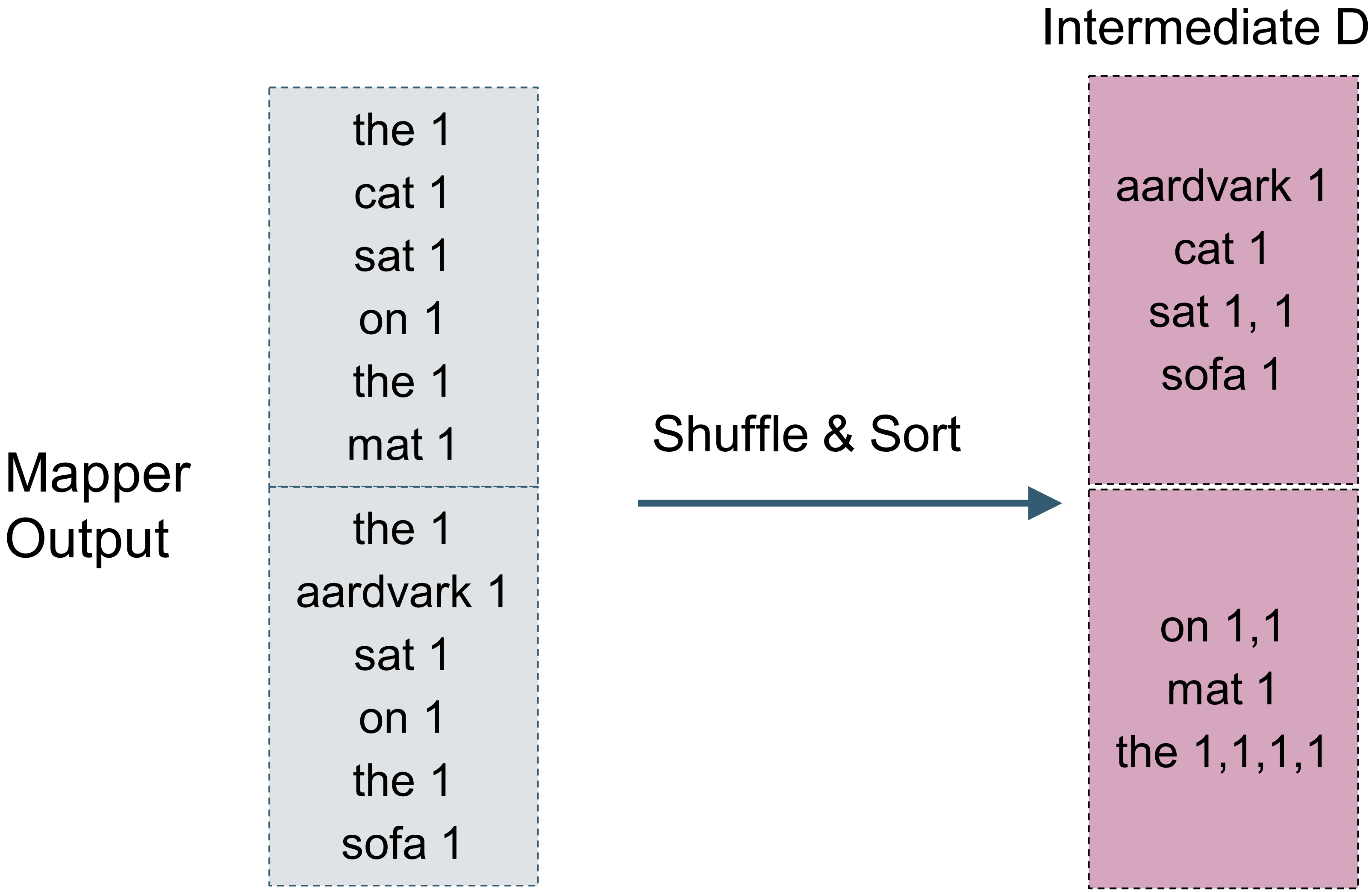
Map, focus on data in shard 1

Map, focus on data in shard 2

the 1
cat 1
sat 1
on 1
the 1
mat 1

the 1
aardvark 1
sat 1
on 1
the 1
sofa 1

Shuffle & Sort



Intermediate Data

Mapper Output

the 1
cat 1
sat 1
on 1
the 1
mat 1

the 1
aardvark 1
sat 1
on 1
the 1
sofa 1

Shuffle & Sort

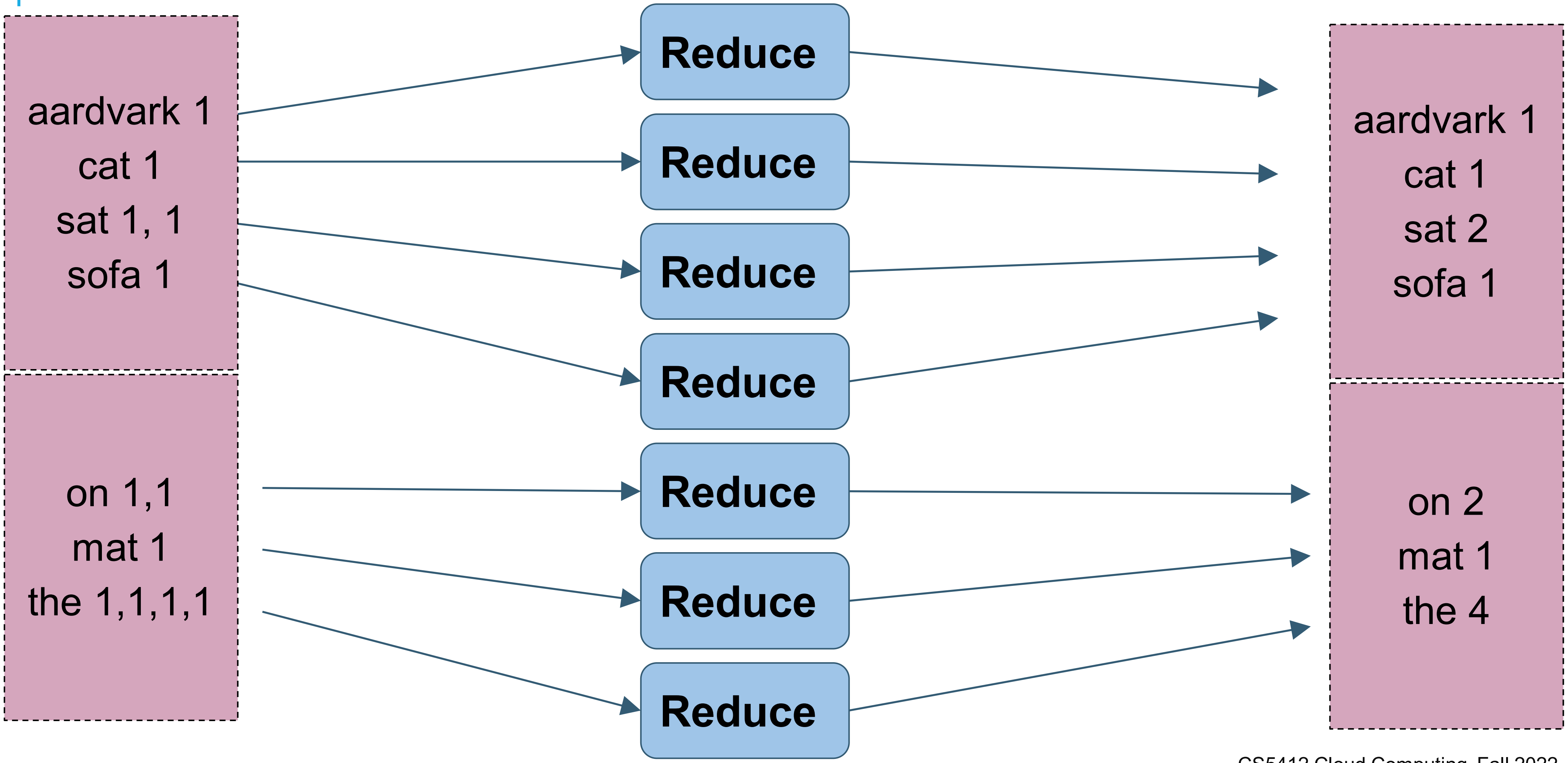
aardvark 1
cat 1
sat 1, 1
sofa 1

on 1,1
mat 1
the 1,1,1,1

Keys that mapped to shard 1 are still on shard 1. The sort was internal to shard 1

Keys that mapped to shard 2

Word Count: Reducer



Notice that…

Data stays sharded at all times. Originally, or document names determined which document was on which shard. Now, after the shuffle exchange, the words themselves are the keys, and determined which shard that word count will be on

Keys are sorted and grouped shard-by-shard. We never merge and sort the full data set

Reduce runs on (key, $\{v_1, \ldots. v_k\}$) and outputs (key,reduced-value), once per key

Output is never collected to one place: We retain it in a sharded form

Who uses MapReduce?

MapReduce is the workhorse of modern cloud computing.

Professor De Sa once commented that if a system can support MapReduce, every major AI and ML algorithm can be trained on it.

High performance computing was stalled (important but not growing) until the AllReduce package was released for a platform called MPI. Now HPC clusters are offered on every major cloud.

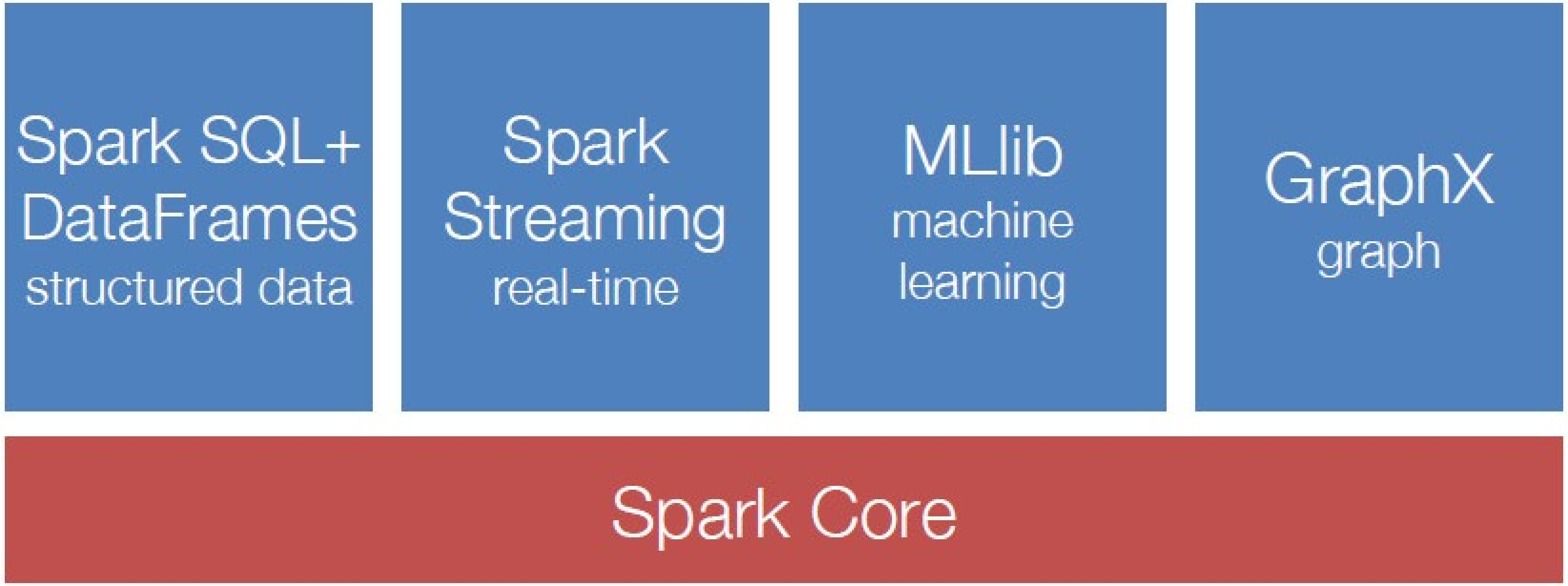
Spark Project

Undertaken at UC Berkeley

Goal was to speed MapReduce up, focusing on the Hadoop version

Part of the Berkeley “View from the clouds” vision for cloud computing research, authored by Ion Stoica

Spark Ecosystem: A Unified Pipeline



Note: Spark is not designed for IoT real-time. The streaming layer is used for continuous input streams like financial data from stock markets, where events occur steadily and must be processed as they occur. But there is no sense of direct I/O from sensors/actuators. For IoT use cases, Spark would not be suitable.

