



Parallel Processing - MapReduce and FlumeJava

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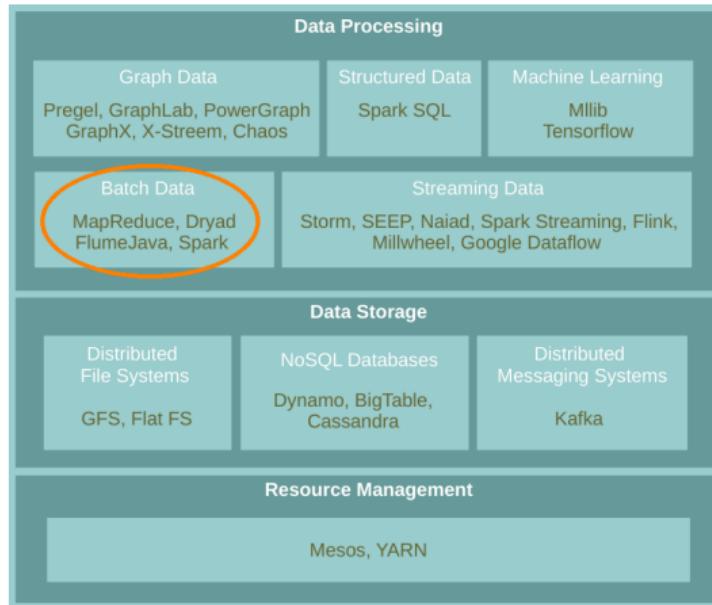


The Course Web Page

<https://id2221kth.github.io>



Where Are We?



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

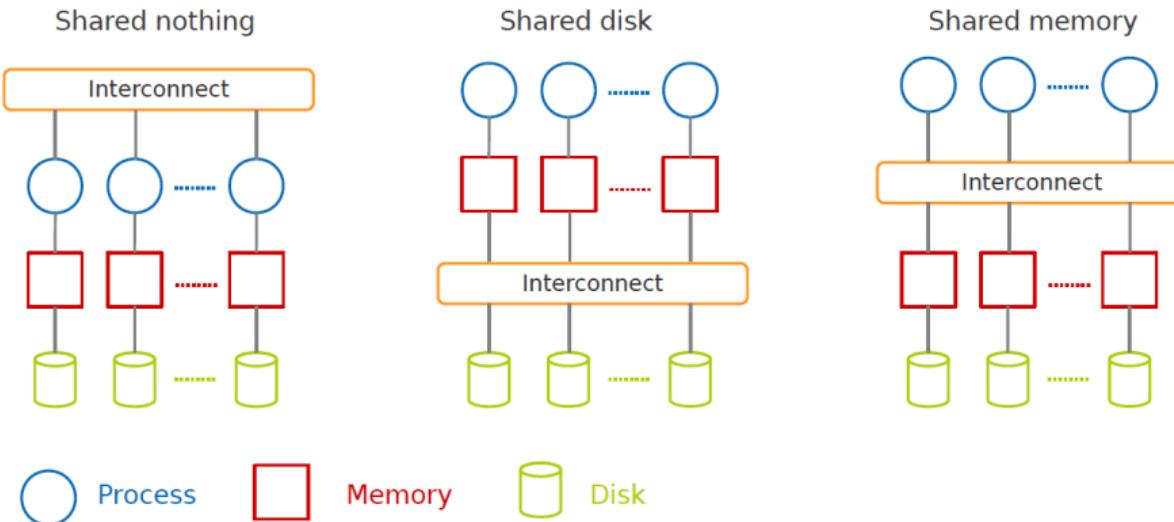


Scale Up vs. Scale Out

- ▶ 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**.

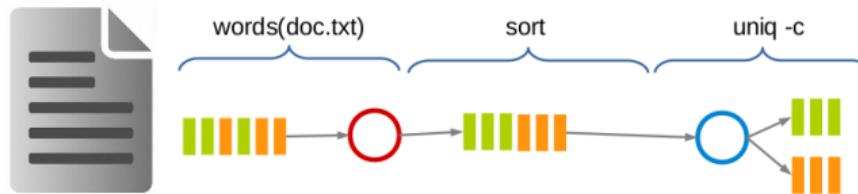


Programming Model



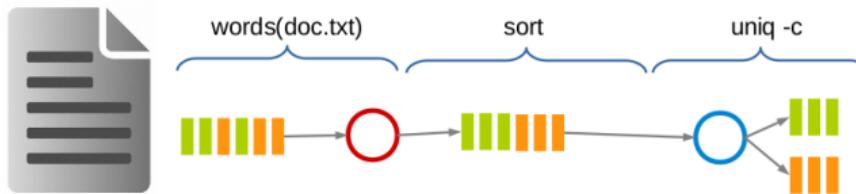
Word Count

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



Word Count

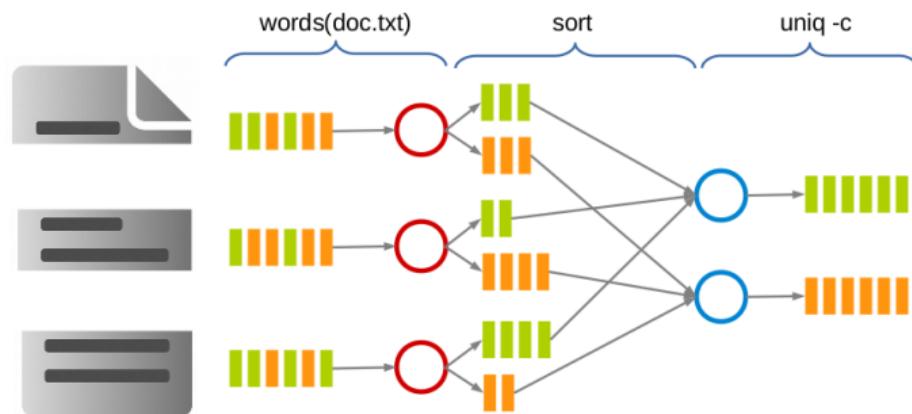
- ▶ Count the number of times each distinct word appears in the file
- ▶ If the file fits in memory: `words(doc.txt) | sort | uniq -c`



- ▶ If not?

