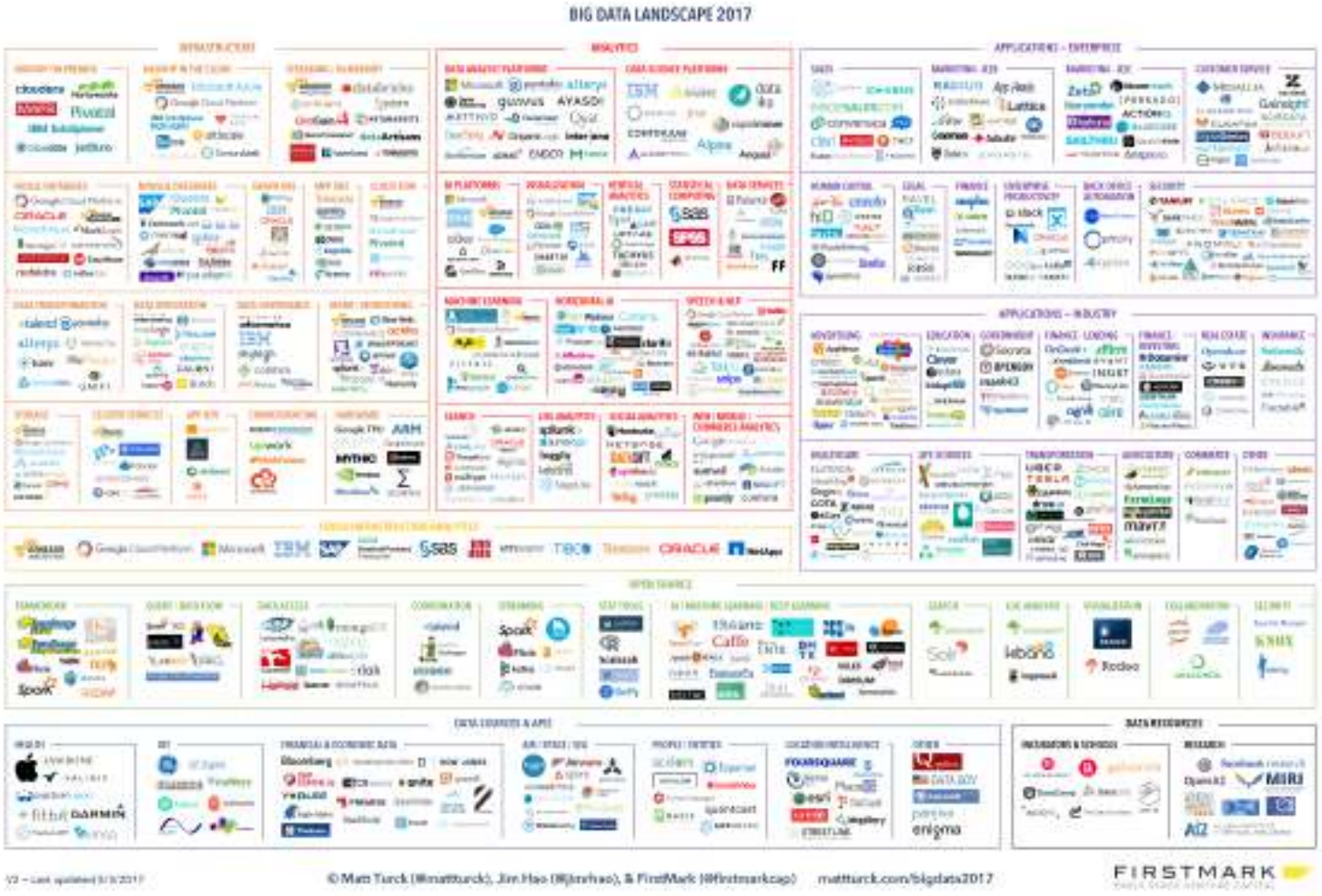
Cloud Computing et informatique distribuée
Cours : Map Reduce

Francesca Bugiotti

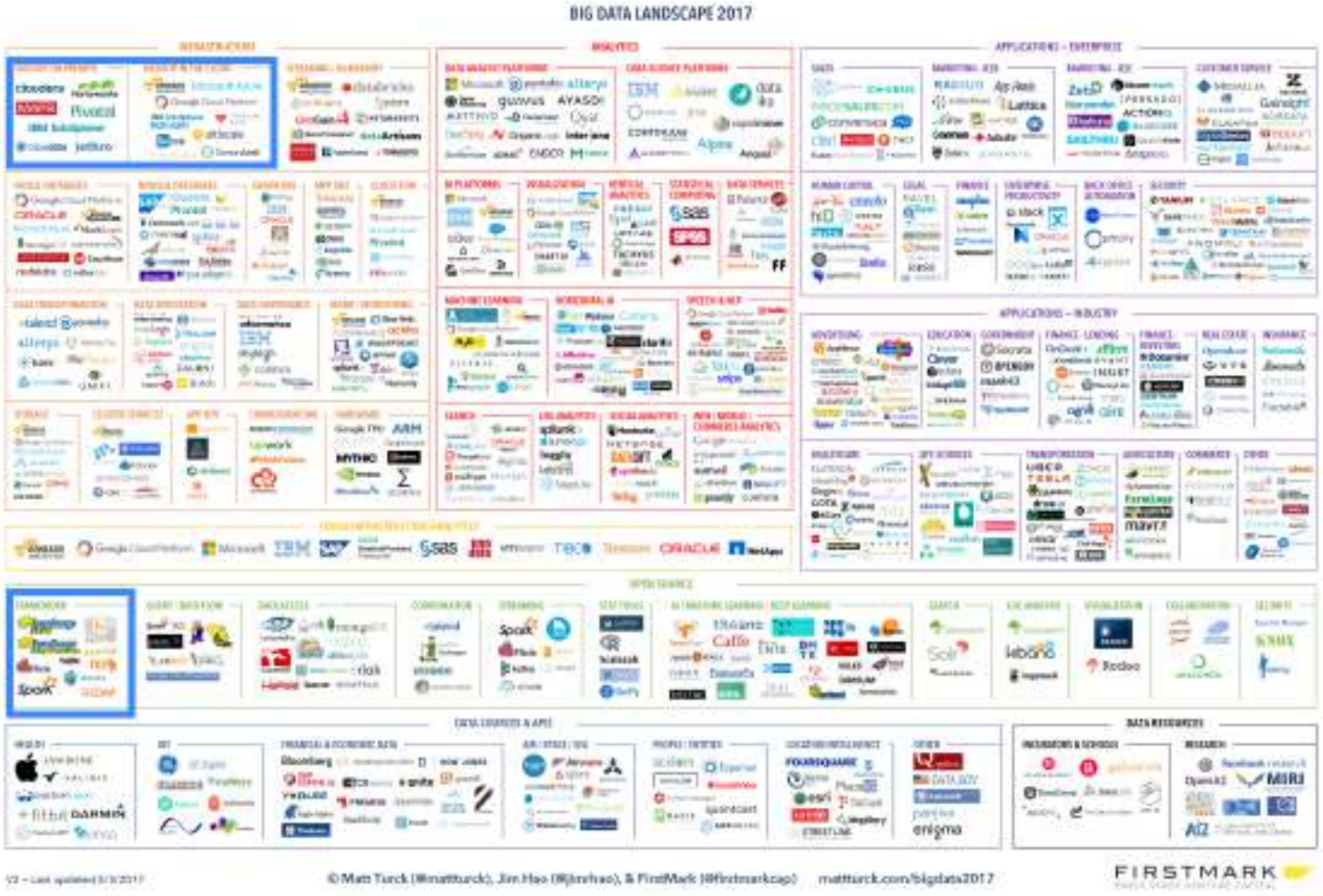
CentraleSupélec

May 7, 2020

Technologies



Technologies



Objectives

- The MapReduce programming model

File System

A File System defines structure and logic rules used to manage the groups of information and their names in a storage device

Long-term information storage

- Providing access for processes
- Storing large amount of information

File System

You have your 2TB disk:

If the space is not sufficient?

- A bigger disk

- An external hard drive

Issues: copy data, transfer data, maintain data, etc.

