# [544] MapReduce and Spark

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# Learning Objectives

- describe the role mappers and reducers have in MapReduce jobs
- describe Spark concepts related to data lineage (RDDs, operations, transformations, actions)
- deploy Spark with multiple workers
- write Spark code using RDD and DataFrame APIs

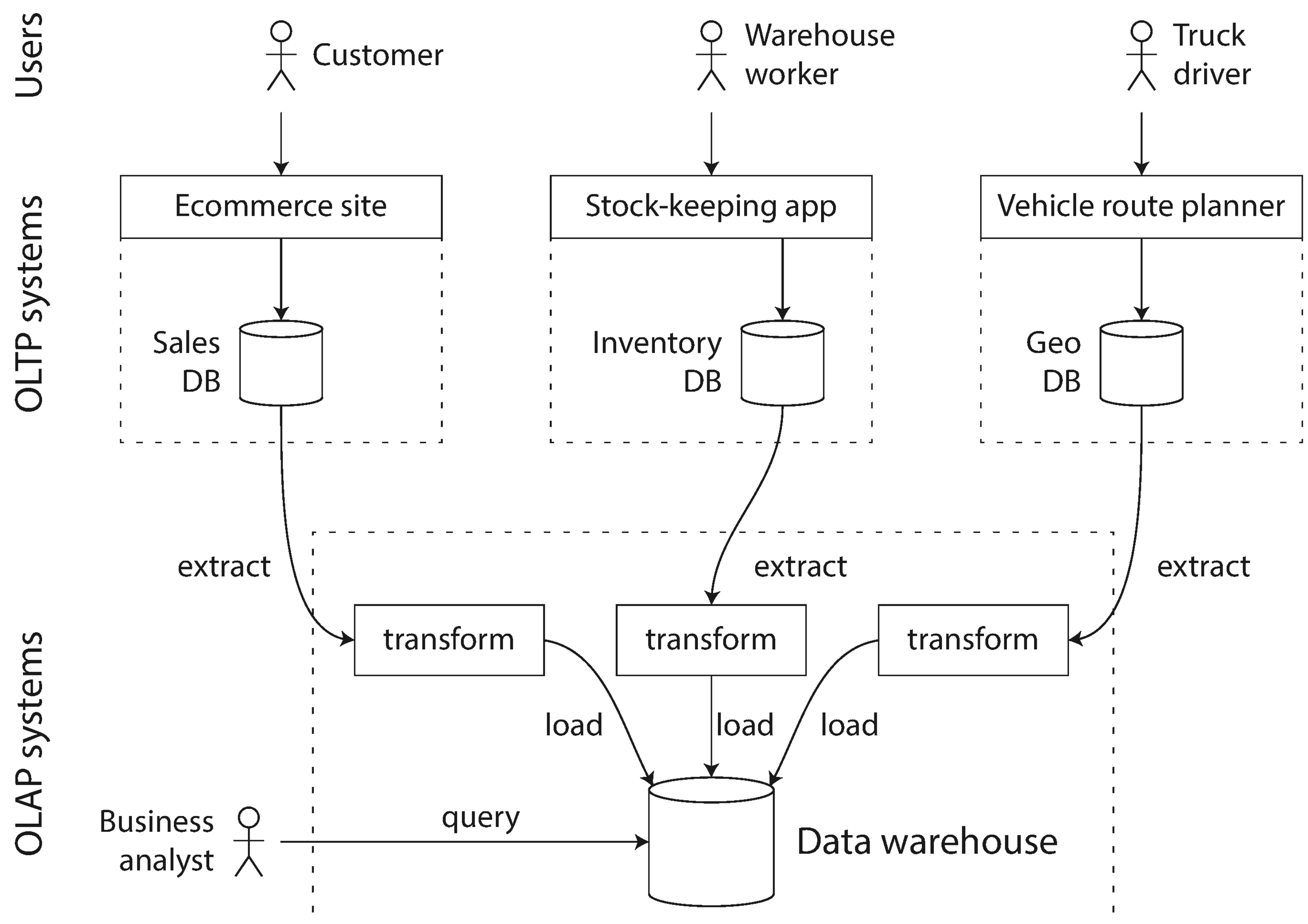
# Outline: MapReduce and Spark

Data Lakes

Hadoop MapReduce

Spark

# Review: Data Warehouse



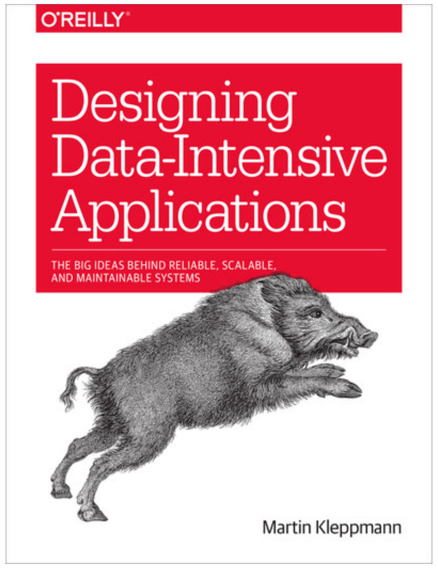
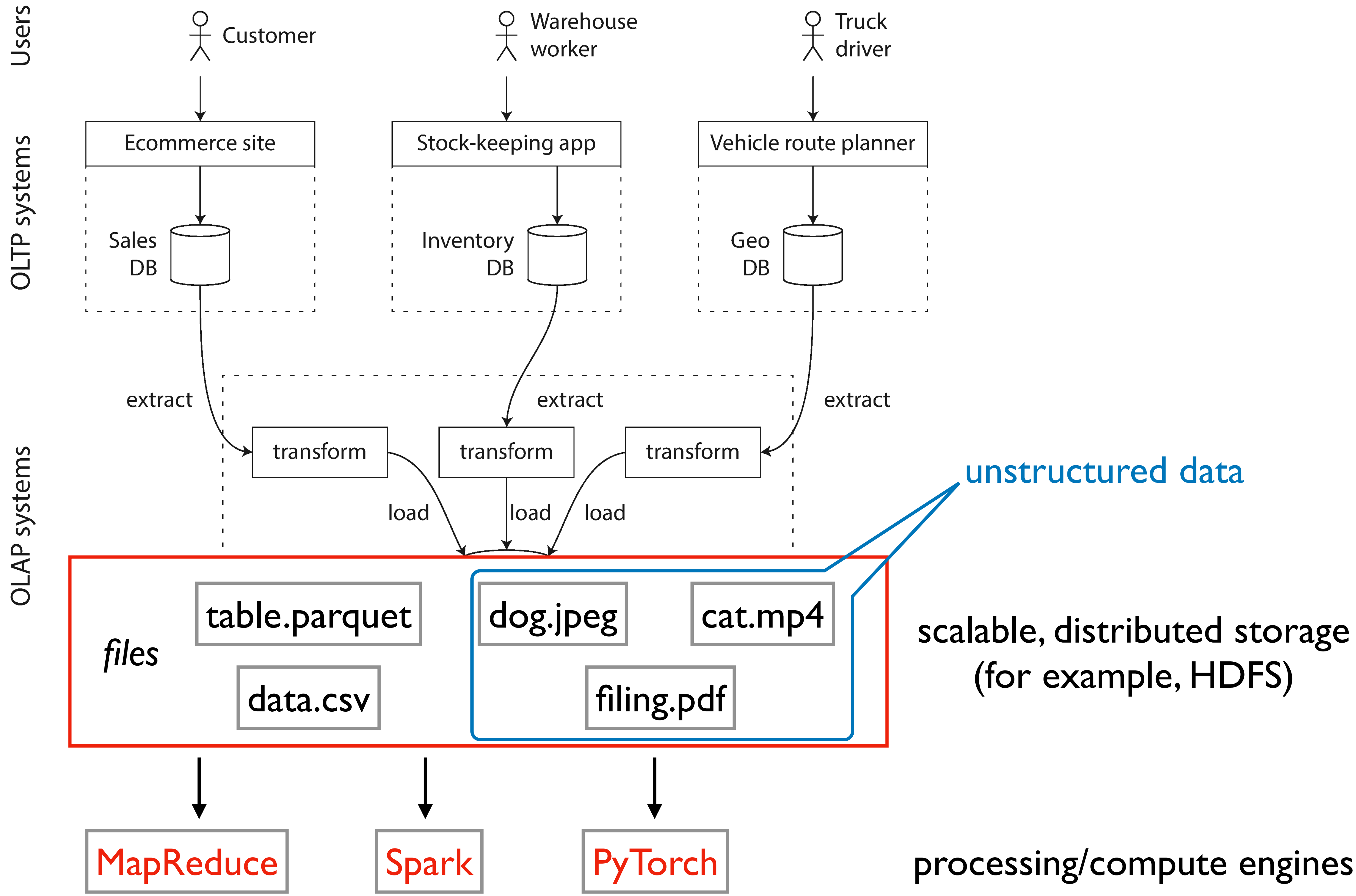




Figure 3-8. Simplified outline of ETL into a data warehouse.
(Chapter 3 of Data-Intensive Applications, by Kleppmann)

Data warehouse: storage + compute are tightly coupled (e.g., indexes)

- Efficient: coupling makes more optimization possible
- Limited: what if you want to do ML instead of running SQL queries?

