# Data-Intensive Distributed Computing

CS 431/461 451/651 (Winter 2019)

## Part 2: From MapReduce to Spark (2/2)

January 24, 2019

Adam Roegiest
Kira Systems

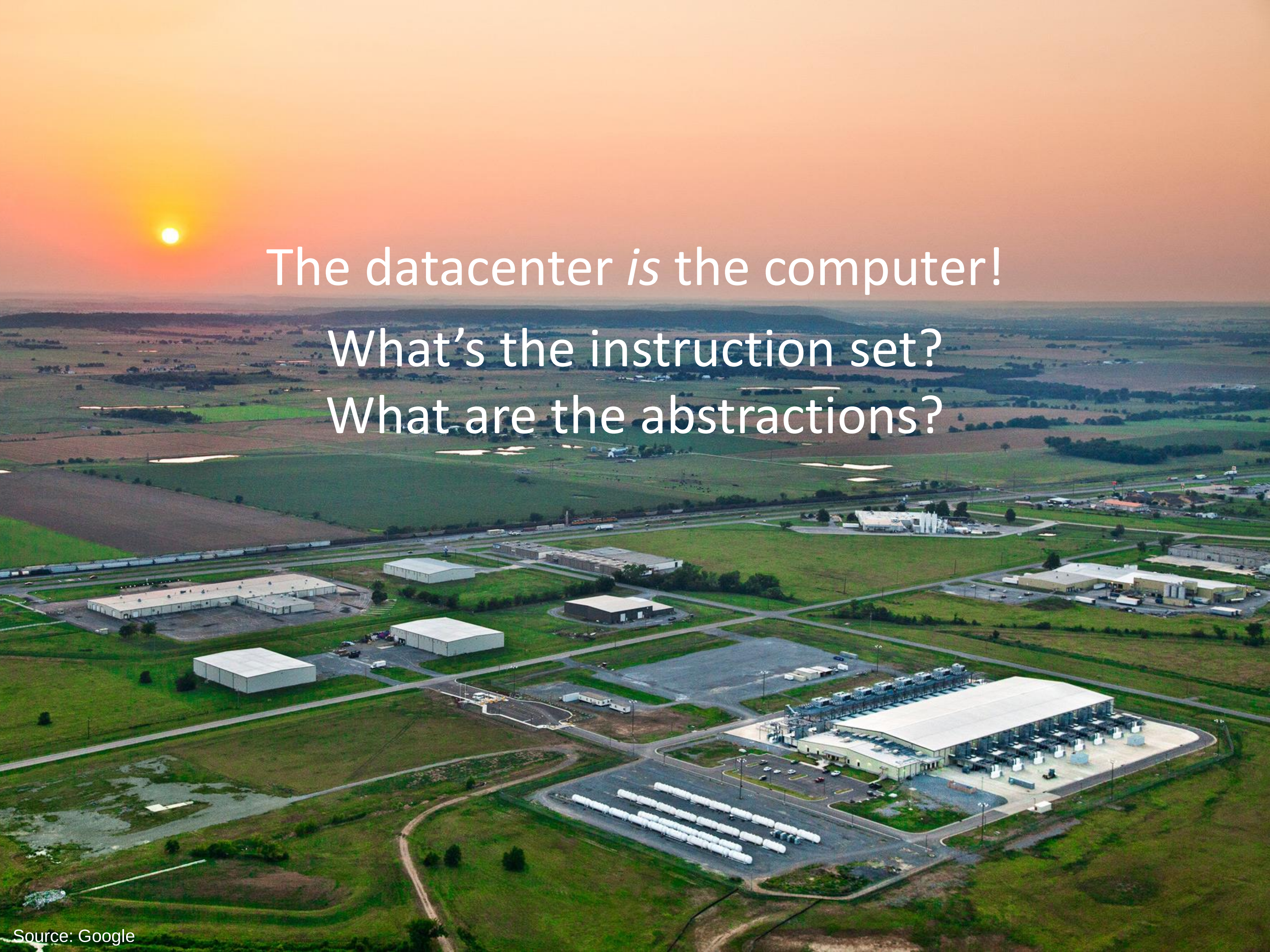
These slides are available at http://roegiest.com/bigdata-2019w/


Source: Wikipedia (The Scream)

# An Apt Quote

All problems in computer science can be solved by another level of indirection... Except for the problem of too many layers of indirection.

- David Wheeler




Source: Google

# MapReduce

List[(K1,V1)]

↓

**map**

f: (K1, V1)

⇒ List[(K2, V2)]

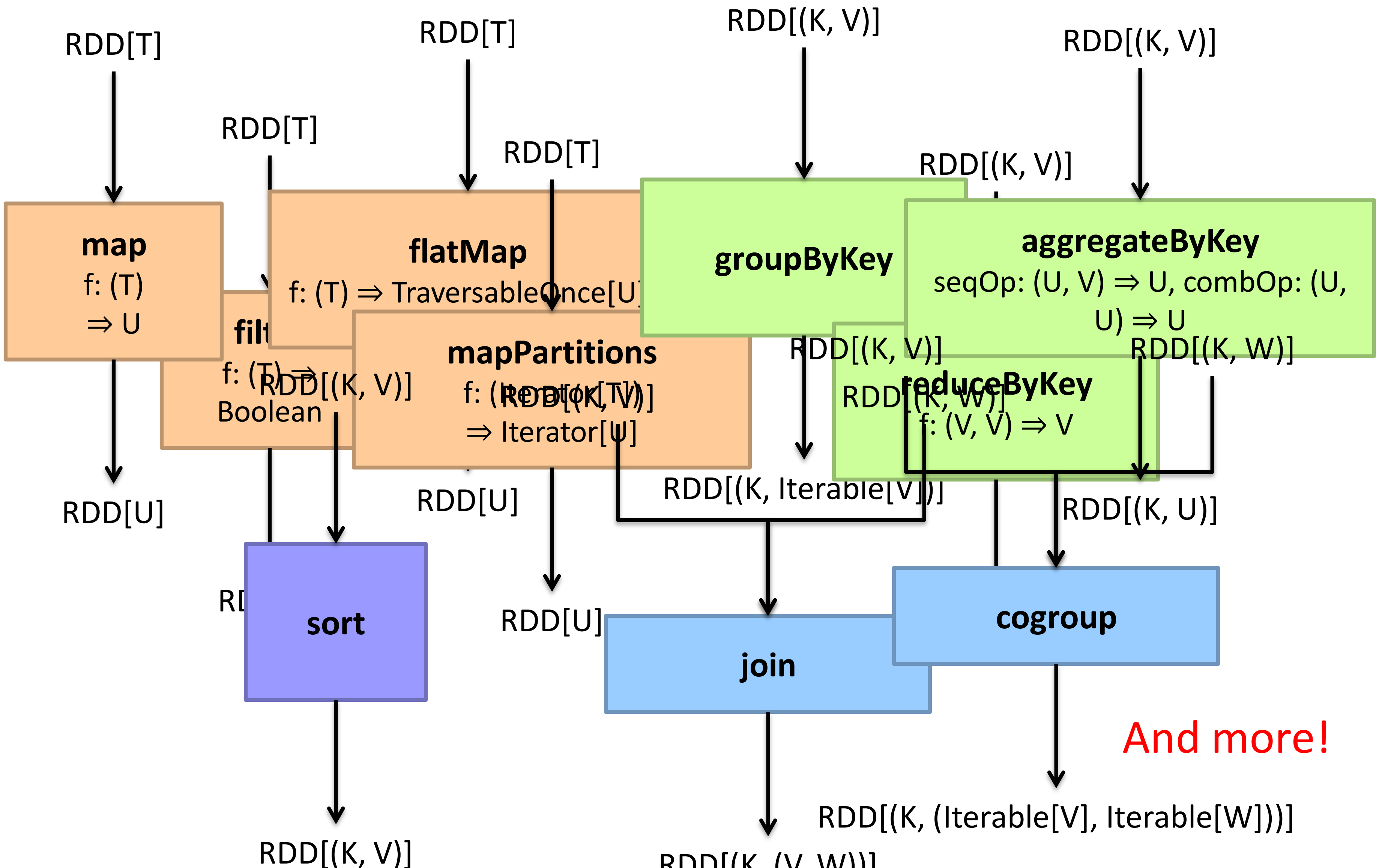
**reduce**

g: (K2, Iterable[V2]) ⇒ List[(K3, V3)]

↓

List[K3,V3])

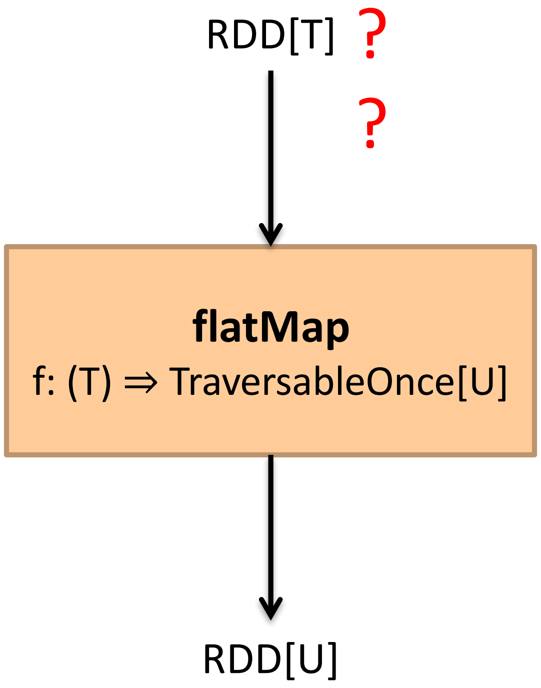
# Spark



RDD[T]
map
f: (T)
⇒ U
RDD[U]
RDD[T]
filter
f: (T) ⇒
Boolean
RDD[T]
flatMap
f: (T) ⇒ TraversableOnce[U]
RDD[U]
RDD[T]
mapPartitions
f: (Iterator[T])
⇒ Iterator[U]
RDD[U]
RDD[(K, V)]
groupByKey
RDD[(K, Iterable[V])]
RDD[(K, V)]
reduceByKey
f: (V, V) ⇒ V
RDD[(K, V)]
aggregateByKey
seqOp: (U, V) ⇒ U, combOp: (U,
U) ⇒ U
RDD[(K, U)]
RDD[(K, V)]
sort
RDD[(K, V)]
RDD[(K, V)]
RDD[(K, W)]
join
RDD[(K, (V, W))]
RDD[(K, V)]
RDD[(K, W)]
cogroup
RDD[(K, (Iterable[V], Iterable[W]))]
And more!

# Spark Word Count

```
val textFile = sc.textFile(args.input())

textFile
  .flatMap(line => tokenize(line))
  .map(word => (word, 1))
  .reduceByKey((x, y) => x + y)
  .saveAsTextFile(args.output())
```



# What’s an RDD?

## Resilient Distributed Dataset (RDD)

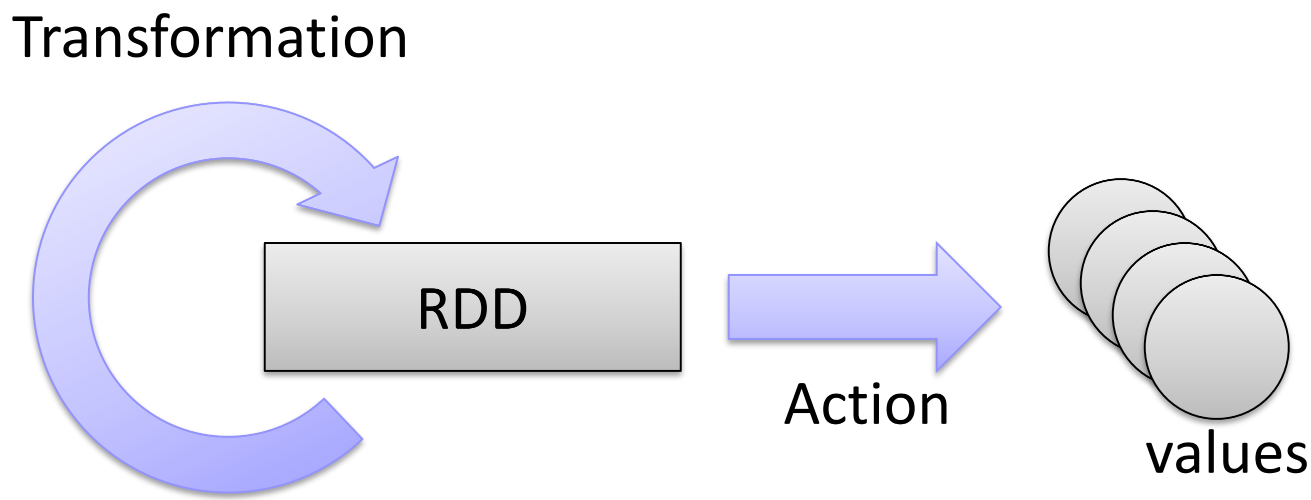
= immutable = partitioned

Wait, so how do you actually do anything?