Many devices implies many disks

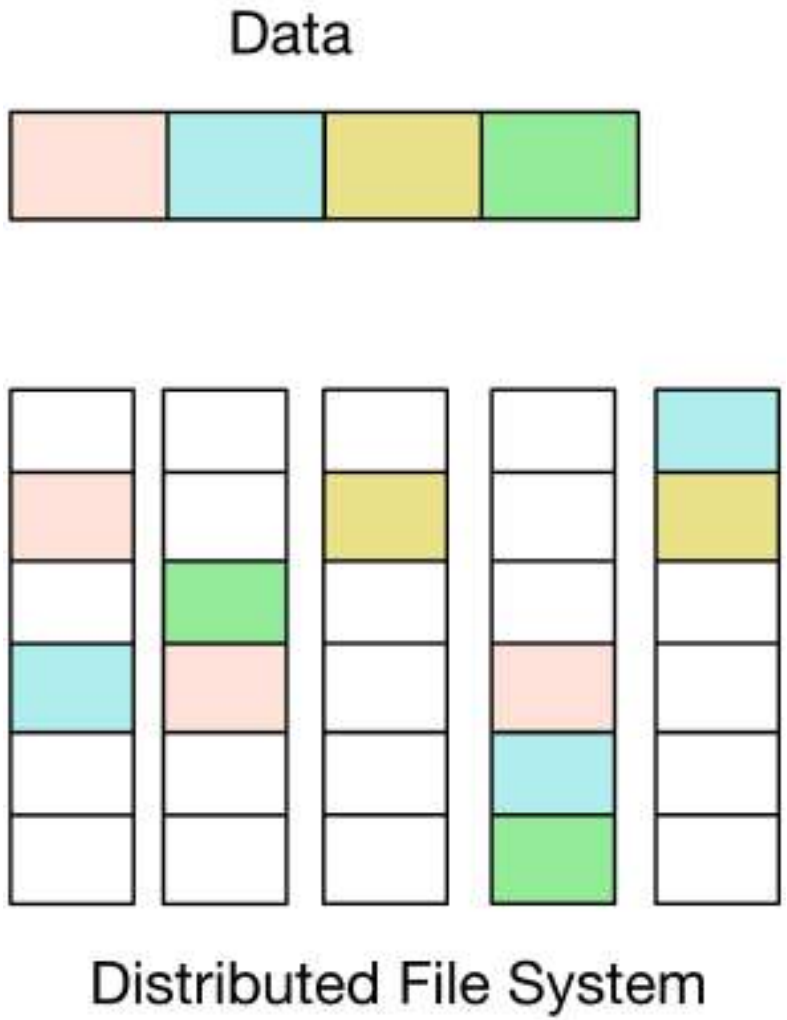
- From two PC

- To many heterogeneous devices

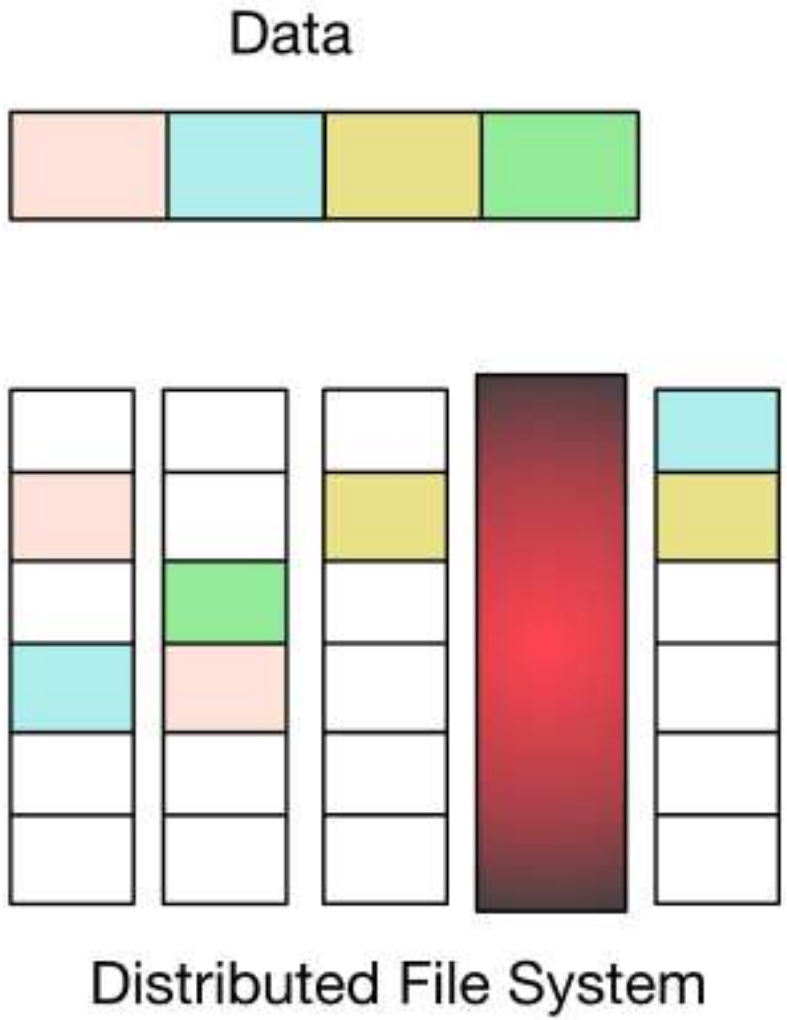
Distributed File System

- Data distributed across the cluster
- Data possibly replicated for fault tolerance

Data Distribution



Data Distribution



Fault tolerance

Fault tolerance: the ability to restart the computation given a failure

- Redundant data storage
- Restart of failed individual parallel jobs

Restart failed jobs

Suppose that we have a set of jobs that collaborate in order to solve a problem and belong to a main process

What can be done if one (or more) fails?

- Start all the process from the beginning
- Record checkpoint information so that you can restart just some jobs if they fail
- Make the jobs independent and restart just the failed jobs

Big Data

Big Data processing includes the features

- Multiple data types
- Large datasets

Big Data

Large volumes of data: splitting data

- Partitioning and placement of data in and out of computer memory
- Model to synchronize the datasets
- Replications and recovery of files

Large volumes of data: access data

- Fast data access
- Move the computation to data
- Scheduling of many parallel tasks
- Support data variety

Programming model

A programming model for Big Data should handle all these features

- Splitting large volumes of data
- Abstraction over a distributed file system
  - Handle replications
  - Synchronize datasets
- Schedule parallel tasks
- Recover from failures
- Handle different data types
- Move the computation near the data

Starting from Pasta

You come back from work on a Friday evening

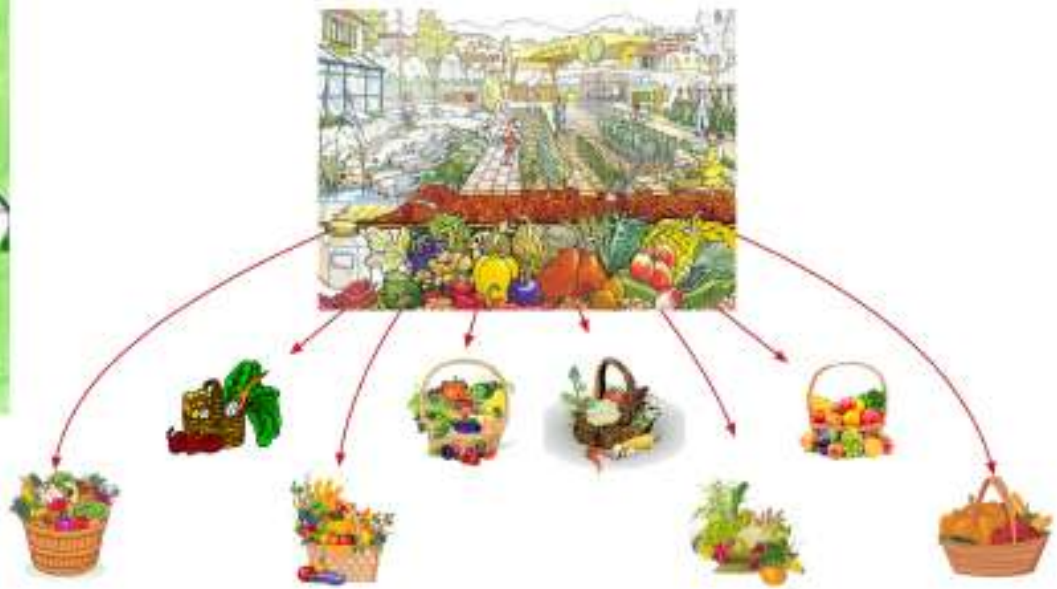
You realize that you have forgotten that you have organized a party at your place that evening

What can be done?

