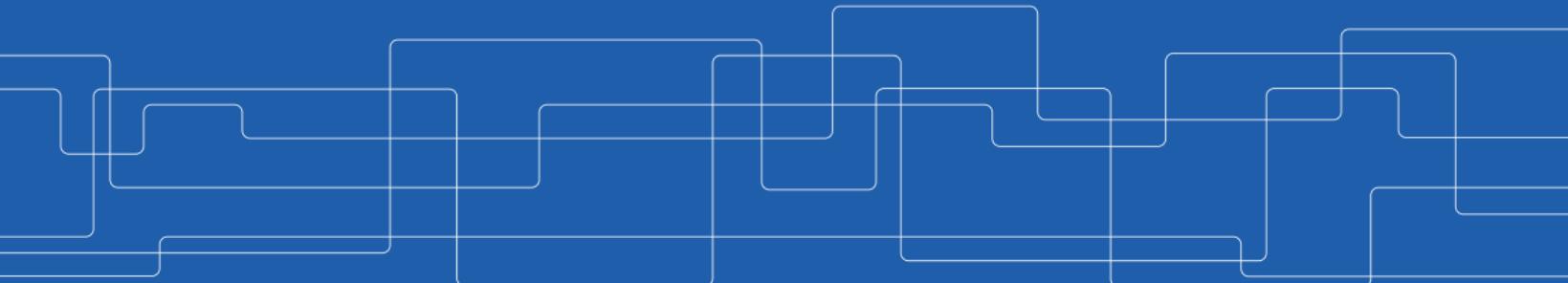




# Parallel Processing - MapReduce

Amir H. Payberah  
[payberah@kth.se](mailto:payberah@kth.se)  
2022-09-13





# The Course Web Page

<https://id2221kth.github.io>

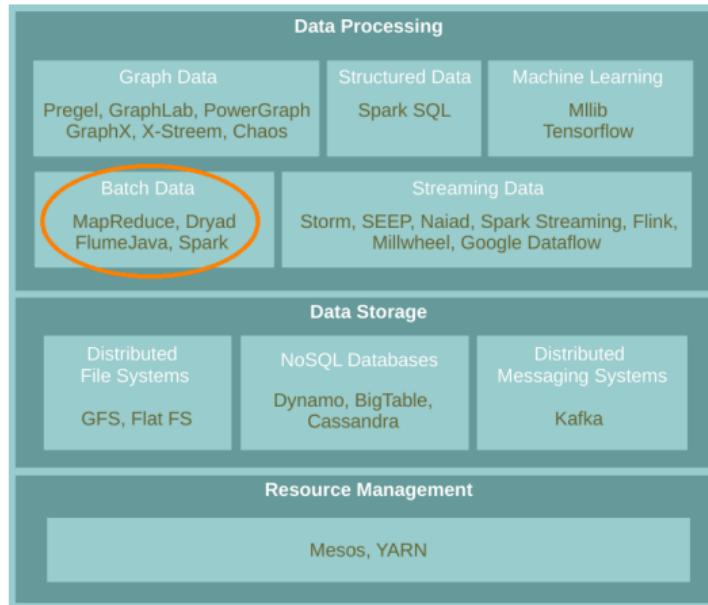


## The Questions-Answers Page

<https://tinyurl.com/bdenpwc5>



# Where Are We?



What do we do when there is **too much data** to process?

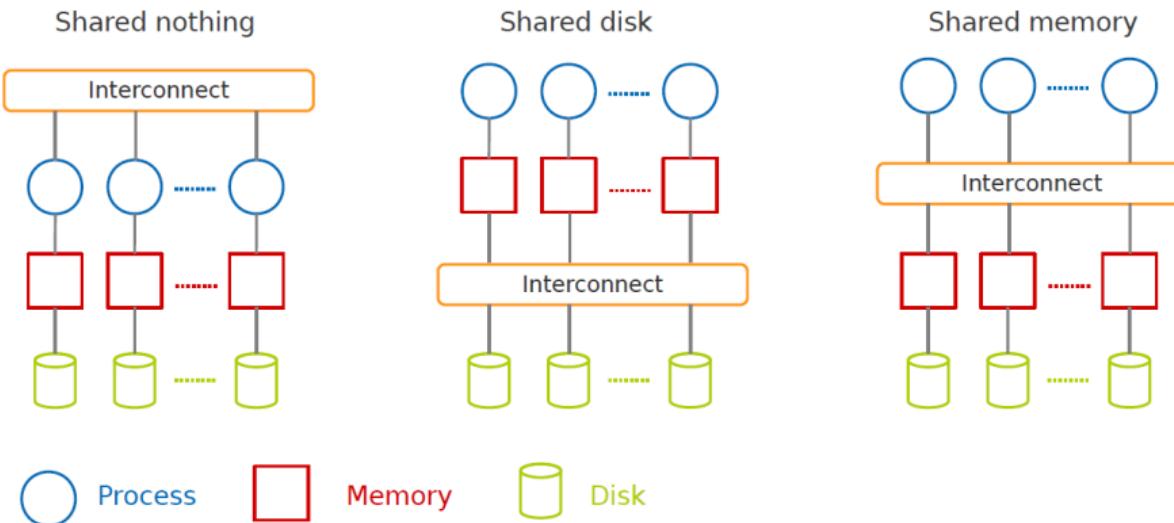


# Scale Up vs. Scale Out

- ▶ Scale **up** or scale **vertically**: adding **resources** to a **single node** in a system.
- ▶ Scale **out** or scale **horizontally**: adding **more nodes** to a system.



# Taxonomy of Parallel Architectures



DeWitt, D. and Gray, J. "Parallel database systems: the future of high performance database systems". ACM Communications, 35(6), 85-98, 1992.



# MapReduce

- ▶ A **shared nothing** architecture for processing **large data** sets with a **parallel/distributed** algorithm on **clusters of commodity hardware**.



# Challenges

- ▶ How to **distribute computation**?
- ▶ How can we make it **easy** to write **distributed programs**?
- ▶ Machines failure.



# Simplicity

- ▶ MapReduce takes care of parallelization, fault tolerance, and data distribution.
- ▶ Hide system-level details from programmers.



[<http://www.johnlund.com/page/8358/elephant-on-a-scooter.asp>]



# MapReduce Definition

- ▶ A **programming model**: to **batch** process large data sets (inspired by **functional programming**).
- ▶ An **execution framework**: to run parallel algorithms on **clusters of commodity hardware**.