Developers define *transformations* on RDDs

Framework keeps track of lineage

# RDD Lifecycle




Transformations are lazy:
Framework keeps track of lineage

Actions trigger actual execution

# Spark Word Count

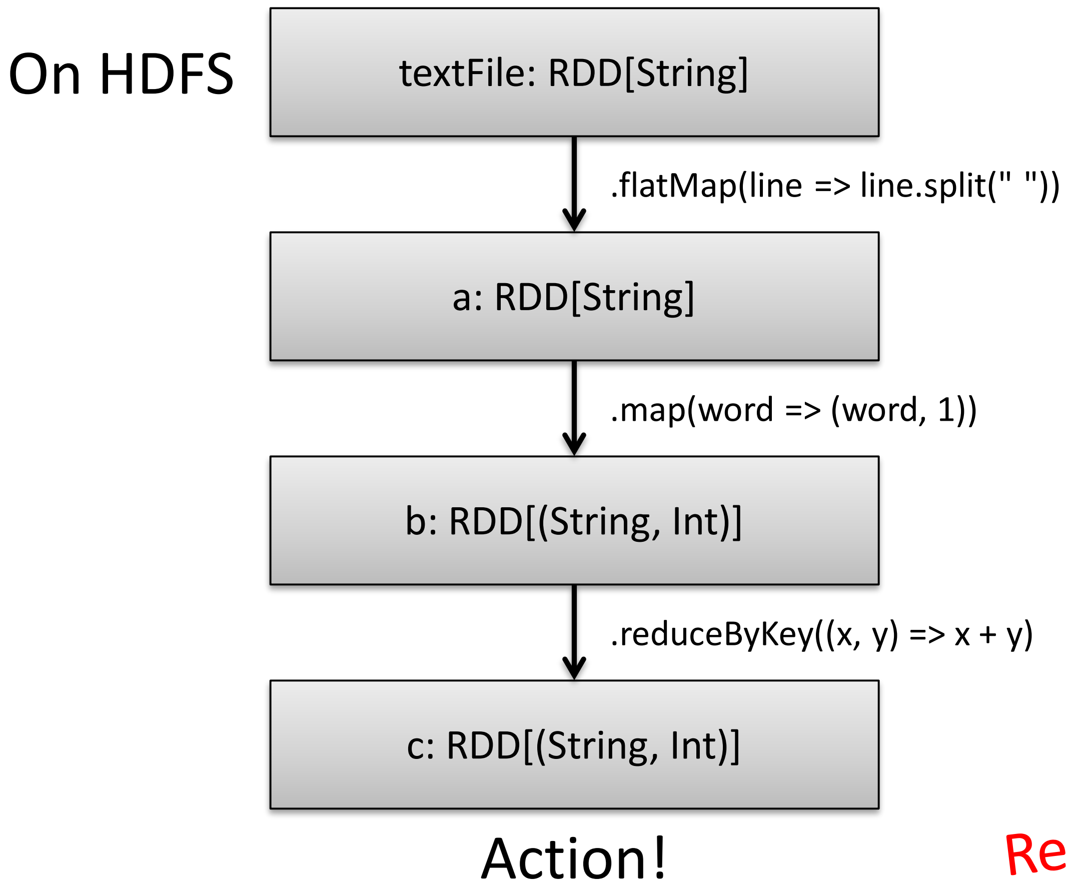
RDDs

```
val textFile = sc.textFile(args.input())

val a = textFile.flatMap(line => line.split(" "))
val b = a.map(word => (word, 1))
val c = b.reduceByKey((x, y) => x + y)

c.saveAsTextFile(args.output())
```

Action

Transformations

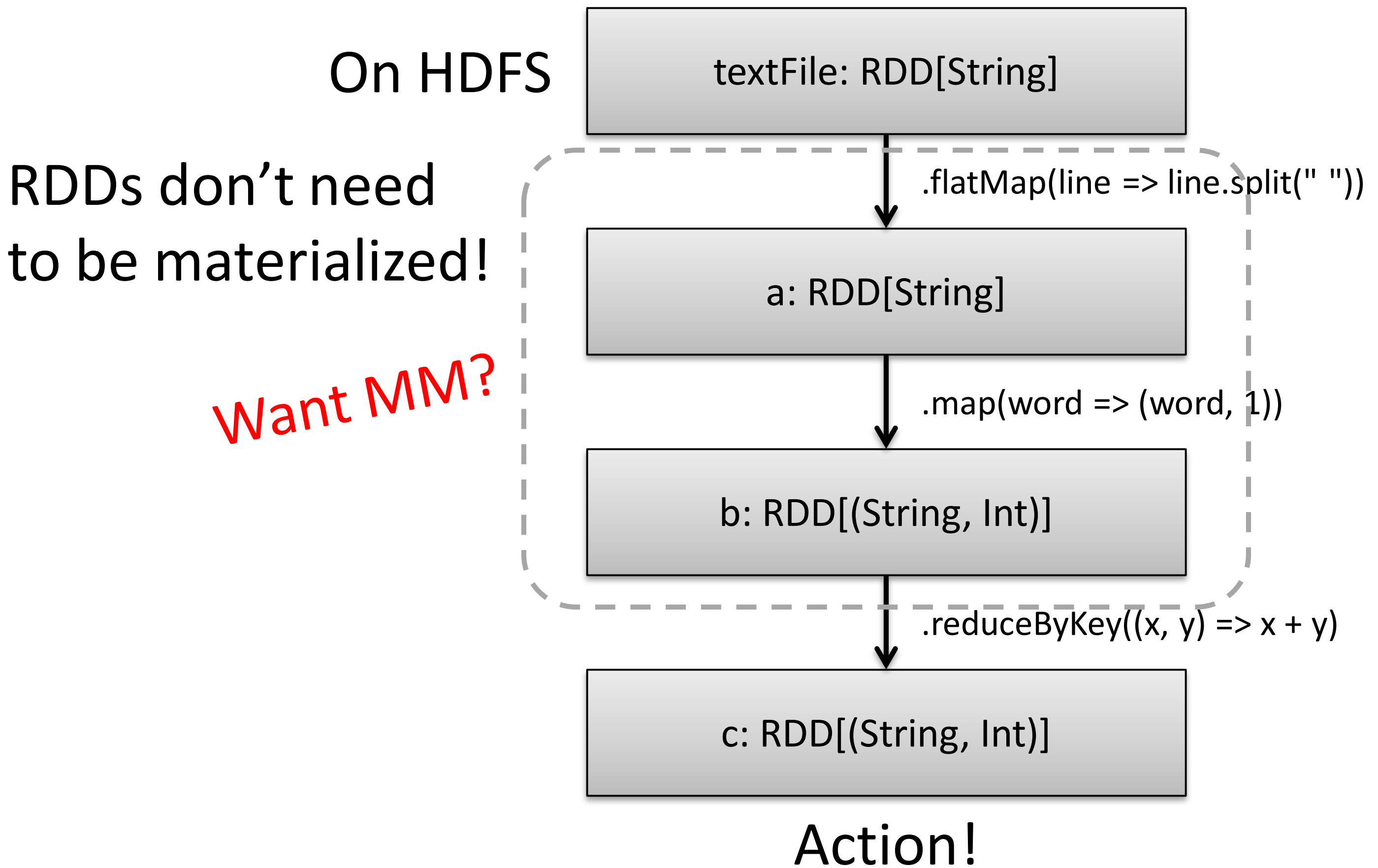
# RDDs and Lineage




Remember, transformations are lazy!

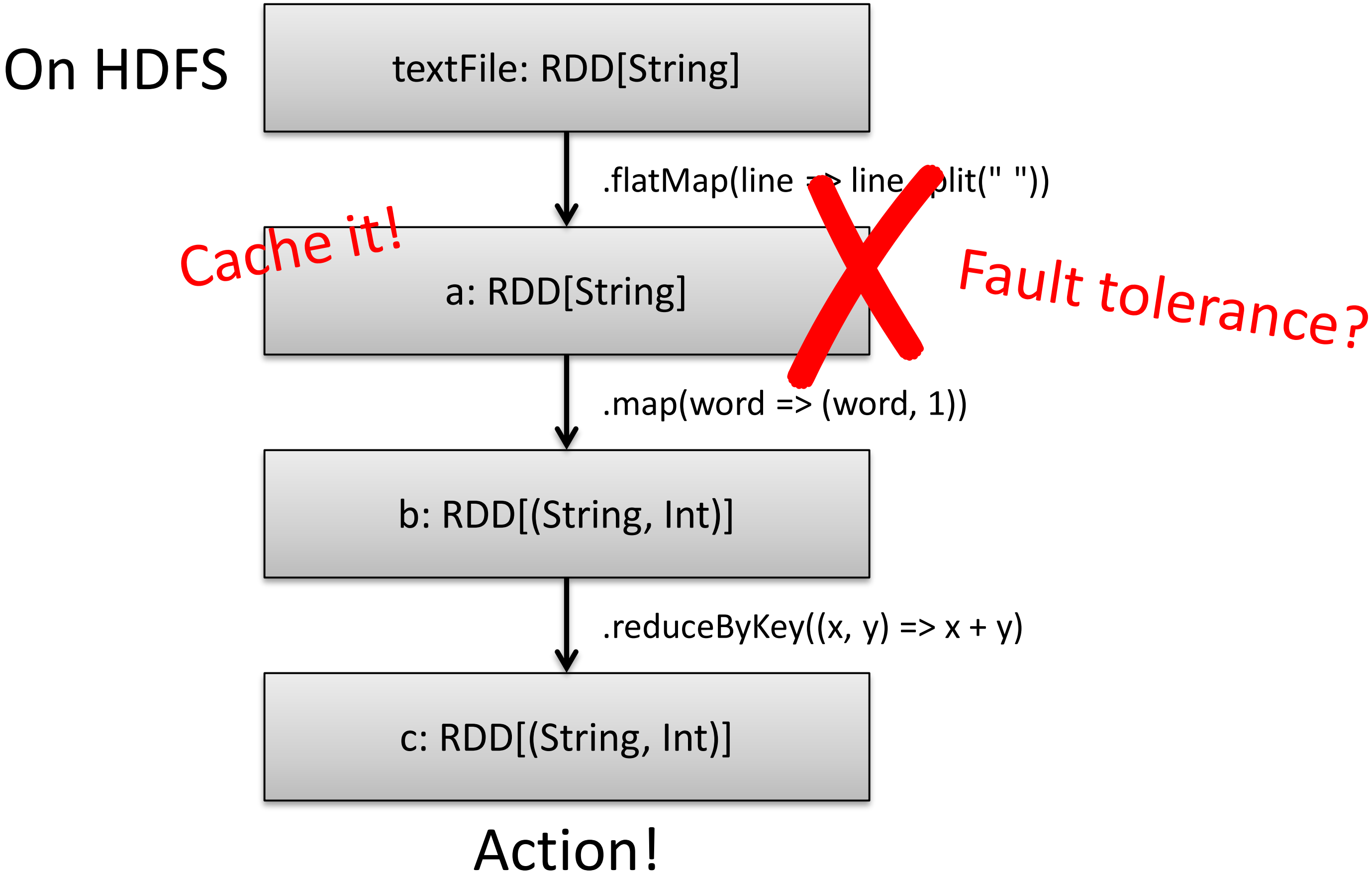
# RDDs and Optimizations

Lazy evaluation creates optimization opportunities



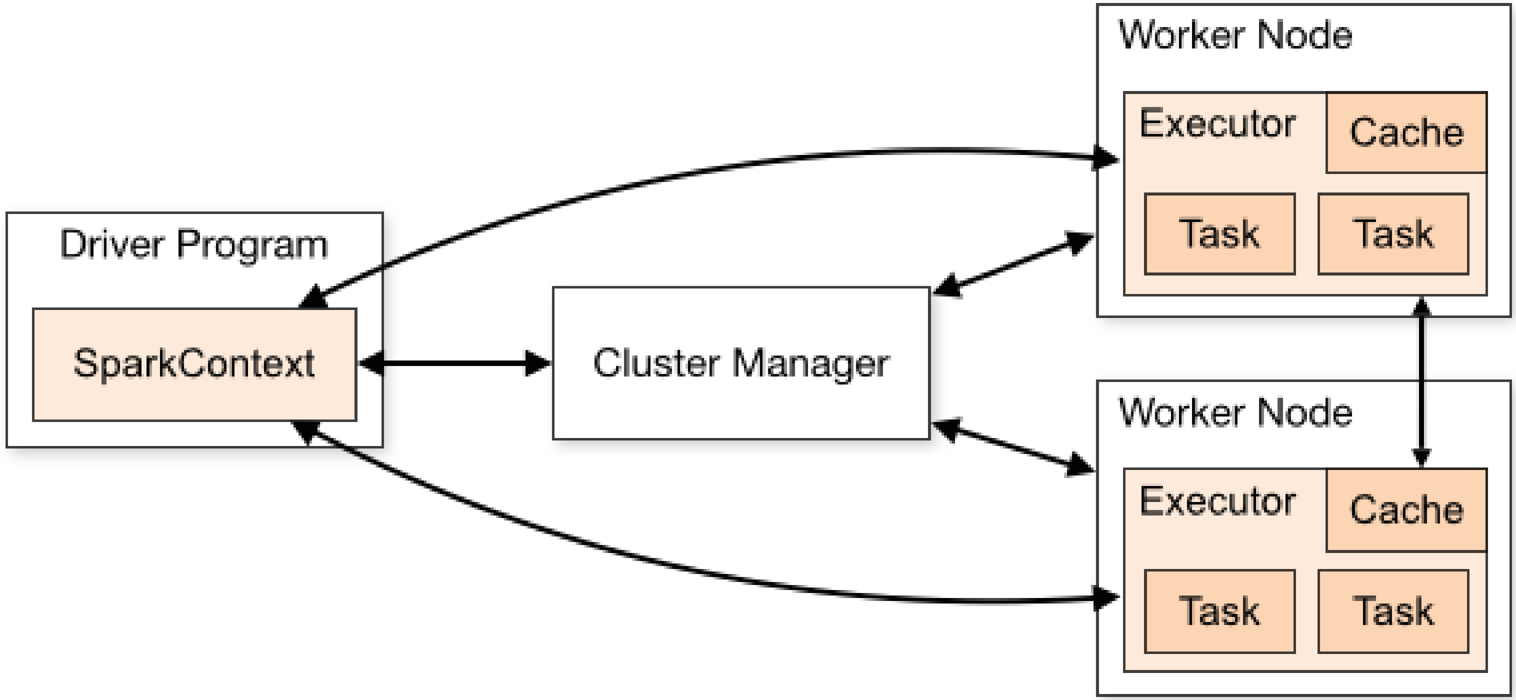
# RDDs and Caching

RDDs can be materialized in memory (and on disk)!