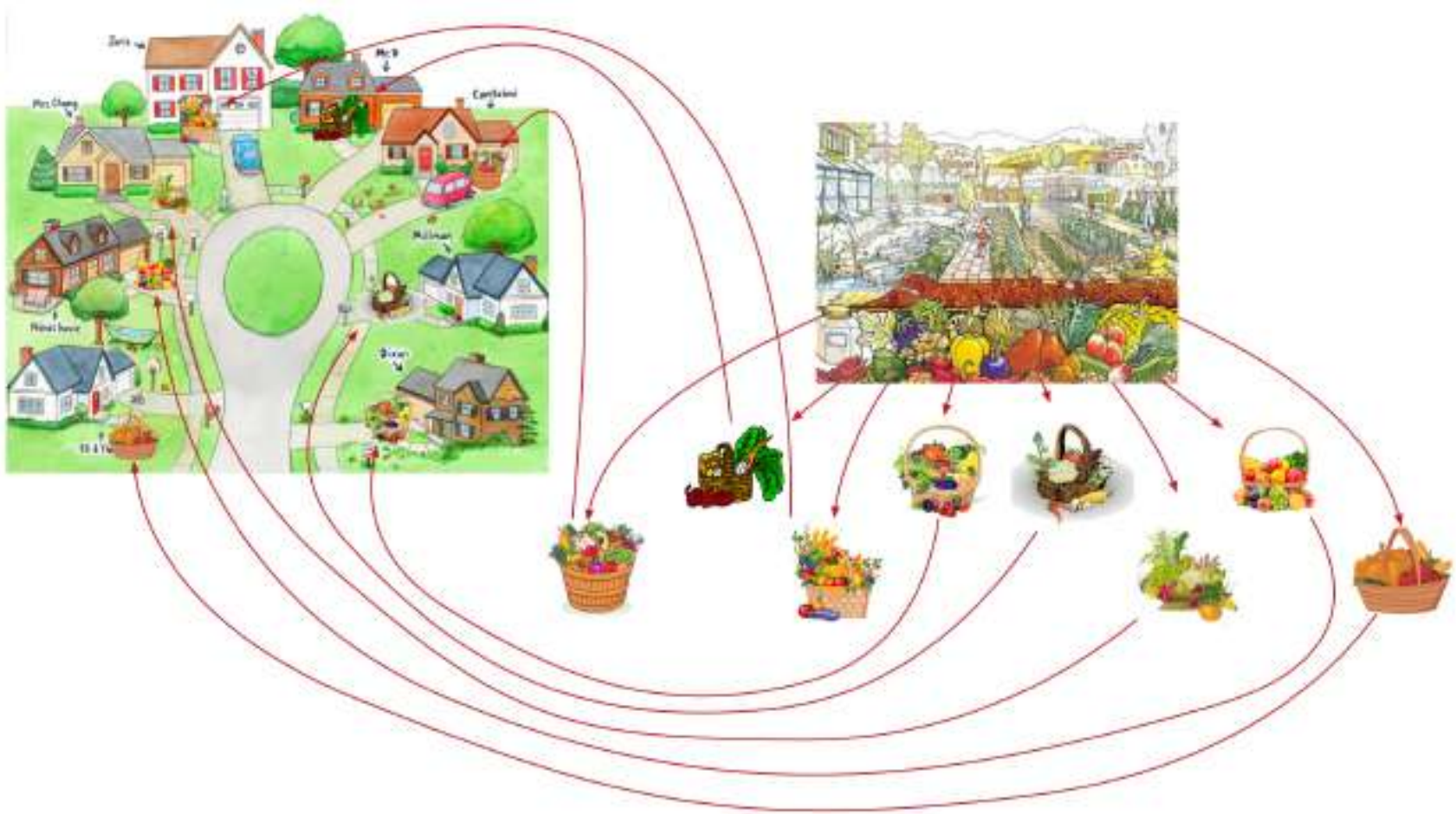
Italian solution: prepare a pasta party!

Pasta Party

Pasta Party



Pasta Party



Pasta Party

Pasta Party

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Pasta Party

A Programming model: MapReduce

- Splitting large volumes of data
- Abstraction over a distributed file system
  - Handle replications
  - Synchronize datasets
- Schedule parallel tasks
- Recover from failures
- Handle different data types
- Move the computation near the data

Implemented by a large number of frameworks including Hadoop

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A Programming model: MapReduce

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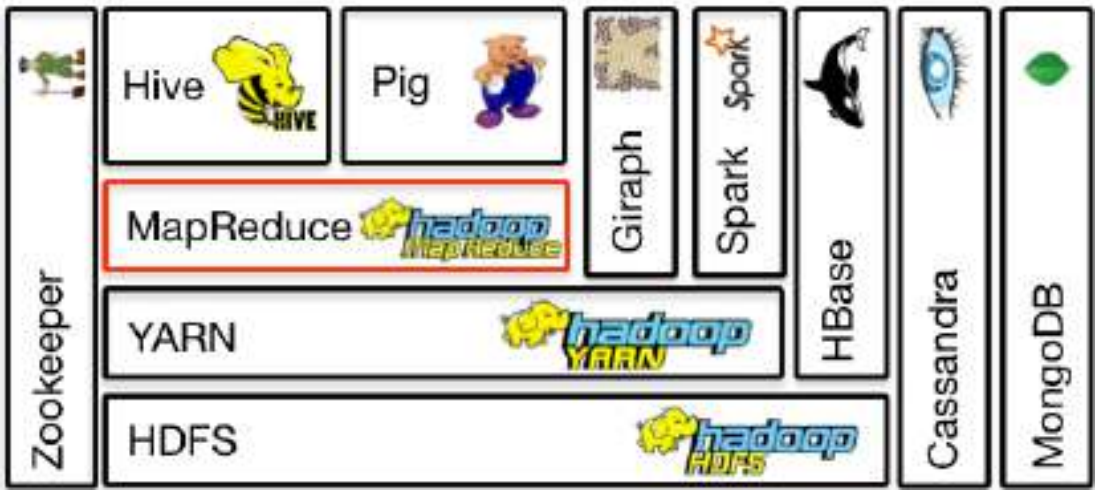
MapReduce



Hadoop MapReduce [1]

With MapReduce you must create: map tasks, reduce tasks and run them

Past

Traditional parallel programming

- Locks
- Semaphores
- Monitors

An incorrect usage:

- Incorrect programs
- Performance impact

Impact

Map

takes as input an object with a key (k,v) and returns a bunch of key-value pairs:

$$(k_1,v1),(k_2,v_2), \ldots ,(k_n,v_n)$$

Shuffle

The framework collects all the pairs with the same key k and associates with k all the values for k:

$$(k,[v_1, \ldots ,vn])$$

Reduce

takes as input a key and a list of values $(k,[v_1, \ldots ,v_n])$ and combine them somehow

MapReduce programming

Programmers specify two functions:

- map $(k_1, v_1) \rightarrow [(k_2, v_2)]$
- reduce $(k_1, [v_1]) \rightarrow [(k_2, v_2)]$

where (k, v) denotes a (key, value) pair and [...] denotes a list

MapReduce program

A MapReduce program, referred to as a job, consists of:

- Code for Map and a code for Reduce packaged together
- Configuration parameters (where the input lies, where the output should be stored)
- The input, stored on the underlying distributed file system
- Each MapReduce job is divided by the system into smaller units called tasks
  - Map tasks
  - Reduce tasks
- Input and output of MapReduce jobs are stored on the underlying distributed file system