Key ideas

In Hadoop, each developer tends to invent his or her own style of work

With Spark, serious effort to standardize around the idea that people are writing parallel code that often runs for many “cycles” or “iterations” in which a lot of reuse of information occurs.

Spark centers on Resilient Distributed Dataset, RDDs, that capture the information being reused.

How this works

You express your application as a graph of RDDs.

The graph is only evaluated as needed, and they only compute the RDDs actually needed for the output you have requested.

Then Spark can be told to cache the reuseable information either in memory, in SSD storage or even on disk, based on *when* it will be needed again, *how big it is*, and *how costly it would be to recreate.*

You write the RDD logic and control all of this via hints

Spark Basics

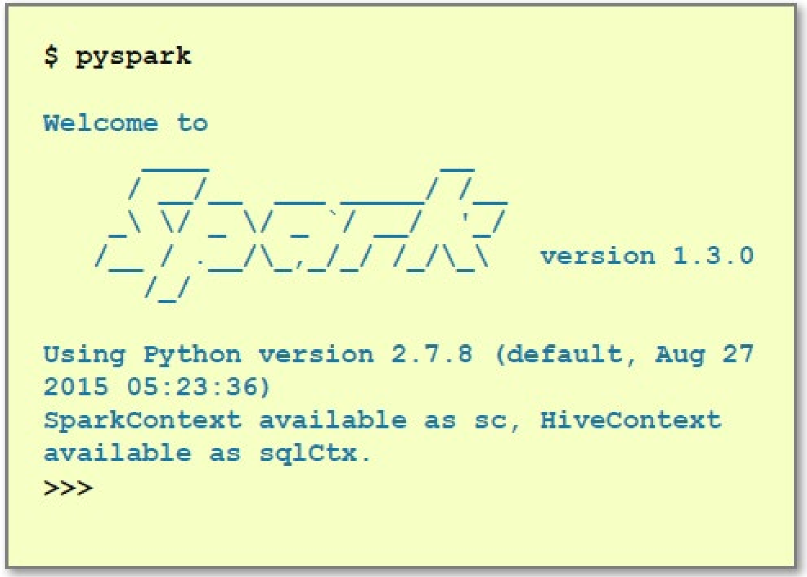
There are two ways to manipulate data in Spark

- Spark Shell:
  - Interactive – for learning or data exploration
  - Python or Scala
- Spark Applications
  - For large scale data processing
  - Python, Scala, or Java

Spark Shell

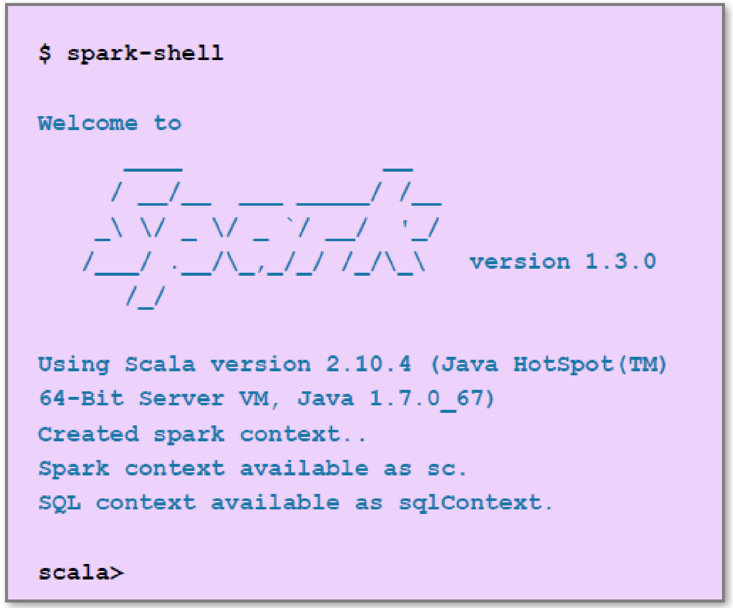
The Spark Shell provides interactive data exploration (REPL)

Python Shell: **pyspark**



```
$ pyspark

Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 1.3.0
      /_/

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

Scala Shell: **spark-shell**

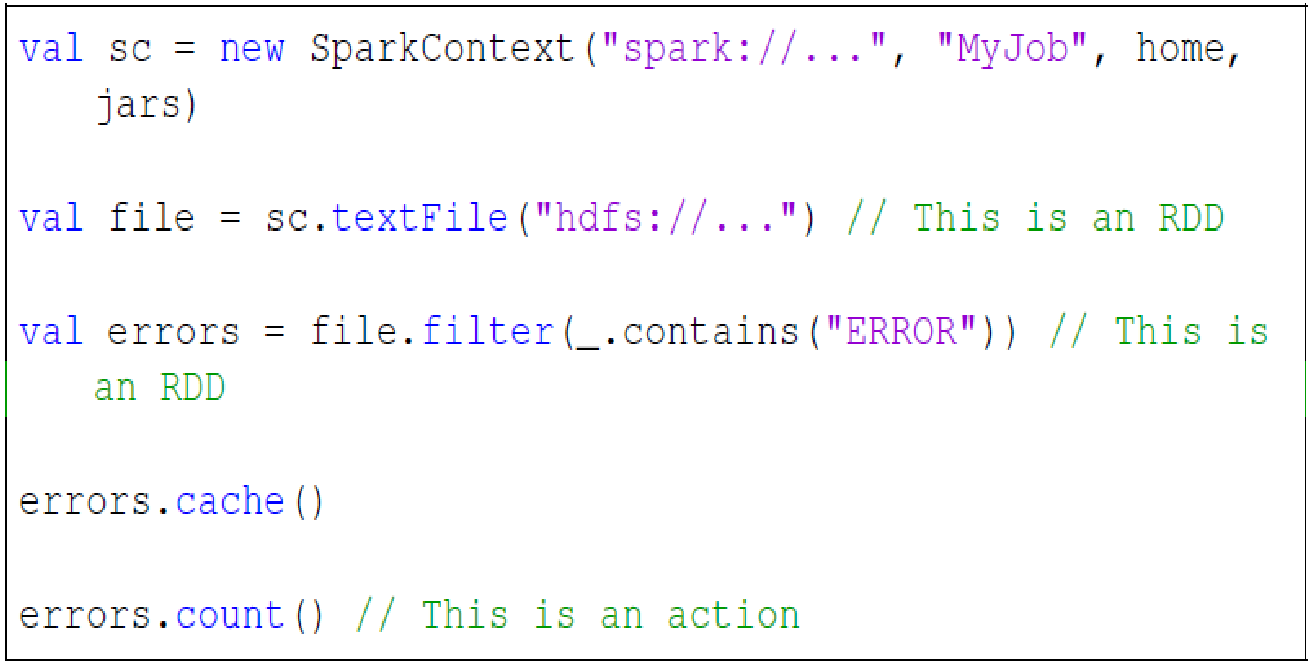


```
$ spark-shell

Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 1.3.0
      /_/

Using Scala version 2.10.4 (Java HotSpot(TM)
64-Bit Server VM, Java 1.7.0_67)
Created spark context..
Spark context available as sc.
SQL context available as sqlContext.

scala>
```

REPL: Repeat/Evaluate/Print Loop

Spark Fundamentals

Example of an application:



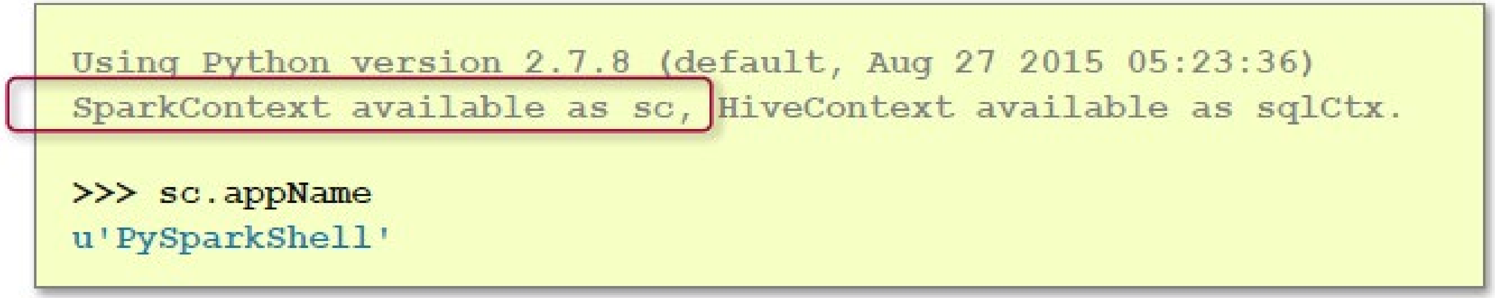
```
val sc = new SparkContext("spark://...", "MyJob", home,
   jars)

val file = sc.textFile("hdfs://...") // This is an RDD

val errors = file.filter(_.contains("ERROR")) // This is
   an RDD

errors.cache()