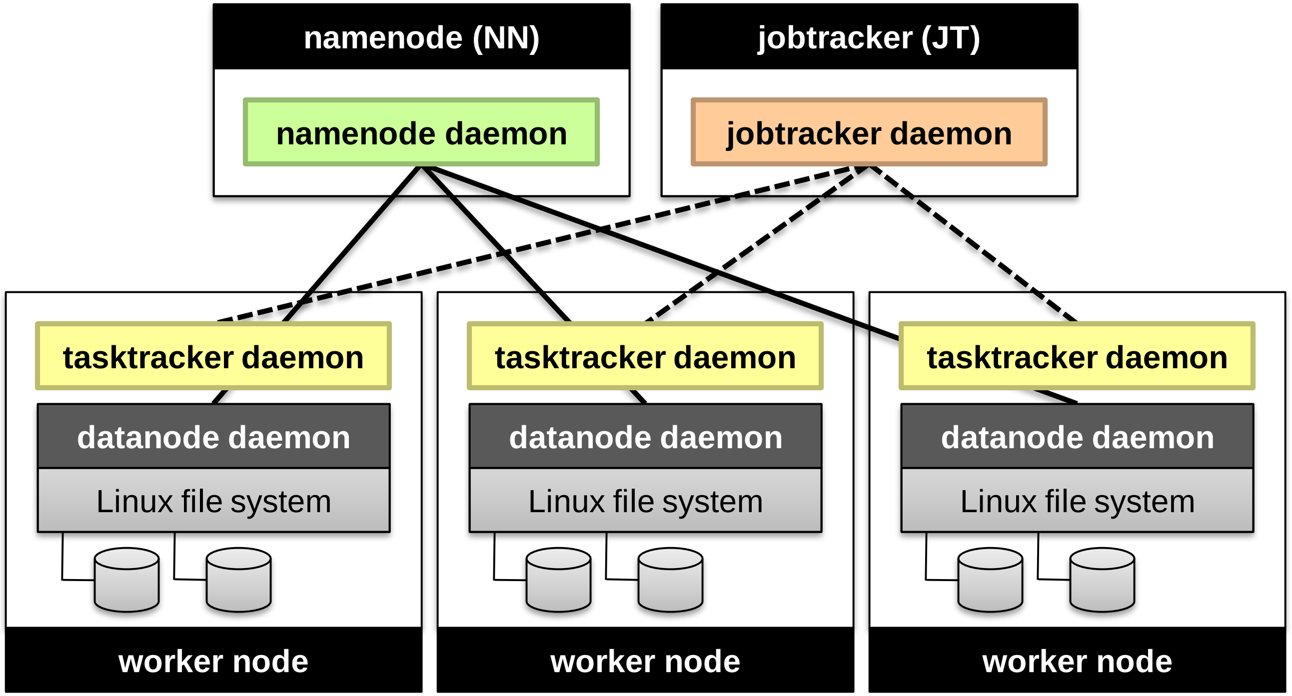



Spark works even if the RDDs are *partially* cached!

# Spark Architecture



# Hadoop MapReduce Architecture



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- David Wheeler

# YARN

Hadoop's (original) limitations:

Can only run MapReduce

What if we want to run other distributed frameworks?

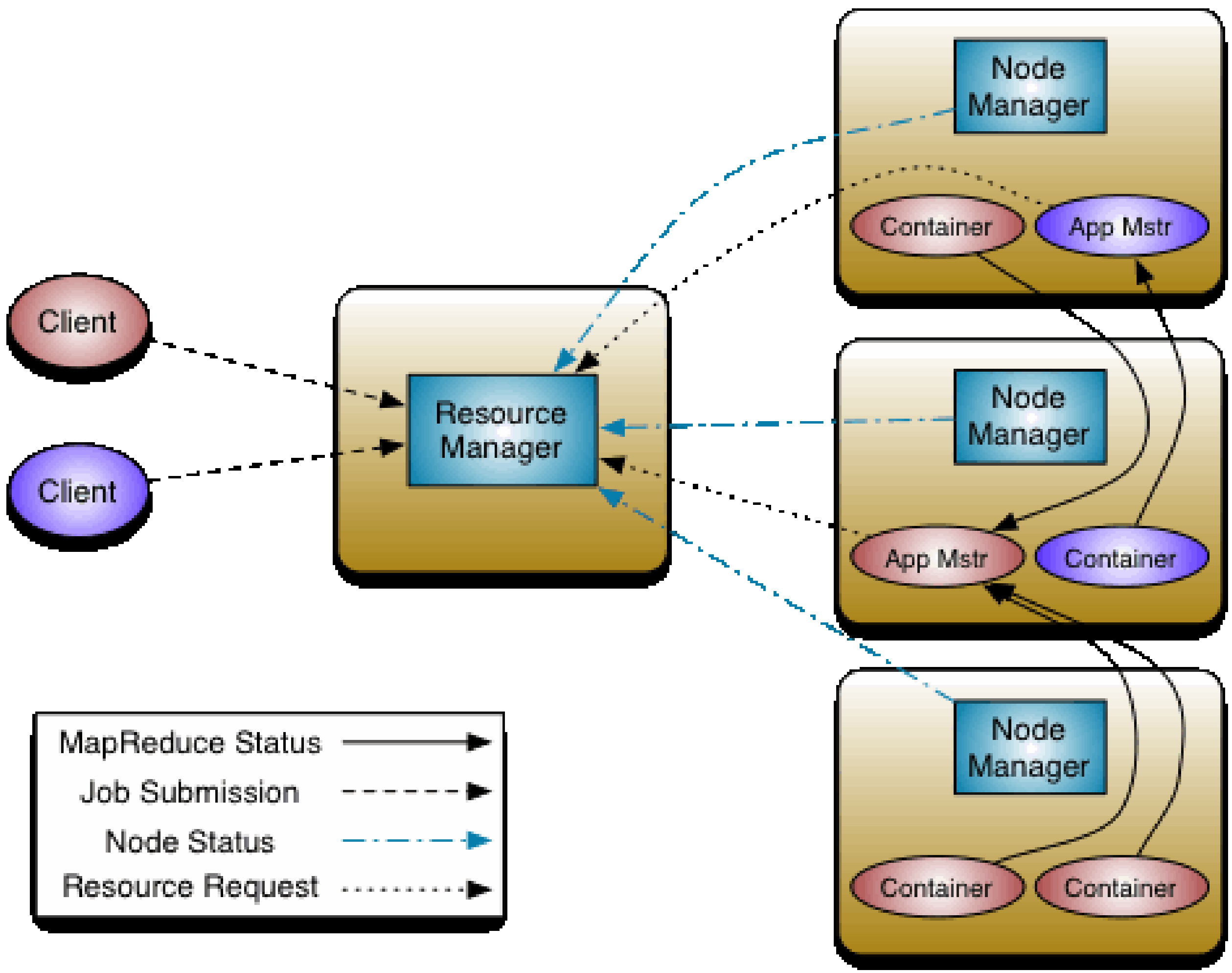
YARN = Yet-Another-Resource-Negotiator

Provides API to develop any generic distributed application

Handles scheduling and resource request

MapReduce (MR2) is one such application in YARN

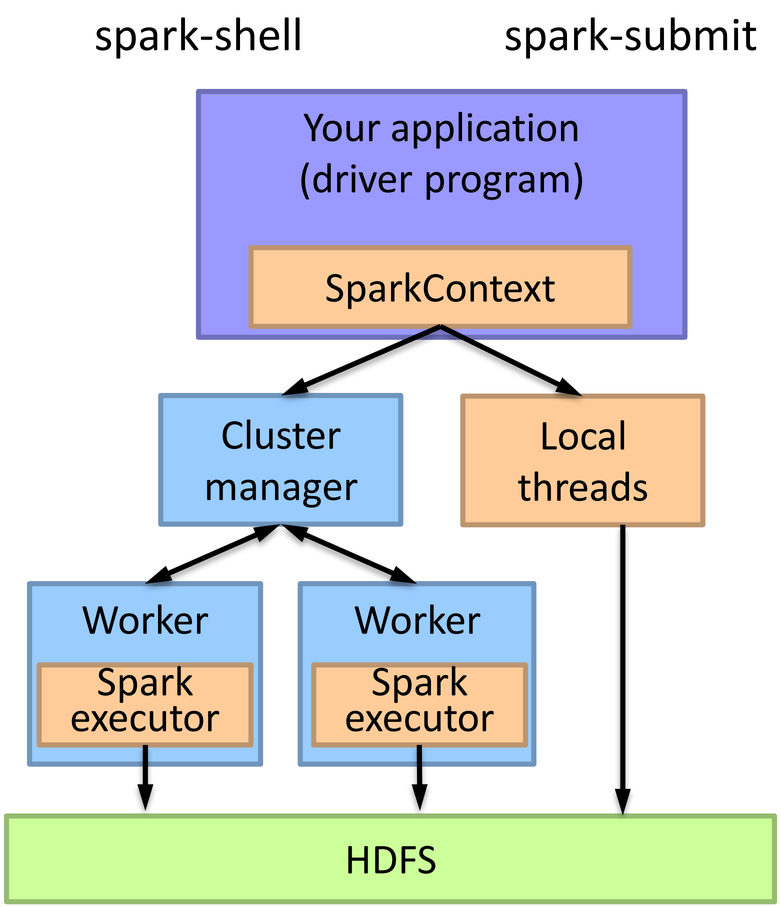
# YARN



Client
Client
Resource Manager
Node Manager
Container
App Mstr
Node Manager
App Mstr
Container
Node Manager
Container
Container
MapReduce Status
Job Submission
Node Status
Resource Request

# Spark Programs

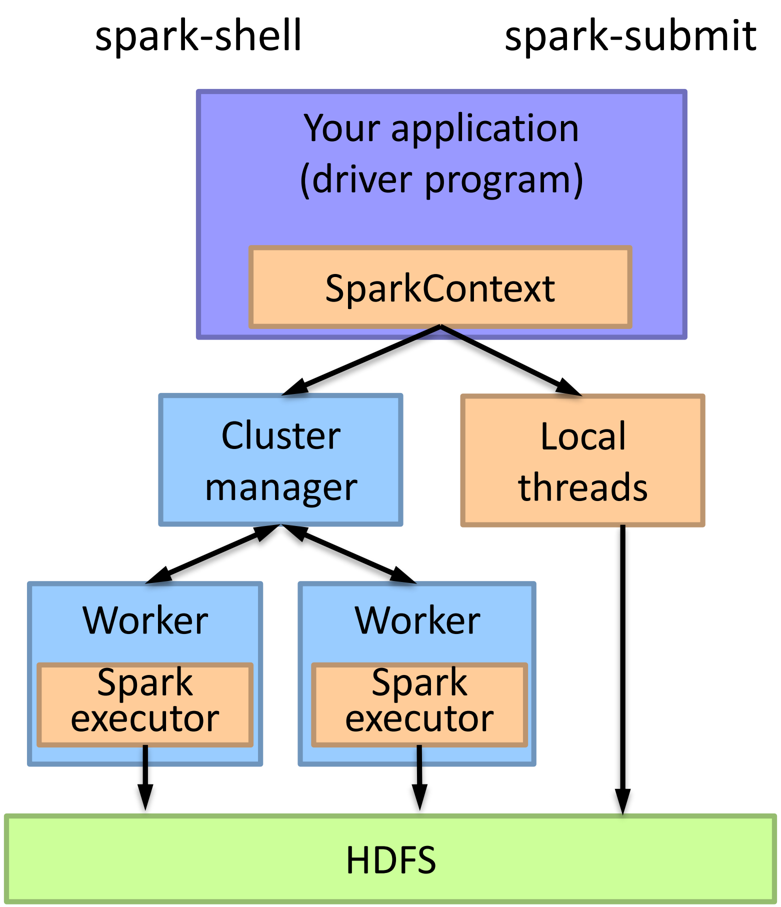
Scala, Java, Python, R




Spark context: tells the framework where to find the cluster

Use the Spark context to create RDDs

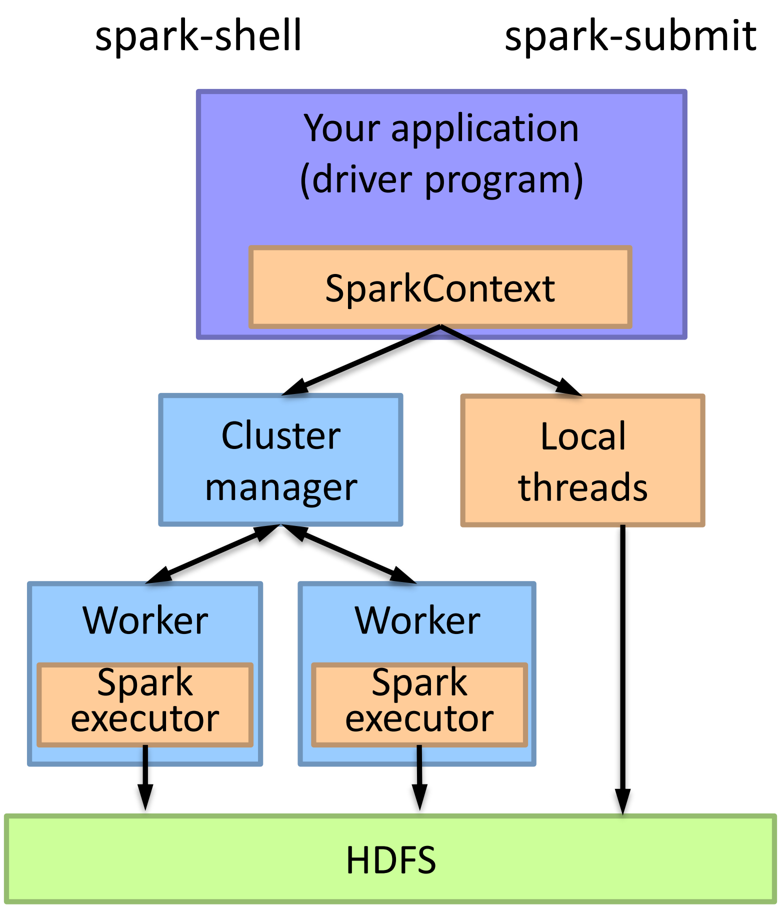
# Spark Driver




```
val textFile =
  sc.textFile(args.input())

textFile
  .flatMap(line => tokenize(line))
  .map(word => (word, 1))
  .reduceByKey((x, y) => x + y)
  .saveAsTextFile(args.output())
```

What's happening
to the functions?