# "Data Lake" (new term for decoupled storage/compute for analytics)



# Outline: MapReduce and Spark

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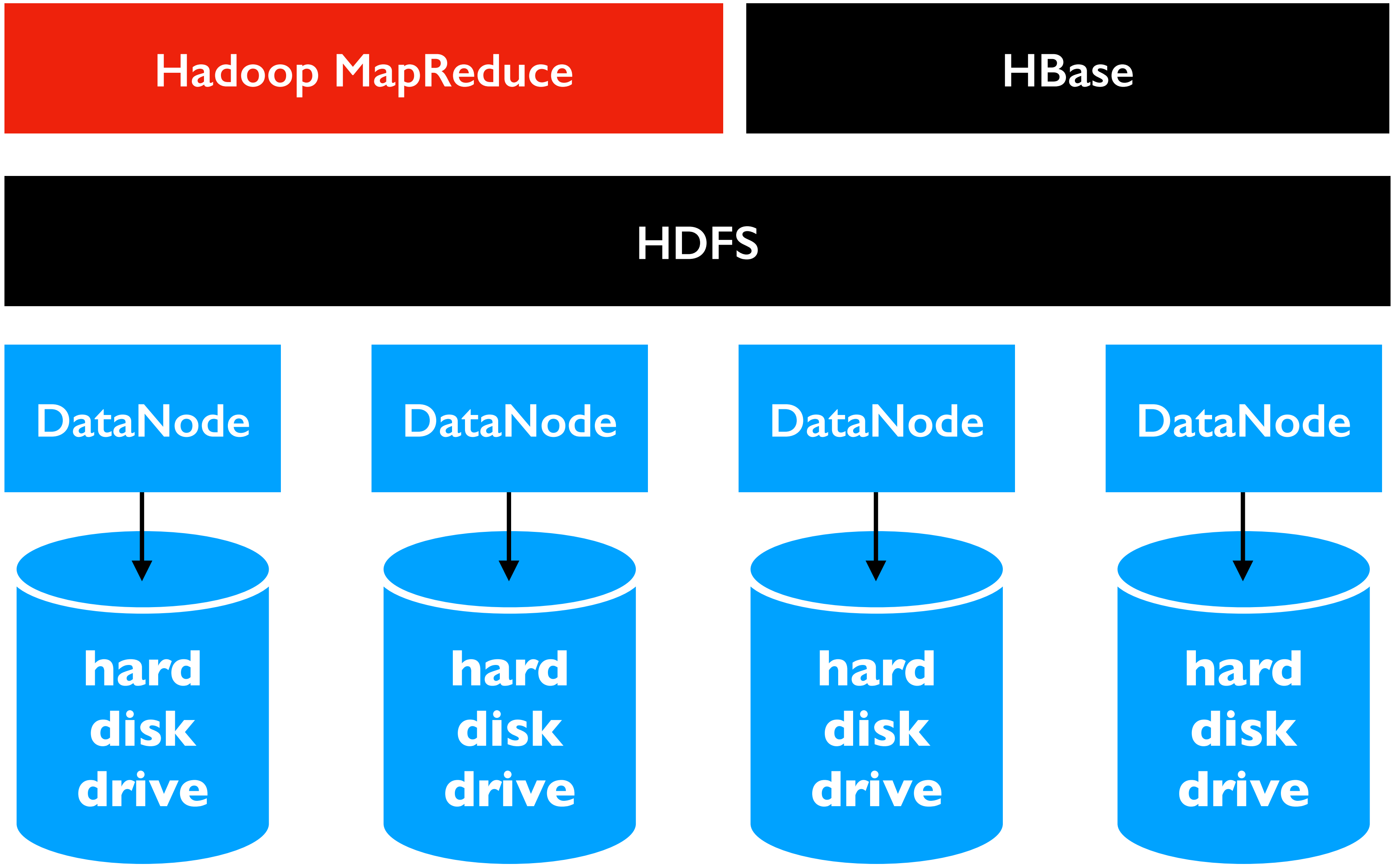
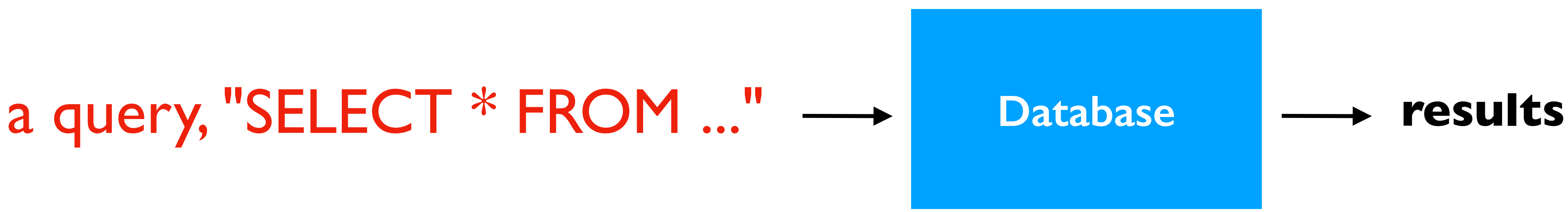
# MapReduce



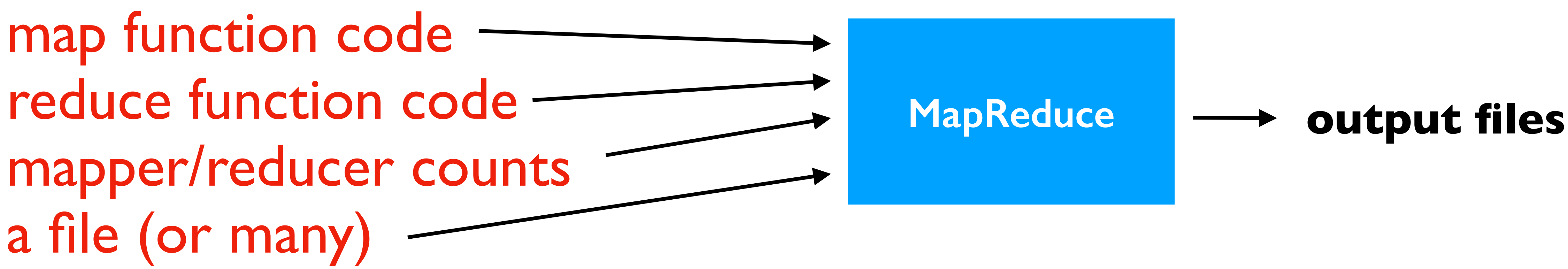
Hadoop MapReduce
HBase
HDFS
DataNode
DataNode
DataNode
DataNode
hard disk drive
hard disk drive
hard disk drive
hard disk drive

# How do we answer questions?

SQL:

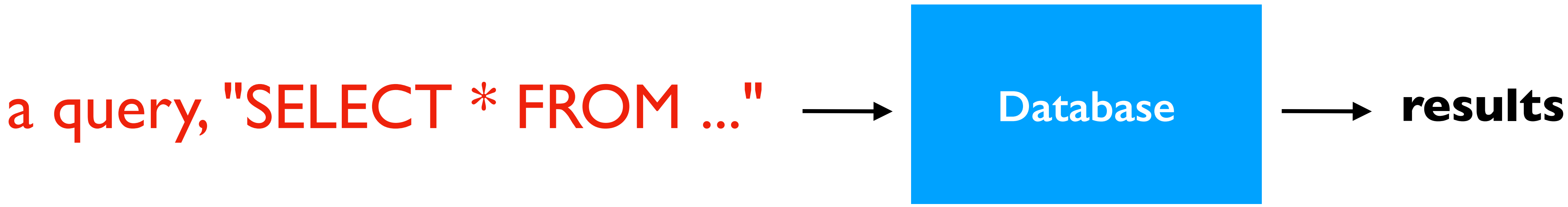



MapReduce

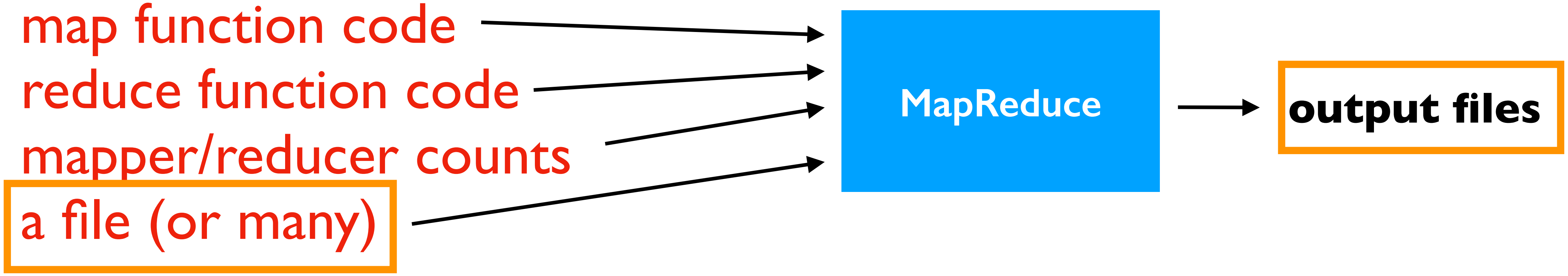


# How do we answer questions?

SQL:



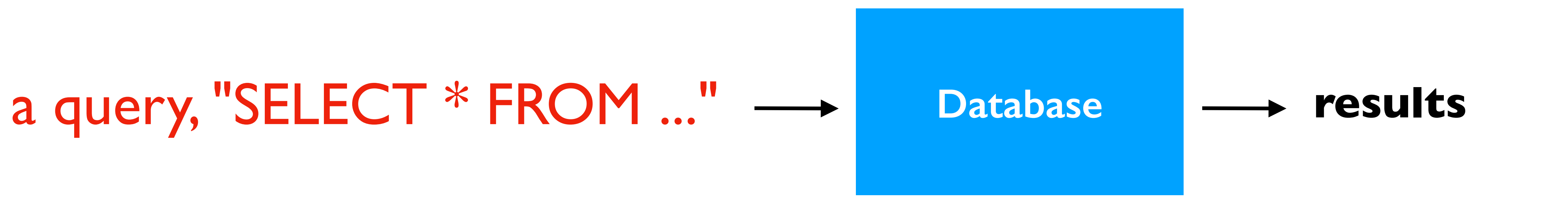

MapReduce



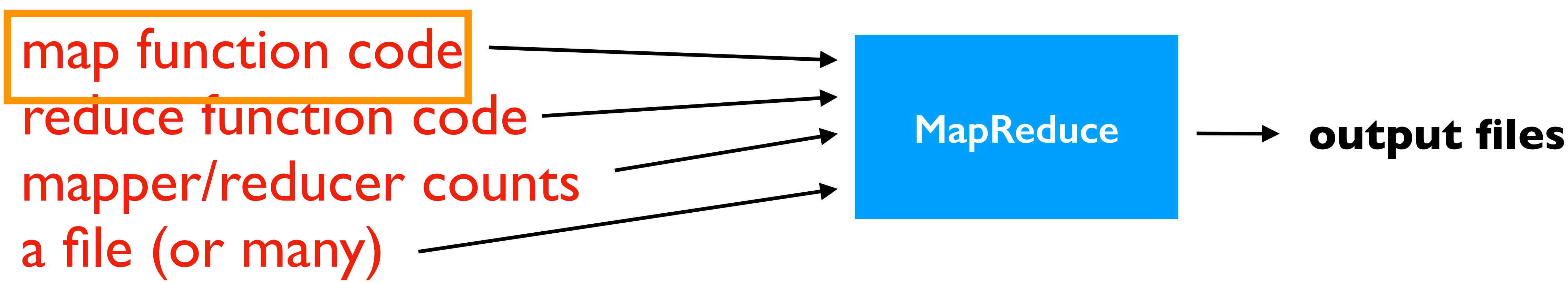

**input/output files are generally in HDFS**

# How do we answer questions?

SQL:




MapReduce



# Mappers by example: what are the colors of the squares?

**input.csv (in HDFS):**

```
color, shape,   size
red,   circle,  3
red,   square,  5
blue,  oval,    1
green, square,  3
```

```
def map(key, value):
    ...
```

**In SQL:**

SELECT color FROM table WHERE shape = "square";

# Mappers by example: what are the colors of the squares?

**input.csv (in HDFS):**

```
color, shape,   size
red,   circle,  3
red,   square,  5
blue,  oval,    1
green, square,  3
```

0

red,circle,3

```
def map(key, value):
    ...
```

zero or more output key/value pairs

# Mappers by example: what are the colors of the squares?

**input.csv (in HDFS):**

```
color, shape,   size
red,   circle,  3
red,   square,  5
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green, square,  3
```

1

red,square,5

```
def map(key, value):
    ...
```

zero or more output key/value pairs

# Mappers by example: what are the colors of the squares?

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```
color, shape,   size
red,   circle,  3
red,   square,  5
blue,  oval,    1
green, square,  3
```

1    red,square,5

```
def map(key, value):
    if value.shape = square:
        emit(key, value.color)
```

| **key** | **value** |
|---|---|
| 1 | red |
| 3 | green |

# Mappers by example: what are the colors of the squares?

what if the data is huge?

**input.csv (in HDFS):**

```
color, shape,   size
red,   circle,  3
red,   square,  5
blue,  oval,    1
green, square,  3
```

1

red,square,5

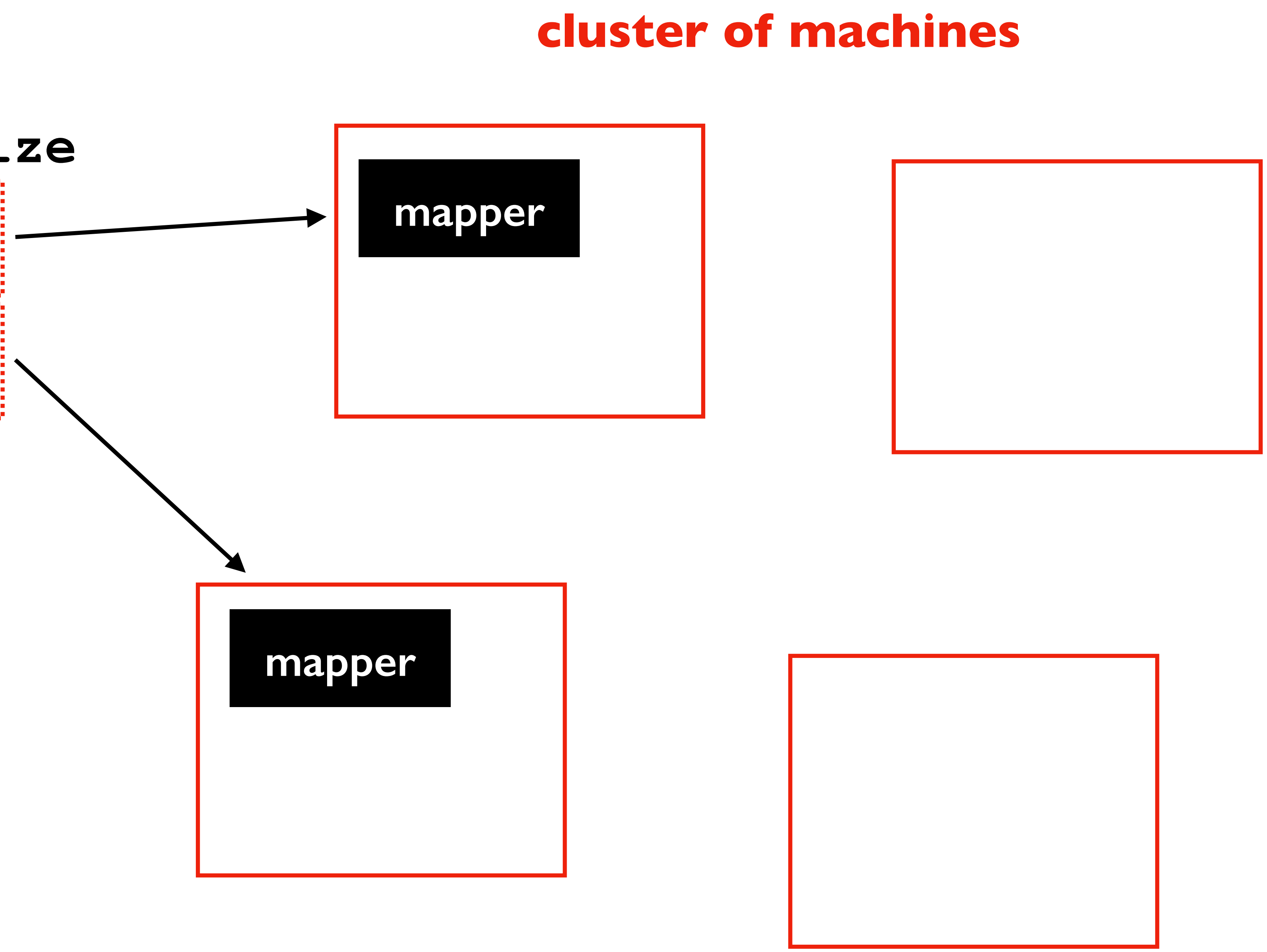
```
def map(key, value):
    if value.shape = square:
        emit(key, value.color)
```

| key | value |
|---|---|
| 1 | red |
| 3 | green |

# Mappers Run on Multiple Machines at Once

**input.csv (in HDFS):**

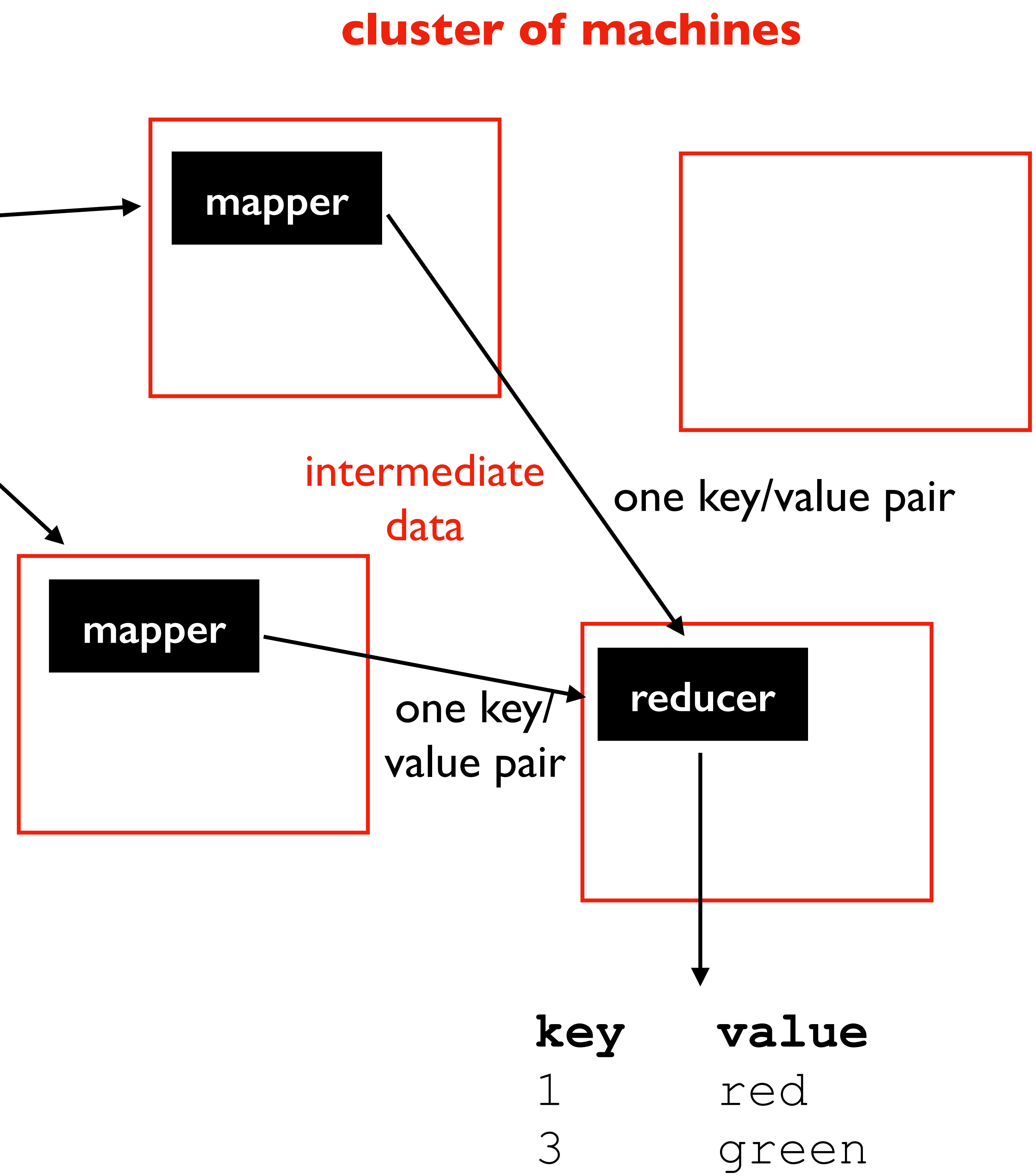
```
color, shape,   size
red,   circle,  3
red,   square,  5
blue,  oval,    1
green, square,  3
```



# Reducers

**input.csv (in HDFS):**