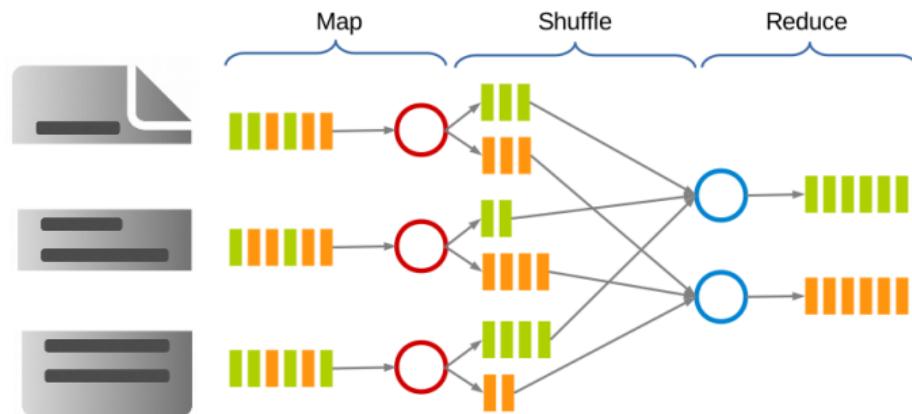
Data-Parallel Processing (1/2)

- ▶ Parallelize the data and process.



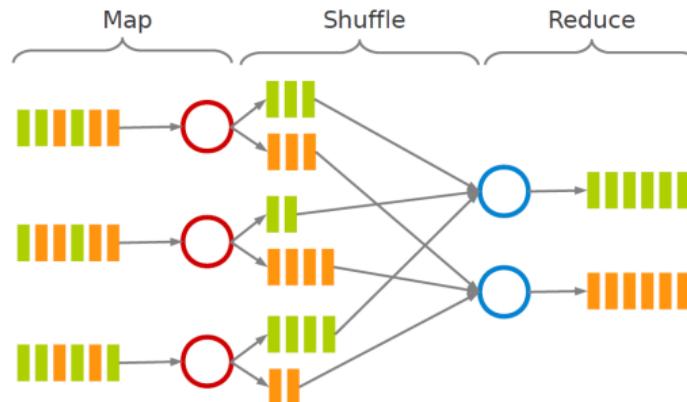
Data-Parallel Processing (2/2)

► MapReduce



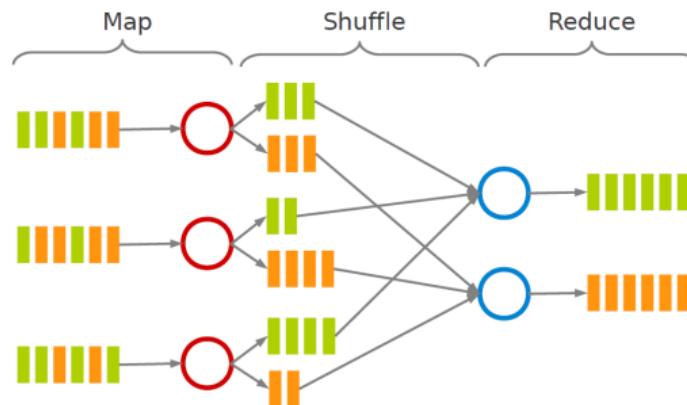
MapReduce Stages - Map

- ▶ 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**.



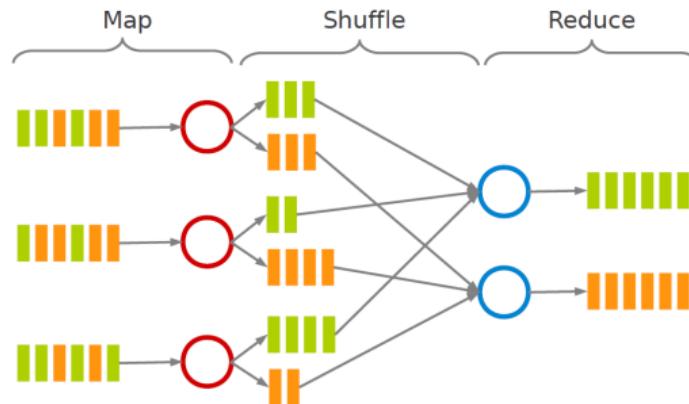
MapReduce Stages - Shuffle and Sort

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



MapReduce Stages - Reduce

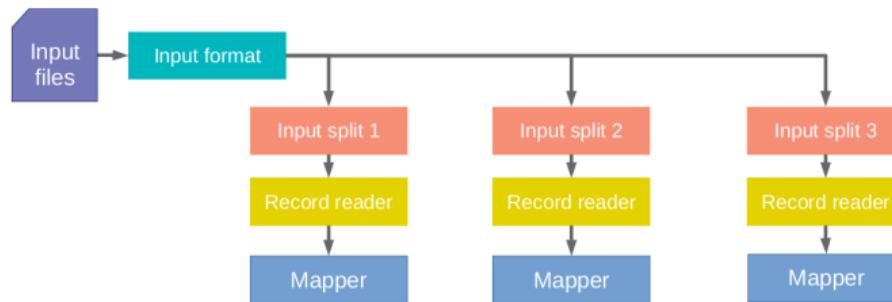
- ▶ Each **Reduce task** operates on all **intermediate values** associated with the **same intermediate key**.
- ▶ Produces the **final output**.