# Spark Driver

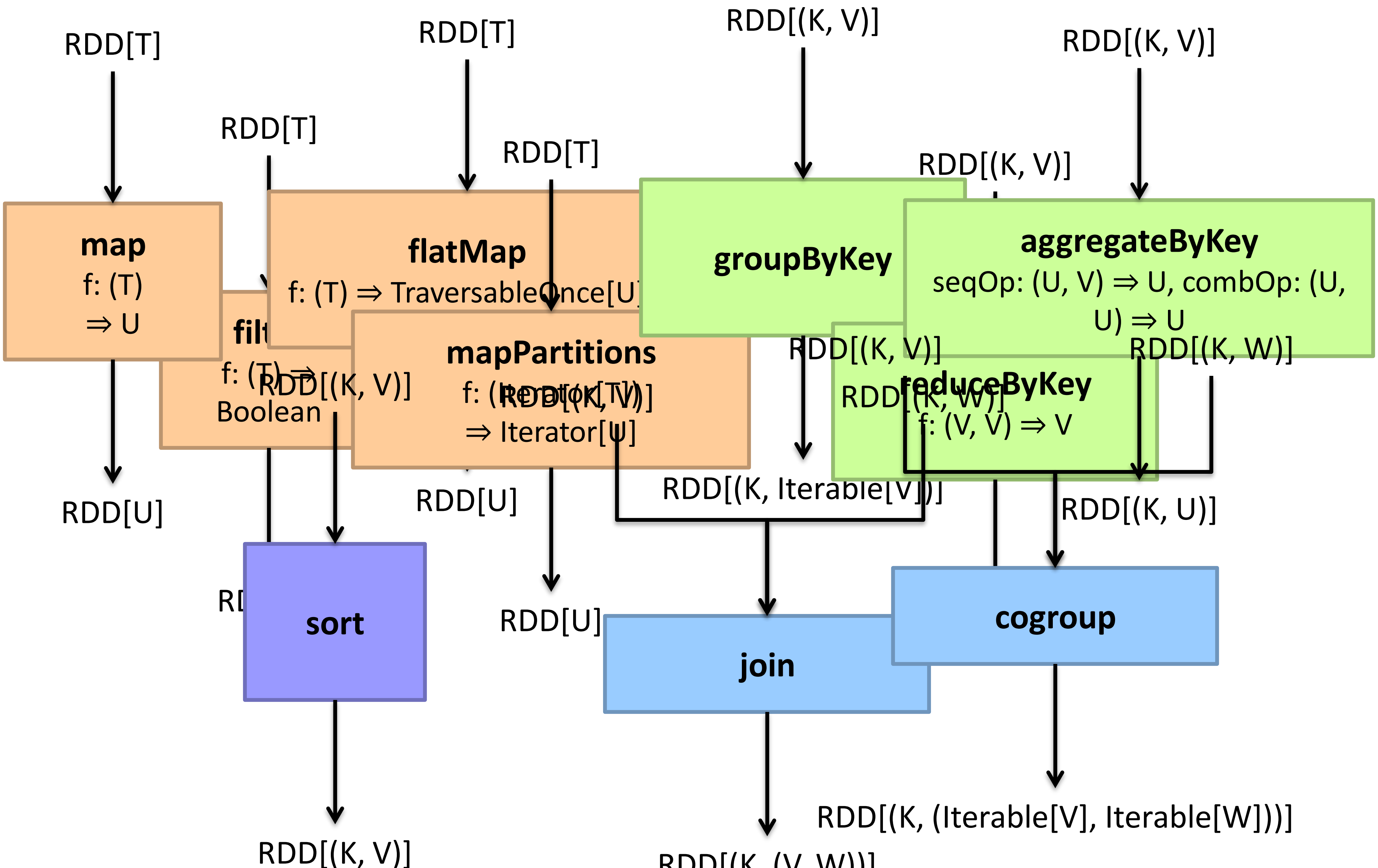



```
val textFile =
  sc.textFile(args.input())

textFile
  .flatMap(line => tokenize(line))
  .map(word => (word, 1))
  .reduceByKey((x, y) => x + y)
  .saveAsTextFile(args.output())
```

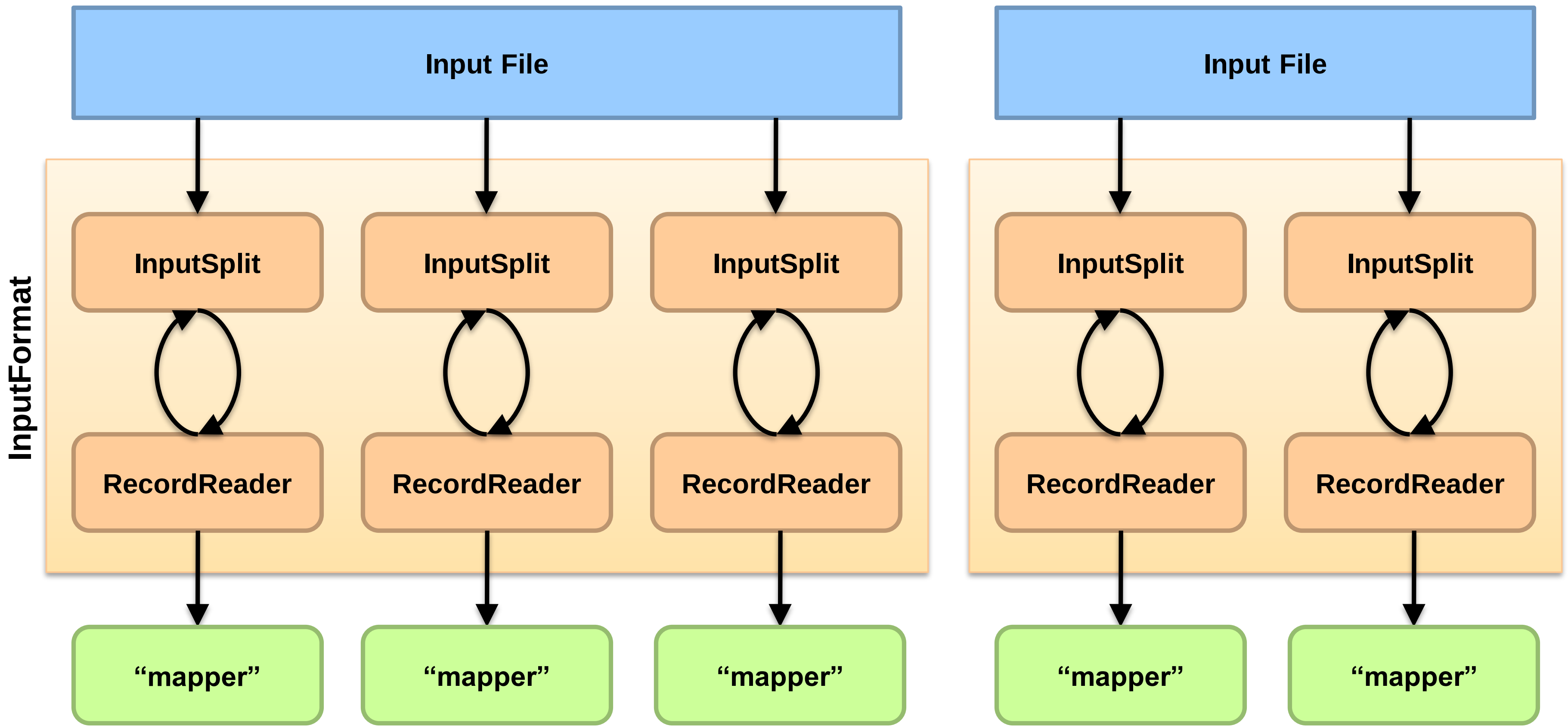
Note: you can run code “locally”, integrate cluster-computed values!

Beware of the collect action!