```
color, shape,   size
red,   circle,  3
red,   square,  5
blue,  oval,    1
green, square,  3
```




**a simple (default) reduce task can combine output of multiple mappers to a single file**

# Reducers

MapReduce shuffles the data, bringing together intermediate outputs from mappers with the same key. All data with the same key is passed to a single "reduce" call. A reduce task will generally have reduce called many times with different keys.

```
def reduce(key, values):
    for row in values:
        emit(key, row)
```

**reducers can output exactly their input, OR have further computation**

# Reducers

| **color,** | **shape,** | **size** |
|---|---|---|
| red, | circle, | 3 |
| red, | square, | 5 |
| blue, | oval, | 1 |
| green, | square, | 3 |

```
def map(key, value):
    emit(value.color, value)
```

| **key** | **value** | | |
|---|---|---|---|
| blue | blue, | oval, | 1 |
| green | green, | square, | 3 |
| red | red, | circle, | 3 |
| red, | red, | square, | 5 |

```
def reduce(key, values):
    count = 0
    for row in values:
        count = count + 1
    emit(key, count)
```

**intermediate data is grouped and sorted by key**

reduce will be called 3 times (once for each group). The calls could happen in one reduce task (or be split over many)

# Reducers

| color, | shape, | size |
|---|---|---|
| red, | circle, | 3 |
| red, | square, | 5 |
| blue, | oval, | 1 |
| green, | square, | 3 |

```
def map(key, value):
    emit(value.color, value)
```

| key | value | | |
|---|---|---|---|
| blue | blue, | oval, | 1 |
| green | green, | square, | 3 |
| red | red, | circle, | 3 |
| red, | red, | square, | 5 |

```
def reduce(key, values):
    count = 0
    for row in values:
        count = count + 1
    emit(key, count)
```

**intermediate data is grouped and sorted by key**

| key | value |
|---|---|
| blue | 1 |

# Reducers

| color, | shape, | size |
|---|---|---|
| red, | circle, | 3 |
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def map(key, value):
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| key | value | | |
|---|---|---|---|
| blue | blue, | oval, | 1 |
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**intermediate data is grouped and sorted by key**

```
def reduce(key, values):
    count = 0
    for row in values:
        count = count + 1
    emit(key, count)
```

| key | value |
|---|---|
| blue | 1 |
| green | 1 |

# Reducers

| color, | shape, | size |
|---|---|---|
| red, | circle, | 3 |
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```
def map(key, value):
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```

| key | value | | |
|---|---|---|---|
| blue | blue, | oval, | 1 |
| green | green, | square, | 3 |
| red | red, | circle, | 3 |
| red, | red, | square, | 5 |

**intermediate data is grouped and sorted by key**

```
def reduce(key, values):
    count = 0
    for row in values:
        count = count + 1
    emit(key, count)
```

| key | value |
|---|---|
| blue | 1 |
| green | 1 |
| red | 2 |

# What is the SQL equivalent of this MapReduce program?

| **color,** | **shape,** | **size** |
|---|---|---|
| red, | circle, | 3 |
| red, | square, | 5 |
| blue, | oval, | 1 |
| green, | square, | 3 |

```
def map(key, value):
    emit(value.color, value)
```

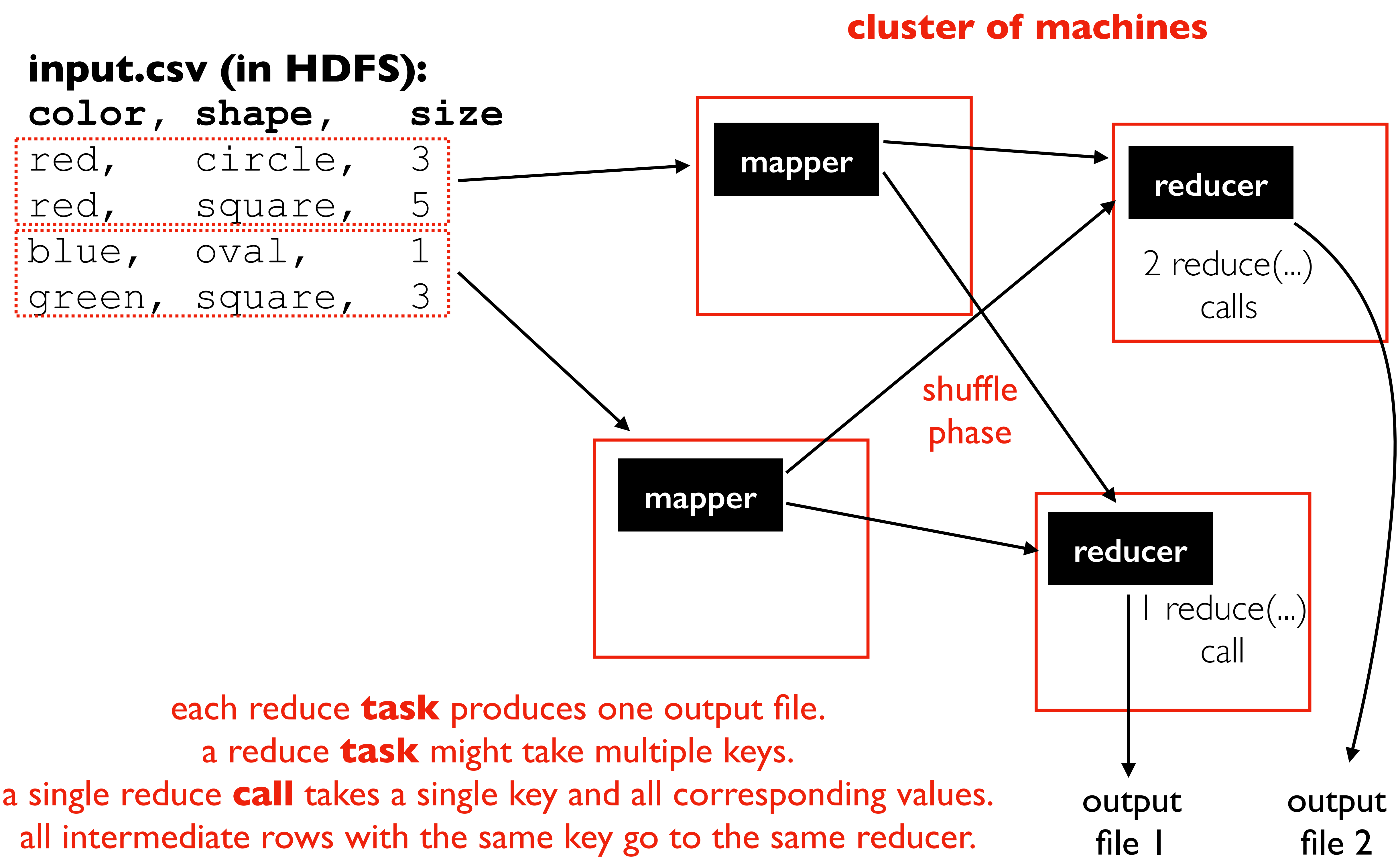
| **key** | **value** | | |
|---|---|---|---|
| blue | blue, | oval, | 1 |
| green | green, | square, | 3 |
| red | red, | circle, | 3 |
| red, | red, | square, | 5 |

**intermediate data is grouped and sorted by key**