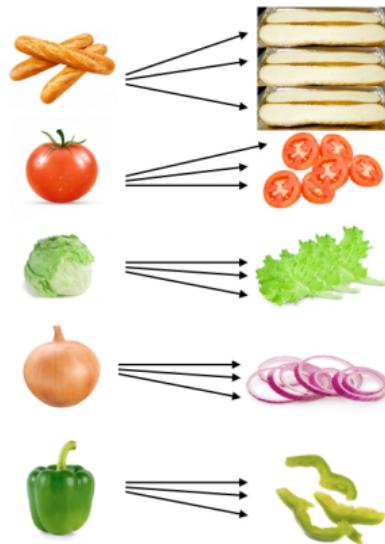


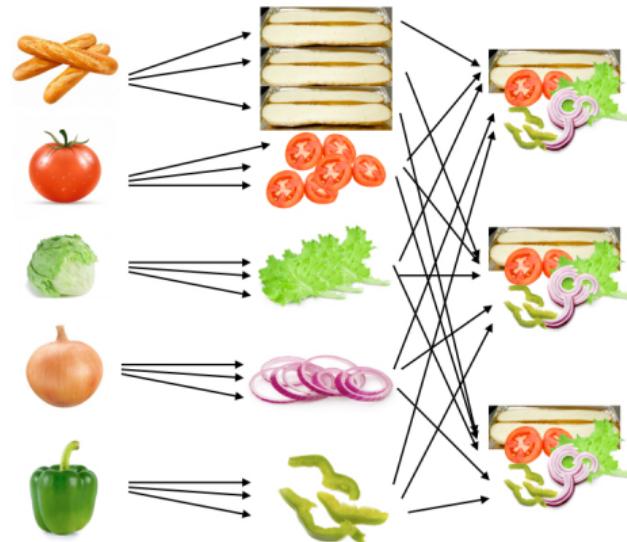
# Programming Model

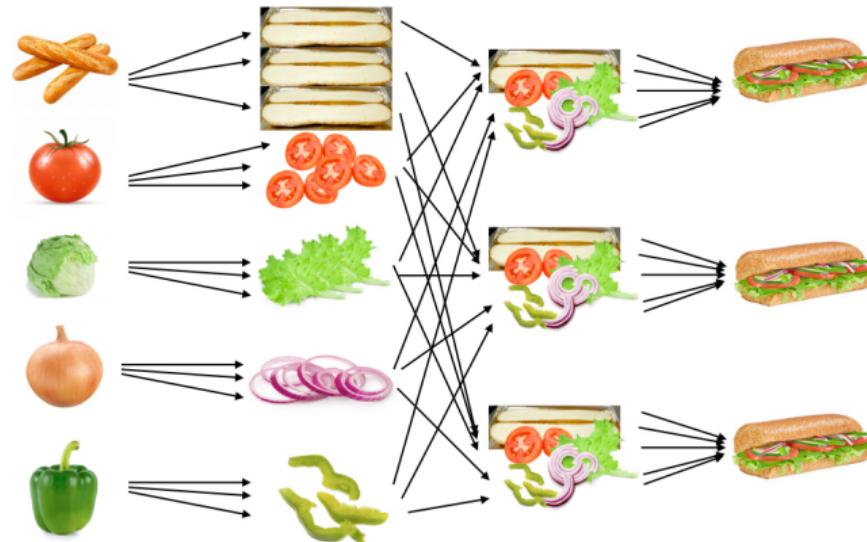
**I'm glad I don't  
have to hunt for  
my food,**

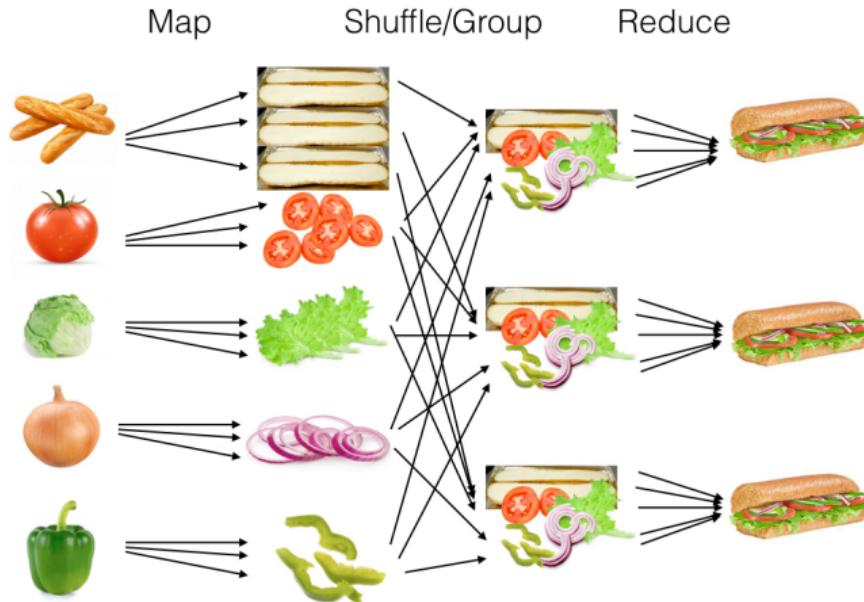


**I don't even  
know where  
sandwiches live.**





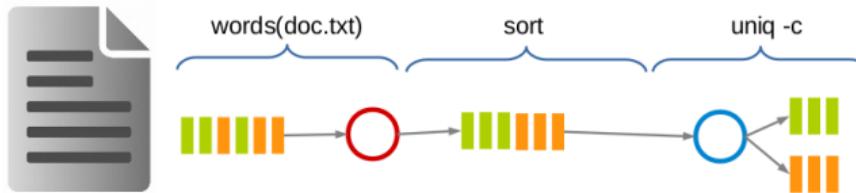






# Word Count

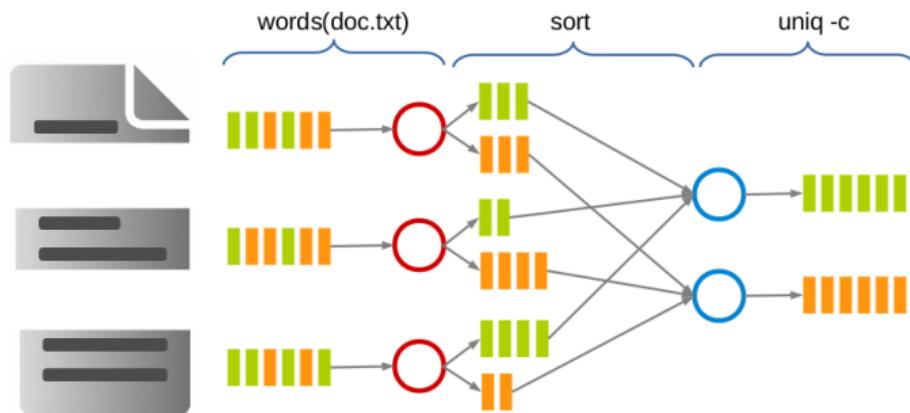
- ▶ Count the number of times each distinct word appears in the file
- ▶ If the file fits in memory: `words(doc.txt) | sort | uniq -c`



- ▶ If not?

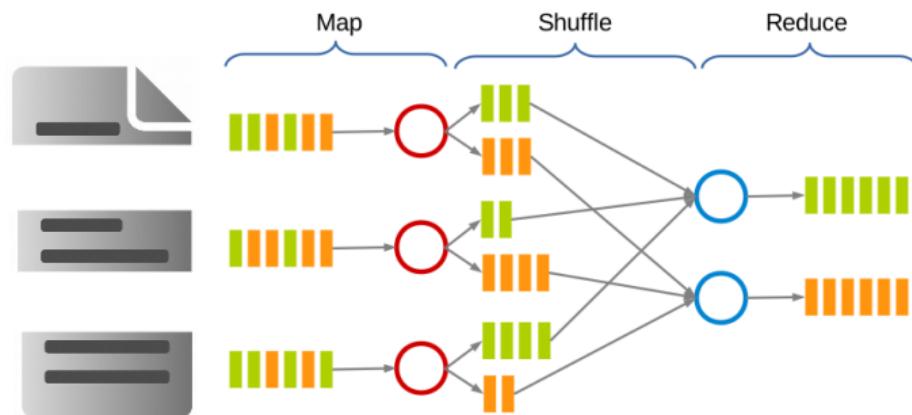
# Data-Parallel Processing (1/2)

- ▶ Parallelize the data and process.



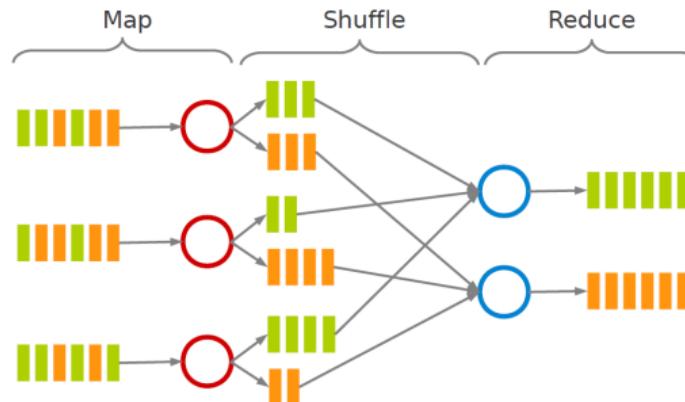
# Data-Parallel Processing (2/2)

## ► MapReduce



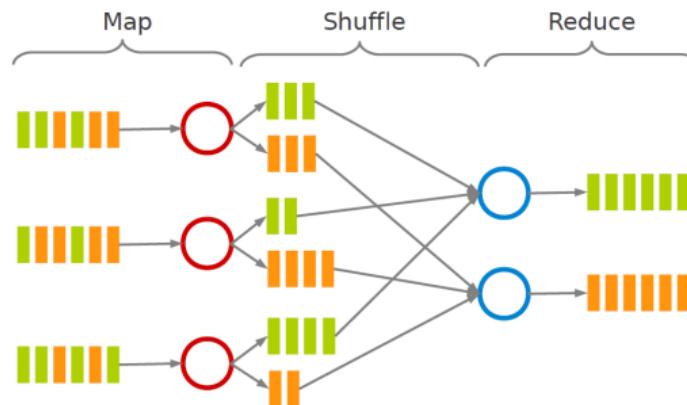
## MapReduce Stages - Map

- ▶ Each **Map task** (typically) operates on a **single HDFS block**.
- ▶ **Map tasks** (usually) run on the **node** where the **block** is stored.
- ▶ Each **Map task** generates a set of **intermediate key/value pairs**.