# Spark Transformations

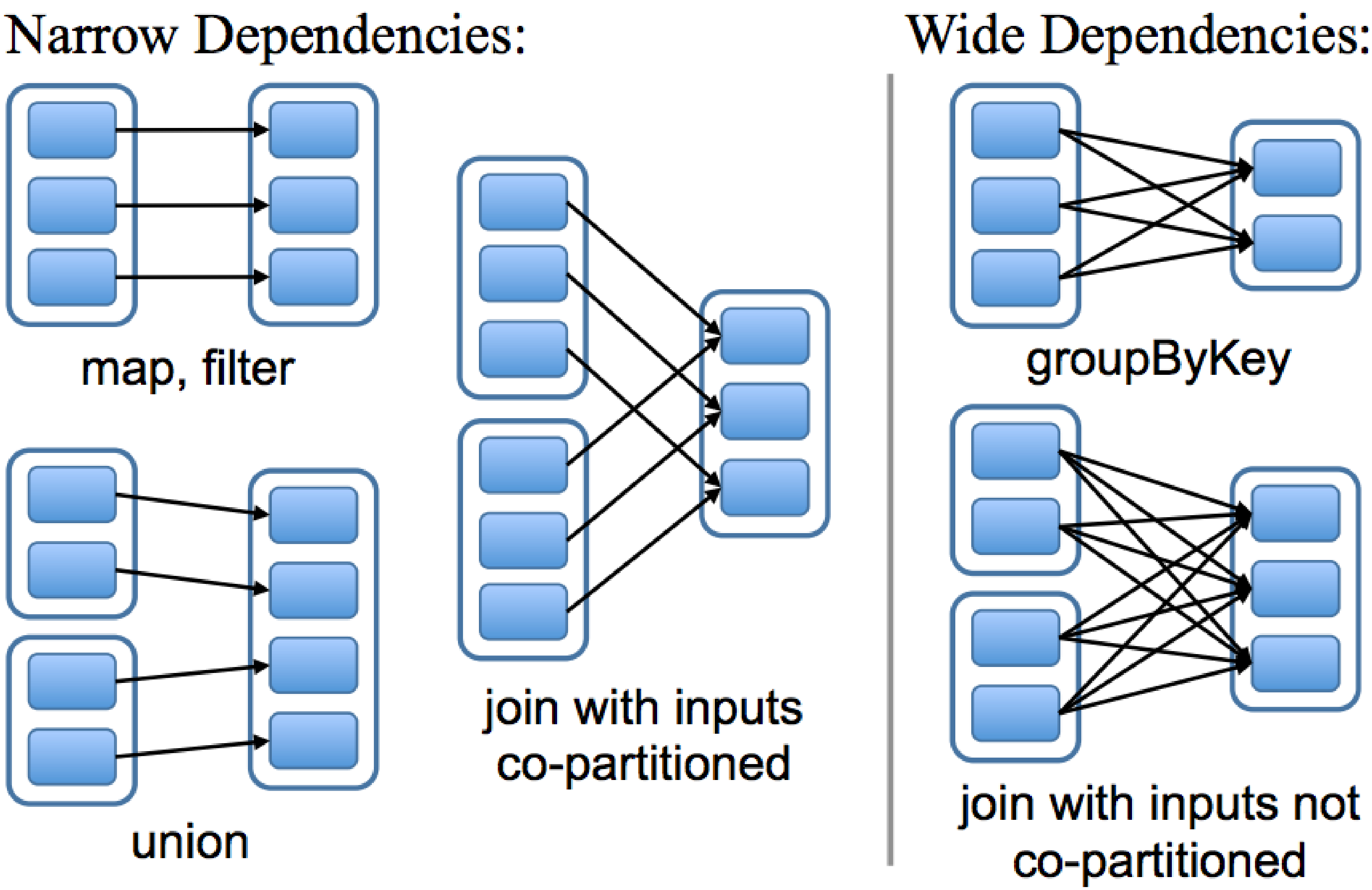


# Starting Points

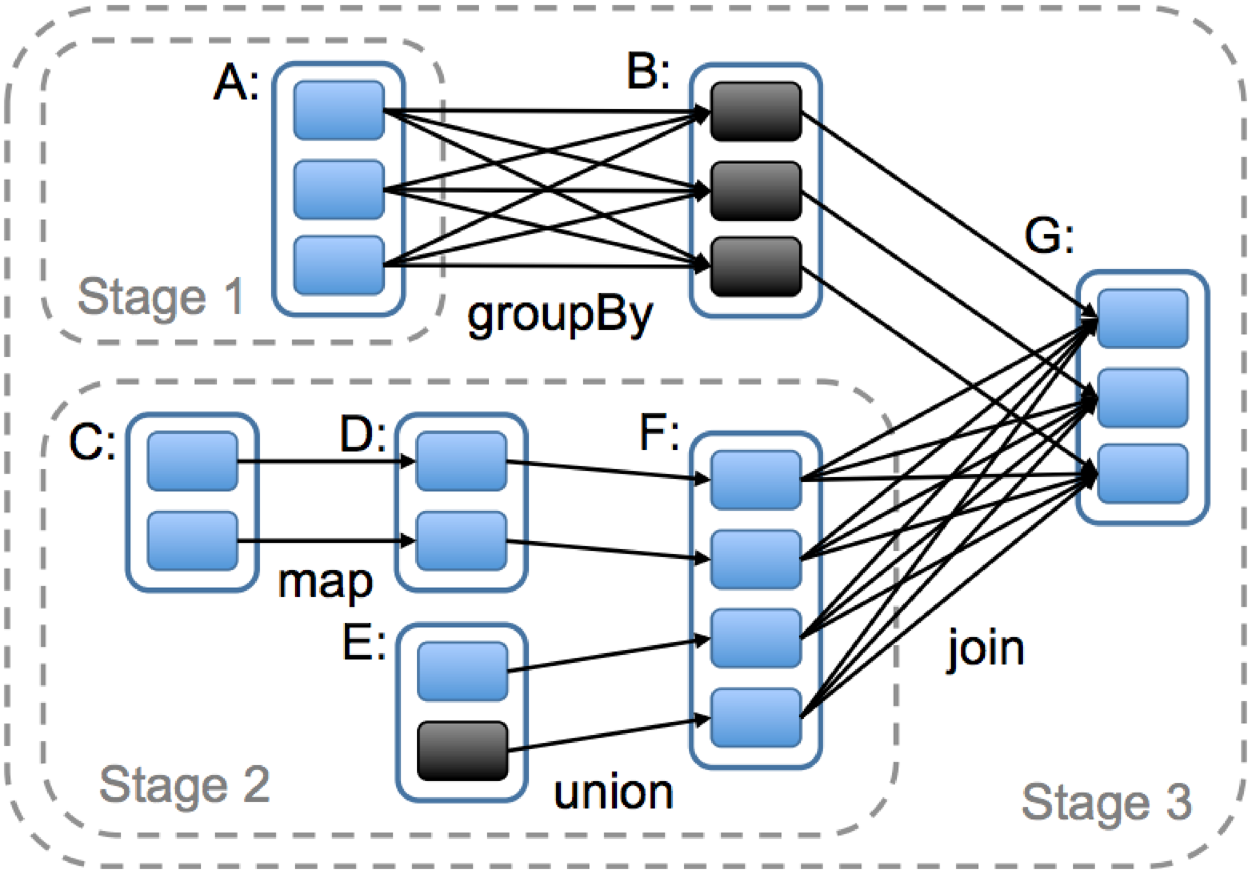



Source: redrawn from a slide by Cloduera, cc-licensed

# Physical Operators



# Execution Plan

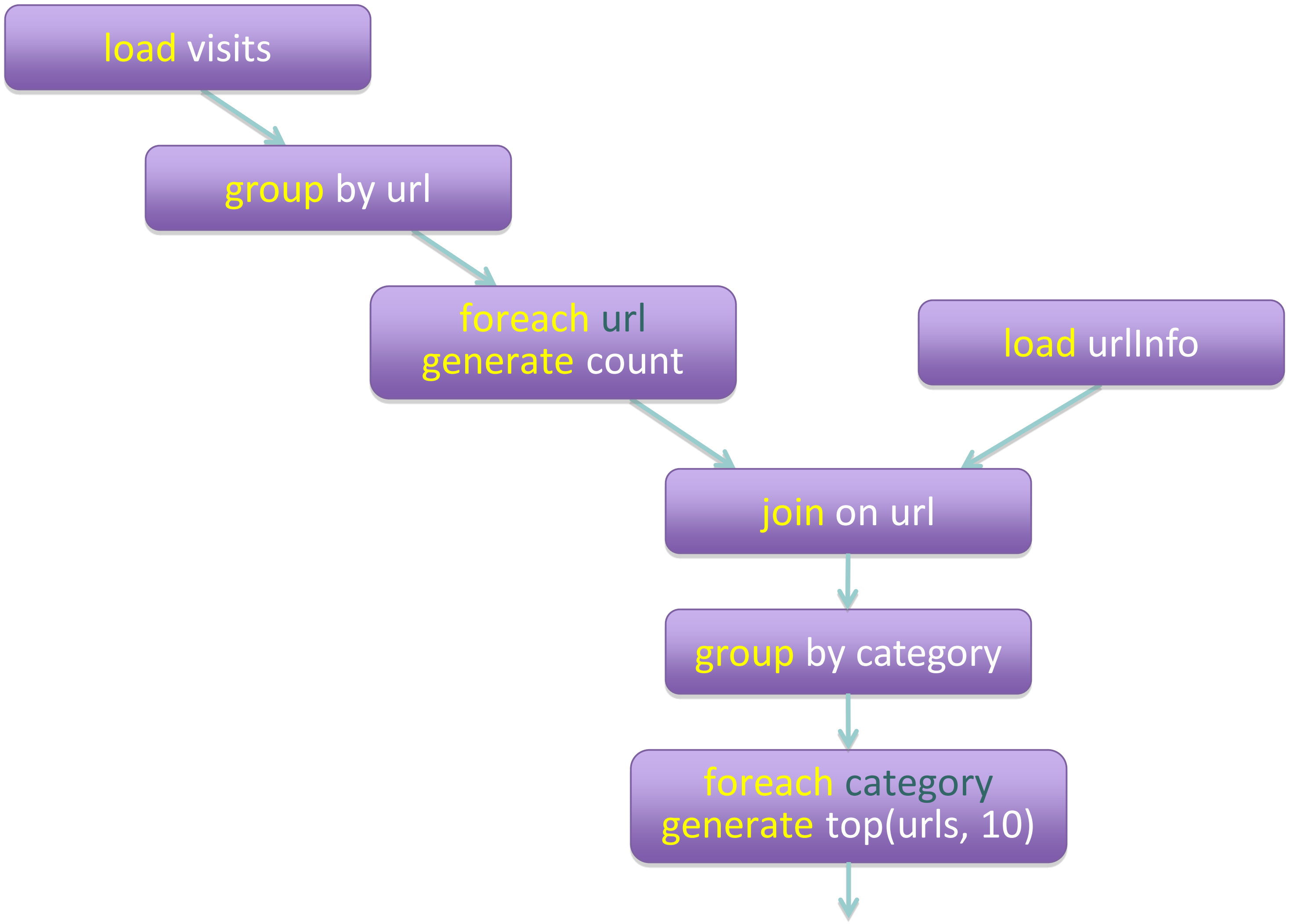



Wait, where have we seen this before?

# Pig: Example Script

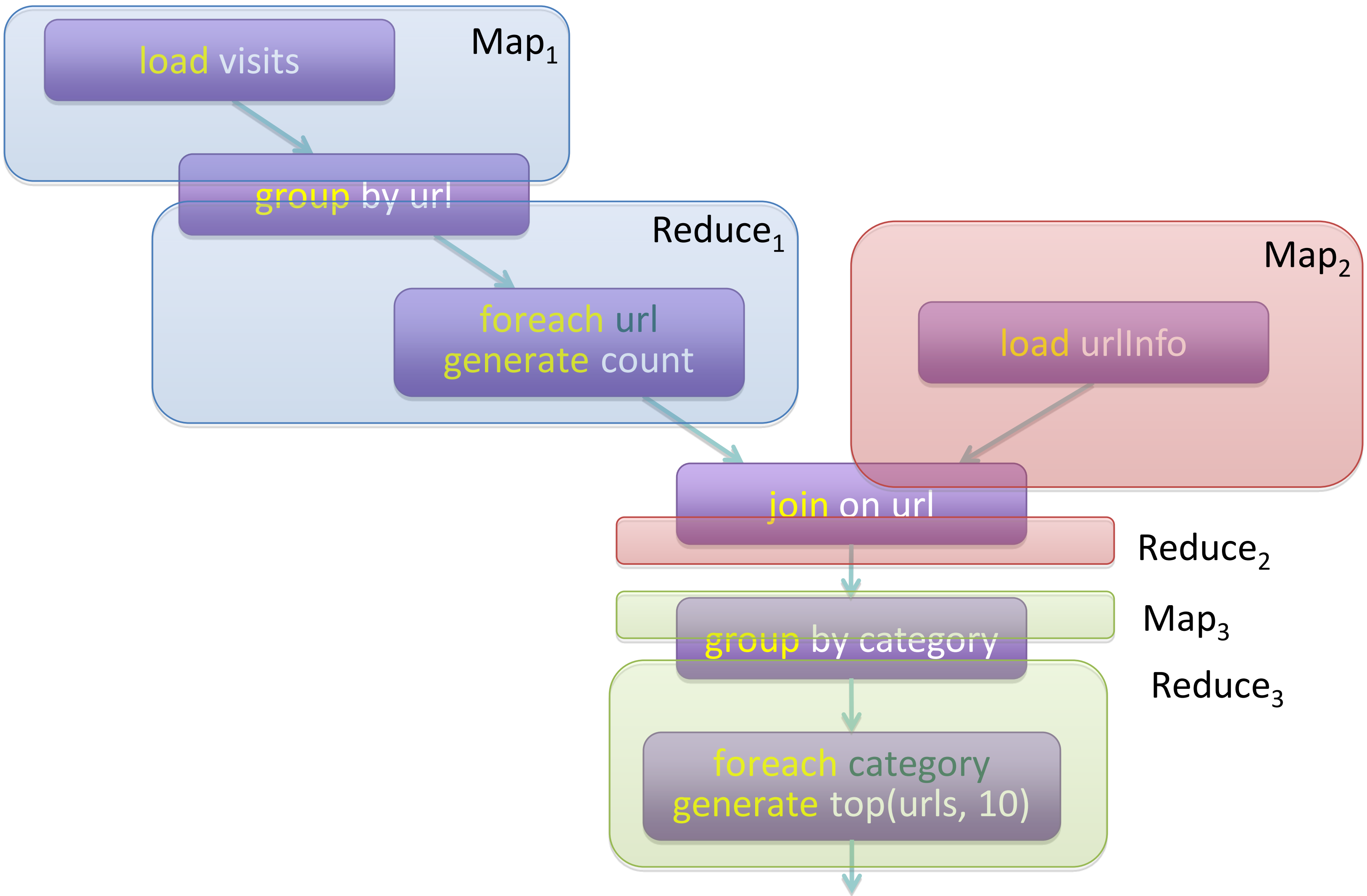
```
visits = load '/data/visits' as (user, url, time);
gVisits = group visits by url;
visitCounts = foreach gVisits generate url, count(visits);
urlInfo = load '/data/urlInfo' as (url, category, pRank);
visitCounts = join visitCounts by url, urlInfo by url;
gCategories = group visitCounts by category;
topUrls = foreach gCategories generate top(visitCounts,10);

store topUrls into '/data/topUrls';
```

# Pig Query Plan



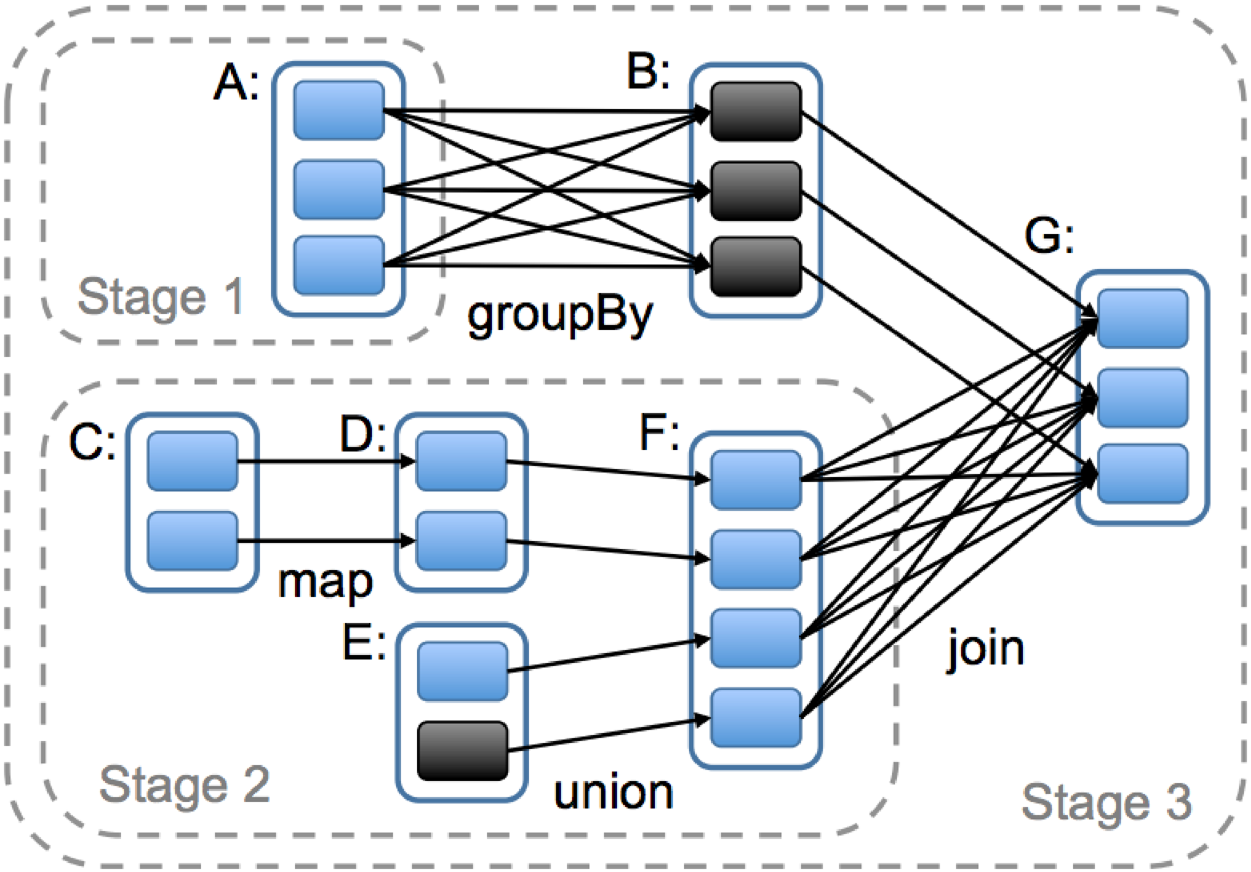

Pig Slides adapted from Olston et al. (SIGMOD 2008)