```
def reduce(key, values):
    count = 0
    for row in values:
        count = count + 1
    emit(key, count)
```

| **key** | **value** |
|---|---|
| blue | 1 |
| green | 1 |
| red | 2 |

# Multiple Reducers (for big intermediate data)




each reduce **task** produces one output file.
a reduce **task** might take multiple keys.
a single reduce **call** takes a single key and all corresponding values.
all intermediate rows with the same key go to the same reducer.

# SQL => MapReduce

**Map Phase**

- SELECT, WHERE, GROUP BY, JOIN

**Shuffle Phase (bringing related data to same place)**

- ORDER BY, GROUP BY, JOIN

**Reduce Phase**

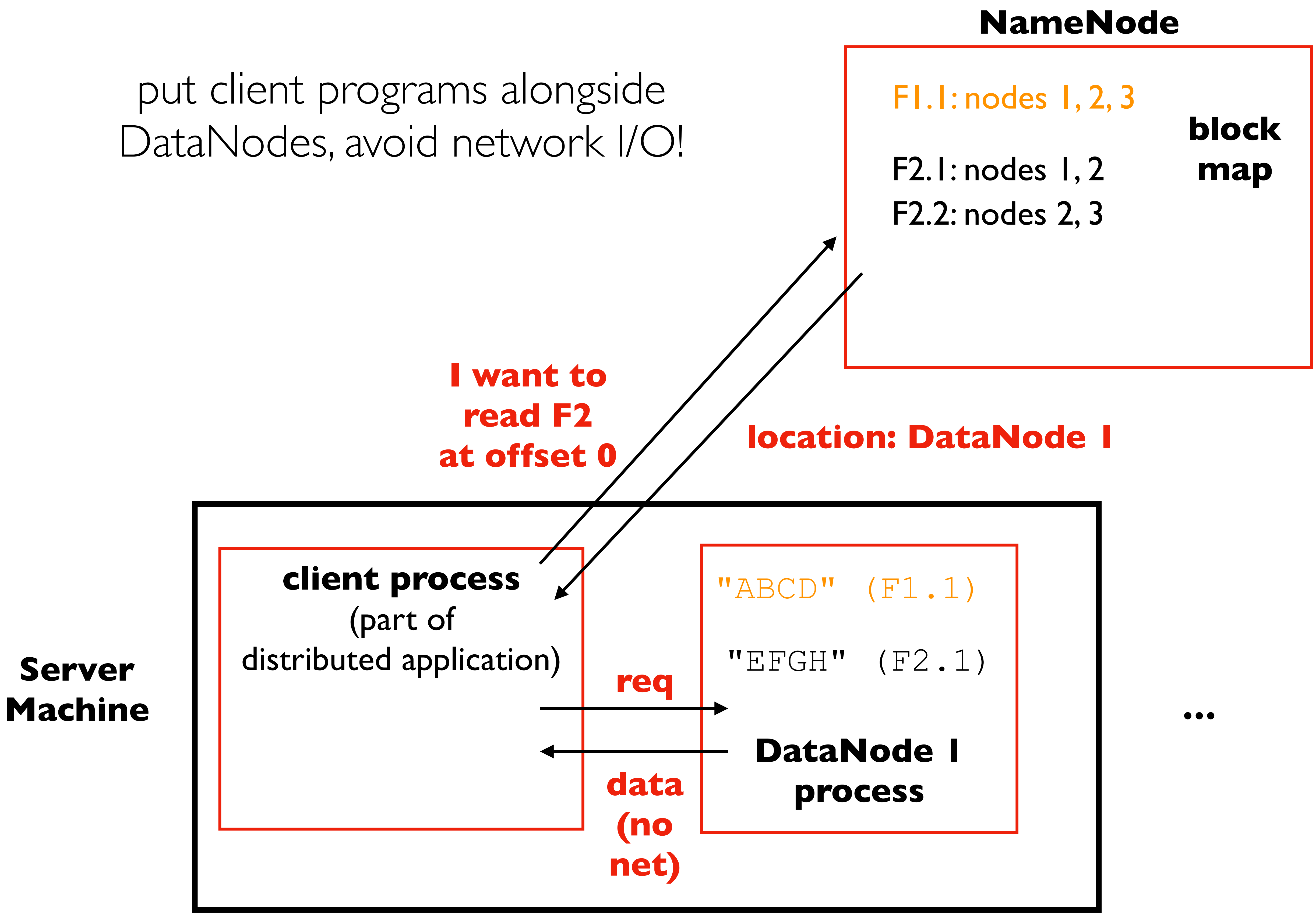
- SELECT, AGGREGATE, HAVING, JOIN

MapReduce is more flexible. (for example, how to do a GROUP BY where one row goes to mutliple groups in SQL?)

Projects like **HiveQL** try to make MapReduce more accessible.

# Review: HDFS Data Locality

put client programs alongside DataNodes, avoid network I/O!

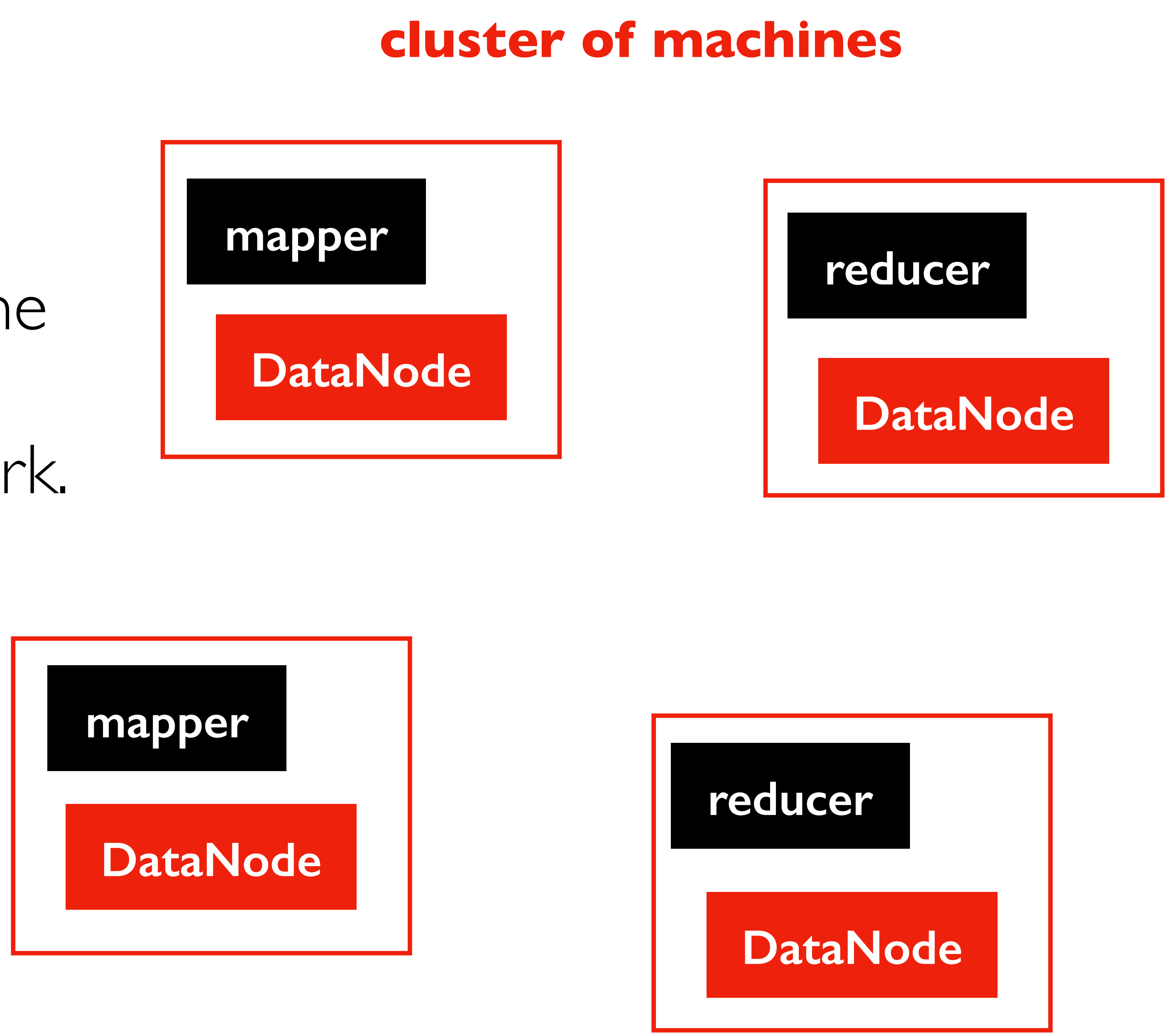


# Example: MapReduce with HDFS

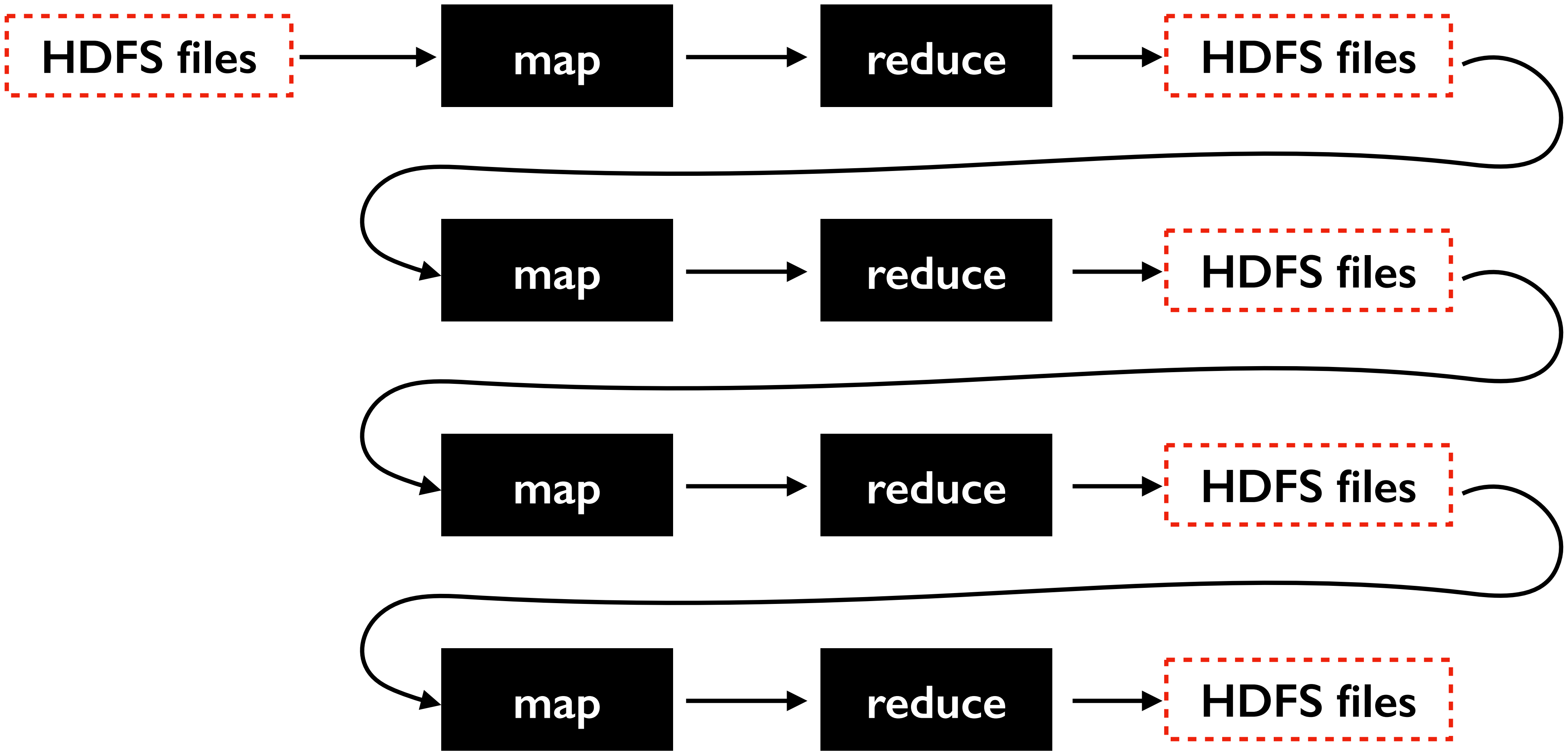