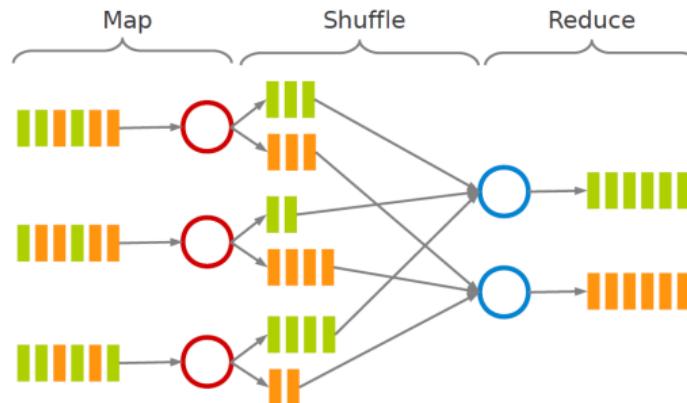
# MapReduce Stages - Shuffle and Sort

- ▶ Sorts and consolidates **intermediate data** from all mappers.
- ▶ Happens **after** all **Map tasks** are complete and **before** **Reduce tasks** start.

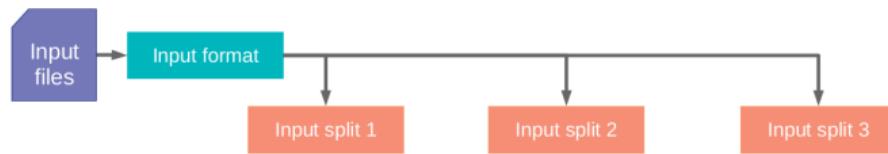


## MapReduce Stages - Reduce

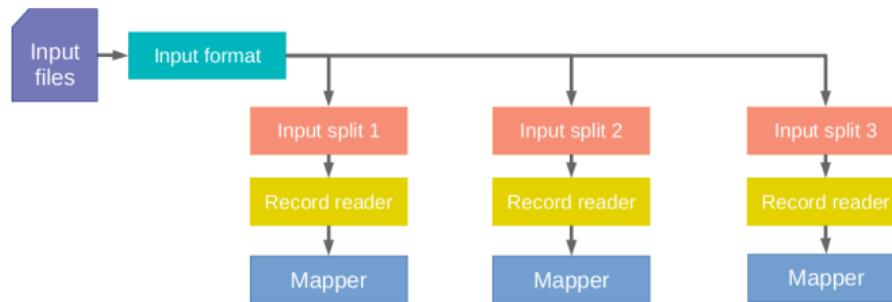
- ▶ Each **Reduce task** operates on all **intermediate values** associated with the **same intermediate key**.
- ▶ Produces the **final output**.



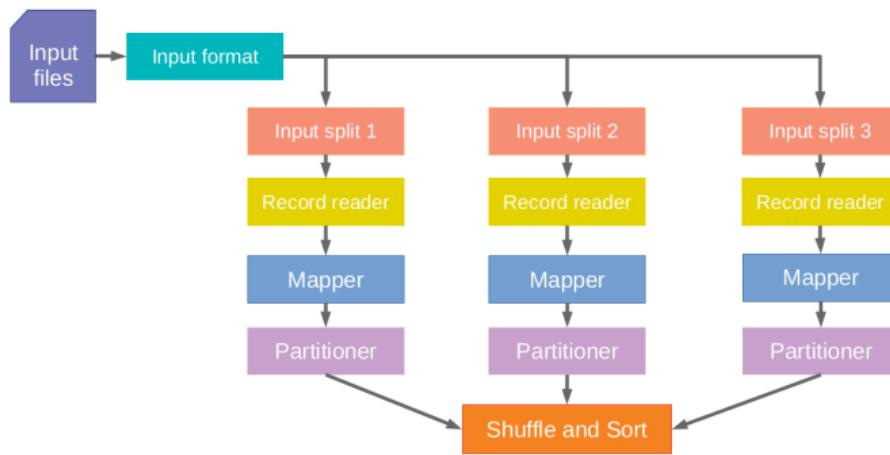
# MapReduce Data Flow (1/5)



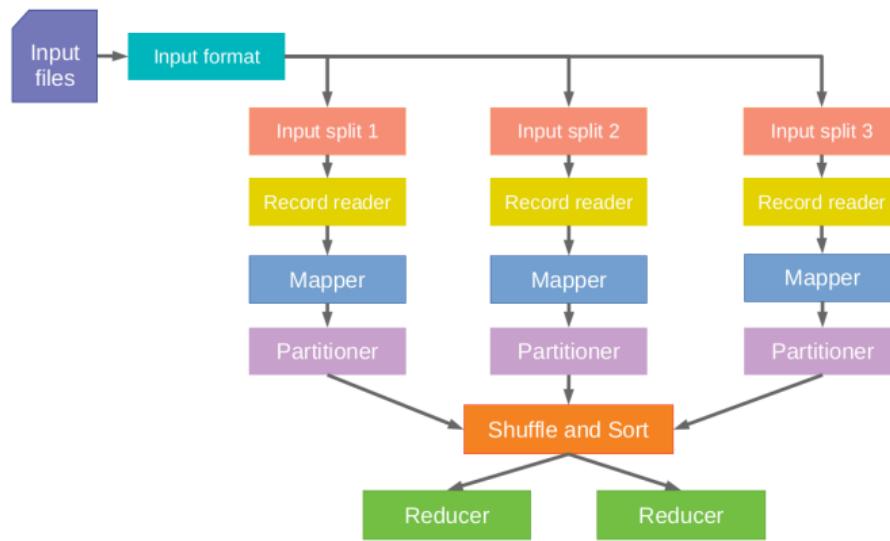
## MapReduce Data Flow (2/5)



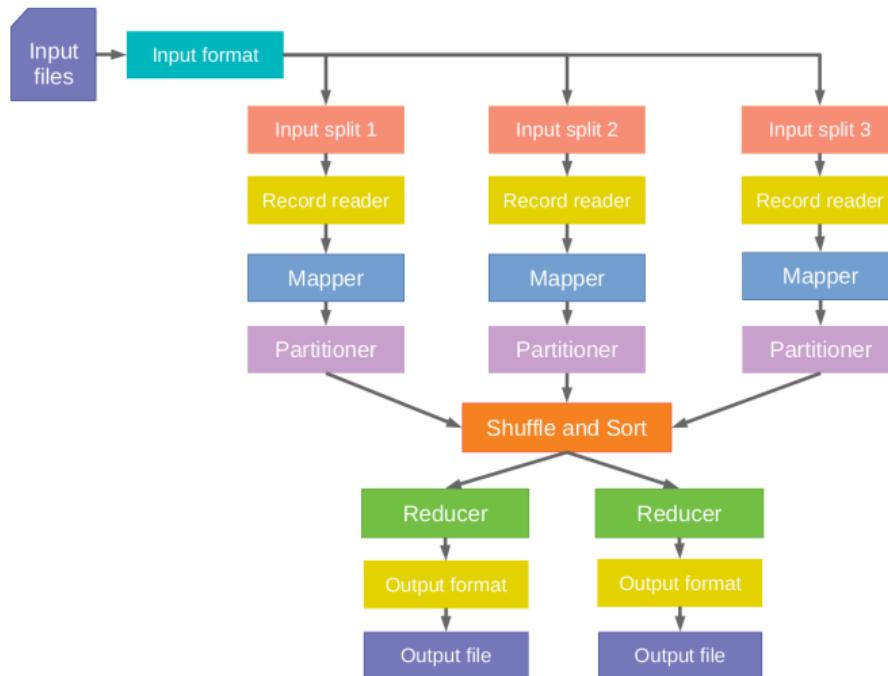
## MapReduce Data Flow (3/5)