errors.count() // This is an action
```

- **Spark Context**
- **Resilient Distributed Data**
- **Transformations**
- **Actions**

Spark Context (1)

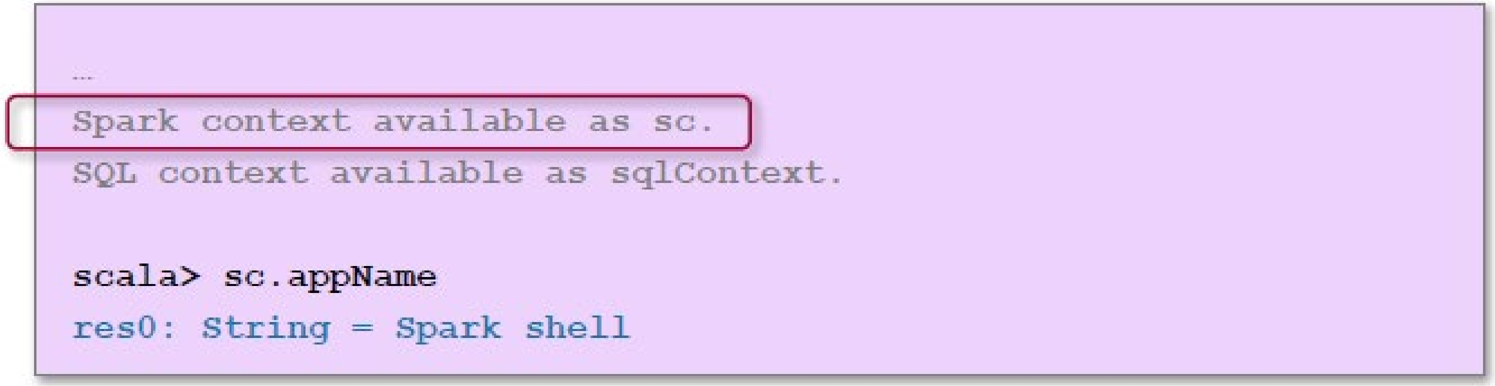
- Every Spark application requires a *spark context*: the main entry point to the Spark API
- Spark Shell provides a preconfigured Spark Context called "sc"

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

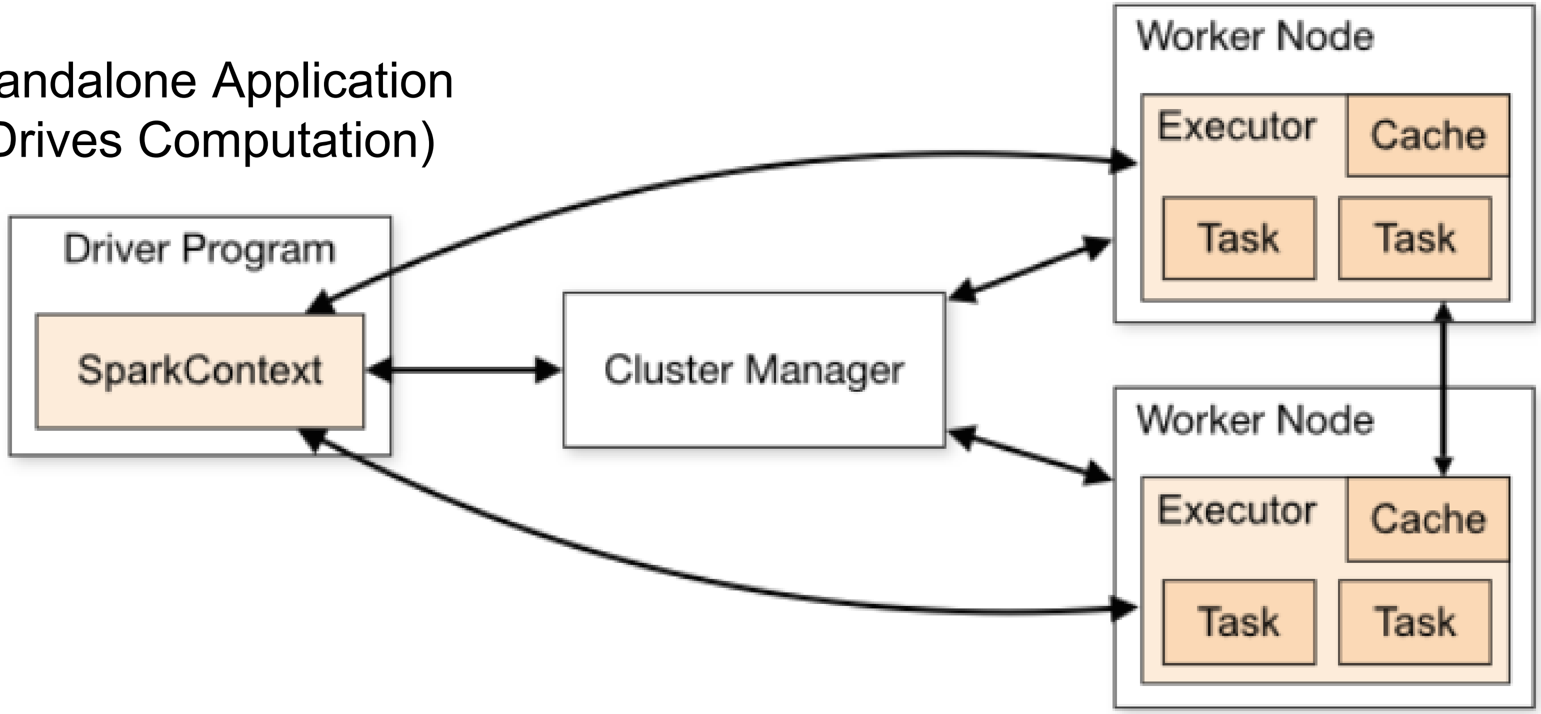


```
...
Spark context available as sc.
SQL context available as sqlContext.

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

Spark Context (2)

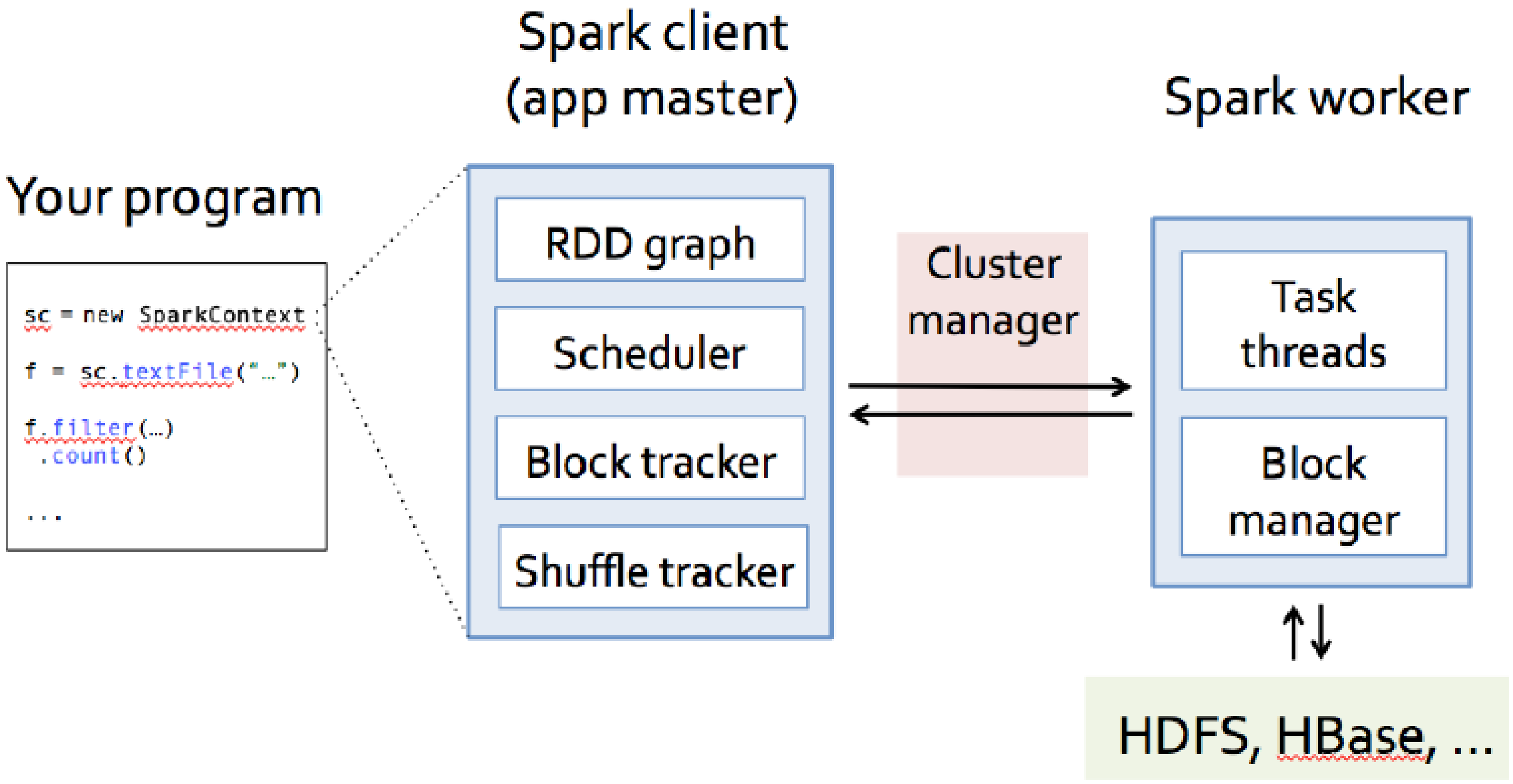
- Standalone applications → Driver code → Spark Context
- Spark Context holds configuration information and represents connection to a Spark cluster

Standalone Application
(Drives Computation)



Spark Context (3)

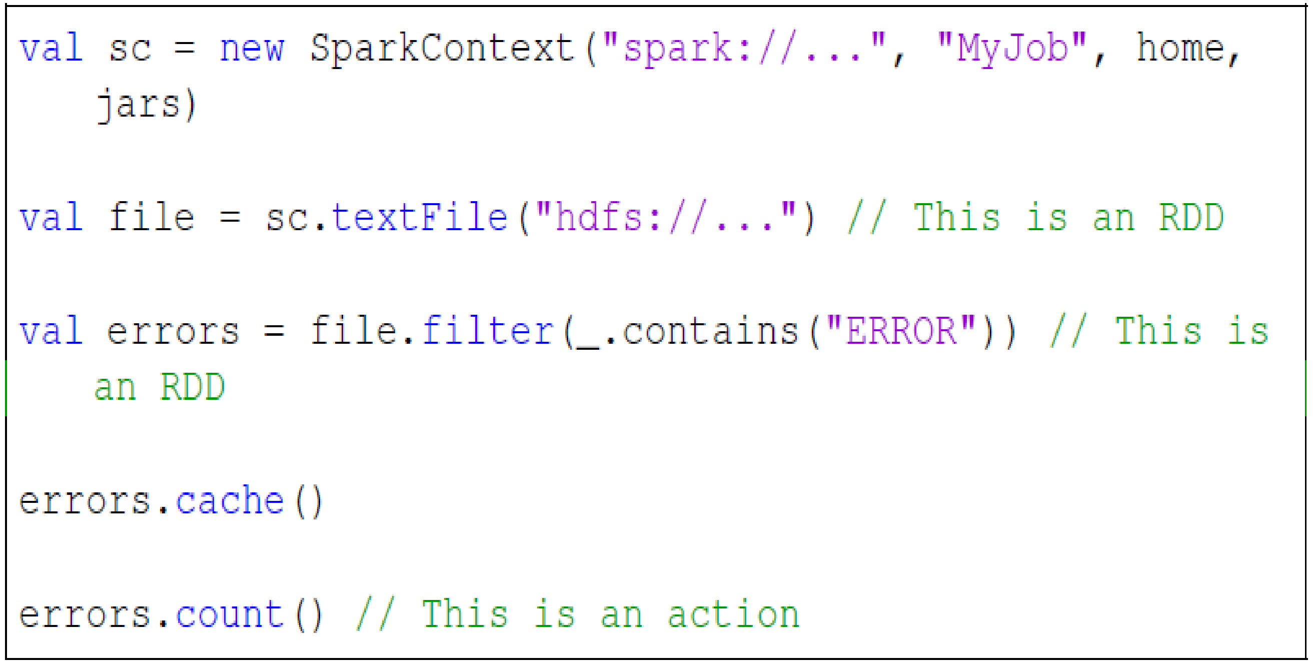
Spark context works as a client and represents connection to a Spark cluster



```
sc = new SparkContext
f = sc.textFile("…")
f.filter(…)
  .count()
...
```

Spark Fundamentals

Example of an application:



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- Spark Context
- **Resilient Distributed Data**
- Transformations
- Actions

Resilient Distributed Dataset (RDD)

The RDD (Resilient Distributed Dataset) is the fundamental unit of data in Spark**:** An *Immutable* collection of objects (or records, or elements) that can be operated on “in parallel” (spread across a cluster)

Resilient -- if data in memory is lost, it can be recreated

- Recover from node failures
- An RDD keeps its lineage information → it can be recreated from parent RDDs

Distributed -- processed across the cluster

- Each RDD is composed of one or more partitions → (more partitions – more parallelism)

Dataset -- initial data can come from a file or be created

RDDs

Key Idea: Write applications in terms of transformations on distributed datasets. One RDD per transformation.