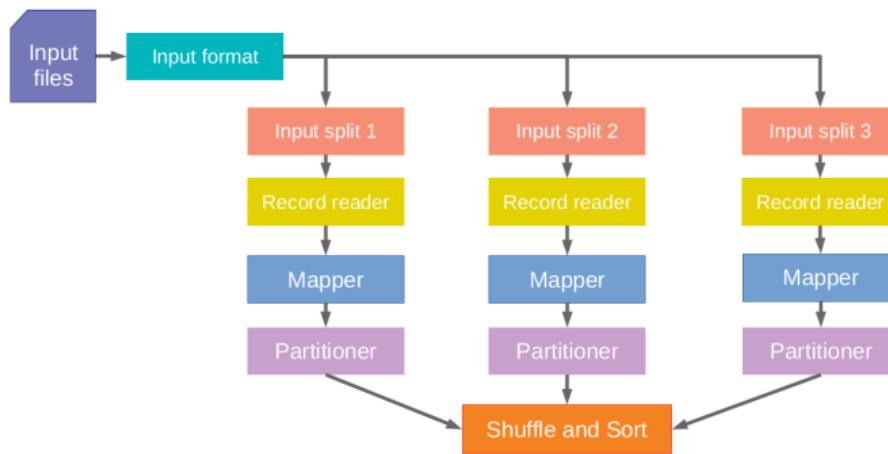
MapReduce Data Flow (1/5)



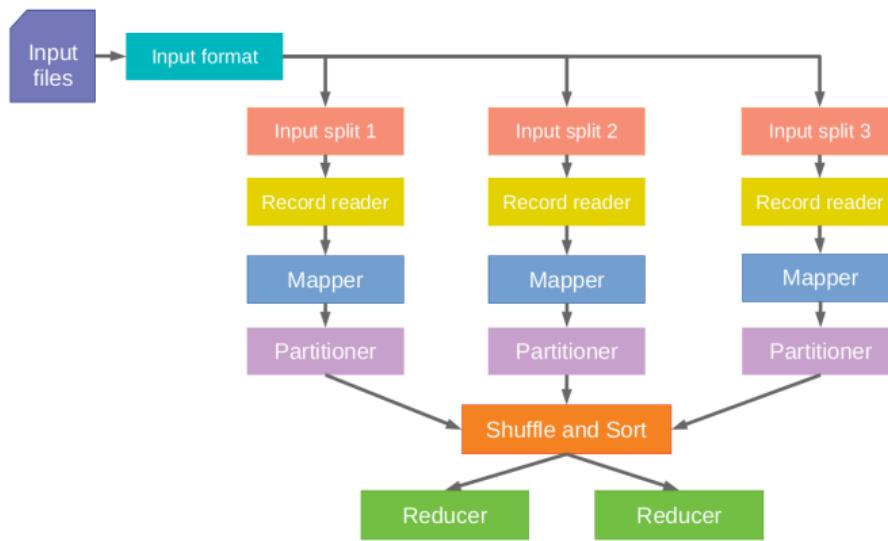
MapReduce Data Flow (2/5)



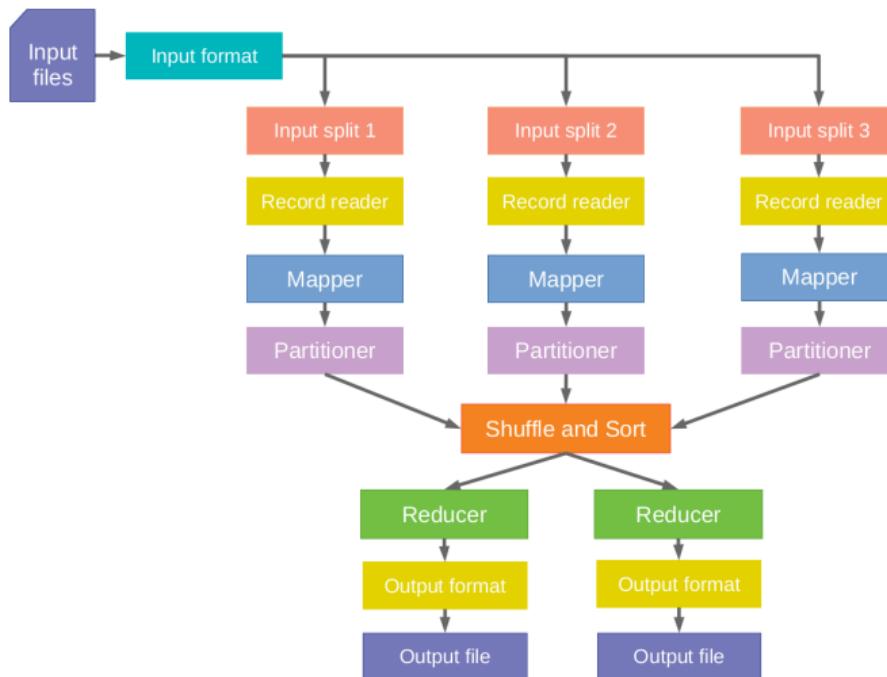
MapReduce Data Flow (3/5)



MapReduce Data Flow (4/5)

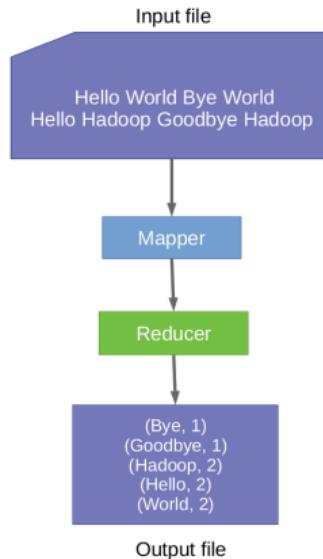


MapReduce Data Flow (5/5)