## MapReduce Data Flow (4/5)

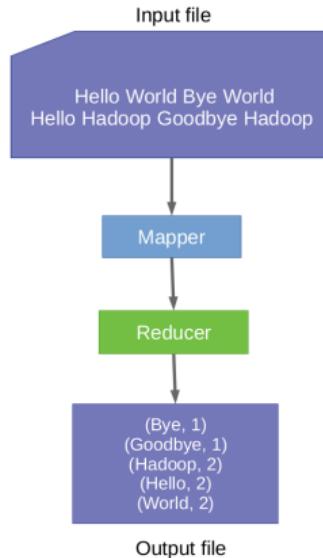


# MapReduce Data Flow (5/5)

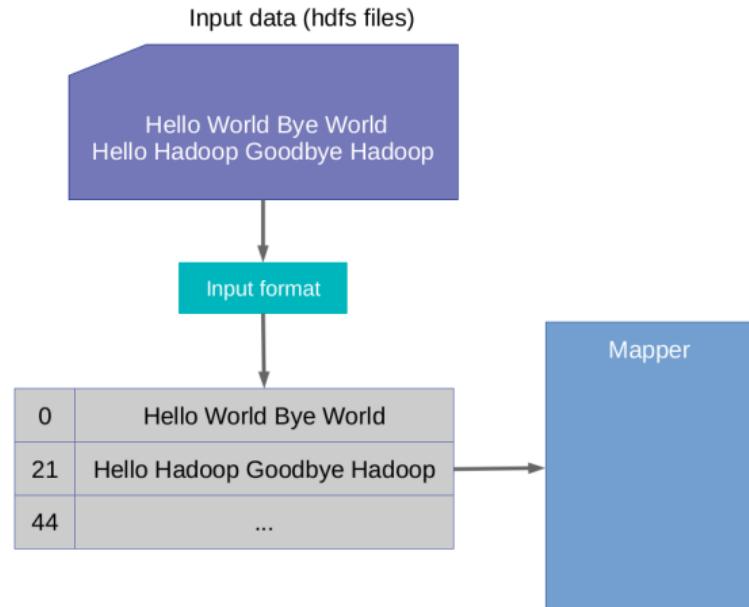


# Word Count in MapReduce

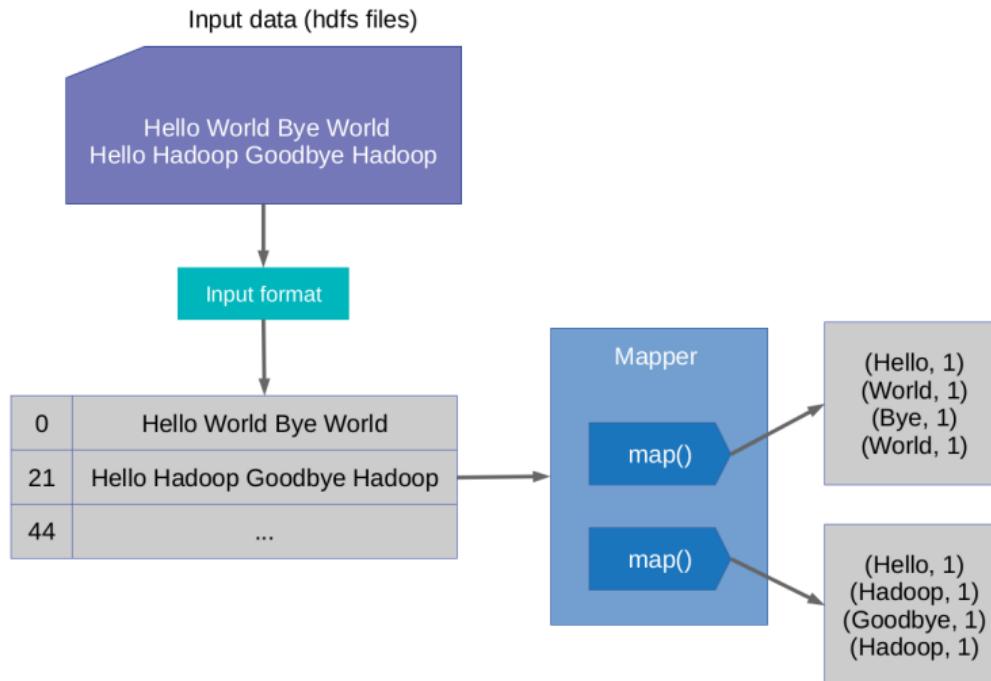
- ▶ Consider doing a word count of the following file using MapReduce



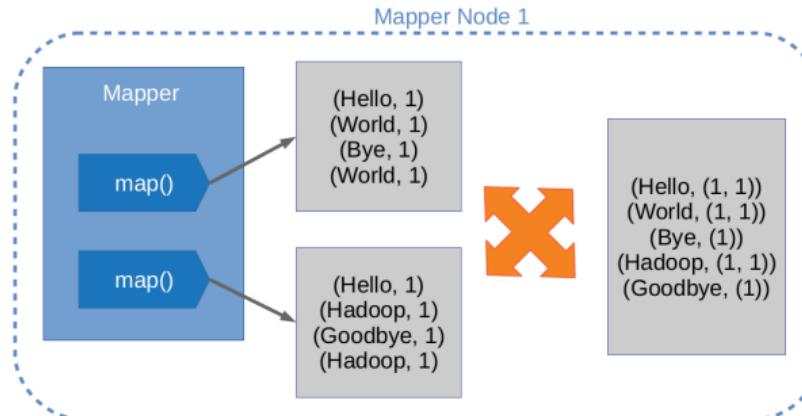
# Word Count in MapReduce - Map (1/2)



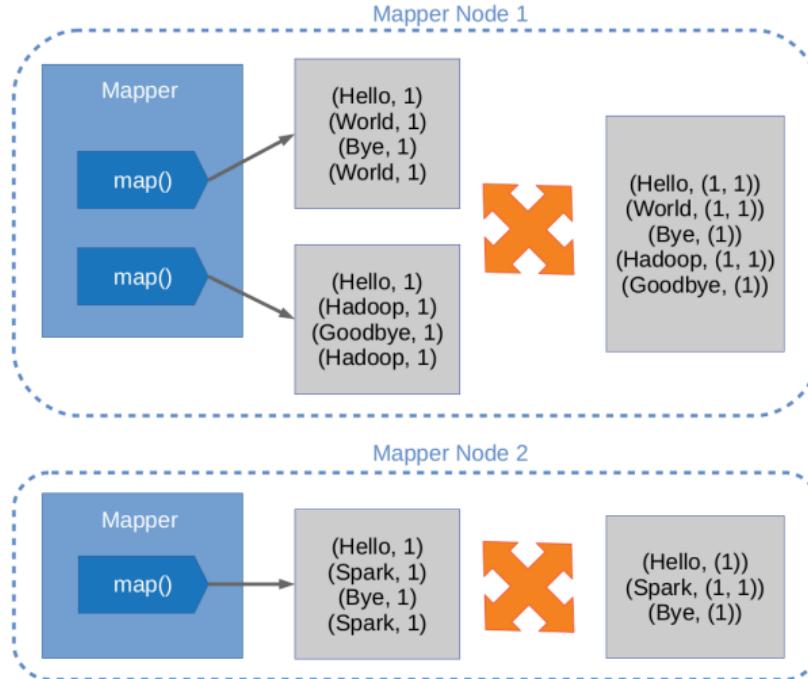
## Word Count in MapReduce - Map (2/2)



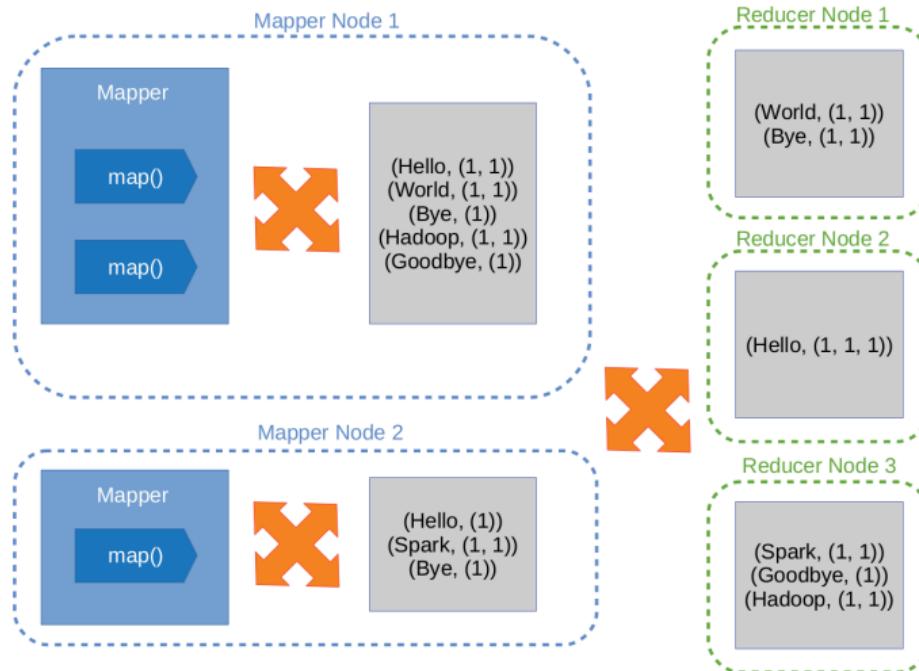
# Word Count in MapReduce - Shuffle and Sort (1/3)