MapReduce execution process I

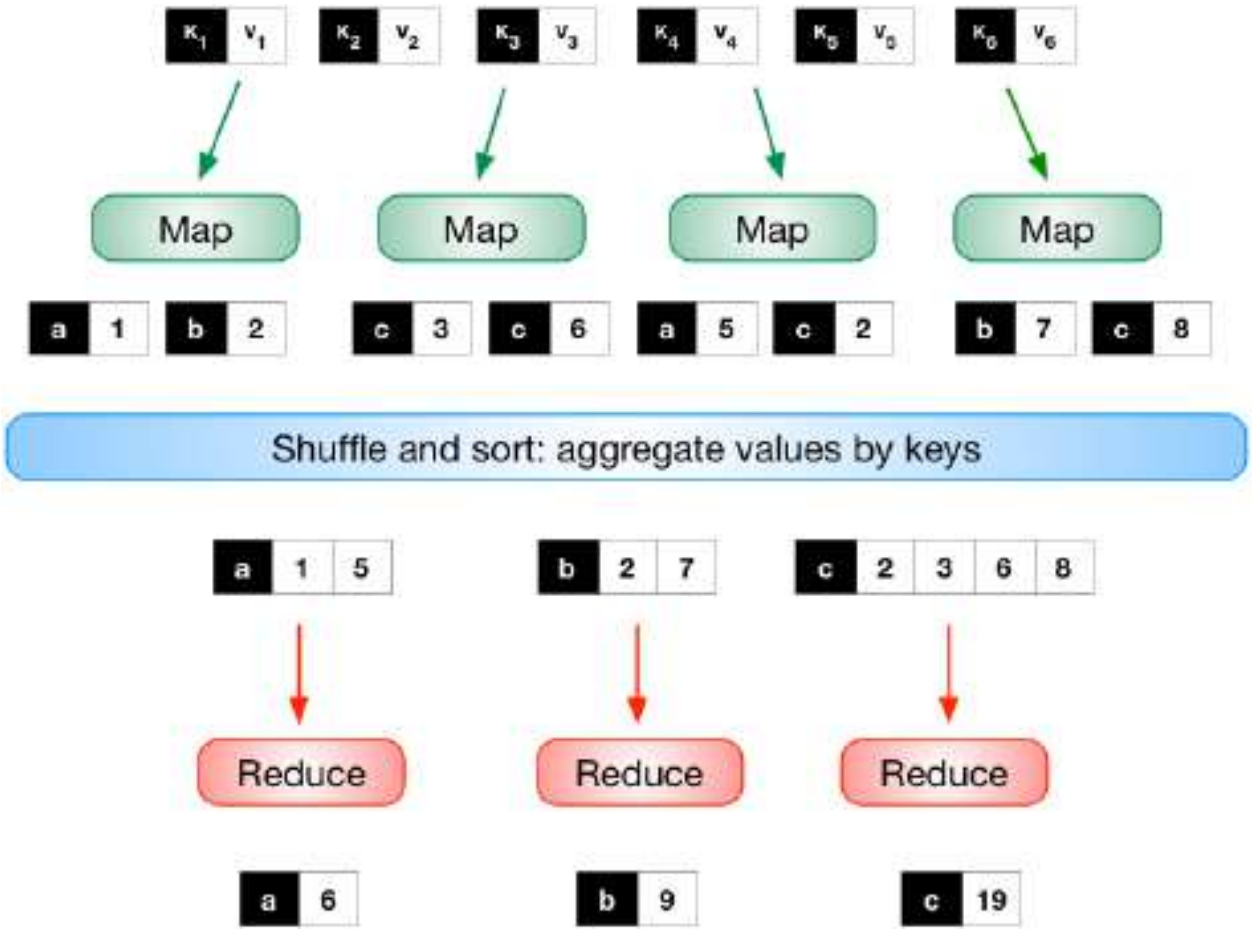
1. Some Map tasks are given each one or more chunks of data
2. Each Map task turns the chunk into a sequence of key-value pairs
    - The way key-value pairs are produced is determined by the code written by the user for the Map function
3. The key-value pairs from each Map task are collected by a master controller and sorted and grouped by key (Shuffle and Sort)
4. The keys are divided among all the Reduce tasks, so all key-value pairs with the same key wind up at the same Reduce task
5. The Reduce tasks work on one key at a time, and combine all the values associated with that key in some way

MapReduce execution process II

- The way values are combined is determined by the code written by the user for the Reduce function

6. Output: key-value pairs from each reducer are written persistently back onto the distributed file system
7. The output ends up in r files, where r is the number of reducers
   - The r files often serve as input to yet another MapReduce job

MapReduce


Map
Map
Map
Map
Shuffle and sort: aggregate values by keys
Reduce
Reduce
Reduce

Counting words I

Problem:

counting the number of occurrences of each word in a collection of documents

- Input: a repository of documents, each document is an element
- Map: reads a document and emits a sequence of key-value pairs where keys are words of the documents and values are equal to 1:

$$(w_1, 1), (w_2, 1), \ldots , (w_n, 1)$$

- Shuffle: groups by key and generates pairs of the form

$$(w_1, [1, 1, \ldots , 1]) , \ldots , (w_n, [1, 1, \ldots , 1])$$

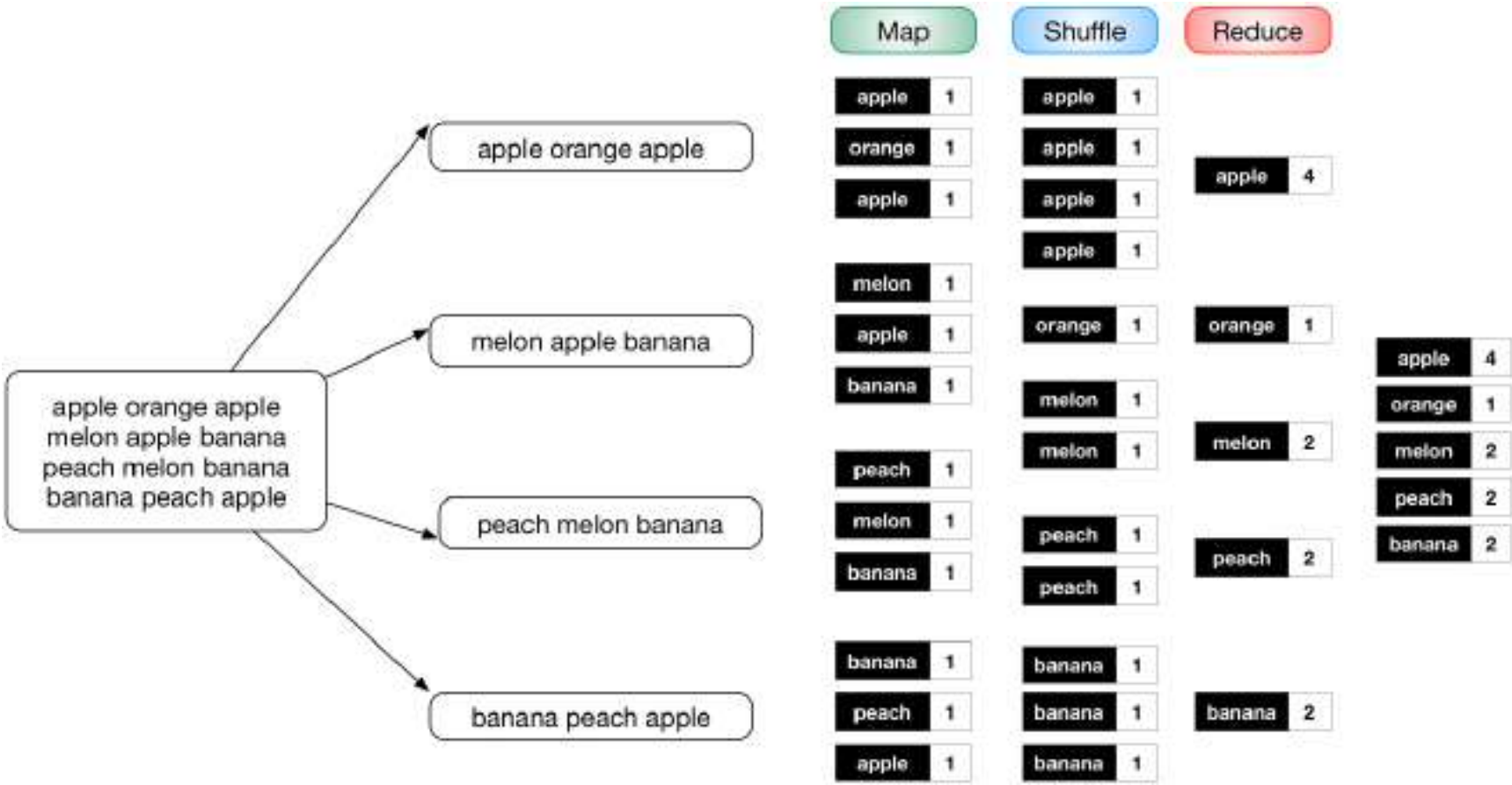
Counting words II

- Reduce: adds up all the values and emits:

$$(w_1, k) , \ldots , (w_n, l)$$

- Output: (w,m) pairs, where w is a word that appears at least once among all the input documents and m is the total number of occurrences of w among all those documents