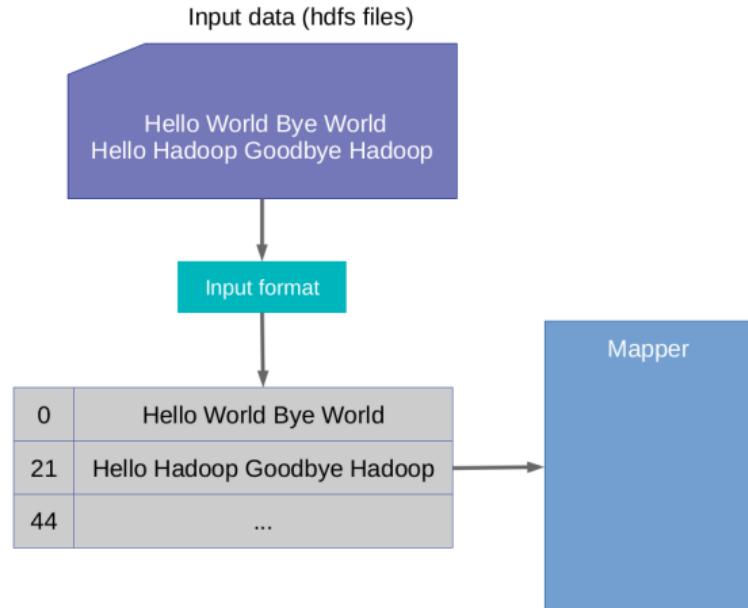


Word Count in MapReduce

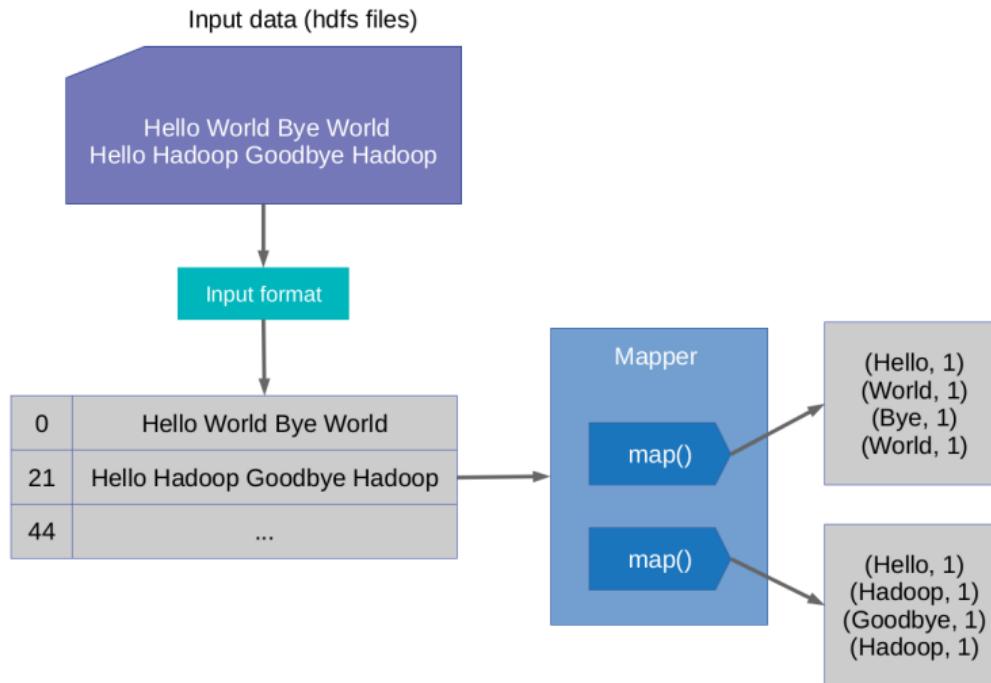
- ▶ Consider doing a word count of the following file using MapReduce



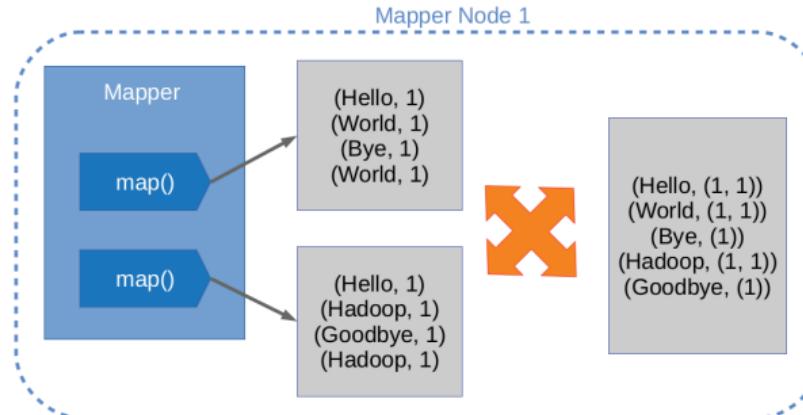
Word Count in MapReduce - Map (1/2)



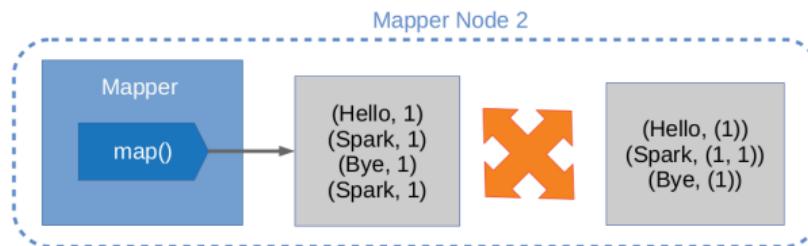
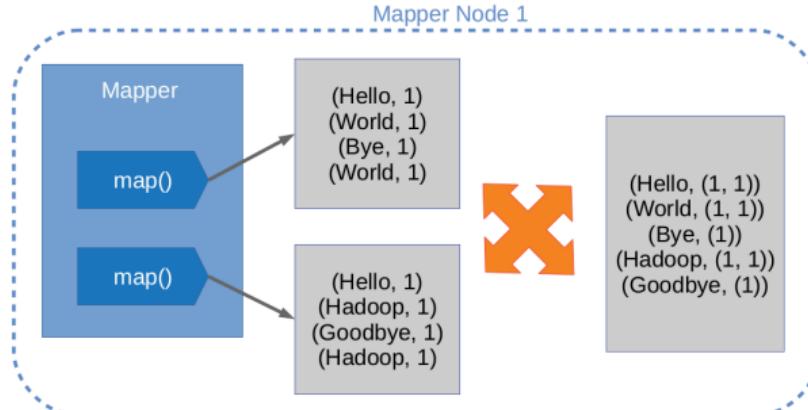
Word Count in MapReduce - Map (2/2)