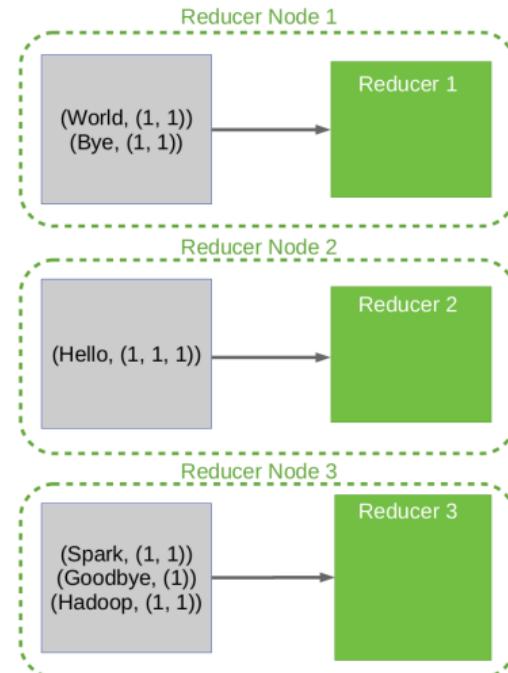
## Word Count in MapReduce - Shuffle and Sort (2/3)



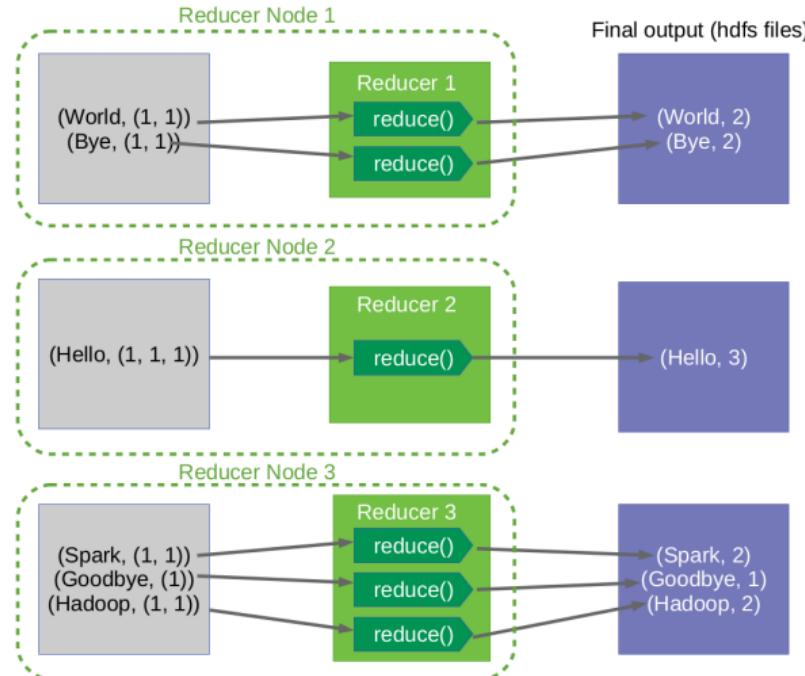
# Word Count in MapReduce - Shuffle and Sort (3/3)



# Word Count in MapReduce - Reduce (1/2)



# Word Count in MapReduce - Reduce (2/2)





# Mapper



# The Mapper

- ▶ **Input:** (key, value) pairs
- ▶ **Output:** a list of (key, value) pairs
- ▶ The Mapper may use or completely ignore the input key.
- ▶ A standard pattern is to read one line of a file at a time.
  - Key: the byte offset
  - Value: the content of the line

```
map(in_key, in_value) -> list of (inter_key, inter_value)
```

```
(in_key, in_value) ⇒ map() ⇒ (inter_key1, inter_value1)  
                                (inter_key2, inter_value2)  
                                (inter_key3, inter_value3)  
                                (inter_key4, inter_value4)
```

...



## The Mapper Example (1/3)

- ▶ Turn input into **upper case**

```
map(k, v) = emit (k.to_upper, v.to_upper)
```

(kth, this is the course id2221) ⇒ **map()** ⇒ (KTH, THIS IS THE COURSE ID2221)



## The Mapper Example (2/3)

- ▶ Count the **number of characters** in the input

```
map(k, v) = emit (k, v.length)
```

(kth, this is the course id2221) ⇒ map() ⇒ (kth, 26)



## The Mapper Example (3/3)

- ▶ Turn each word in the input into pair of (word, 1)

```
map(k, v) = foreach w in v emit (w, 1)
```

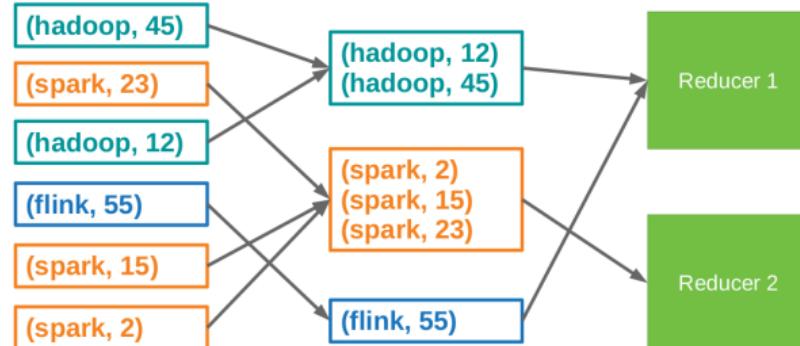
(21, Hello Hadoop Goodbye Hadoop)  $\Rightarrow$  map()  $\Rightarrow$  (Hello, 1)  
(Hadoop, 1)  
(Goodbye, 1)  
(Hadoop, 1)



# Reducer

# Shuffle and Sort

- ▶ After the Map phase, all **intermediate** (key, value) pairs are **grouped** by the **intermediate keys**.
- ▶ Each **(key, list of values)** is passed to a **Reducer**.





## The Reducer

- ▶ **Input:** (key, list of values) pairs
- ▶ **Output:** a (key, value) pair or list of (key, value) pairs
- ▶ The Reducer outputs zero or more final (key, value) pairs

```
reduce(inter_key, [inter_value1, inter_value2, ...]) -> (out_key, out_value)
```

$(\text{inter\_k}, [\text{inter\_v1}, \text{inter\_v2}, \dots]) \Rightarrow \text{reduce}() \Rightarrow (\text{out\_k}, \text{out\_v})$

or

$(\text{inter\_k}, [\text{inter\_v1}, \text{inter\_v2}, \dots]) \Rightarrow \text{reduce}() \Rightarrow (\text{out\_k}, \text{out\_v1})$   
 $\qquad\qquad\qquad (\text{out\_k}, \text{out\_v2})$

...



## The Reducer Example (1/3)

- ▶ Add up all the values associated with each intermediate key

```
reduce(k, vals) = {
    sum = 0
    foreach v in vals sum += v
    emit (k, sum)
}
```

(Hello, [1, 1, 1])  $\Rightarrow$  reduce()  $\Rightarrow$  (Hello, 3)

(Bye, [1])  $\Rightarrow$  reduce()  $\Rightarrow$  (Bye, 1)



## The Reducer Example (2/3)

- ▶ Get the **maximum** value of each intermediate key

```
reduce(k, vals) = emit (k, max(vals))
```

(KTH, [5, 1, 12, 7])  $\Rightarrow$  **reduce()**  $\Rightarrow$  (KTH, 12)



## The Reducer Example (3/3)

- ▶ Identify reducer

```
reduce(k, vals) = foreach v in vals emit (k, v)
```

(KTH, [5, 1, 12, 7])  $\Rightarrow$  **reduce()**  $\Rightarrow$  (KTH, 5)  
(KTH, 1)  
(KTH, 12)  
(KTH, 7)



## Example: Word Count - map

```
public static class MyMap extends Mapper<...> {
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(LongWritable key, Text value, Context context)
        throws IOException, InterruptedException {
        String line = value.toString();
        StringTokenizer tokenizer = new StringTokenizer(line);

        while (tokenizer.hasMoreTokens()) {
            word.set(tokenizer.nextToken());
            context.write(word, one);
        }
    }
}
```



## Example: Word Count - reduce

```
public static class MyReduce extends Reducer<...> {
    public void reduce(Text key, Iterator<...> values, Context context)
        throws IOException, InterruptedException {
        int sum = 0;

        while (values.hasNext())
            sum += values.next().get();

        context.write(key, new IntWritable(sum));
    }
}
```