**Run on same machines**

- HDFS DataNodes
- MapReduce executor

Try to run mappers on machine where DataNode has needed data. Uses disk but not network.



# Pipelines: Sequence of MapReduce Jobs




Efficiency: is storing intermediate data in HDFS a good idea?

- replication on data we could re-compute seems wasteful (could set replication to 1x)
- could we sometimes connect output from one stage more directly to the next?
- treating each stage independently prevents optimization tools from improving the whole pipeline

# Outline: MapReduce and Spark

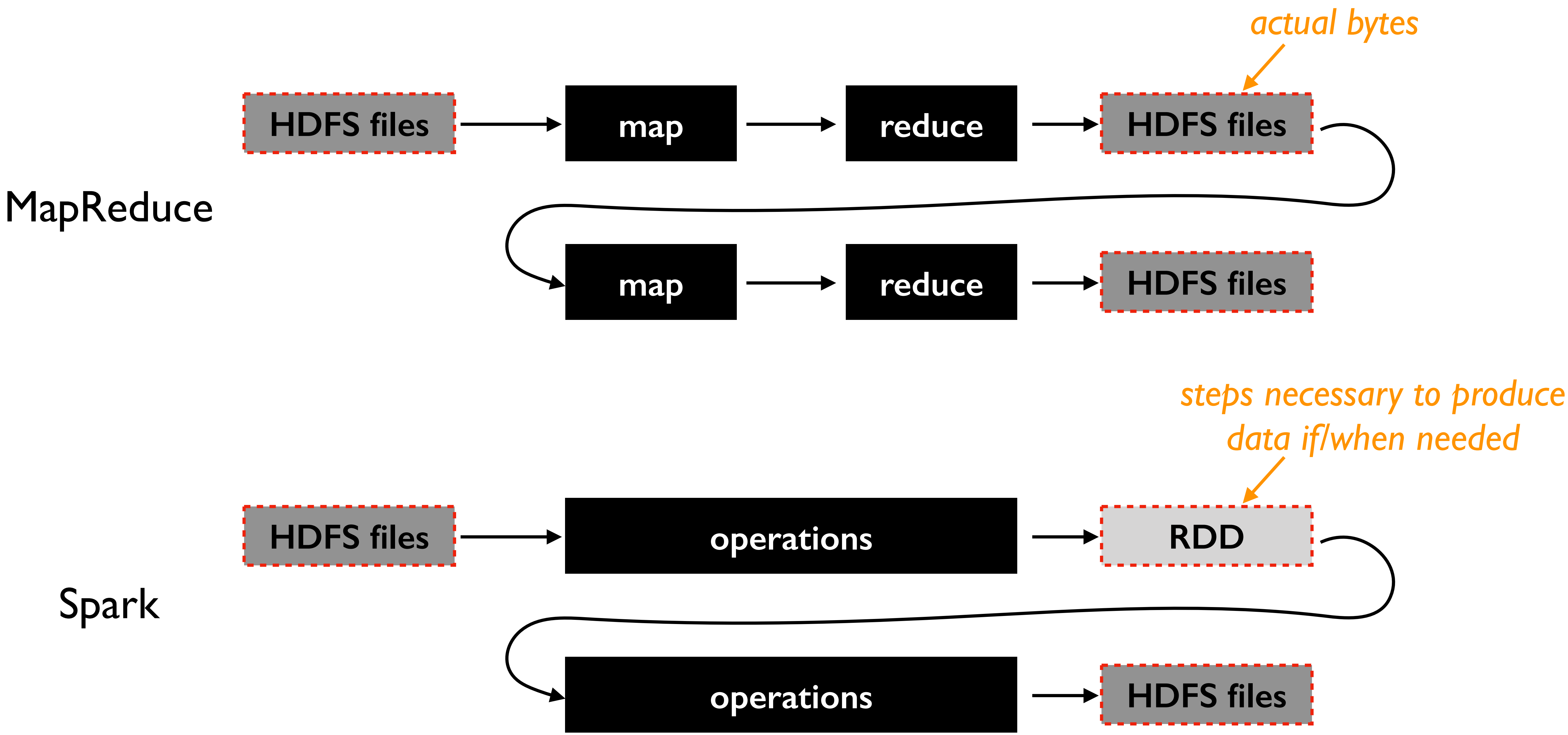
Data Lakes

Hadoop MapReduce

Spark

- Resilient Distributed Datasets (RDDs)
- SQL and DataFrames
- Deployment

# Intermediate Data: MapReduce vs. Spark




Resilient Distributed Datasets (RDD)

- data lineage: record series of operations on other data necessary to obtain results
- lazy evaluation: computation only done when results needed (to write file, make plot, etc.)
- immutability: you can't change an RDD, but you can define a new one in terms of another

# Data Lineage: Transformations and Actions