- Organize the RDDs into a DAG showing how data flows.
- RDD can be saved and reused or recomputed. Spark can save it to disk if the dataset does not fit in memory
- Built through parallel transformations (map, filter, group-by, join, etc). Automatically rebuilt on failure
- Controllable persistence (e.g. caching in RAM)

RDDs are designed to be “immutable”

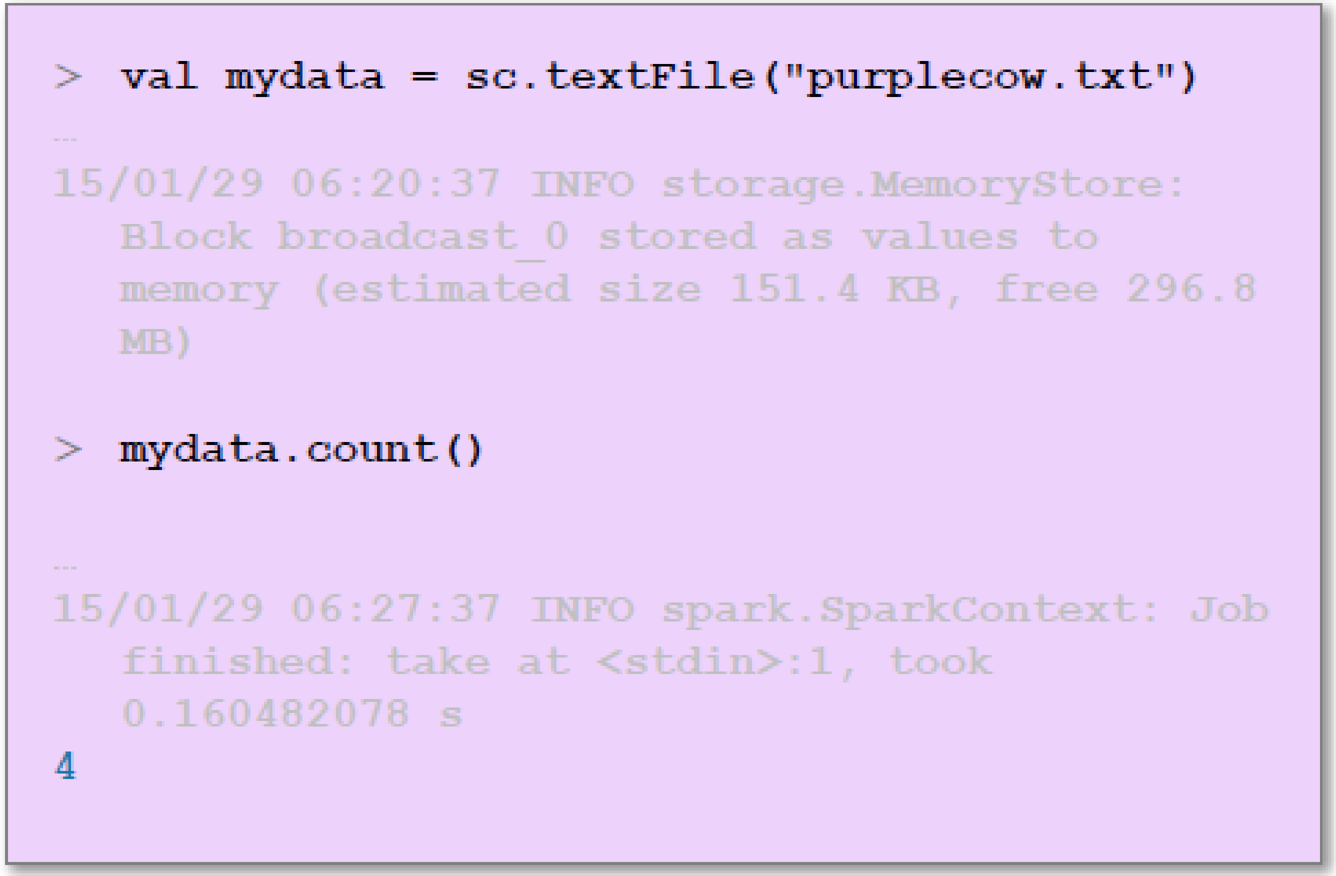
- Create once, then reuse without changes. Spark knows lineage → can be recreated at any time → Fault-tolerance
- Avoids data inconsistency problems (no simultaneous updates) → Correctness
- Easily live in memory as on disk → Caching → Safe to share across processes/tasks → Improves performance
- Tradeoff: (**Fault-tolerance & Correctness**) vs (**Disk Memory & CPU**)

Creating a RDD

Three ways to create a RDD

- From a file or set of files
- From data in memory
- From another RDD

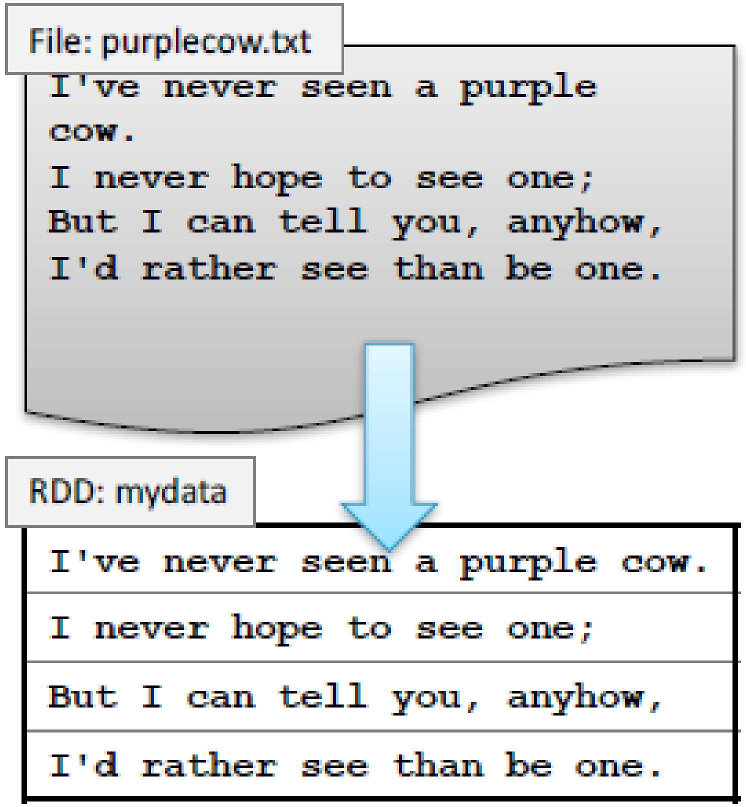
Example: A File-based RDD



```
> val mydata = sc.textFile("purplecow.txt")
…
15/01/29 06:20:37 INFO storage.MemoryStore:
   Block broadcast_0 stored as values to
   memory (estimated size 151.4 KB, free 296.8
   MB)

> mydata.count()

…
15/01/29 06:27:37 INFO spark.SparkContext: Job
   finished: take at <stdin>:1, took
   0.160482078 s
4
```



File: purplecow.txt

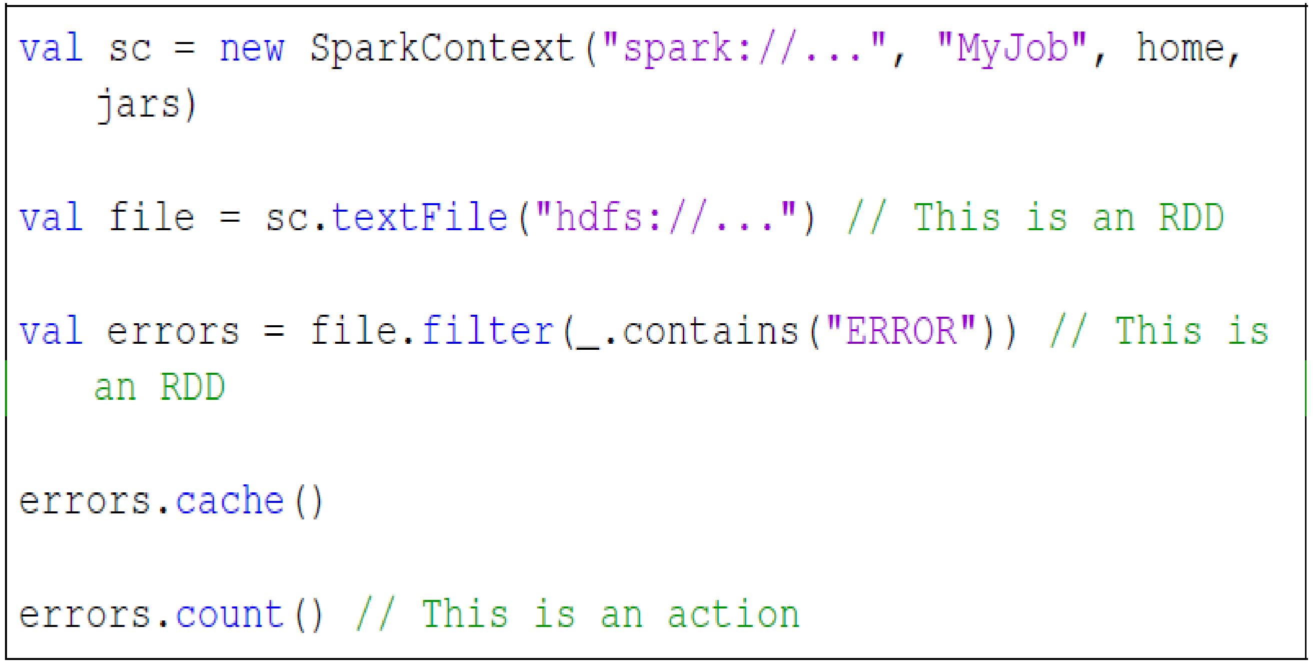
```
I've never seen a purple
cow.
I never hope to see one;
But I can tell you, anyhow,
I'd rather see than be one.
```

RDD: mydata

```
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.
```

Spark Fundamentals

Example of an application:



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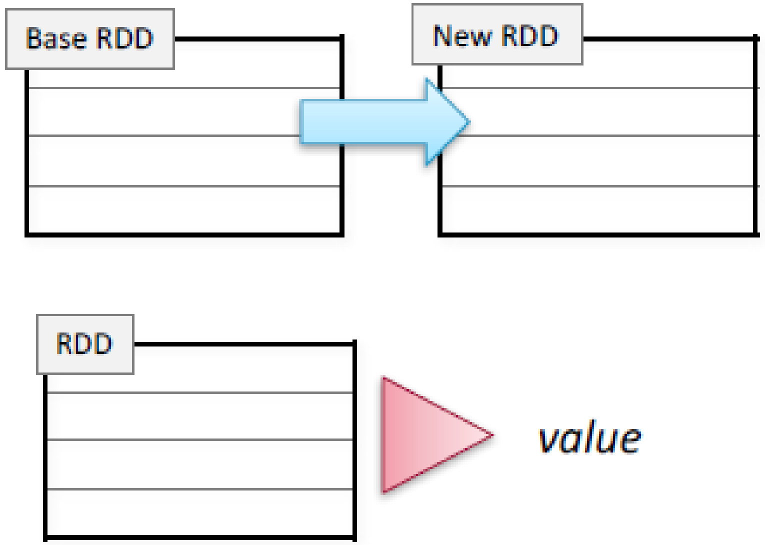
- Spark Context
- **Resilient Distributed Data**
- **Transformations**
- **Actions**