## Example: Word Count - driver

```
public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = new Job(conf, "wordcount");

    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);

    job.setMapperClass(MyMap.class);
    job.setCombinerClass(MyReduce.class);
    job.setReducerClass(MyReduce.class);

    job.setInputFormatClass(TextInputFormat.class);
    job.setOutputFormatClass(TextOutputFormat.class);

    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));

    job.waitForCompletion(true);
}
```



# MapReduce Algorithm Design



# MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ Joining
- ▶ Sorting

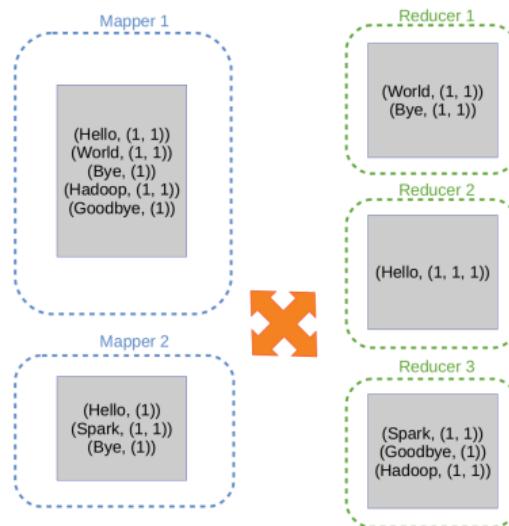


# MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ Joining
- ▶ Sorting

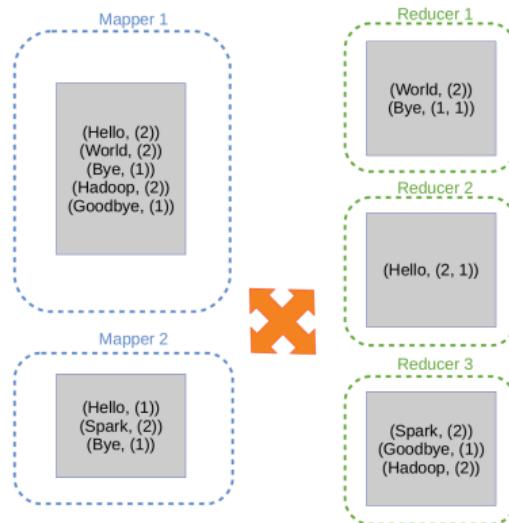
## Local Aggregation - In-Map Combiner (1/2)

- In some cases, there is significant **repetition** in the **intermediate keys** produced by each **map** task, and the **reduce** function is **commutative** and **associative**.



## Local Aggregation - In-Map Combiner (2/2)

- ▶ Merge partially data before it is sent over the network to the **reducer**.
- ▶ Typically the **same code** for the **combiner** and the **reduce function**.



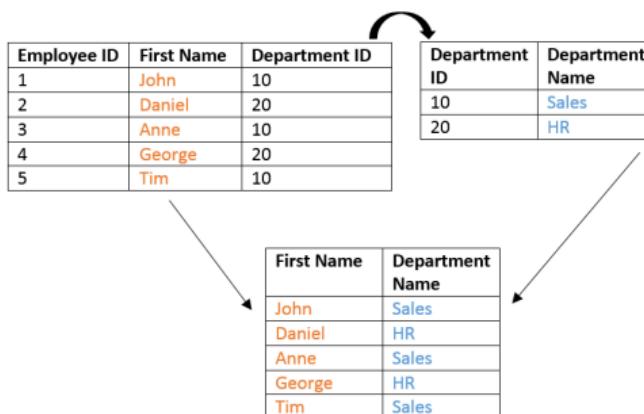


# MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ Joining
- ▶ Sorting

# Joins

- ▶ Joins are **relational** constructs you use to **combine relations together**.
- ▶ In MapReduce joins are applicable in situations where you have **two or more datasets** you want to combine.

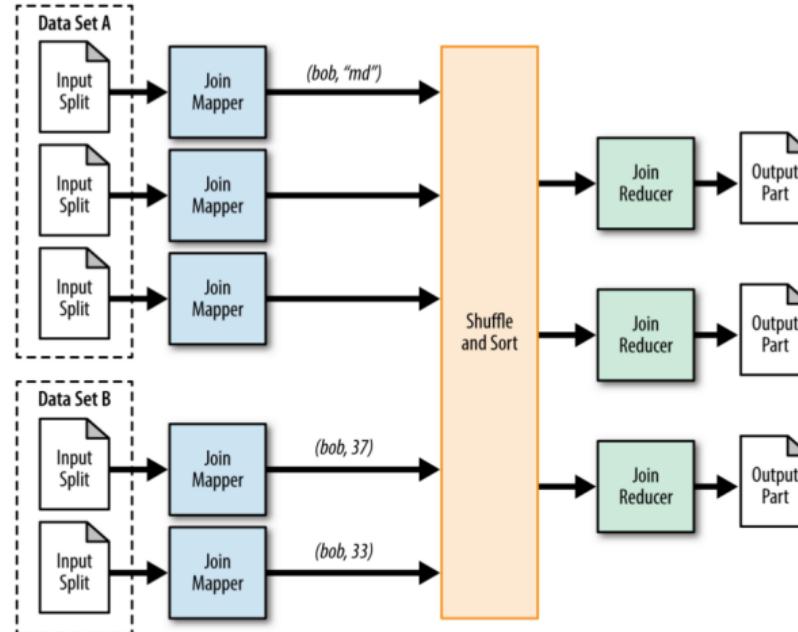




## Joins - Two Strategies

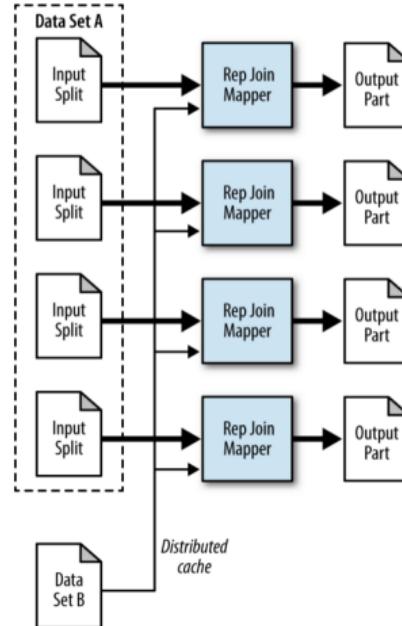
- ▶ Reduce-side join
  - Repartition join
  - When joining **two or more large** datasets together
  
- ▶ Map-side join
  - Replication join
  - When **one of the datasets is small** enough to cache

# Joins - Reduce-Side Join



[M. Donald et al., MapReduce design patterns, O'Reilly, 2012.]

# Joins - Map-Side Join



[M. Donald et al., MapReduce design patterns, O'Reilly, 2012.]

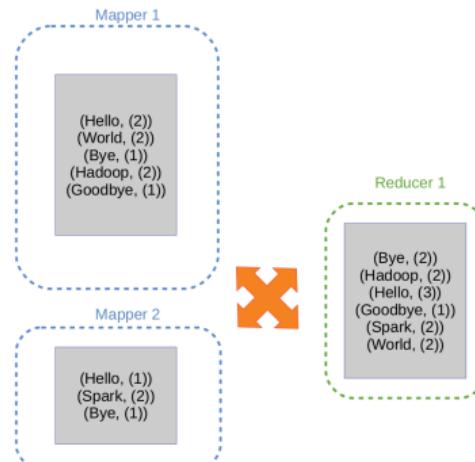


# MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ Joining
- ▶ Sorting

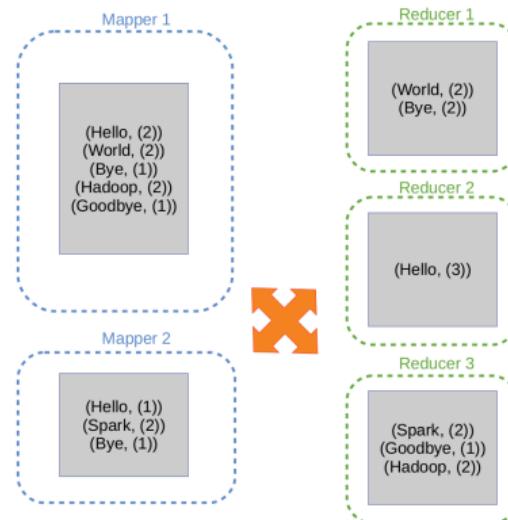
## Sort (1/3)

- ▶ Assume you want to have your job output in **total sort order**.
- ▶ **Trivial** with a **single Reducer**.
  - Keys are passed to the Reducer in **sorted order**.