# Pig: MapReduce Execution



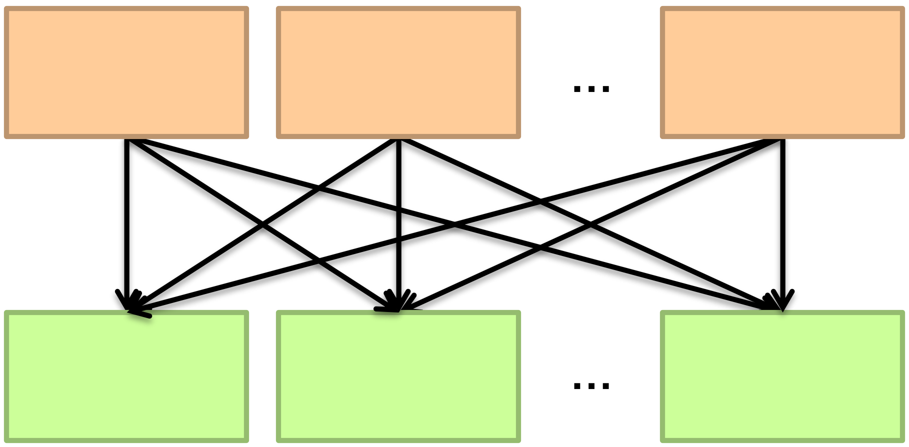

Pig Slides adapted from Olston et al. (SIGMOD 2008)

# Execution Plan



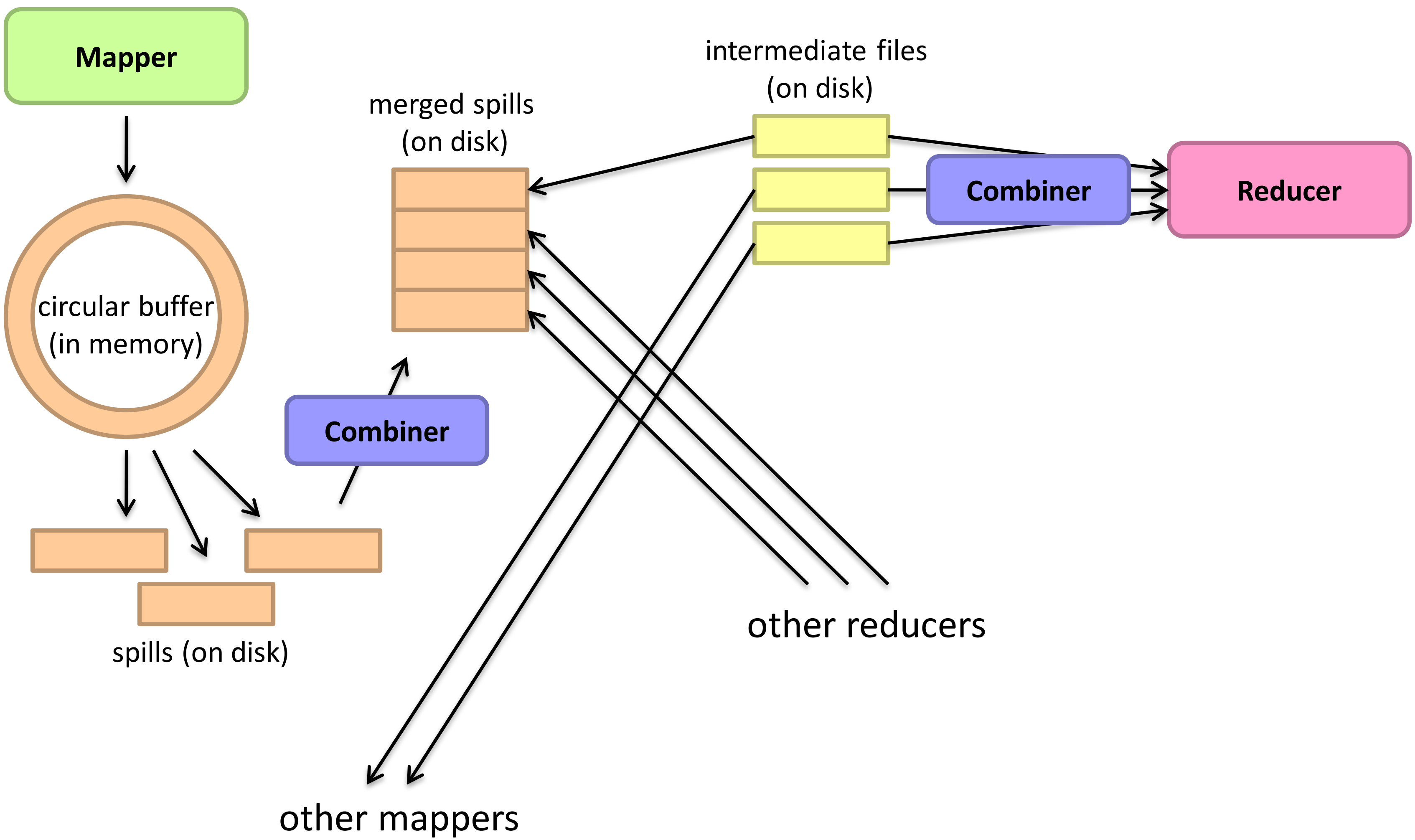

Kinda like a sequence of MapReduce jobs?

# Can’t avoid this!



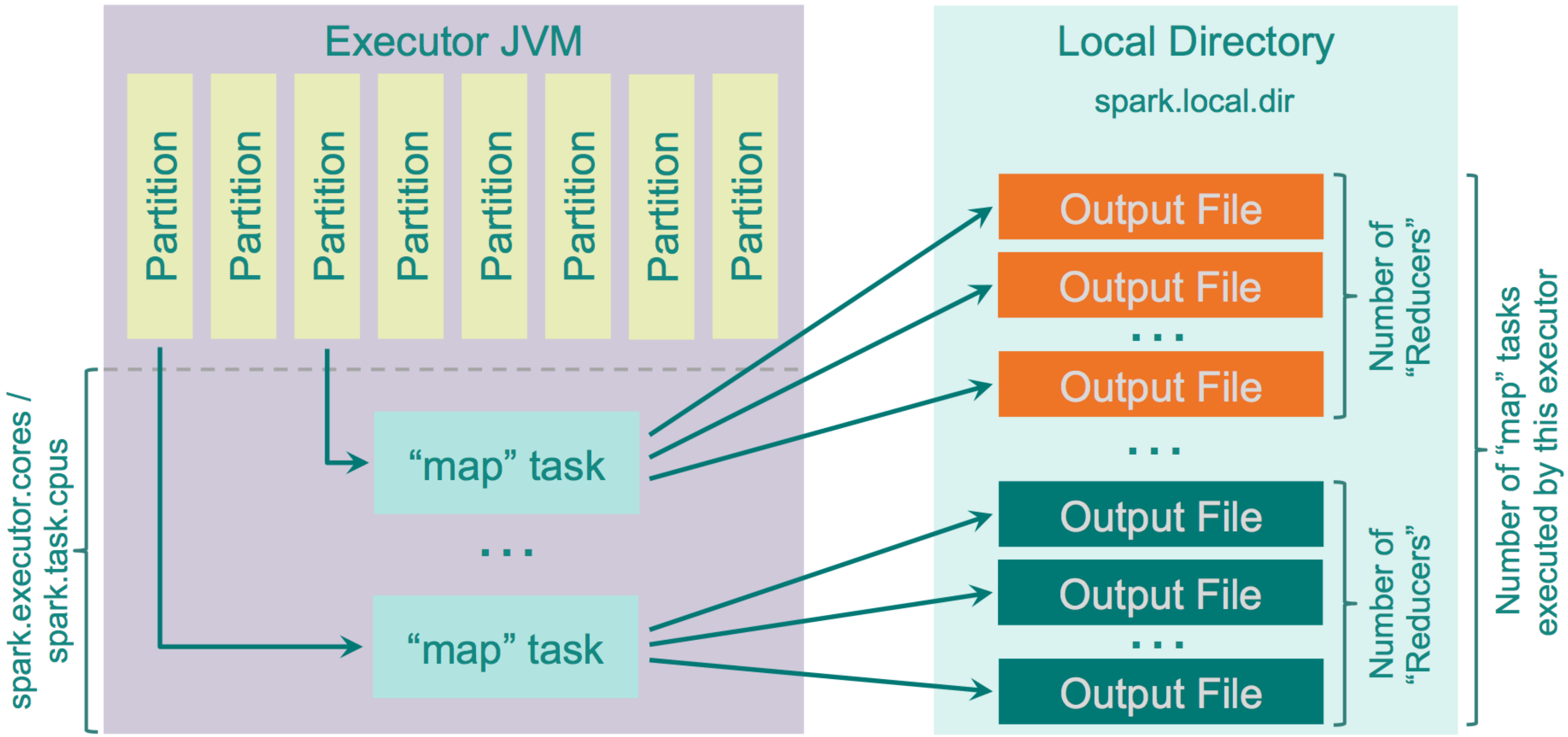

But, what’s the major difference?

# Remember this?



# Spark Shuffle Implementations

## Hash shuffle

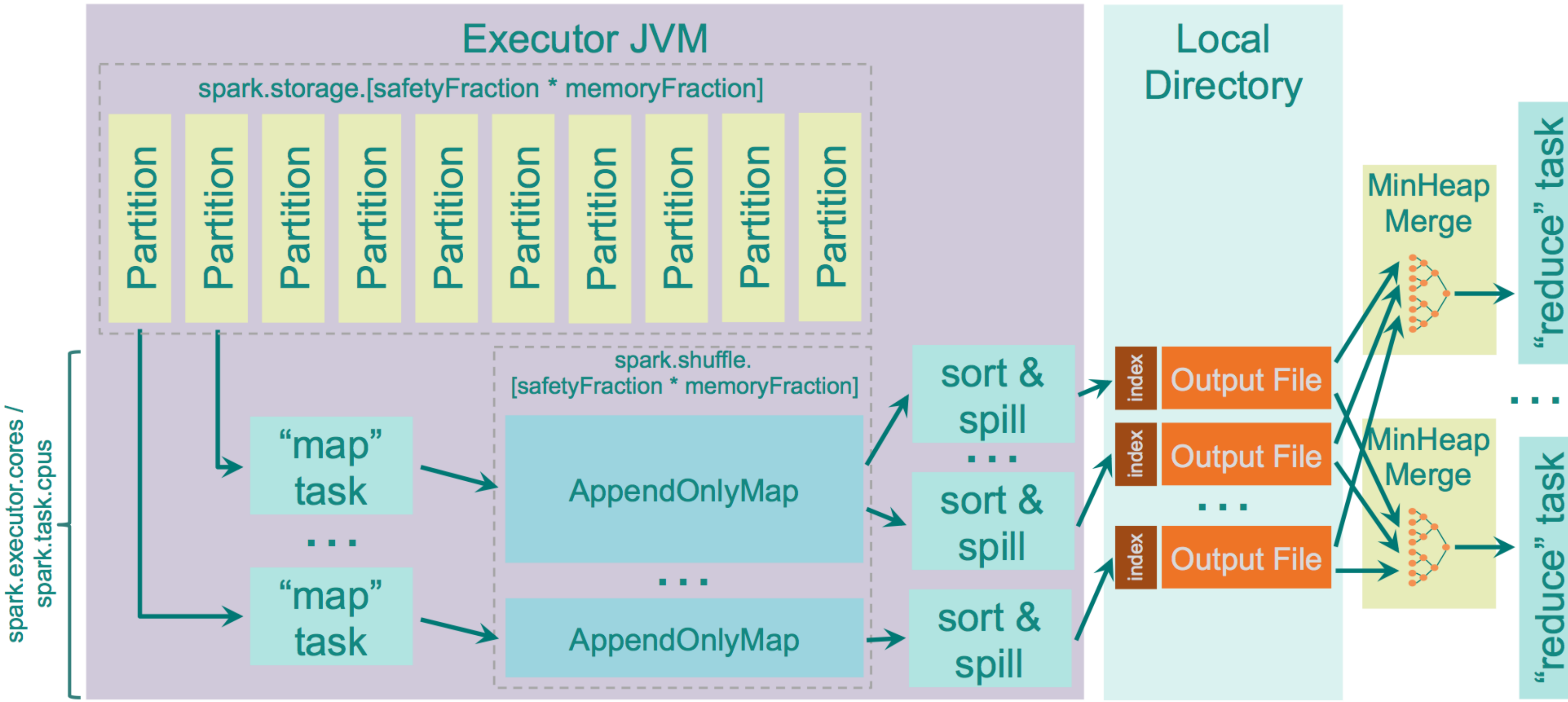



What happened to sorting?