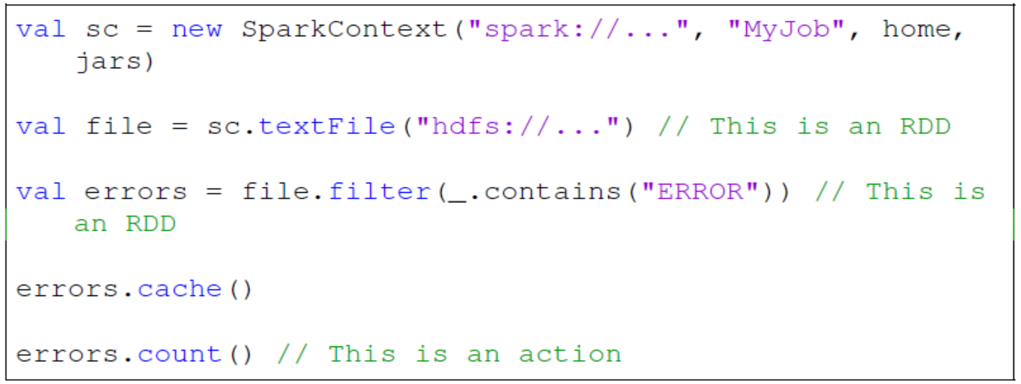
RDD Operations

Two types of operations

Transformations: Define a new RDD based on current RDD(s)

Actions: return values





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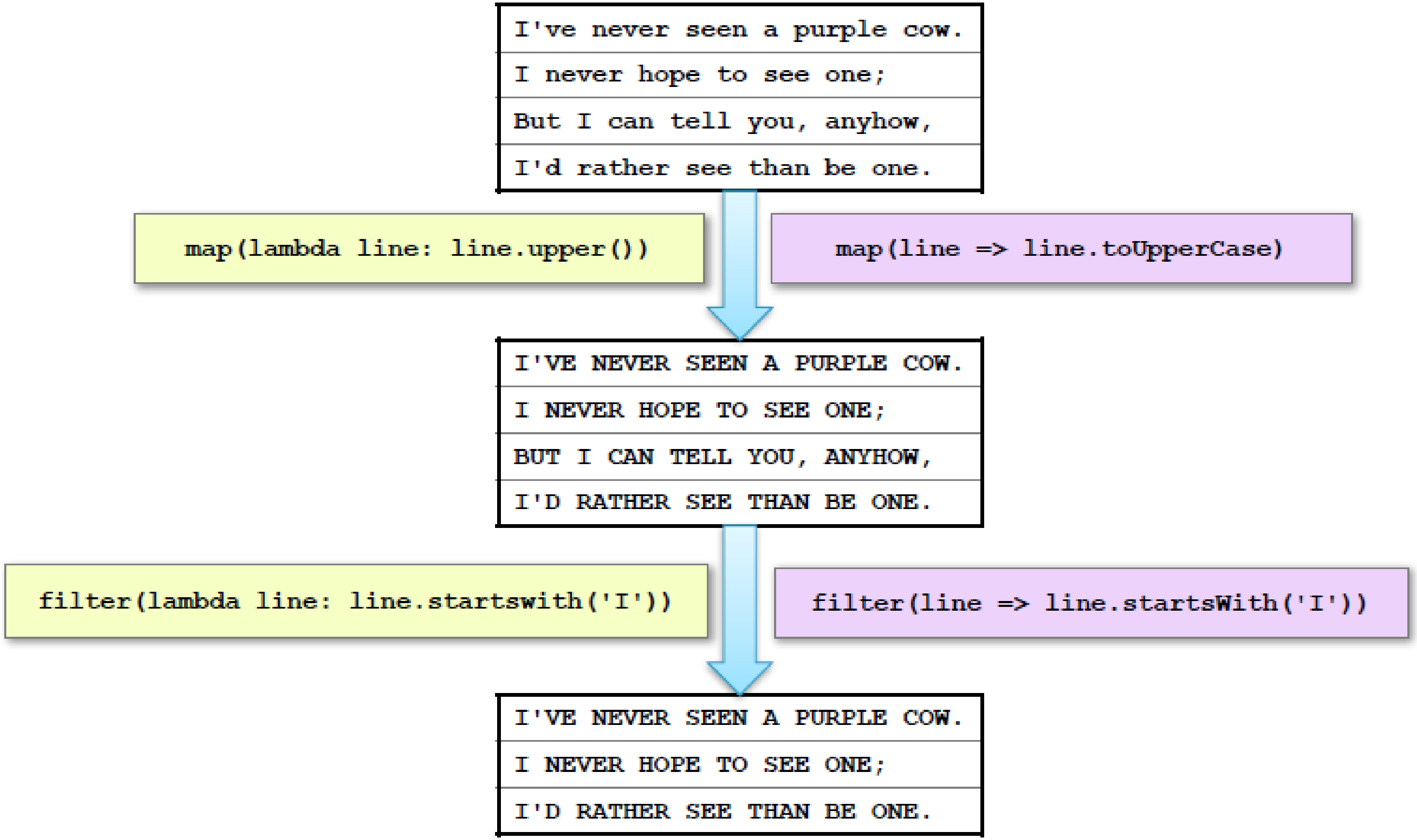
```

RDD Transformations

- Set of operations on a RDD that define how they should be transformed
- As in relational algebra, the application of a transformation to an RDD yields a new RDD (because RDD are immutable)
- Transformations are lazily evaluated, which allow for optimizations to take place before execution
- Examples: map(), filter(), groupByKey(), sortByKey(), etc.

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.

RDD Actions

- Apply transformation chains on RDDs, eventually performing some additional operations (e.g., counting)
- Some actions only store data to an external data source (e.g. HDFS), others fetch data from the RDD (and its transformation chain) upon which the action is applied, and convey it to the driver
- Some common actions
  - count() – return the number of elements
  - take(*n*) – return an array of the first *n* elements
  - collect()– return an array of all elements
  - saveAsTextFile(*file*) – save to text file(s)

Graph of RDDs

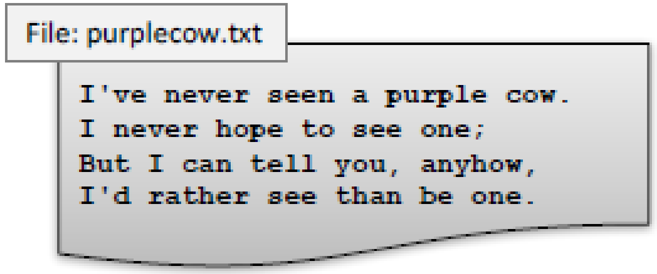
- A collection of RDDs can be understood as a graph

- Nodes in the graph are the RDDs, which means the code but also the actual data object that could would create at runtime when executed on specific parameters + data. Reminder: Hadoop is a “read only” model, so we can “materialize” an RDD any time we like.

- Edges represent how data objects are accessed: RDD B might consume the object created by RDD A. This gives us a directed edge A → B

Lazy Execution of RDDs (1)

Data in RDDs is not processed until an action is performed



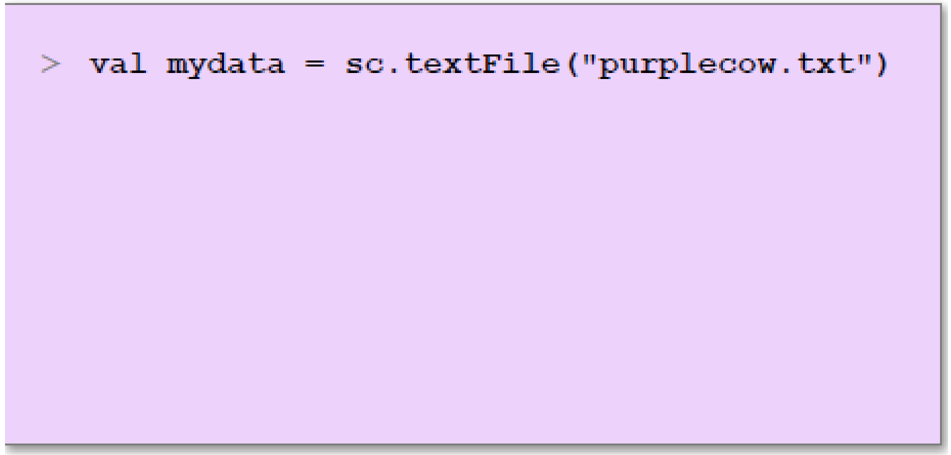
File: purplecow.txt