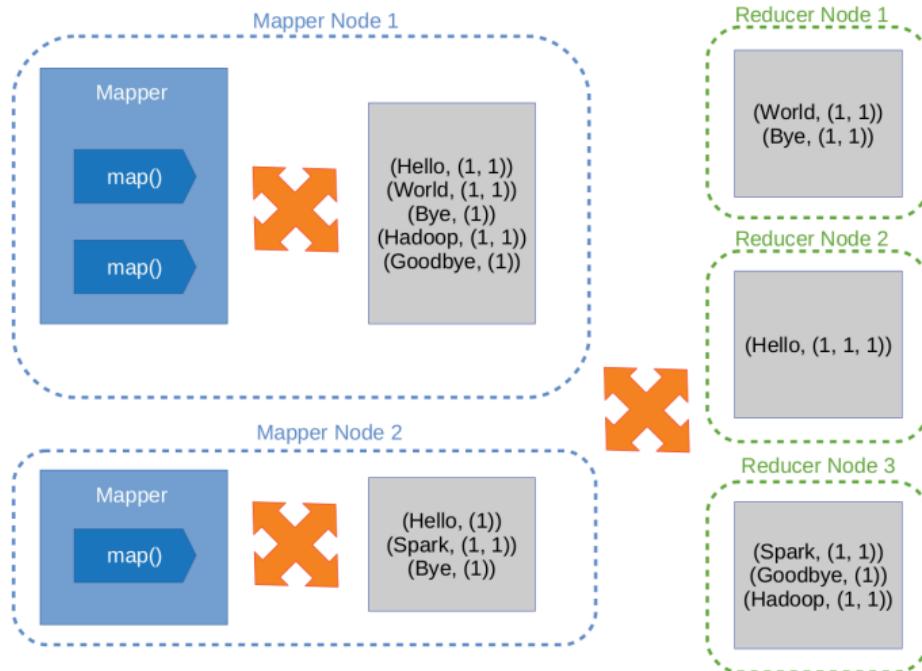
Word Count in MapReduce - Shuffle and Sort (1/3)



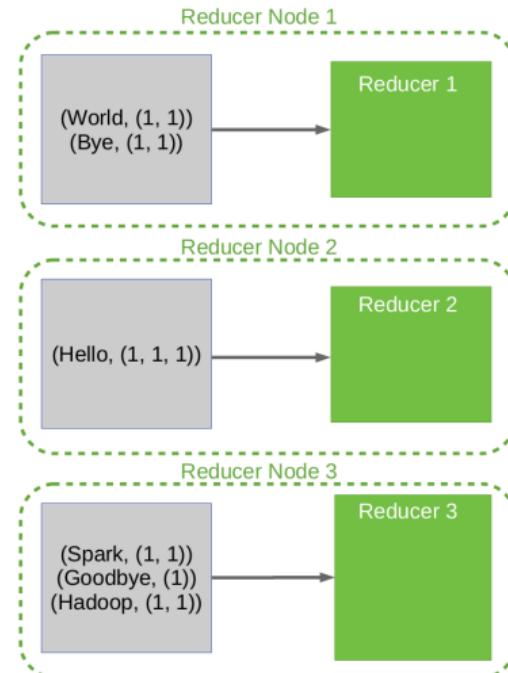
Word Count in MapReduce - Shuffle and Sort (2/3)



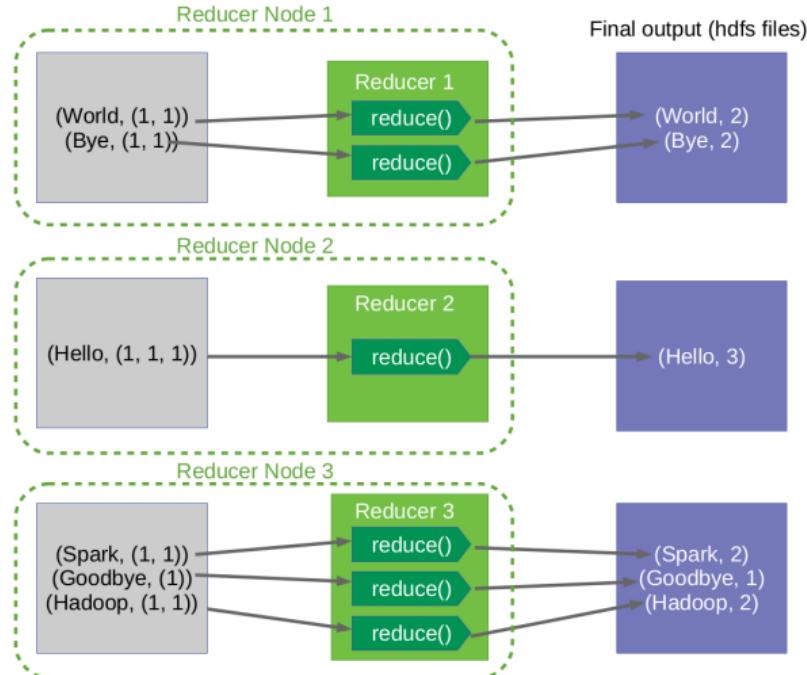
Word Count in MapReduce - Shuffle and Sort (3/3)



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

```
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

- ▶ **Input:** (key, value) pairs
- ▶ **Output:** a list of (key, value) pairs
- ▶ The Mapper may use or completely ignore the input key.

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map(in_key, in_value) -> list of (inter_key, inter_value)
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(in_key, in_value) ⇒ map() ⇒ (inter_key1, inter_value1)  
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                                (inter_key3, inter_value3)  
                                (inter_key4, inter_value4)
```

...



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)
```

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(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)
```

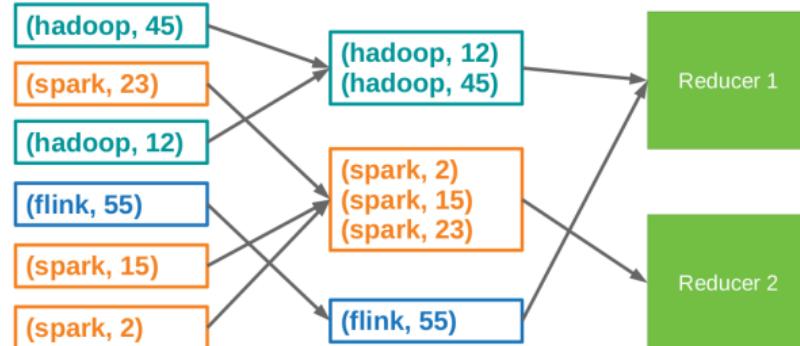
(21, Hello Hadoop Goodbye Hadoop) \Rightarrow map() \Rightarrow (Hello, 1)
(Hadoop, 1)
(Goodbye, 1)
(Hadoop, 1)



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");