Source: http://0x0fff.com/spark-architecture-shuffle/

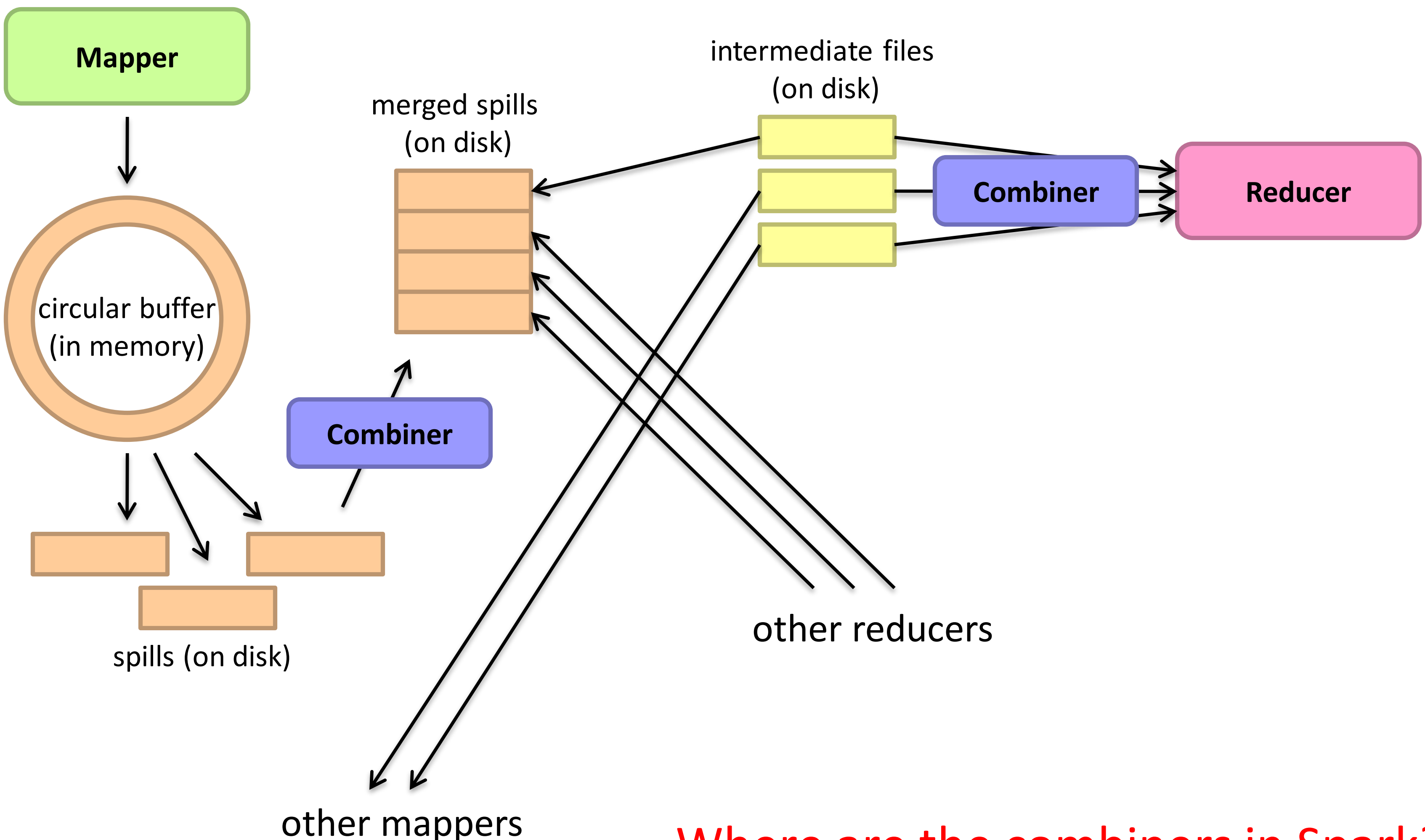
# Spark Shuffle Implementations

## Sort shuffle




Source: http://0x0fff.com/spark-architecture-shuffle/

# Remember this?




Where are the combiners in Spark?

# Reduce-like Operations

RDD[(K, V)]

↓

**reduceByKey**

f: (V, V) ⇒ V

↓

RDD[(K, V)]

RDD[(K, V)]

↓

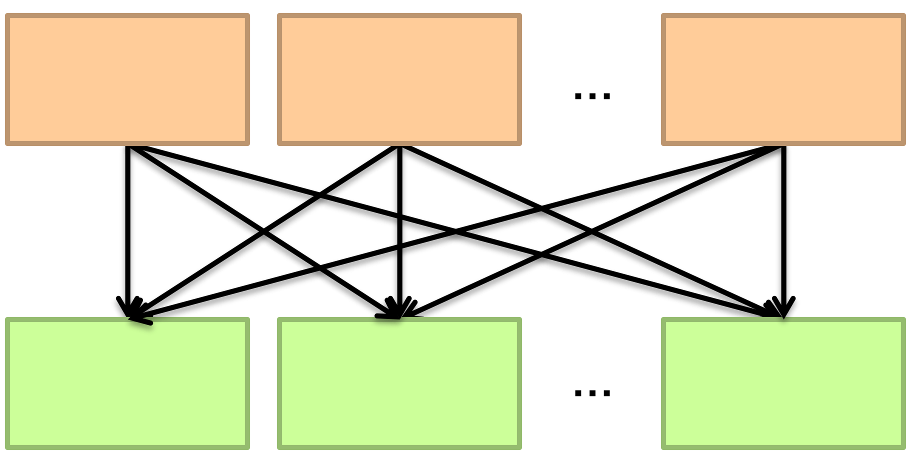
**aggregateByKey**

seqOp: (U, V) ⇒ U, combOp: (U, U) ⇒ U

↓

RDD[(K, U)]

What happened to combiners?



# Spark #wins

Richer operators

RDD abstraction supports optimizations (pipelining, caching, etc.)

Scala, Java, Python, R, bindings

# Spark #wins

Quick Start Using Scala - Data ×

Jimmy

Secure https://cdn2.hubspot.net/hubfs/438089/notebooks/Quick_Start/Quick_Start_Using_Scala.html

databricks

Quick Start Using Scala (Scala)

Import Notebook

```
// Take a look at the file system
display(dbutils.fs.ls("/databricks-datasets/samples/docs/"))
```

| path | name | size |
| --- | --- | --- |
| dbfs:/databricks-datasets/samples/docs/README.md | README.md | 3137 |

```
// Setup the textFile RDD to read the README.md file
//   Note this is lazy
val textFile = sc.textFile("/databricks-datasets/samples/docs/README.md")

textFile: org.apache.spark.rdd.RDD[String] = /databricks-datasets/samples/docs/README.md MapPartitionsRDD[1873222] at textFile at <console>:34
```

RDDs have ***actions***, which return values, and ***transformations***, which return pointers to new RDDs.

```
// When performing an action (like a count) this is when the textFile is read and aggregate calculated
//    Click on [View] to see the stages and executors
textFile.count()

res2: Long = 65
```

## Scala Count (Jobs)

Jobs Stages Storage Environment Executors SQL JDBC/ODBC Server

# Spark #lose

Java serialization (w/ Kryo optmizations)
Scala: poor support for primitives

Source: Wikipedia (Mahout)


Two superpowers:

Associativity
Commutativity
(sorting)

What follows… very basic category theory…

# The Power of Associativity

## You can put parentheses where ever you want!

$$\left( v_1 \oplus v_2 \oplus v_3 \right) \oplus \left( v_4 \oplus v_5 \oplus v_6 \oplus v_7 \right) \oplus \left( v_8 \oplus v_9 \right)$$

$$\left( v_1 \oplus v_2 \right) \oplus \left( v_3 \oplus v_4 \oplus v_5 \right) \oplus \left( v_6 \oplus v_7 \oplus v_8 \oplus v_9 \right)$$

$$\left( v_1 \oplus v_2 \oplus \left( v_3 \oplus v_4 \oplus v_5 \right) \right) \oplus \left( v_6 \oplus v_7 \oplus v_8 \oplus v_9 \right)$$

Credit to Oscar Boykin for the idea behind these slides

# The Power of Commutativity

## You can swap order of operands however you want!

$$\left( v_1 \oplus v_2 \oplus v_3 \right) \oplus \left( v_4 \oplus v_5 \oplus v_6 \oplus v_7 \right) \oplus \left( v_8 \oplus v_9 \right)$$

$$\left( v_4 \oplus v_5 \oplus v_6 \oplus v_7 \right) \oplus \left( v_1 \oplus v_2 \oplus v_3 \right) \oplus \left( v_8 \oplus v_9 \right)$$

$$\left( v_8 \oplus v_9 \right) \oplus \left( v_4 \oplus v_5 \oplus v_6 \oplus v_7 \right) \oplus \left( v_1 \oplus v_2 \oplus v_3 \right)$$

Credit to Oscar Boykin for the idea behind these slides

# Implications for distributed processing?

You don’t know when the tasks begin
You don’t know when the tasks end
You don’t know when the tasks interrupt each other
You don’t know when intermediate data arrive
…

It’s okay!

# Word Count: Baseline

```
class Mapper {
  def map(key: Long, value: String) = {
    for (word <- tokenize(value)) {
      emit(word, 1)
    }
  }
}

class Reducer {
  def reduce(key: String, values: Iterable[Int]) = {
    for (value <- values) {
      sum += value
    }
    emit(key, sum)
  }
}
```

# Fancy Labels for Simple Concepts…

**Semigroup** = ( $M$ , $\oplus$ )

$\oplus$ : $M \times M \rightarrow M$, s.t., $\forall m_1, m_2, m_3 \ni M$

$$(m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3)$$

**Monoid** = Semigroup + identity

$\varepsilon$ s.t., $\varepsilon \oplus m = m \oplus \varepsilon = m, \forall m \ni M$

**Commutative Monoid** = Monoid + commutativity

$\forall m_1, m_2 \ni M, m_1 \oplus m_2 = m_2 \oplus m_1$

A few examples?
(hint, previous slide!)

# Back to these...

RDD[(K, V)]

↓

**reduceByKey**

f: (V, V) ⇒ V

↓

RDD[(K, V)]

RDD[(K, V)]

↓

**aggregateByKey**

seqOp: (U, V) ⇒ U, combOp: (U, U) ⇒ U

↓

RDD[(K, U)]

Wait, I've seen this before?

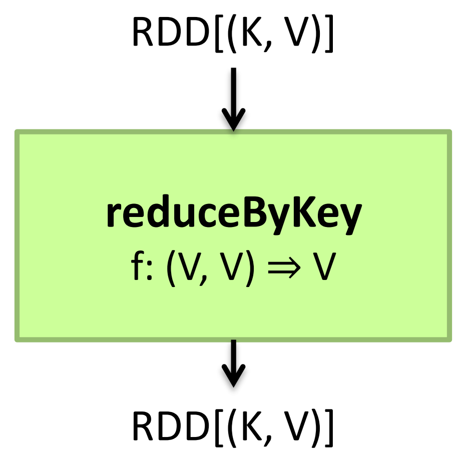
# Computing the Mean: Version 1

```
class Mapper {
  def map(key: String, value: Int) = {
    emit(key, value)
  }
}

class Reducer {
  def reduce(key: String, values: Iterable[Int]) {
    for (value <- values) {
      sum += value
      cnt += 1
    }
    emit(key, sum/cnt)
  }
}
```

# Computing the Mean: Version 3

```
class Mapper {
  def map(key: String, value: Int) =
    emit(key, (value, 1))
}
class Combiner {
  def reduce(key: String, values: Iterable[Pair]) = {
    for ((s, c) <- values) {
      sum += s
      cnt += c
    }
    emit(key, (sum, cnt))
  }
}
class Reducer {
  def reduce(key: String, values: Iterable[Pair]) = {
    for ((s, c) <- values) {
      sum += s
      cnt += c
    }
    emit(key, sum/cnt)
  }
}
```

Wait, I've seen this before?