```
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.
```

```
>
```

Lazy Execution of RDDs (2)

Data in RDDs is not processed until an action is performed



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```
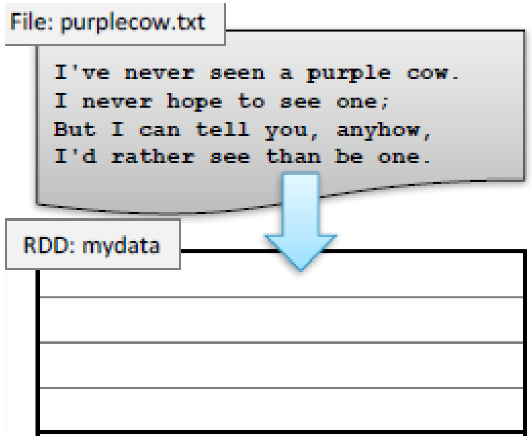
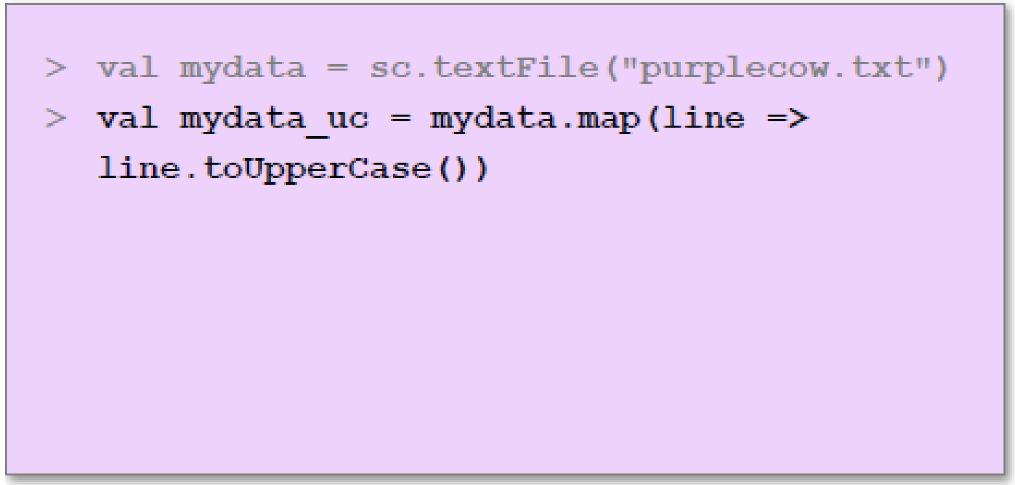



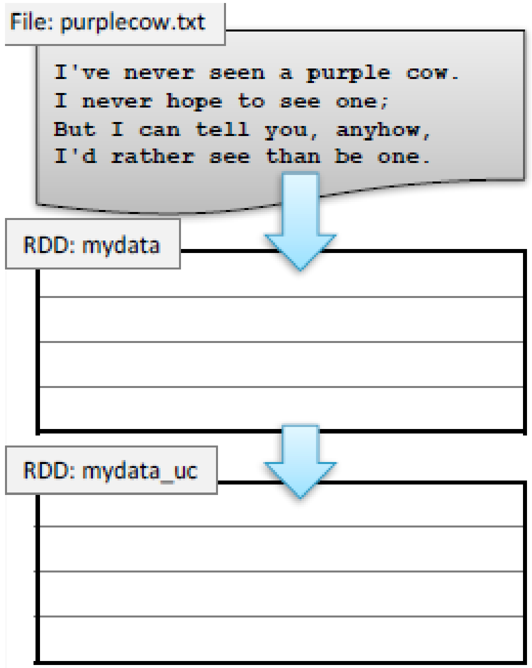
```
I've never seen a purple cow.
I never hope to see one;
But I can tell you, anyhow,
I'd rather see than be one.
```

Lazy Execution of RDDs (3)

Data in RDDs is not processed until an action is performed



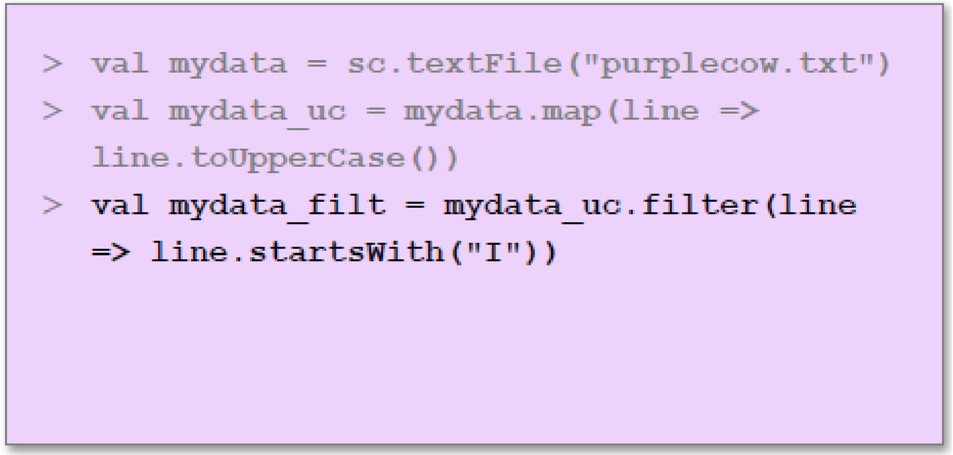
```
> val mydata = sc.textFile("purplecow.txt")
> val mydata_uc = mydata.map(line =>
  line.toUpperCase())
```



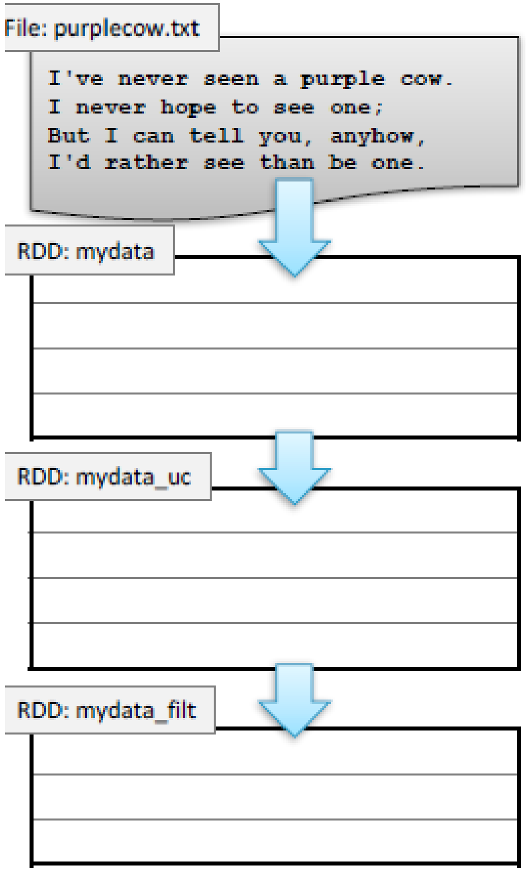
```
I've never seen a purple cow.
I never hope to see one;
But I can tell you, anyhow,
I'd rather see than be one.
```

Lazy Execution of RDDs (4)

Data in RDDs is not processed until an action is performed



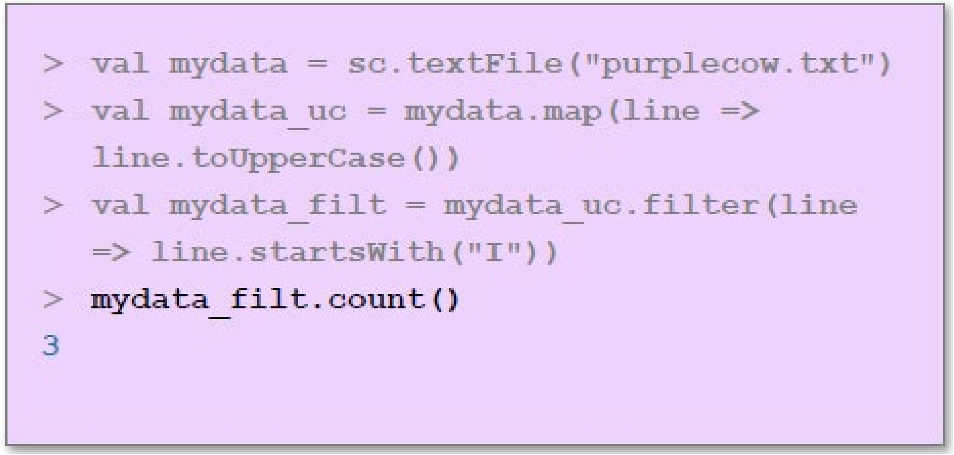
```
> val mydata = sc.textFile("purplecow.txt")
> val mydata_uc = mydata.map(line =>
  line.toUpperCase())
> val mydata_filt = mydata_uc.filter(line
  => line.startsWith("I"))
```



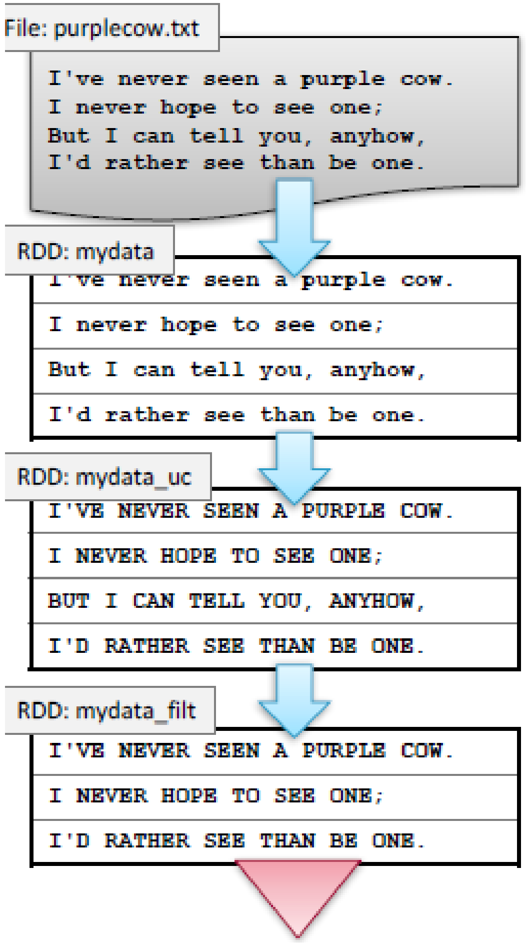
```
I've never seen a purple cow.
I never hope to see one;
But I can tell you, anyhow,
I'd rather see than be one.
```

Lazy Execution of RDDs (5)

Data in RDDs is not processed until an action is performed



```
> val mydata = sc.textFile("purplecow.txt")
> val mydata_uc = mydata.map(line =>
  line.toUpperCase())
> val mydata_filt = mydata_uc.filter(line
  => line.startsWith("I"))
> mydata_filt.count()
3
```



File: purplecow.txt

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.

RDD: mydata

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.

RDD: mydata_uc

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.

RDD: mydata_filt

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

Output Action "triggers" computation, pull model

Opportunities This Enables

- **On-demand optimization**: Spark can behave like a compiler by first building a potentially complex RDD graph, but then trimming away unneeded computations that for today's purpose, won't be used.
- **Caching for later reuse**.
- **Graph transformations**: A significant amount of effort is going into this area. It is a lot like compiler-managed program transformation and aims at simplifying and speeding up the computation that will occur.
- **Dynamic decisions about what to schedule and when**. Concept: *minimum adequate set* of input objects: RDD can run if *all* its inputs are ready

Example: Mine error logs

Load error messages from a log into memory, then interactively search for various patterns:

```
lines = spark.textFile(“hdfs://...”)    HadoopRDD
errors = lines.filter(lambda s: s.startswith(“ERROR”)) FilteredRDD
messages = errors.map(lambda s: s.split(“\t”)[2])
messages.cache()
messages.filter(lambda s: “foo” in s).count()
```

Result: full-text search of Wikipedia in 0.5 sec (vs 20 sec for on-disk data)

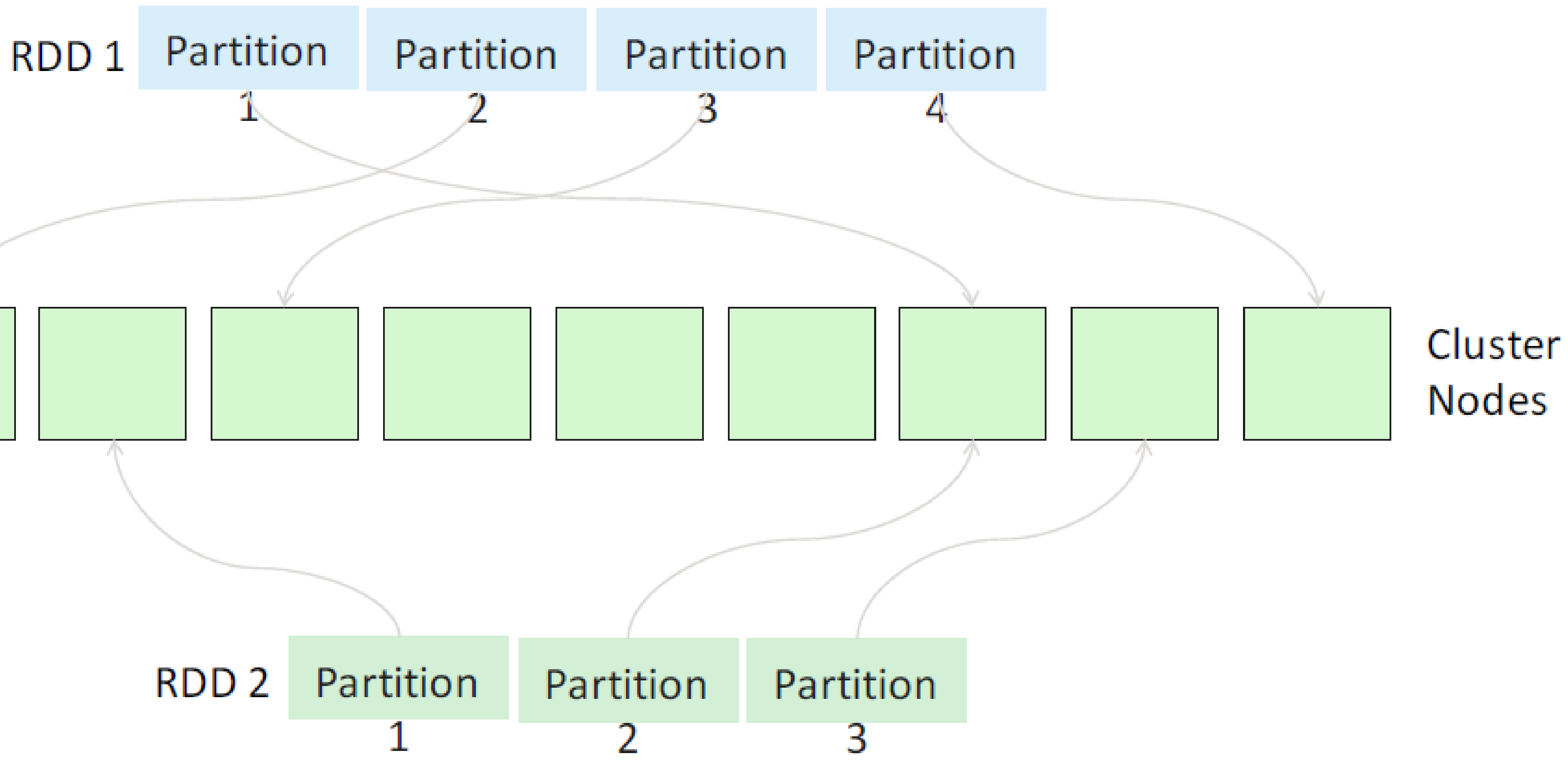
Key Idea: Elastic parallelism

RDDs operations are designed to offer embarrassing parallelism.

Spark will spread the task over the nodes where data resides, offers a highly concurrent execution that minimizes delays. Term: “partitioned computation” .

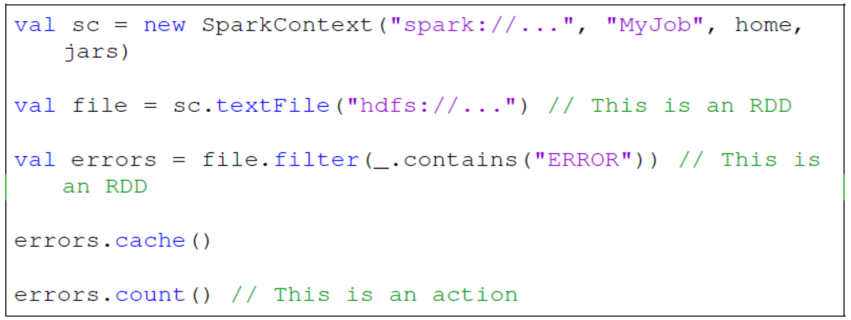
If some component crashes or even is just slow, Spark simply kills that task and launches a substitute.

RDD and Partitions (Parallelism example)

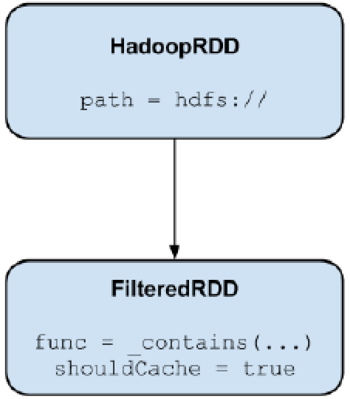


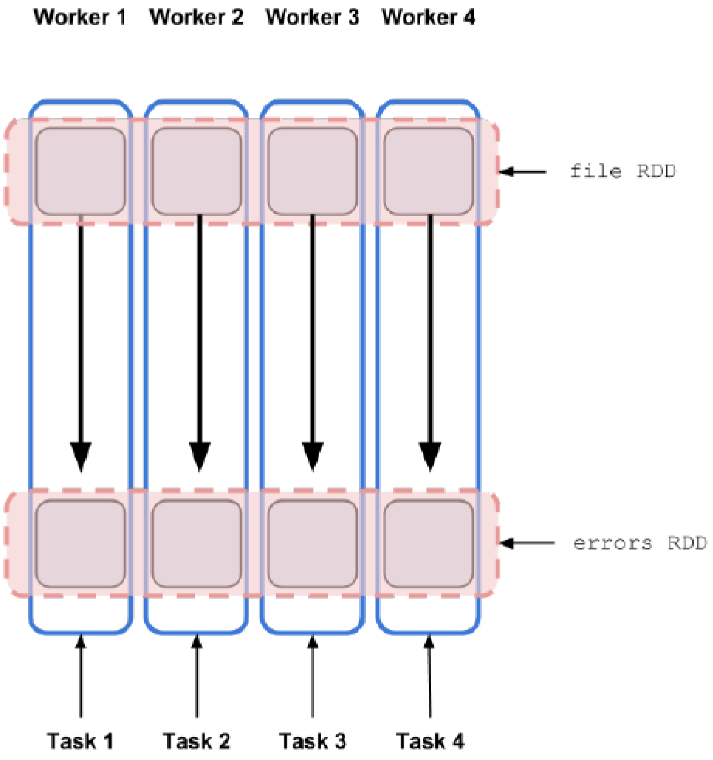
RDD Graph: Data Set vs Partition Views

Much like in Hadoop MapReduce, each RDD is associated to (input) partitions



```
val sc = new SparkContext("spark://...", "MyJob", home,
    jars)

val file = sc.textFile("hdfs://...") // This is an RDD

val errors = file.filter(_.contains("ERROR")) // This is
    an RDD

errors.cache()

errors.count() // This is an action
```





RDDs: Data Locality

- Data Locality Principle
  - Keep high-value RDDs precomputed, in cache or SDD
  - Run tasks that need the specific RDD with those same inputs on the node where the cached copy resides.
  - This can maximize in-memory computational performance.

Requires cooperation between your hints to Spark when you build the RDD, Spark runtime and optimization planner, and the underlying YARN resource manager.

RDDs -- Summary

RDD are partitioned, locality aware, distributed collections

- RDD are immutable

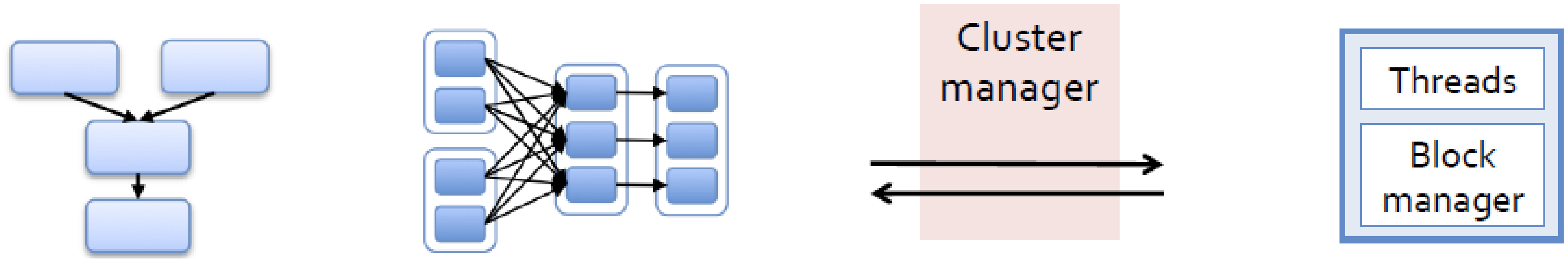
RDD are data structures that:

- Either point to a direct data source (e.g. HDFS)
- Apply some transformations to its parent RDD(s) to generate new data elements

Computations on RDDs

- Represented by lazily evaluated lineage DAGs composed by chained RDDs

Lifetime of a Job in Spark



RDD Objects