MapReduce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orange 1
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melon 1
peach 1
peach 1
banana 1
banana 1
banana 1
apple 4
orange 1
melon 2
peach 2
banana 2
apple 4
orange 1
melon 2
peach 2
banana 2

Implementation - pseudocode

```
Map(String docID, String text):
    for each word w in text:
        Emit(w, 1);

Reduce(String term, counts[]):
   int sum = 0;
   for each c in counts:
       sum += c;
   Emit(term, sum);
```

Implementation Python

```
for line in sys.stdin:
    line = line.strip()
    words = line.split()
    for word in words:
        print '%s\t%s' % (word, 1)
```

Implementation Python

```
current_word = None
current_count = 0
word = None
for line in sys.stdin:
    line = line.strip()
    word, count = line.split('\t', 1)
    try:
        count = int(count)
    except ValueError:
        continue
    if current_word == word:
        current_count += count
    else:
        if current_word:
            print '%s\t%s' % (currentword, currentcount)
        currentcount = count
        currentword = word
if currentword == word:
    print '%s\t%s' % (currentword, currentcount)
```

References I


Hadoop Map Reduce.
http://hadoop.apache.org/docs/current/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html.
Accessed 2016.

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$$(w_1, 1), (w_2, 1), \ldots , (w_n, 1)$$

- Shuffle: groups by key and generates pairs of the form

$$(w_1, [1, 1, \ldots , 1]) , \ldots , (w_n, [1, 1, \ldots , 1])$$

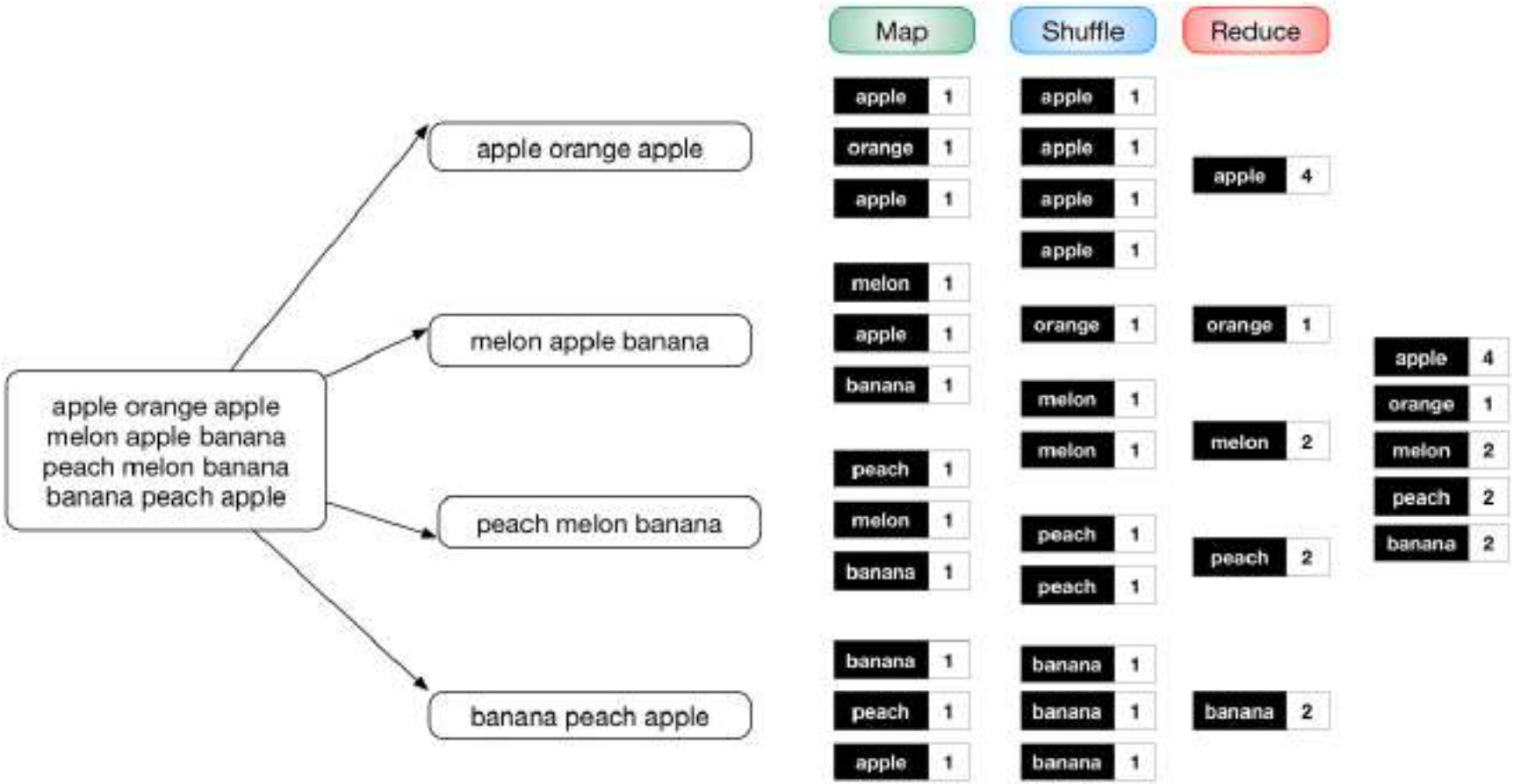
Counting words II

- Reduce: adds up all the values and emits:

$$(w_1, k) , \ldots , (w_n, l)$$

- Output: (w,m) pairs, where w is a word that appears at least once among all the input documents and m is the total number of occurrences of w among all those documents