## Sort (2/3)

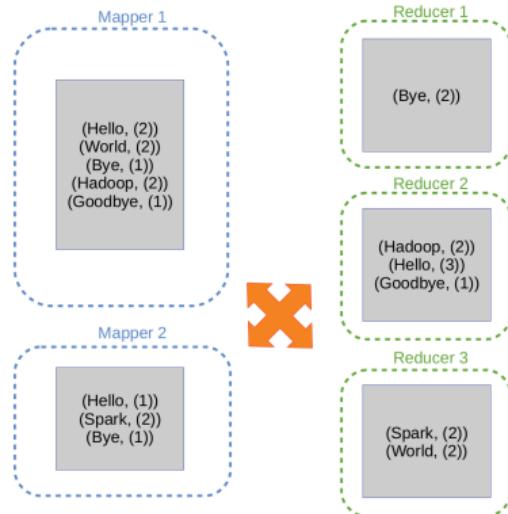
- ▶ What if we have multiple Reducer?

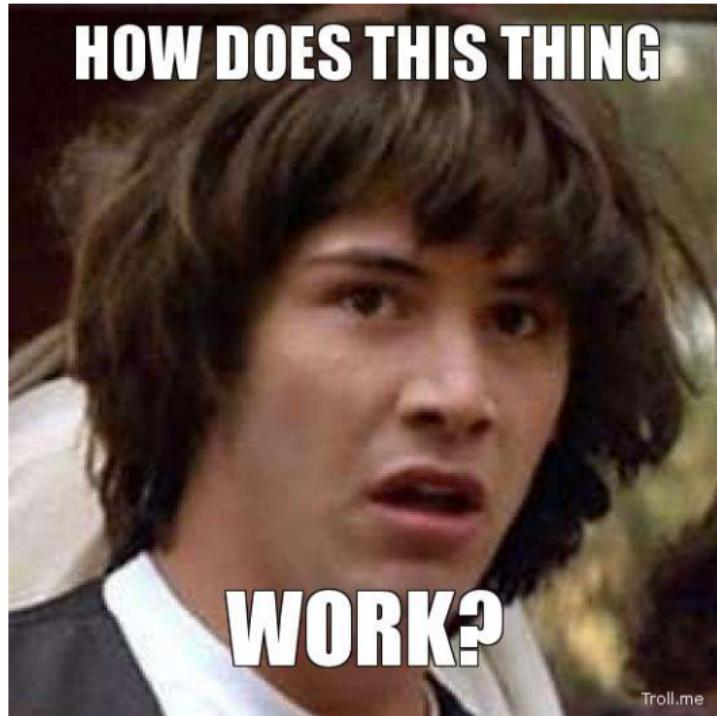


## Sort (3/3)

- ▶ For multiple Reducers we need to choose a partitioning function

$$\text{key1} < \text{key2} \Rightarrow \text{partition}(\text{key1}) \leq \text{partition}(\text{key2})$$

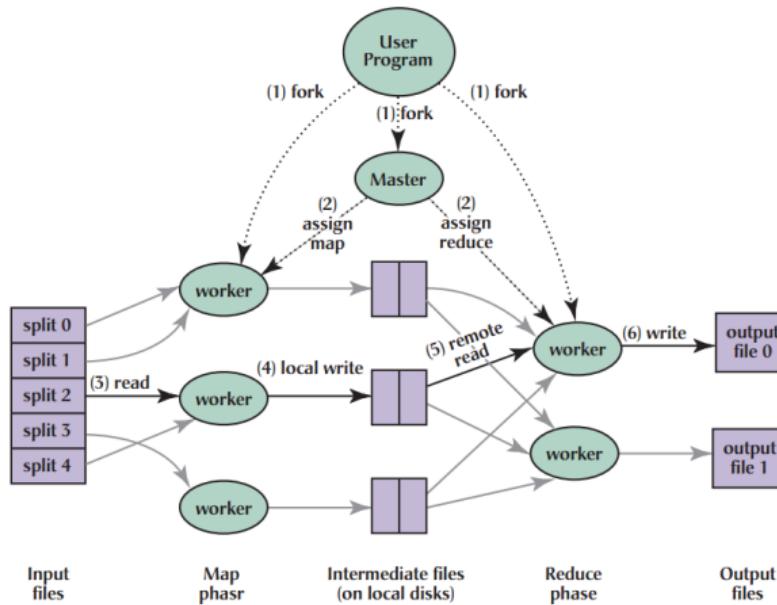






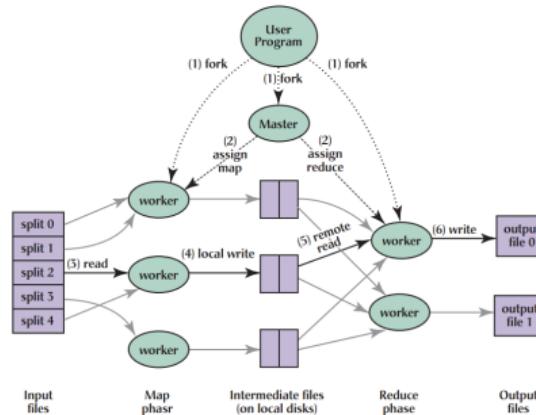
# Implementation

# Architecture



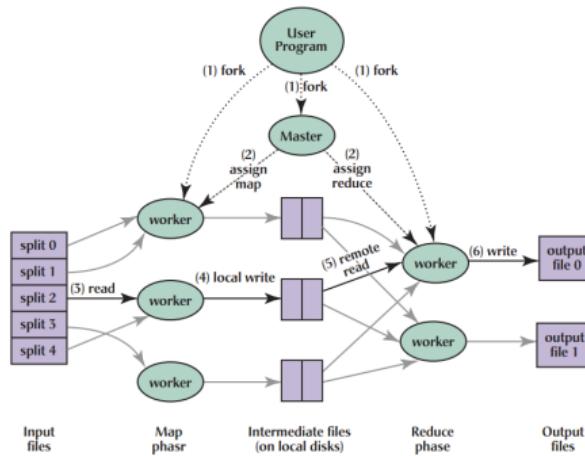
# MapReduce Execution (1/7)

- ▶ The **user program** divides the input files into **M splits**.
  - A typical size of a split is the size of a **HDFS** block (64 MB).
  - Converts them to **key/value** pairs.
- ▶ It starts up many copies of the program on a cluster of machines.



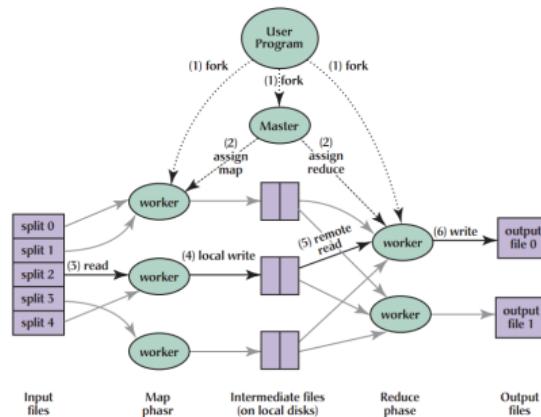
## MapReduce Execution (2/7)

- ▶ One of the copies of the program is **master**, and the rest are **workers**.
- ▶ The **master** assigns works to the **workers**.
  - It picks **idle** workers and assigns each one a **map** task or a **reduce** task.



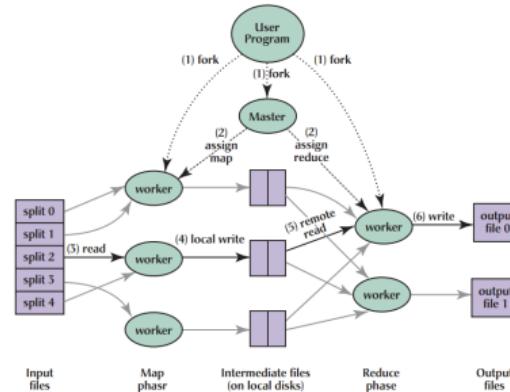
## MapReduce Execution (3/7)

- ▶ A **map worker** reads the contents of the corresponding input **splits**.
- ▶ It parses key/value pairs out of the input data and passes each pair to the **user defined map function**.
- ▶ The **key/value** pairs produced by the **map** function are buffered in **memory**.