```
data = [
      ("A", 1),
      ("B", 2),
      ("A", 3),
      ("B", 4)
]
```

```
def mult2(row):
    return (row[0], row[1] * 2)

def onlyA(row):
    return row[0] == "A"
```

goal: get 2 times the second column wherever the first column is "A"

```
table = sc.parallelize(data)
double = table.map(mult2)
doubleA = double.filter(onlyA)
doubleA.collect()
```

```
[('A', 2),
 ('A', 6)]
```

The computation is a sequence of 4 operations. Operations come in two types:

- transformation: create a new RDD (lazy, so no execution yet). Here: parallelize, map, and filter.
- action: perform all operations in the graph to get an actual result. Here: collect.

# Data Lineage: Transformations and Actions

```
data = [
      ("A", 1),
      ("B", 2),
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]
```

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def mult2(row):
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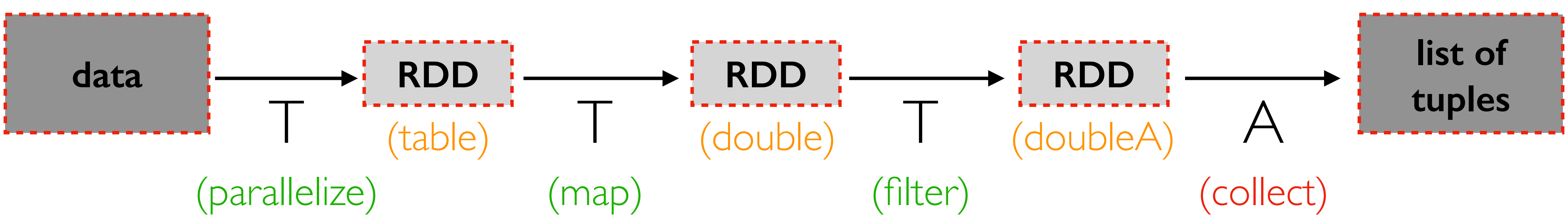


*are there alternative paths you could create from the start to end node?*

# Optimization

Transformation vs. action

- transformation: intermediate results (means to an end)
- action: final results we care about
- this distinction creates opportunities for **optimize**, choosing a more efficient sequence of transformations to reach the same endpoint
- tools need to know what transformations are doing (difficult with Python functions) to automatically optimize

goal: get 2 times the second column wherever the first column is "A"

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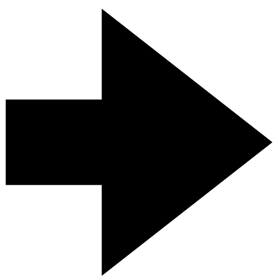
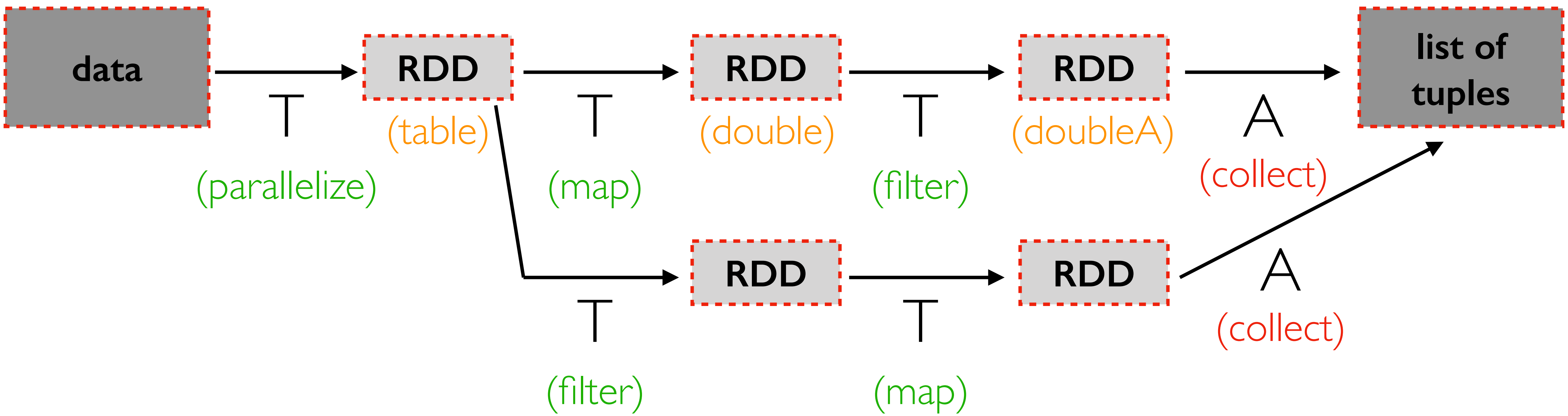
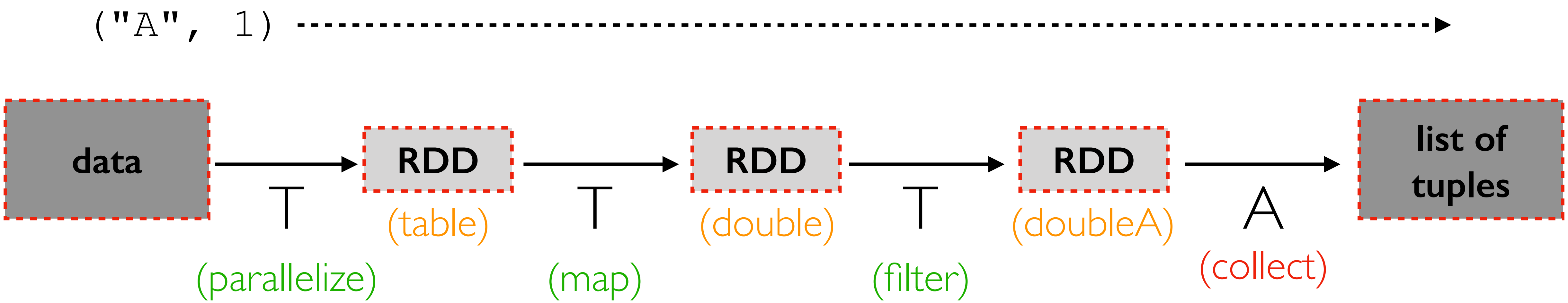


```
[('A', 2),
 ('A', 6)]
```



# Partitions




In what granularity should data flow through the transformations?

- whole dataset: it could all proceed through, one transformation at a time, but might not fit in memory
- row: in this pipeline, nothing prevents each row from passing through independantly, but probably slower than computing in bulk
- partition: Spark users can specify the number of partitions for an RDD

```
sc.parallelize(data, 1)
    data = [
        ("A", 1),
        ("B", 2),
        ("A", 3),
        ("B", 4)
    ]
```

partition

```
sc.parallelize(data, 2)
    data = [
        ("A", 1),
        ("B", 2),
        ("A", 3),
        ("B", 4)
    ]
```

partition

partition

# Tasks

Spark work

- spark code is converted to jobs, which consist of stages, which consist of tasks
- tasks:
  - run on a single CPU core
  - operate on a single partition, which is loaded entirely to memory

**Choosing partition count directly affects number of tasks necessary to do a job.**

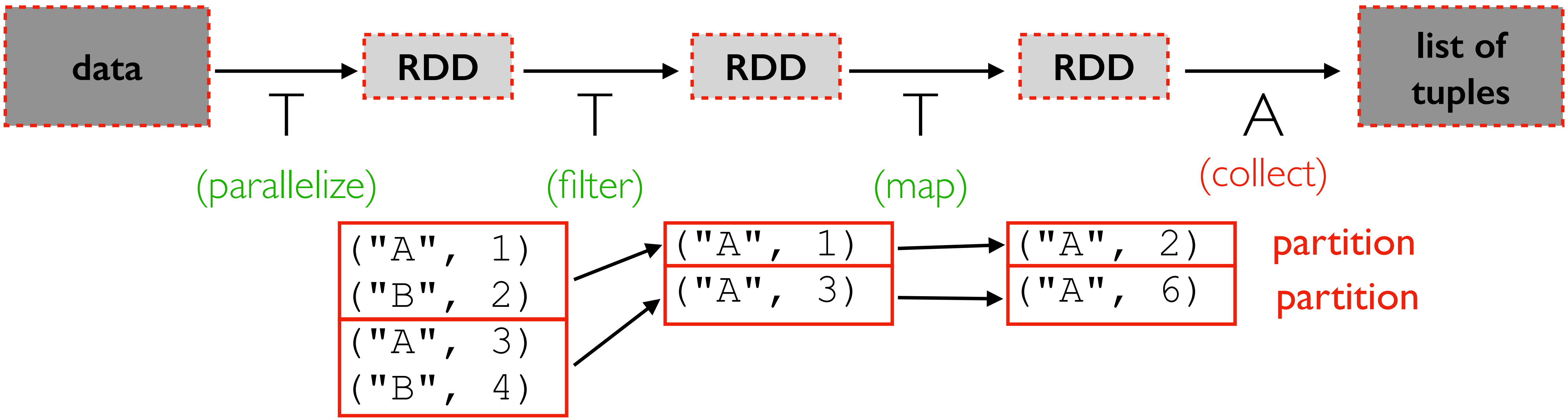
Advantages of larger partitions

- less overhead in starting tasks

Disadvantages of larger partitions

- might not have enough to use all cores that are available
- harder to balance work evenly
- uses more memory per partition at a time (is there enough)?

# Repartitioning




Many operations (like filter and map) output the same number of partitions as they receive

- if the data is growing/shrinking a lot after a transformation, you might want to change the partition count
- rdd.getNumPartitions() # check how many
- rdd2 = rdd.repartition(10) # change how many (might be expensive!)

**Examples:**

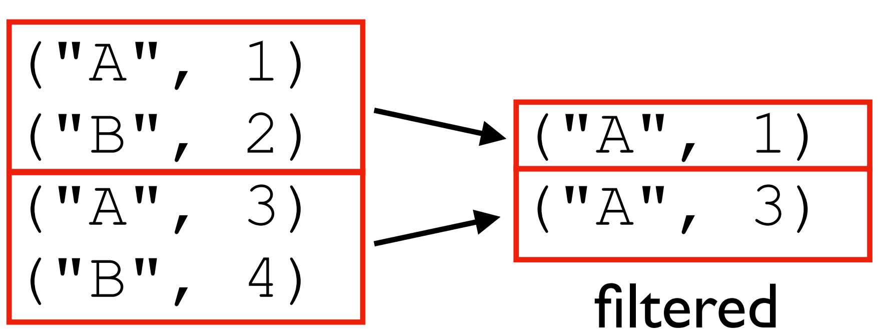
```
table.filter(onlyA).map(mult2).collect()
table.filter(onlyA).repartition(1).map(mult2).collect()
```

# Transformations: Narrow vs. Wide

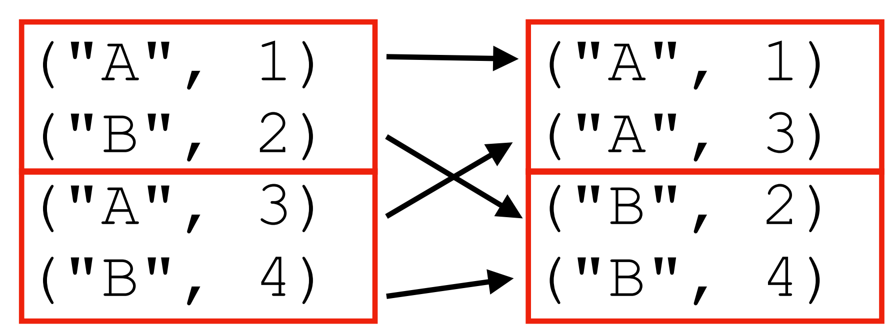
If a transformation creates a child RDD from one or more parent RDDs, and all partitions of parent RDD(s) are used by at most ONE partition of a child RDD, the transformation is "narrow".

Others are *wide* transformations.