MapReduce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melon 1
peach 1
peach 1
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        currentcount = count
        currentword = word
if currentword == word:
    print '%s\t%s' % (currentword, currentcount)
```

Counting words I

Problem:

Counting how many times a word appears in the documents

- q1: is it necessary to emit a key-value?
- q2: what about the reduce?
- q3: the reduce operation runs on how many nodes of a distributed environment?

Combiners

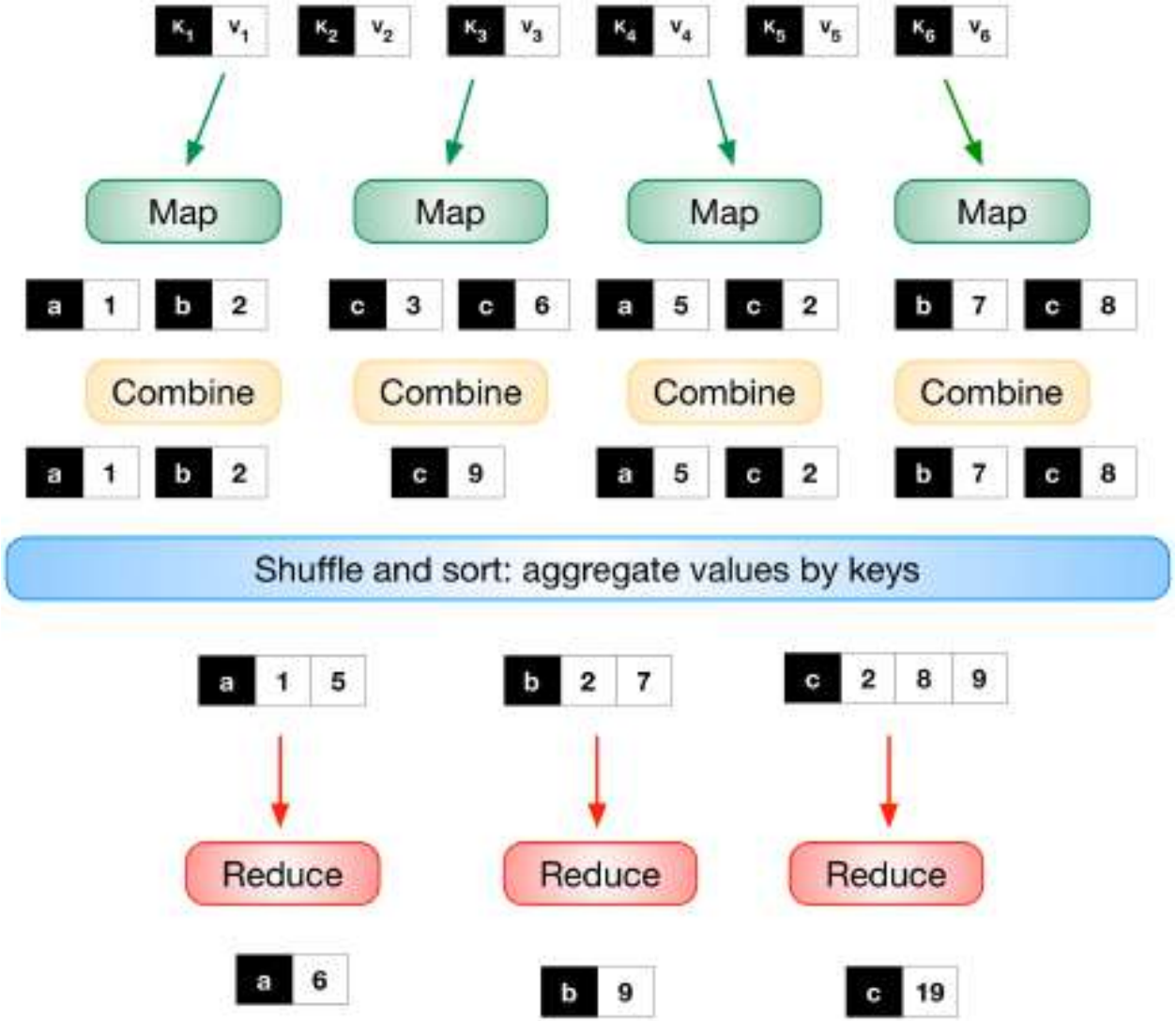
When the Reduce function is associative and commutative, we can push some of what the reducers do to the Map tasks

- In this case we also apply a combiner to the Map function
- In many cases the same function can be used for combining as the final reduction
- Shuffle and sort is still necessary!

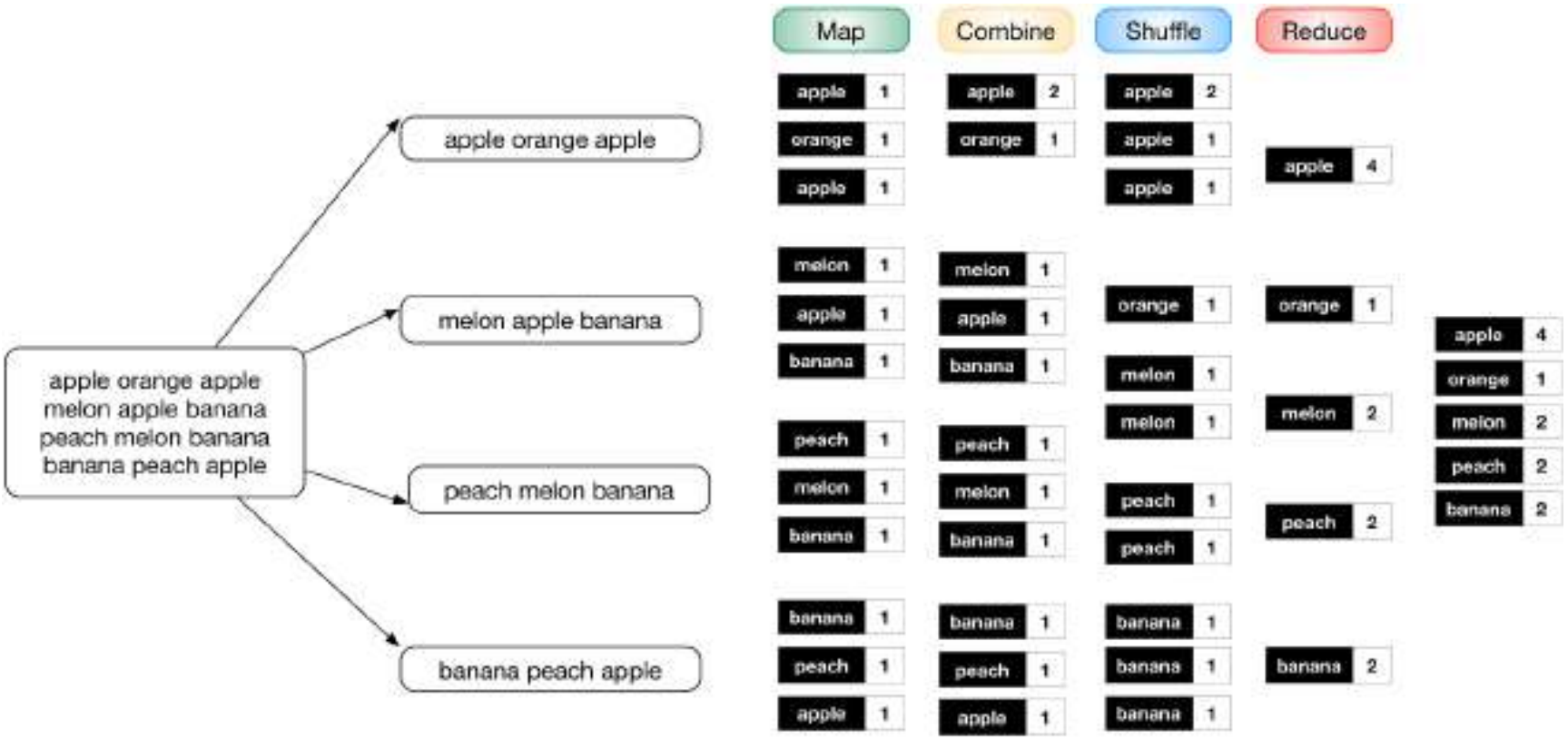
Advantages:

- It reduces the amount of intermediate data
- It reduces the network traffic

MapReduce


K1 V1
K2 V2
K3 V3
K4 V4
K5 V5
K6 V6
Map
Map
Map
Map
a 1
b 2
c 3
c 6
a 5
c 2
b 7
c 8
Combine
Combine
Combine
Combine
a 1
b 2
c 9
a 5
c 2
b 7
c 8
Shuffle and sort: aggregate values by keys
a 1 5
b 2 7