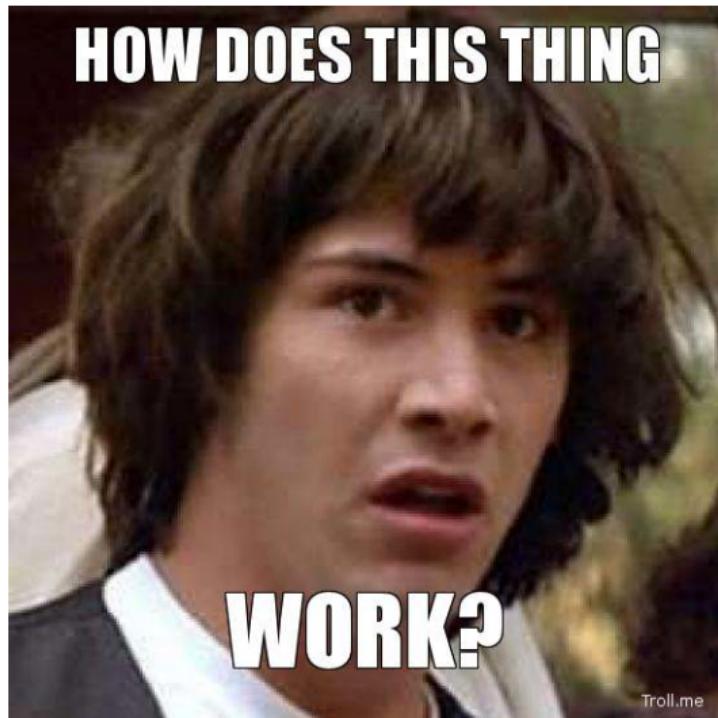
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);

    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]));