```
data = [("A", 1),("B", 2),("A", 3),("B", 4)]
table = sc.parallelize(data, 2)
filtered = table.filter(lambda row: row[0] == "A")
ordered = table.sortBy(lambda row: row[0])
```



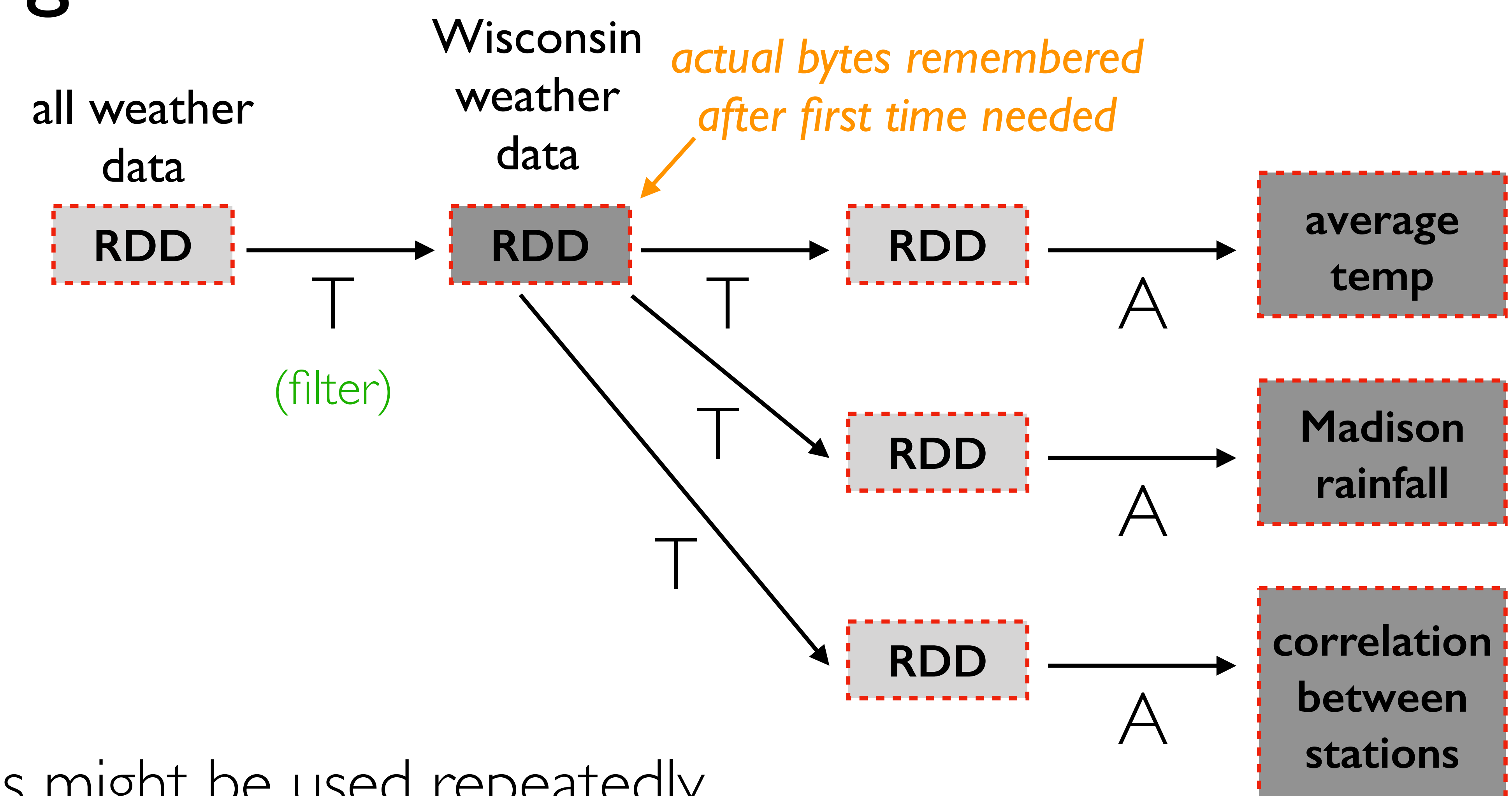

**filtered
(narrow)**




**ordered
(wide)**

Wide transformations often require network resources. Unless all input partitions are on the same machine, some will need to be transferred.

# Caching




Some RDDs might be used repeatedly

- Spark might cache a copy of the computed results
- OR we can tell it to

```
all_weather = ...
wi_weather = all_weather.filter(...)
wi_weather.cache()
...
wi_weather.unpersist() # stop caching
```

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# Spark SQL and DataFrames

## Spark SQL

- builds on RDDs
- write standard queries (ANSI SQL:2003)
- automatic optimization possible because Spark knows what transformations are doing

## DataFrame API

- builds on Spark SQL (so also optimizable)
- DataFrames are immutable because RDDs are immutable
- DataFrames aren't materialized in memory by default. Contents are computed as needed in parallel across many workers.

# DataFrames: Pandas vs. Spark

```
pandas_df = pd.DataFrame({"x": [1,2,3]})
```

| | x |
|---|---|
| 0 | 1 |
| 1 | 2 |
| 2 | 3 |

```
# pandas DFs are mutable
pandas_df["y"] = pandas_df["x"] ** 2
```

| | x | y |
|---|---|---|
| 0 | 1 | 1 |
| 1 | 2 | 4 |
| 2 | 3 | 9 |

```
spark_df = spark.createDataFrame(pandas_df)

# could convert back:
# spark_df2.toPandas()

# cannot add column to immutable Spark DF
# can only create a new DF
spark_df2 = spark_df.withColumn("y", col("x") ** 2)
```

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# Deployment

| Mode | Spark driver | Spark executor | Cluster manager |
|---|---|---|---|
| Local | Runs on a single JVM, like a laptop or single node | Runs on the same JVM as the driver | Runs on the same host |
| Standalone | Can run on any node in the cluster | Each node in the cluster will launch its own | Can be allocated arbitrarily to any host in the cluster |
| YARN (client) | Runs on a client, not part of the cluster | YARN's NodeManager's container | YARN's Resource Manager works with YARN's Application |
| YARN (cluster) | Runs with the YARN Application Master | Same as YARN client mode | Same as YARN client mode |
| Kubernetes | Runs in a Kubernetes pod | Each worker runs within its own pod | Kubernetes Master |

Table 1-1 from *Learning Spark* book

# Deployment

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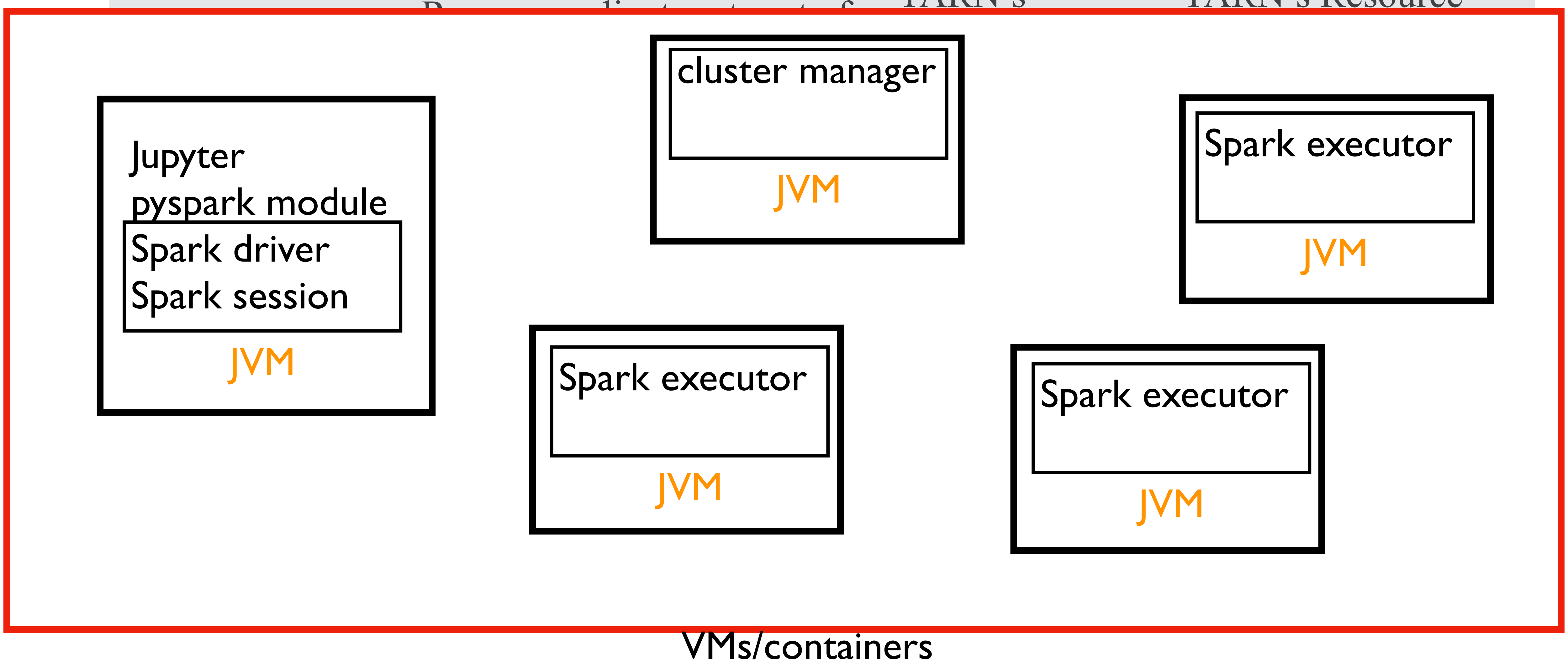
| | [illegible] | YARN's | YARN's Resource |



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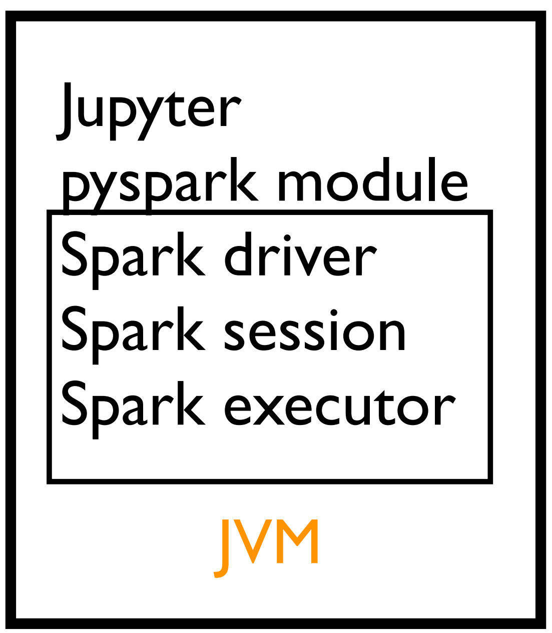
| | | YARN's | YARN's Resource |




this mode is fine for testing/development, but misses the benefits of distributed computing

VMs/containers