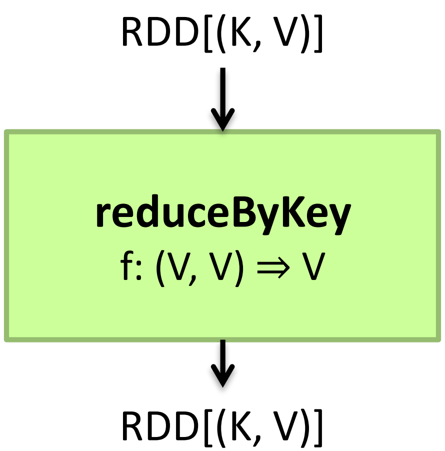


# Co-occurrence Matrix: Stripes

```
class Mapper {
  def map(key: Long, value: String) = {
    for (u <- tokenize(value)) {
      val map = new Map()
      for (v <- neighbors(u)) {
        map(v) += 1
      }
      emit(u, map)
    }
  }
}
```

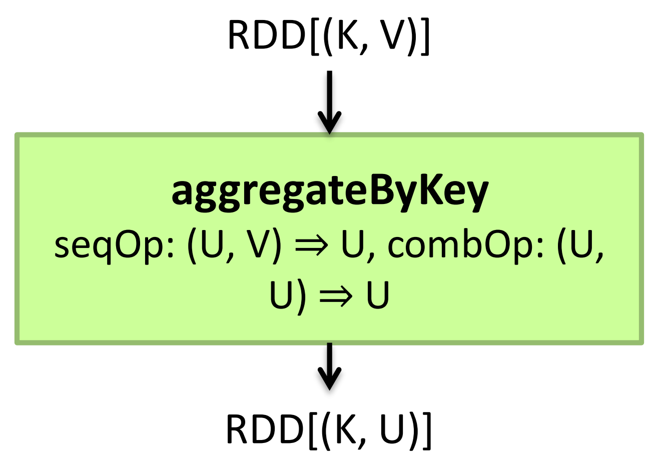
Wait, I’ve seen this before?

```
class Reducer {
  def reduce(key: String, values: Iterable[Map]) = {
    val map = new Map()
    for (value <- values) {
      map += value
    }
    emit(key, map)
  }
}
```



# Computing the Mean: Version 2

```
class Mapper {
  def map(key: String, value: Int) =
    emit(key, value)
}
class Combiner {
  def reduce(key: String, values: Iterable[Int]) = {
    for (value <- values) {
      sum += value
      cnt += 1
    }
    emit(key, (sum, cnt))
  }
}
class Reducer {
  def reduce(key: String, values: Iterable[Pair]) = {
    for ((s, c) <- values) {
      sum += s
      cnt += c
    }
    emit(key, sum/cnt)
  }
}
```



# Synchronization: Pairs vs. Stripes

Approach 1: turn synchronization into an ordering problem

Sort keys into correct order of computation

Partition key space so each reducer receives appropriate set of partial results

Hold state in reducer across multiple key-value pairs to perform computation

Illustrated by the "pairs" approach

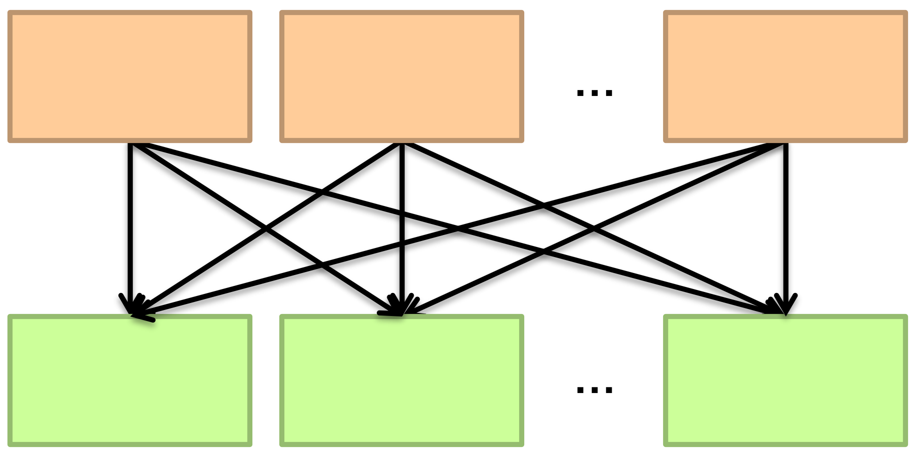
Approach 2: data structures that bring partial results together

Each reducer receives all the data it needs to complete the computation

Illustrated by the "stripes" approach

Commutative monoids!

# Because you can't avoid this…




But commutative monoids help

# Synchronization: Pairs vs. Stripes

Approach 1: turn synchronization into an ordering problem

Sort keys into correct order of computation

Partition key space so each reducer receives appropriate set of partial results

Hold state in reducer across multiple key-value pairs to perform computation

Illustrated by the "pairs" approach

What about this?

Approach 2: data structures that bring partial results together

Each reducer receives all the data it needs to complete the computation

Illustrated by the "stripes" approach

Commutative monoids!

# f(B|A): “Pairs”

(a, *) → 32 Reducer holds this value in memory

| | | |
|---|---|---|
| $(a, b_1) \rightarrow 3$ | | $(a, b_1) \rightarrow 3 / 32$ |
| $(a, b_2) \rightarrow 12$ | ⇒ | $(a, b_2) \rightarrow 12 / 32$ |
| $(a, b_3) \rightarrow 7$ | | $(a, b_3) \rightarrow 7 / 32$ |
| $(a, b_4) \rightarrow 1$ | | $(a, b_4) \rightarrow 1 / 32$ |
| … | | … |

For this to work:

Emit extra (a, *) for every $b_n$ in mapper
Make sure all a’s get sent to same reducer (use partitioner)
Make sure (a, *) comes first (define sort order)
Hold state in reducer across different key-value pairs

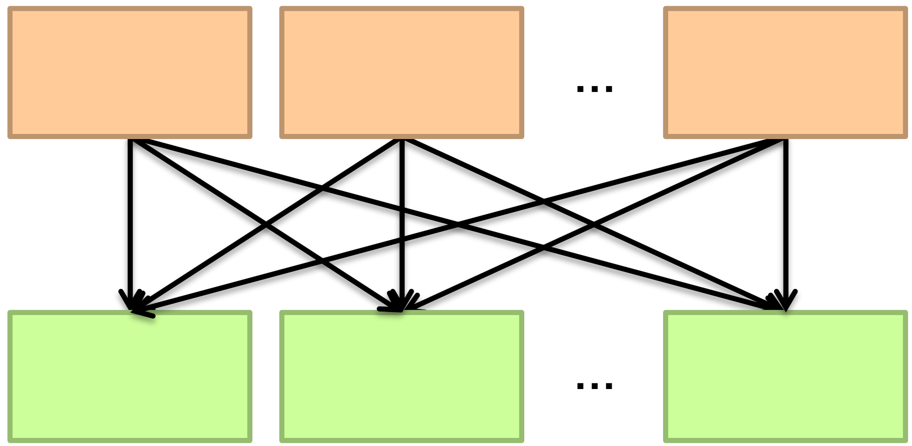

Two superpowers:

Associativity

Commutativity

(sorting)

# When you can’t “monoidify”

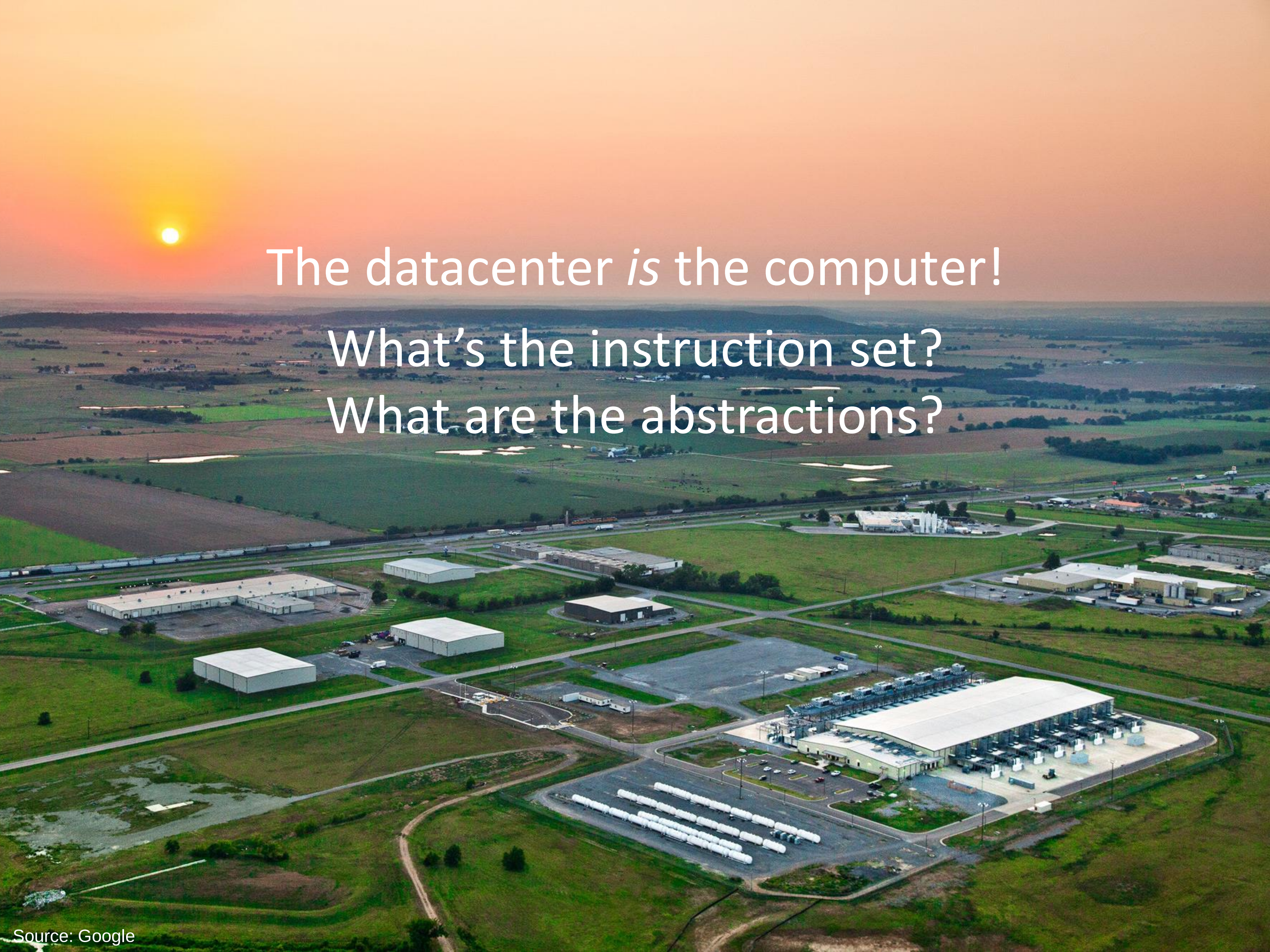



Sequence your computations by sorting

# An Apt Quote

All problems in computer science can be solved by another level of indirection... Except for the problem of too many layers of indirection.

- David Wheeler

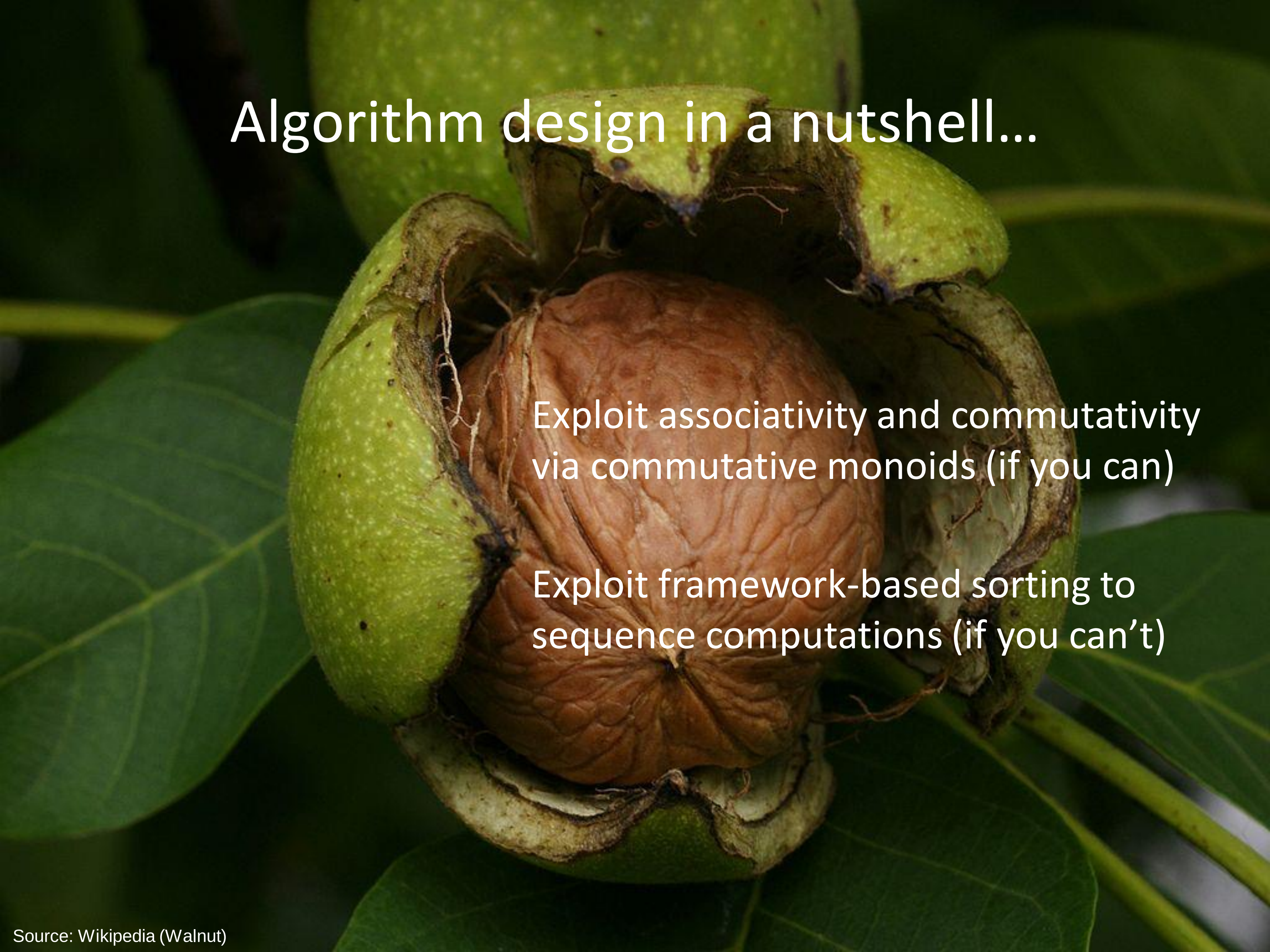


Source: Google

# Algorithm design in a nutshell…

Exploit associativity and commutativity via commutative monoids (if you can)

Exploit framework-based sorting to sequence computations (if you can't)



Source: Wikipedia (Walnut)

Source: Wikipedia (Japanese rock garden)