c 2 8 9
Reduce
Reduce
Reduce
a 6
b 9
c 19

MapReduce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peach 1
apple 1
apple 2
orange 1
melon 1
apple 1
banana 1
peach 1
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banana 1
peach 1
apple 1
apple 2
apple 1
apple 1
orange 1
melon 1
melon 1
peach 1
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banana 1
banana 1
banana 1
apple 4
orange 1
melon 2
peach 2
banana 2
apple 4
orange 1
melon 2
peach 2
banana 2

Counting words with combiners I

Problem:

counting the number of occurrences for each word in a collection of documents

- Input: a repository of documents, each document is an element
- Map: reads a document and emits a sequence of key-value pairs where keys are words of the documents and values are equal to 1:

$$(w_1, 1), \ldots, (w_n, 1)$$

- Combiner: groups by key, adds up all the values and emits:

$$(w_1, i), \ldots, (w_n, j)$$

- Shuffle: groups by key and generates pairs of the form

Counting words with combiners II

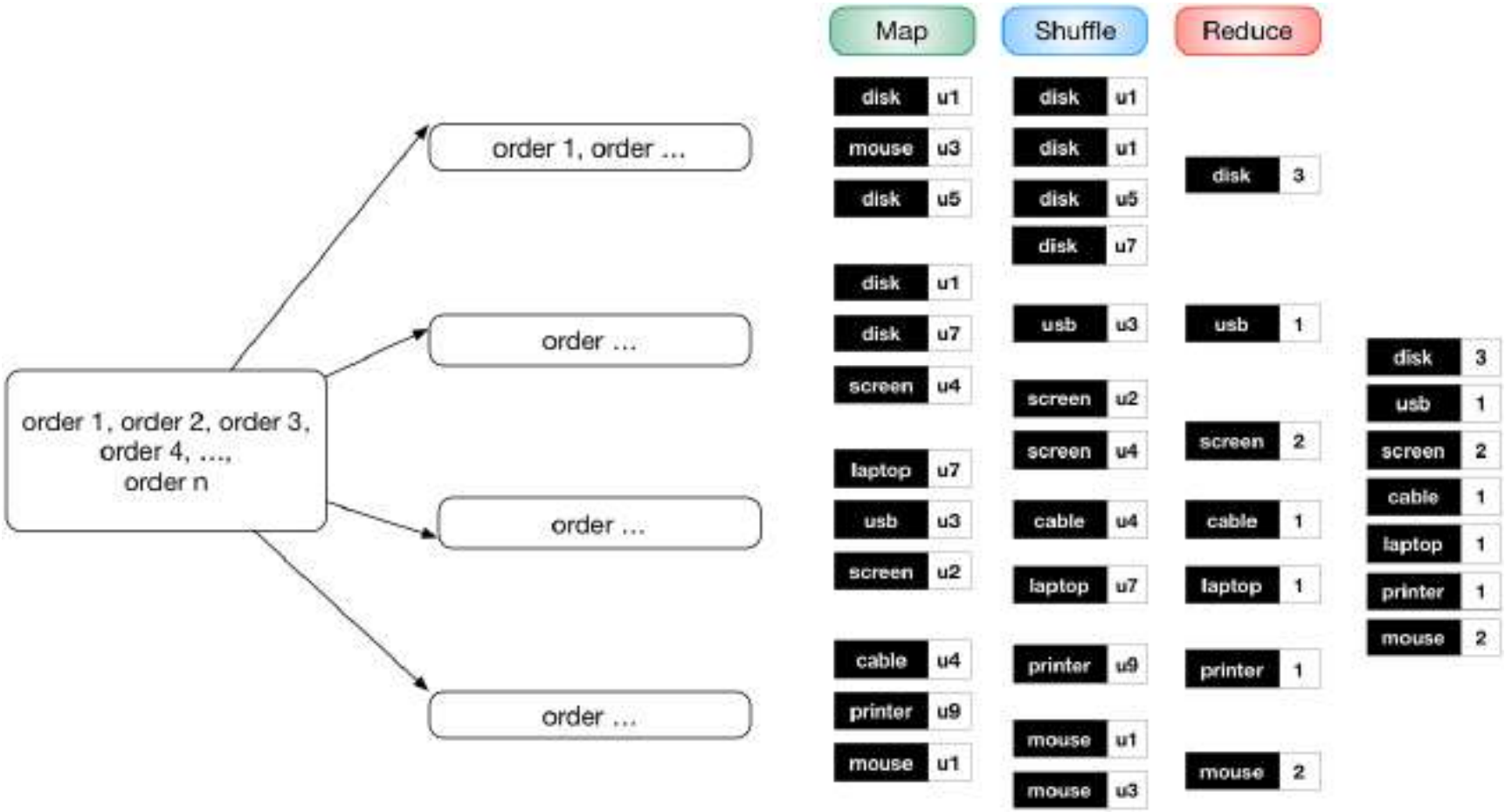
$$(w_1, [1, 1, \ldots, 1]) , \ldots , (w_n, [1, 1, \ldots, 1])$$

- Reduce: adds up all the values and emits:

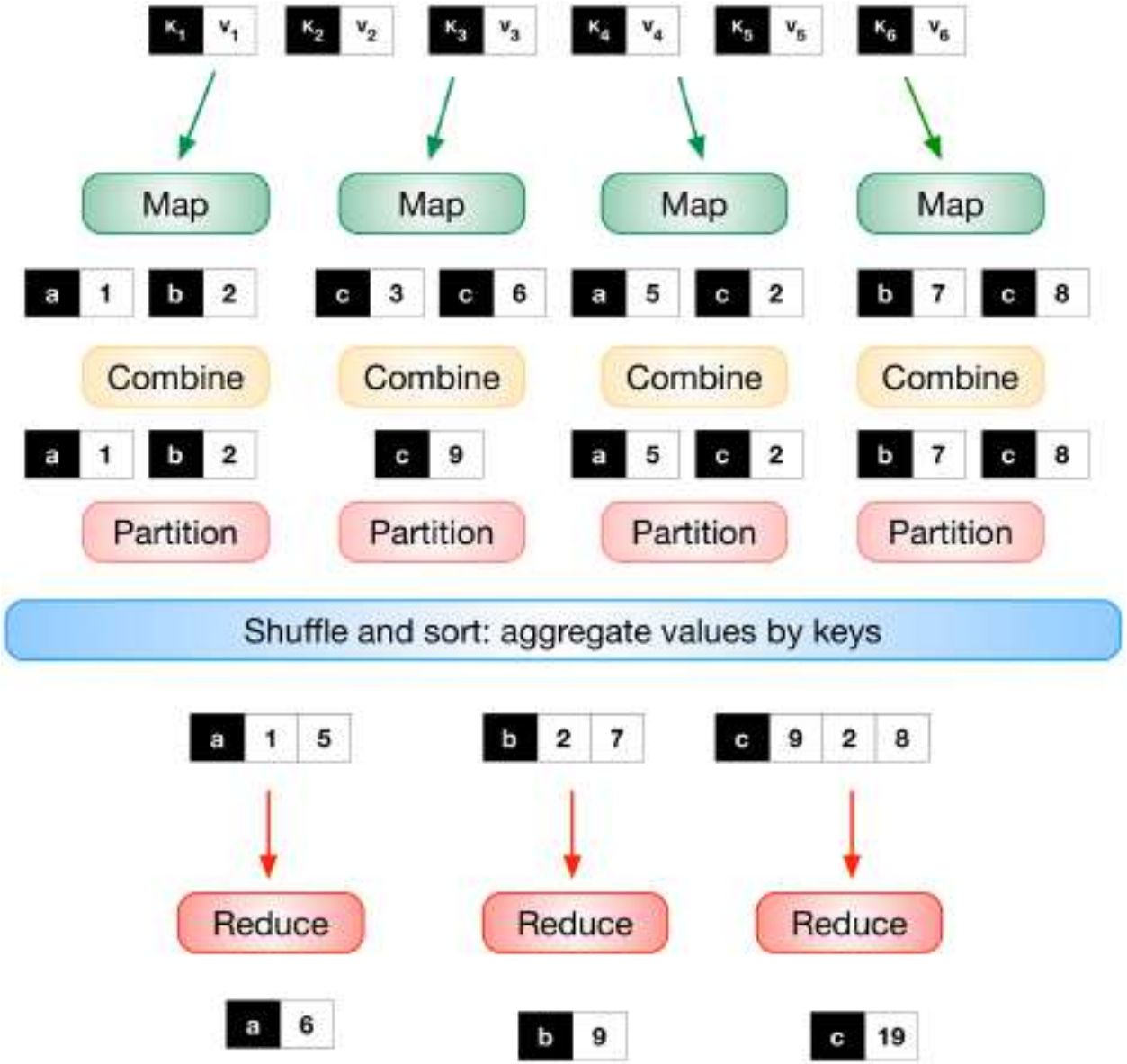