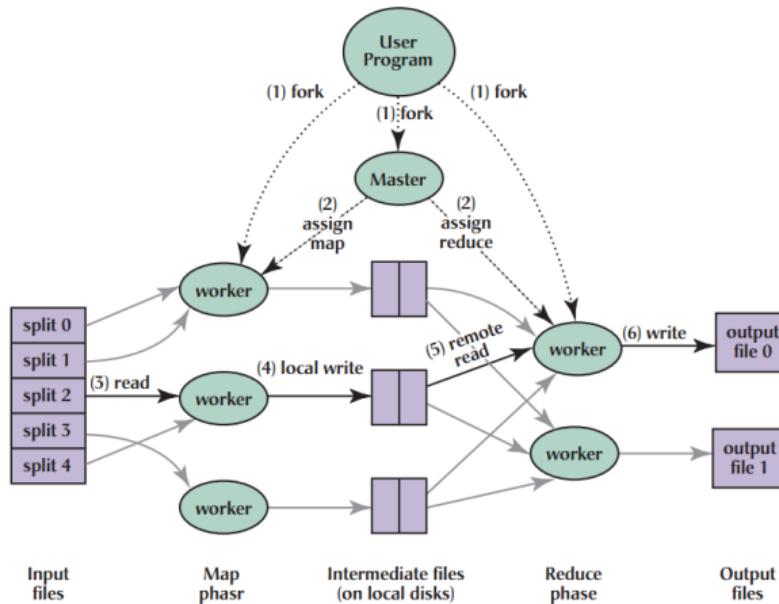
    job.waitForCompletion(true);
}
```





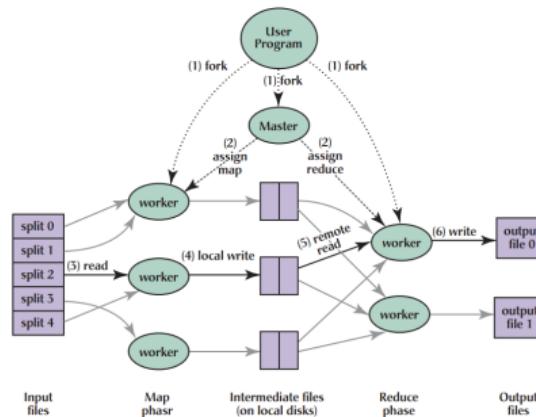
Implementation

Architecture



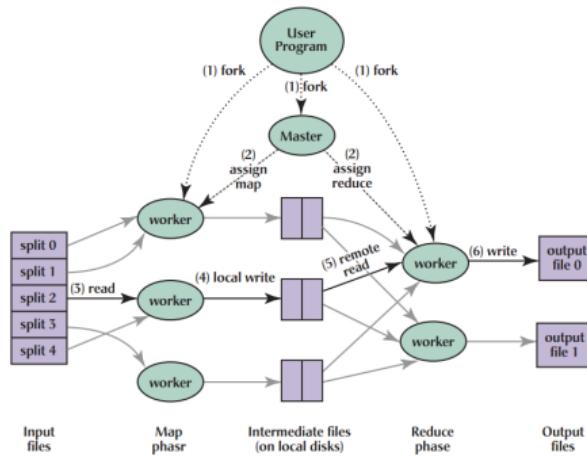
MapReduce Execution (1/7)

- ▶ 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.



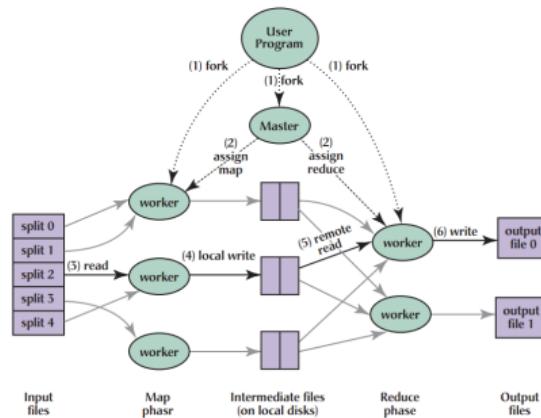
MapReduce Execution (2/7)

- ▶ 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.



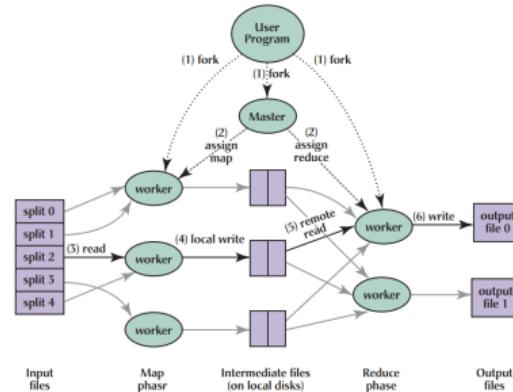
MapReduce Execution (3/7)

- ▶ 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**.



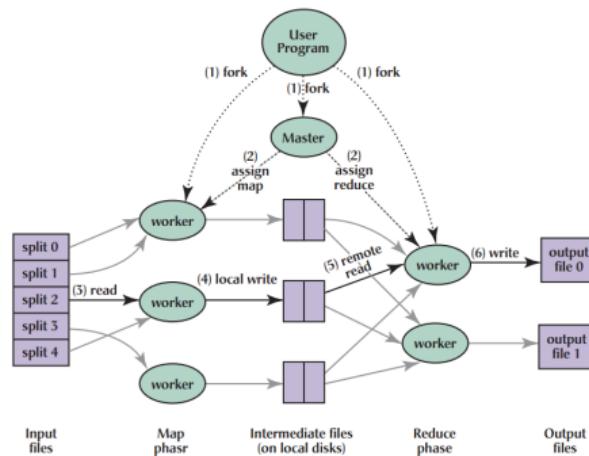
MapReduce Execution (4/7)

- ▶ 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**.



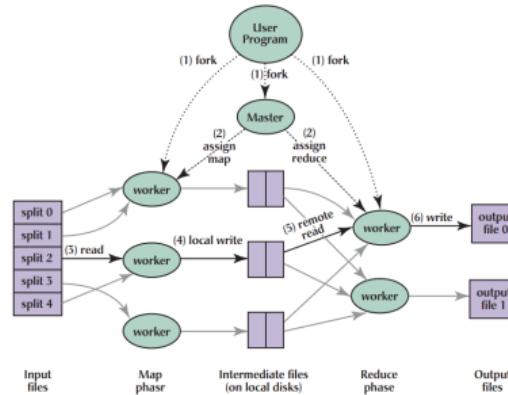
MapReduce Execution (5/7)

- ▶ 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**.



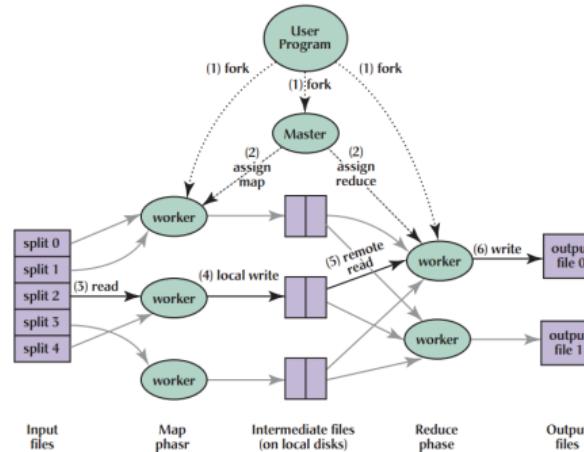
MapReduce Execution (6/7)

- ▶ 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.

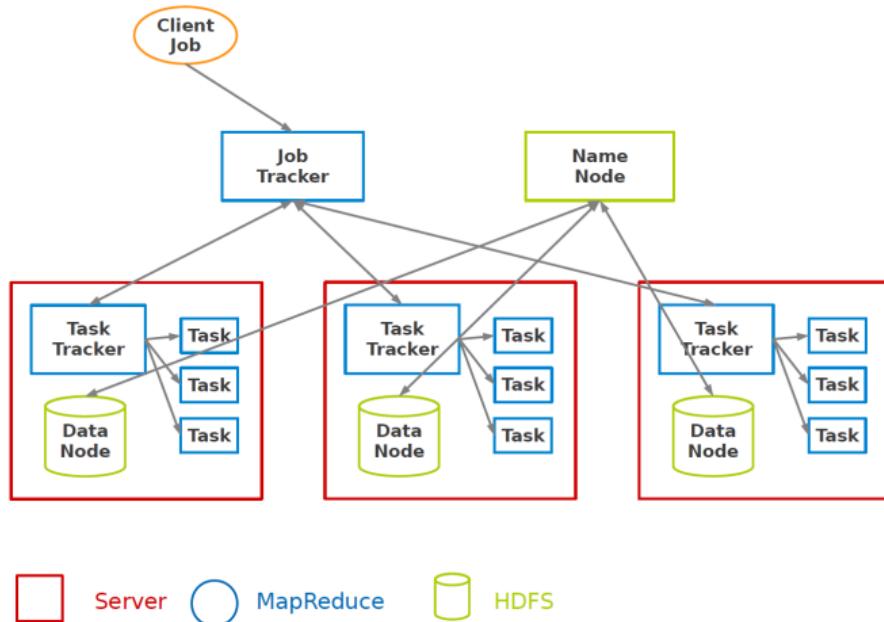


MapReduce Execution (7/7)

- 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.