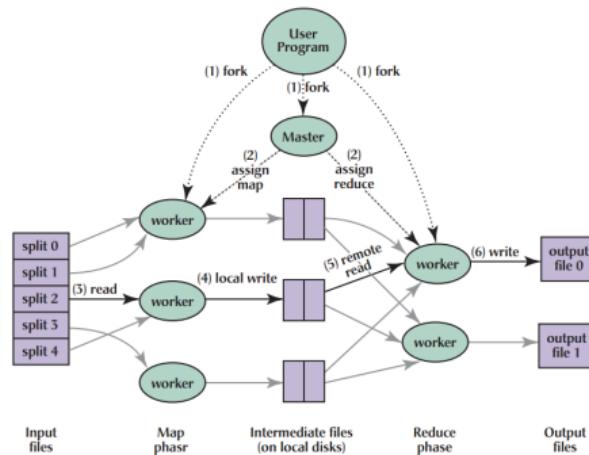
# MapReduce Execution (4/7)

- ▶ The buffered pairs are **periodically** written to **local disk**.
  - They are partitioned into **R regions** ( $\text{hash}(\text{key}) \bmod R$ ).
- ▶ The **locations** of the buffered pairs on the local disk are passed back to the **master**.
- ▶ The **master** forwards these locations to the **reduce workers**.



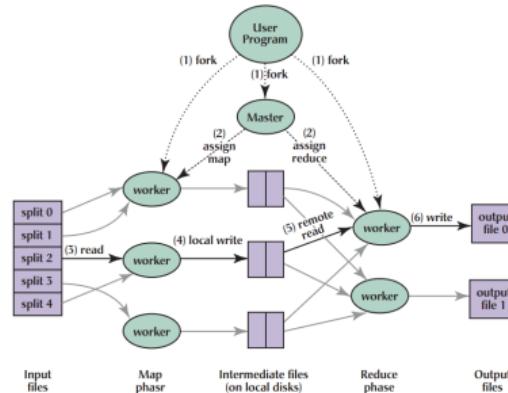
# MapReduce Execution (5/7)

- ▶ A **reduce worker reads** the buffered data from the local disks of the map workers.
- ▶ When a reduce worker has read all intermediate data, it sorts it by the **intermediate keys**.



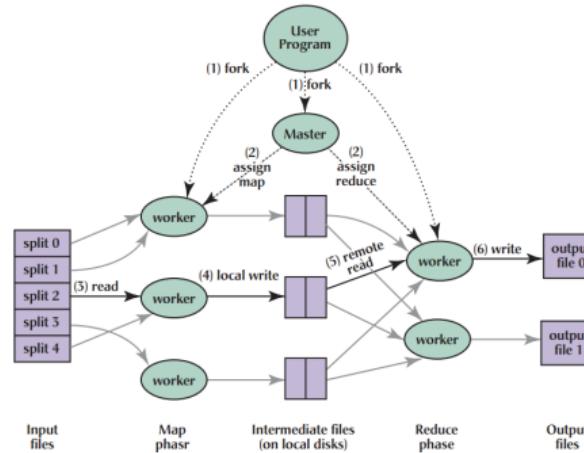
# MapReduce Execution (6/7)

- ▶ The reduce worker iterates over the **intermediate data**.
- ▶ For each **unique intermediate key**, it passes the key and the corresponding set of intermediate values to the **user defined reduce function**.
- ▶ The output of the reduce function is appended to a **final output file** for this reduce partition.

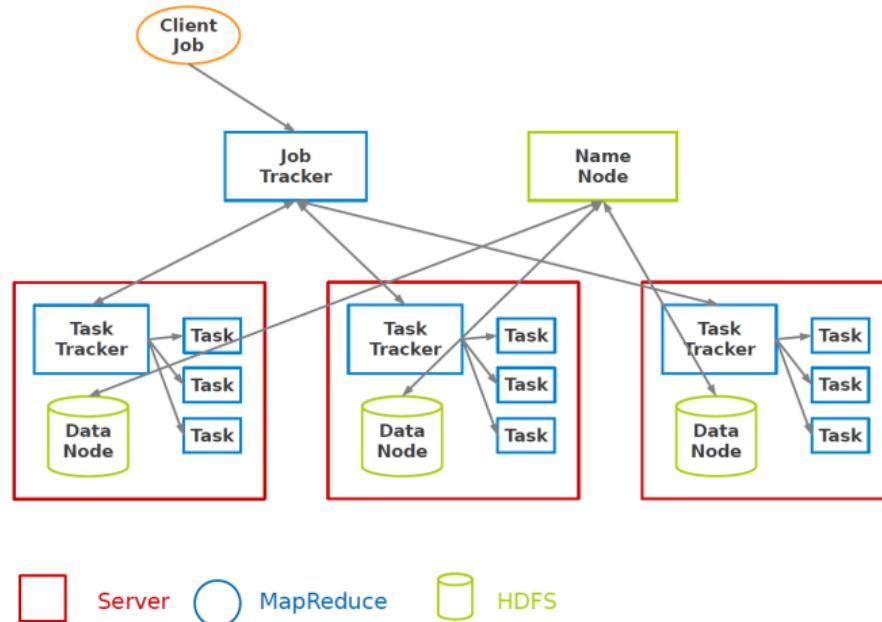


# MapReduce Execution (7/7)

- When all map tasks and reduce tasks have been completed, the **master** wakes up the **user program**.



# Hadoop MapReduce and HDFS





## Fault Tolerance - Worker

- ▶ Detect failure via periodic heartbeats.
- ▶ Re-execute **in-progress map** and **reduce** tasks.
- ▶ Re-execute **completed map** tasks: their output is stored on the local disk of the failed machine and is therefore inaccessible.
- ▶ **Completed reduce** tasks do not need to be re-executed since their output is stored in a global filesystem.



## Fault Tolerance - Master

- ▶ State is periodically **checkpointed**: a new copy of master starts from the last checkpoint state.



# FlumeJava



## FlumeJava (1/4)

- ▶ It is easy in MapReduce:

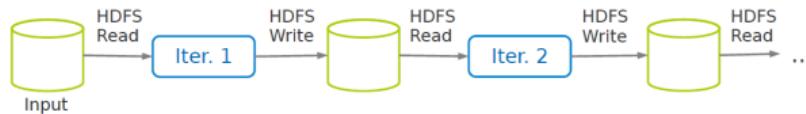
```
words(doc.txt) | sort | uniq -c
```

- ▶ What about this one?

```
words(doc.txt) | grep | sed | sort | awk | perl
```

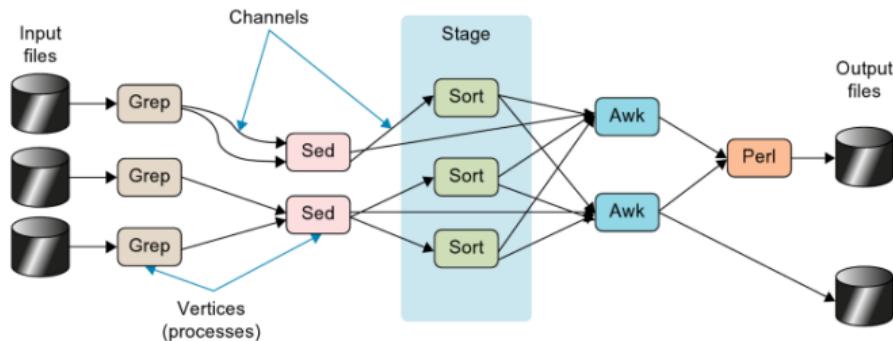
## FlumeJava (2/4)

- ▶ Big jobs in MapReduce run in more than one Map-Reduce stages.
- ▶ Reducers of each stage write to replicated storage, e.g., HDFS.



## FlumeJava (3/4)

- ▶ FlumeJava is a **library** provided by Google to simply the creation of **pipelined MapReduce tasks**.





## FlumeJava (4/4)

- ▶ Providing a couple of **immutable parallel collections**
  - `PCollection<T>` and `PTable<K, V>`
- ▶ Providing a number of **parallel operations** for processing the **parallel collections**
  - `parallelDo`, `groupByKey`, `combineValues` and `flatten`
- ▶ Building an **execution plan dataflow graph**
- ▶ **Optimizing** the execution plan, and then **executing** it



# Summary



# Summary

- ▶ Scaling out: shared nothing architecture
- ▶ MapReduce
  - Programming model: Map and Reduce
  - Execution framework
- ▶ FlumeJava: Dataflow DAG

## References

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# Questions?