```
 rdd1.join(rdd2)
.groupBy(...)
.filter(...)
```

Build the operator DAG

DAG Scheduler

Split the DAG into *stages of tasks*

Submit each stage and its tasks as ready

Task Scheduler

Launch tasks via Master

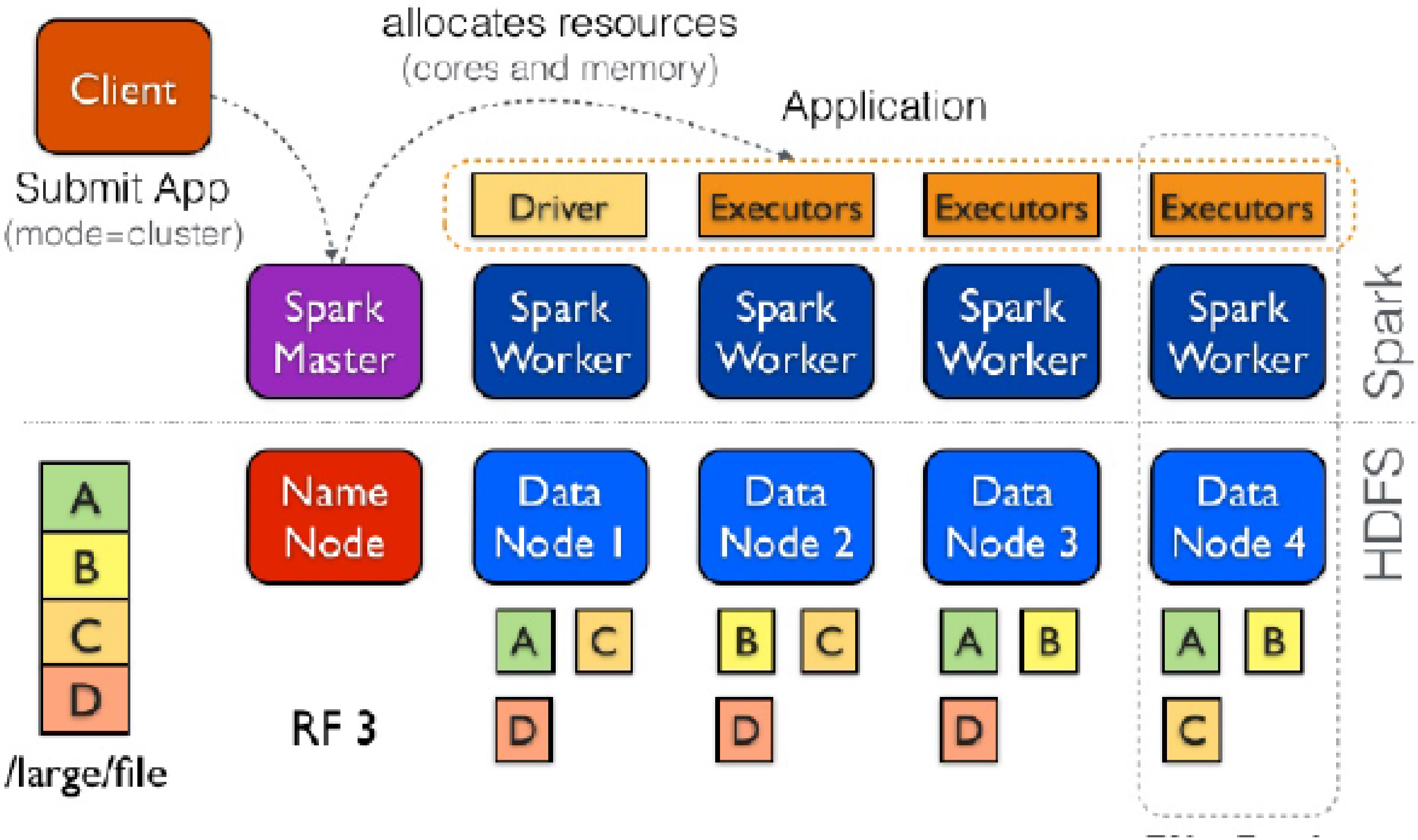
Retry failed and straggler tasks

Worker

Execute tasks

Store and serve blocks

Anatomy of a Spark Application



Cluster Manager
(YARN/Mesos)

Typical RDD pattern of use

Instead of doing a lot of work in each RDD, developers split tasks into lots of small RDDs

These are then organized into a DAG.

Developer anticipates which will be costly to recompute and hints to Spark that it should cache those.

Why is this a good strategy?

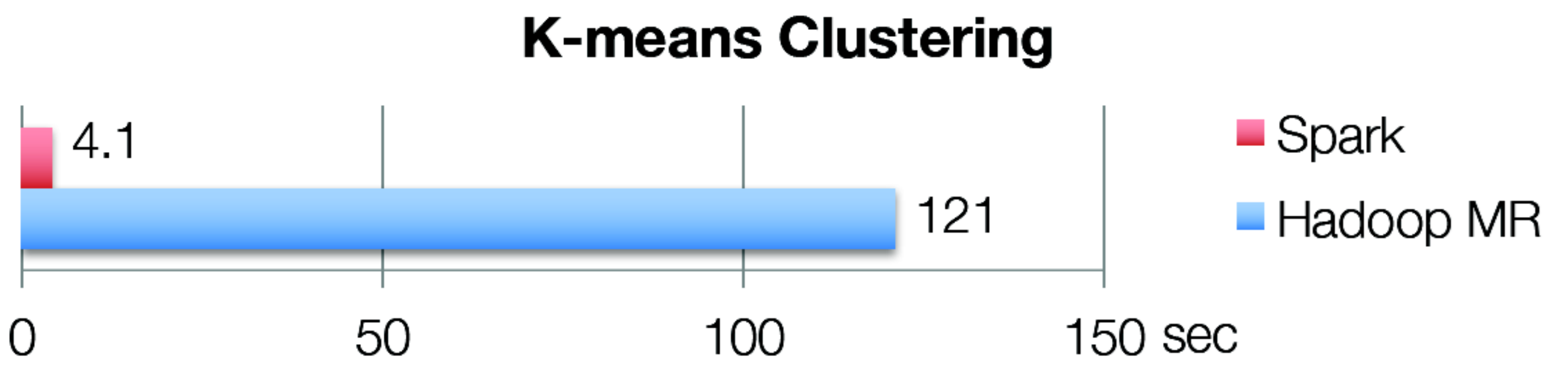
Spark tries to run tasks that will need the same intermediary data on the same nodes.

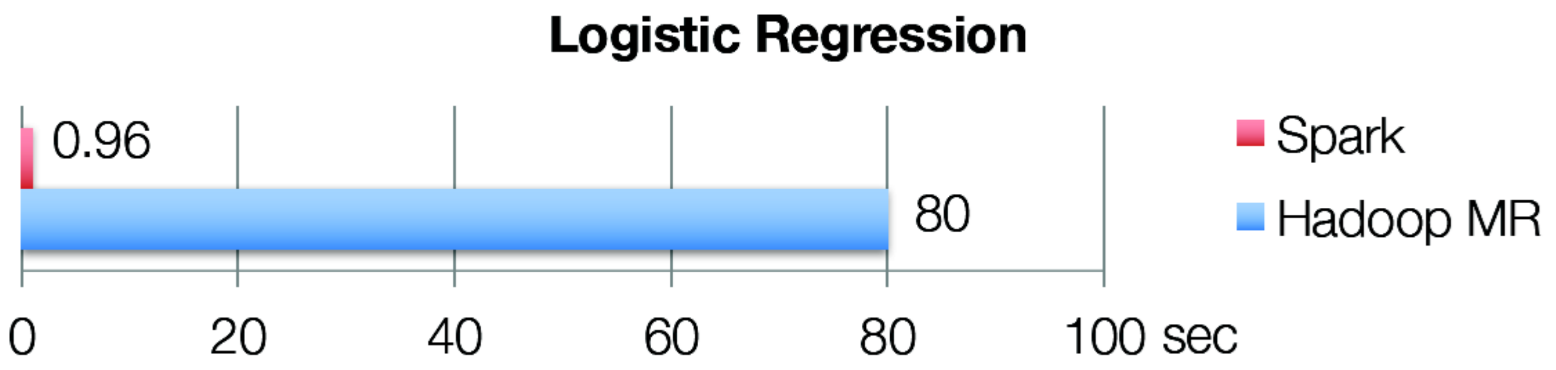
If MapReduce jobs were arbitrary programs, this wouldn't help because reuse would be very rare.

But in fact the MapReduce model is very repetitious and iterative, and often applies the same transformations again and again to the same input files.

- Those particular RDDs become great candidates for caching.
- MapReduce programmer may not know how many iterations will occur, but Spark itself is smart enough to evict RDDs if they don't actually get reused.

Iterative Algorithms: Spark vs MapReduce


K-means Clustering


Logistic Regression

Today’s Topics

Motivation

Spark Basics

Spark Programming

Spark Programming (1)

Creating RDDs

```
# Turn a Python collection into an RDD
sc.parallelize([1, 2, 3])

# Load text file from local FS, HDFS, or S3
sc.textFile(“file.txt”)
sc.textFile(“directory/*.txt”)
sc.textFile(“hdfs://namenode:9000/path/file”)

# Use existing Hadoop InputFormat (Java/Scala only)
sc.hadoopFile(keyClass, valClass, inputFmt, conf)
```

Spark Programming (2)

Basic Transformations

```
nums = sc.parallelize([1, 2, 3])

# Pass each element through a function
squares = nums.map(lambda x: x*x) // {1, 4, 9}

# Keep elements passing a predicate
even = squares.filter(lambda x: x % 2 == 0) // {4}
```

Spark Programming (3)

Basic Actions

```
nums = sc.parallelize([1, 2, 3])

# Retrieve RDD contents as a local collection
nums.collect() # => [1, 2, 3]

# Return first K elements
nums.take(2) # => [1, 2]

# Count number of elements
nums.count() # => 3

# Merge elements with an associative function
nums.reduce(lambda x, y: x + y) # => 6
```

Spark Programming (4)

Working with Key-Value Pairs

Spark’s “distributed reduce” transformations operate on RDDs of key-value pairs

```
Python:  pair = (a, b)
           pair[0] # => a
           pair[1] # => b

Scala:   val pair = (a, b)
           pair._1 // => a
           pair._2 // => b

Java: Tuple2 pair = new Tuple2(a, b);
           pair._1 // => a
           pair._2 // => b
```

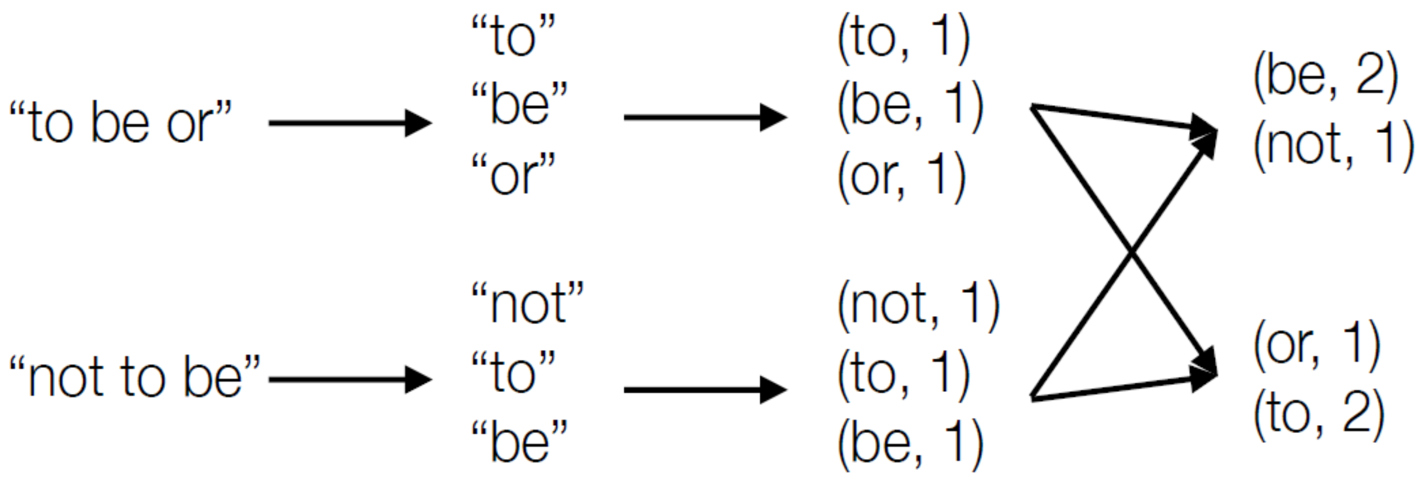
Spark Programming (5)

Some Key-Value Operations

```
pets = sc.parallelize([(“cat”, 1), (“dog”, 1), (“cat”, 2)])

pets.reduceByKey(lambda x, y: x + y)    # => {(cat, 3), (dog, 1)}

pets.groupByKey()     # => {(cat, [1, 2]), (dog, [1])}

pets.sortByKey()      # => {(cat, 1), (cat, 2), (dog, 1)}
```

Example: Word Count

```
lines = sc.textFile(“hamlet.txt”)
counts = lines.flatMap(lambda line: line.split(“ ”))
              .map(lambda word: (word, 1))
              .reduceByKey(lambda x, y: x + y)
```



“to be or”

“to”
“be”
“or”

(to, 1)
(be, 1)
(or, 1)

“not to be”

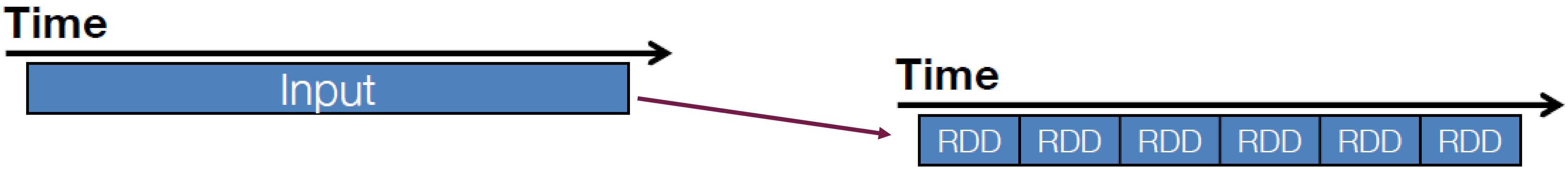
“not”
“to”
“be”

(not, 1)
(to, 1)
(be, 1)

(be, 2)
(not, 1)

(or, 1)
(to, 2)

Example: Spark Streaming



Represents streams as a series of RDDs over time (typically sub second intervals, but it is configurable)

```
val spammers = sc.sequenceFile(“hdfs://spammers.seq”)
sc.twitterStream(...)
   .filter(t => t.text.contains(“Santa Clara University”))
   .transform(tweets => tweets.map(t => (t.user, t)).join(spammers))
   .print()
```

Spark: Combining Libraries (Unified Pipeline)

```
# Load data using Spark SQL
points = spark.sql(“select latitude, longitude from tweets”)

# Train a machine learning model
model = KMeans.train(points, 10)

# Apply it to a stream
sc.twitterStream(...)
   .map(lambda t: (model.predict(t.location), 1))
   .reduceByWindow(“5s”, lambda a, b: a + b)
```

Spark: Setting the Level of Parallelism

All the pair RDD operations take an optional second parameter for number of tasks

```
words.reduceByKey(lambda x, y: x + y, 5)
words.groupByKey(5)
visits.join(pageViews, 5)
```

Summary

Spark is a powerful “manager” for big data computing.

It centers on a job scheduler for Hadoop (MapReduce) that is smart about where to run each task: co-locate task with data.

The data objects are “RDDs”: a kind of recipe for generating a file from an underlying data collection. RDD caching allows Spark to run mostly from memory-mapped data, for speed.

- Online tutorials: spark.apache.org/docs/latest