$$(w_1, k) , \ldots , (w_n, l)$$

- Output: (w,m) pairs, where w is a word that appears at least once among all the input documents and m is the total number of occurrences of w among all those documents

Different combiners and reducers



Different combiners and reducers



Partitioner

- divides up the intermediate key space
- assigns intermediate key-value pairs to reducers
- n partitions and n reducers

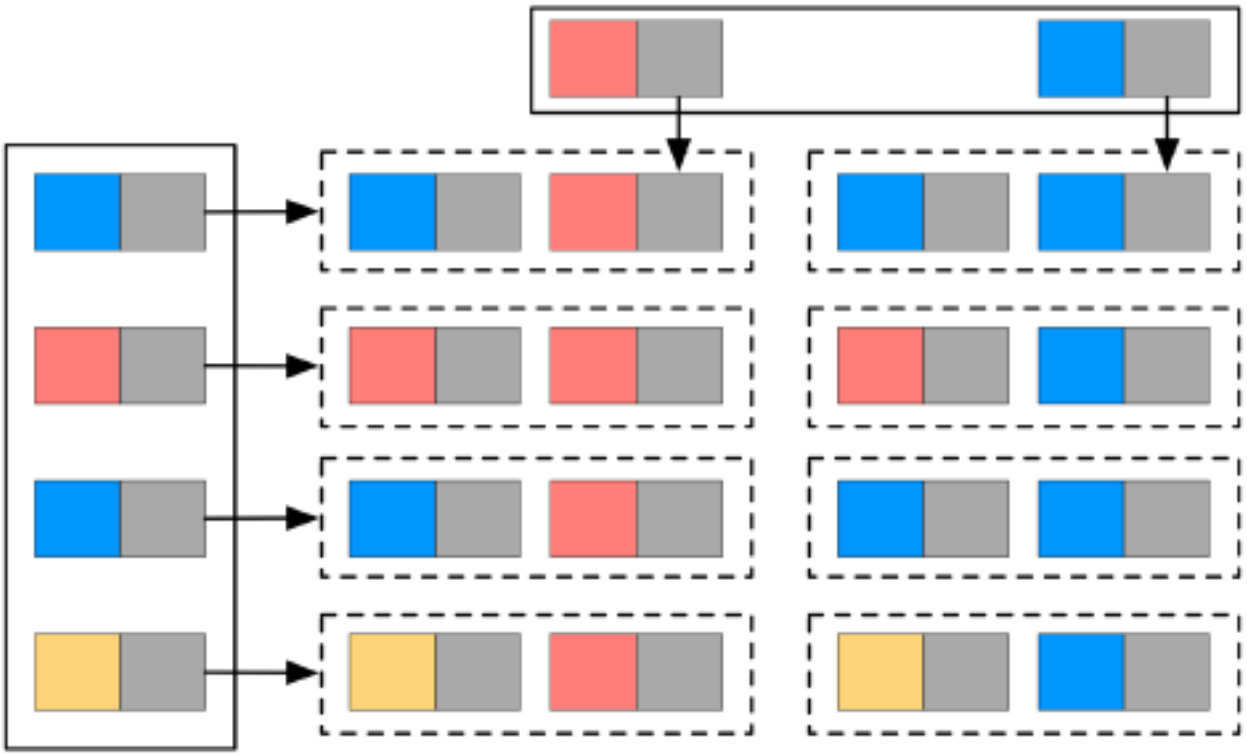
- Assigns approximately the same number of keys to each reducer
- Considers the key and ignores the value
  - Word frequency in inverted indexes

More operations

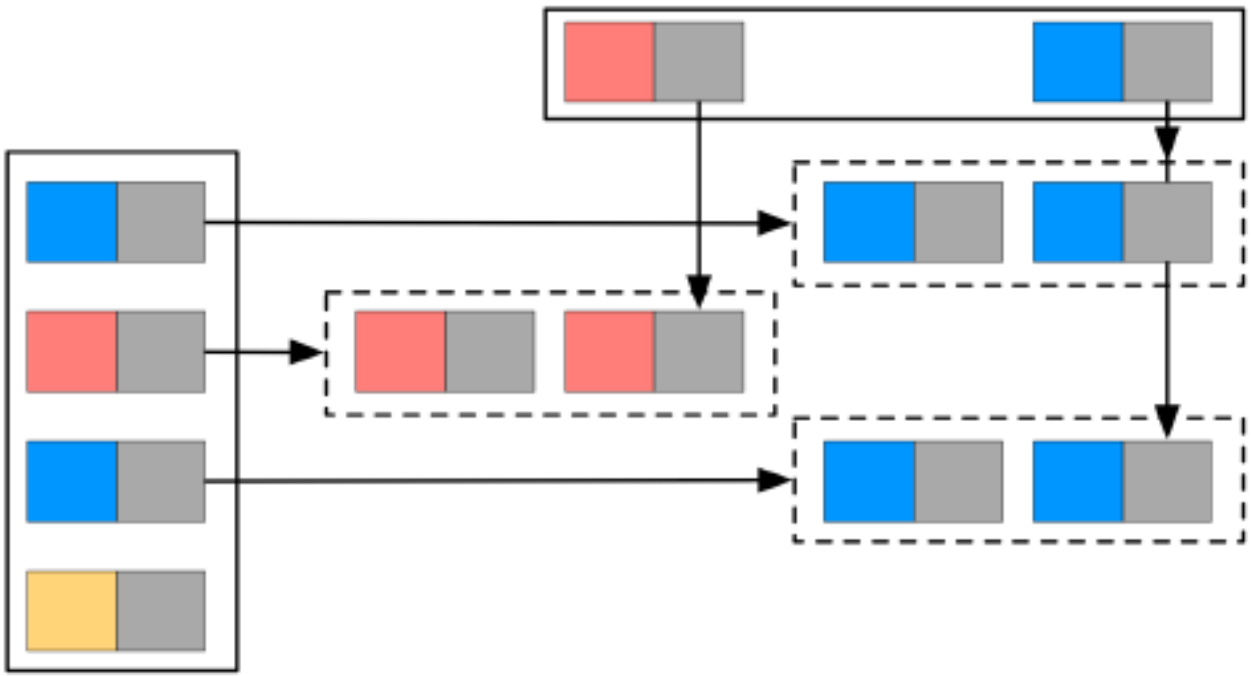
Map and reduce are transformations that work on a single list of keys. We can play with collections sharing the same keys:

- cross product, or a cartesian product
- match or join
- co-group

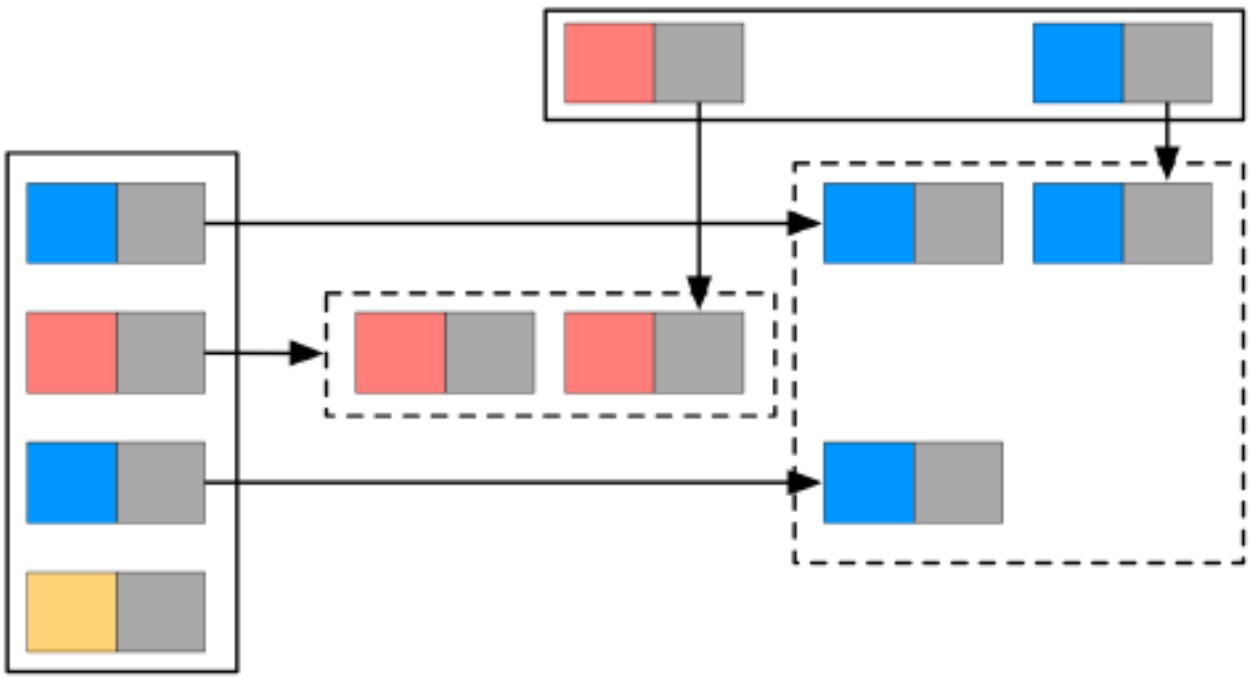
Cartesian Product



Match



Co-group



Summary

MapReduce hides complexities of parallel programming and greatly simplifies building parallel applications

- Data gets reduced to a smaller set at each step

Not good if:

- Data is frequently changing
- Map and reduce are dependent
- You need intermediate results

References I