MapReduce Algorithm Design



MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ Joining
- ▶ Sorting

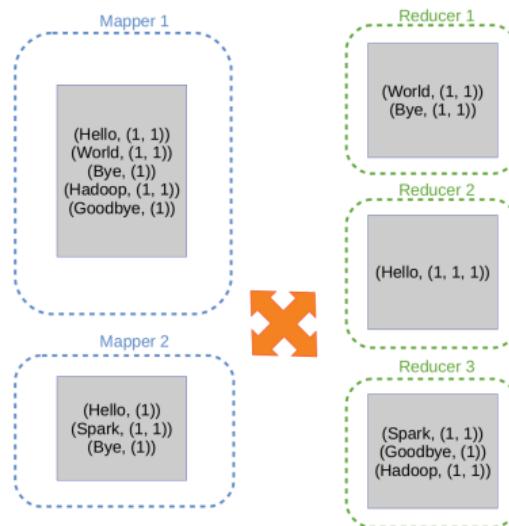


MapReduce Algorithm Design

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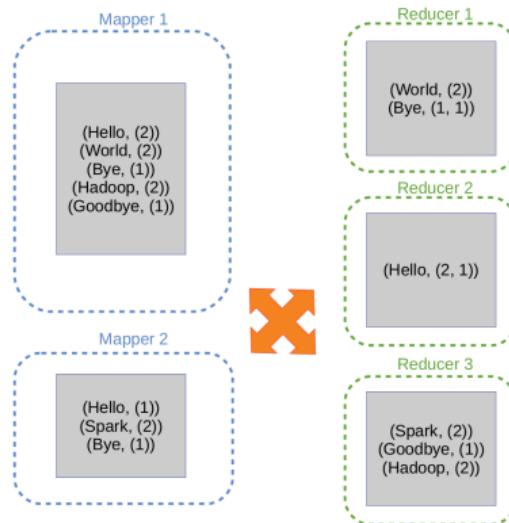
Local Aggregation - In-Map Combiner (1/2)

- 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**.



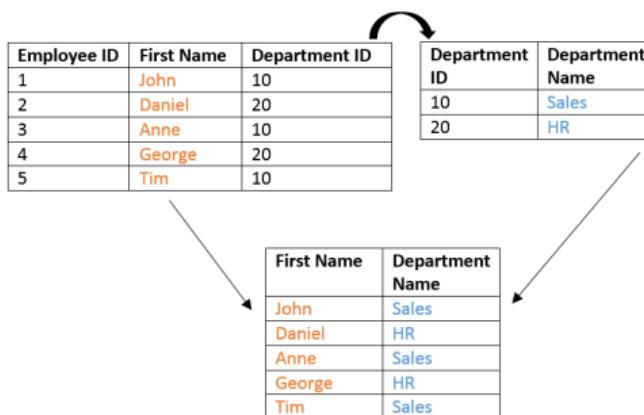


MapReduce Algorithm Design

- ▶ 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.

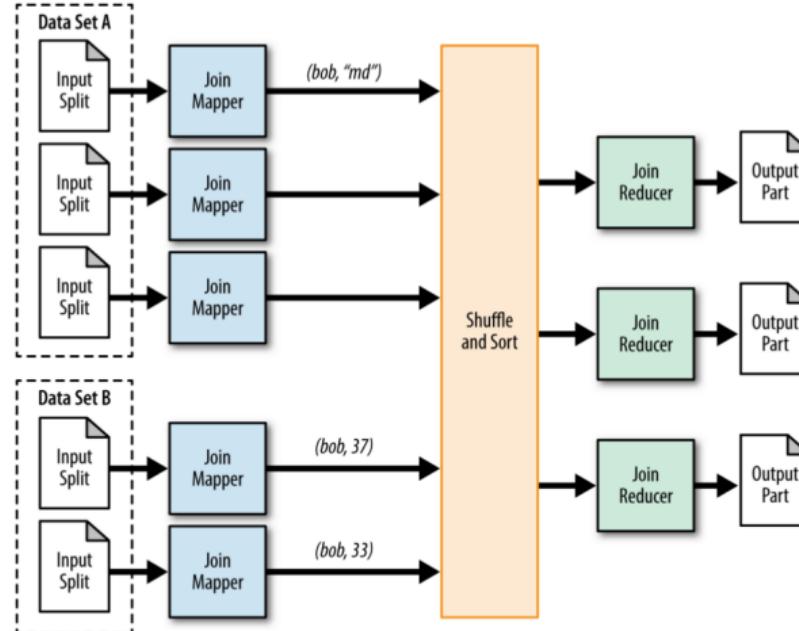




Joins - Two Strategies

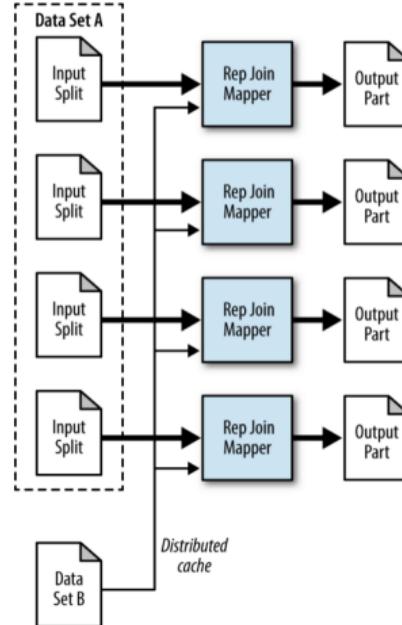
- ▶ Reduce-side join
 - Repartition join
 - When joining **two or more large** datasets together
- ▶ Map-side join
 - Replication join
 - When **one of the datasets is small** enough to cache

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.]

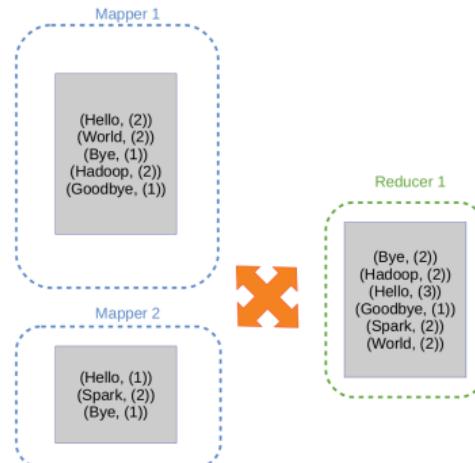


MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ Joining
- ▶ Sorting

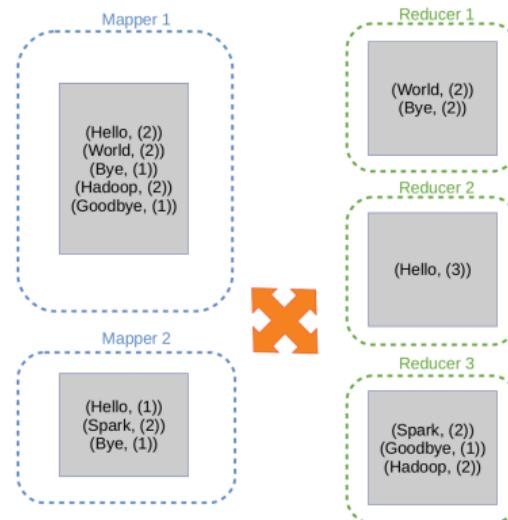
Sort (1/3)

- ▶ 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)

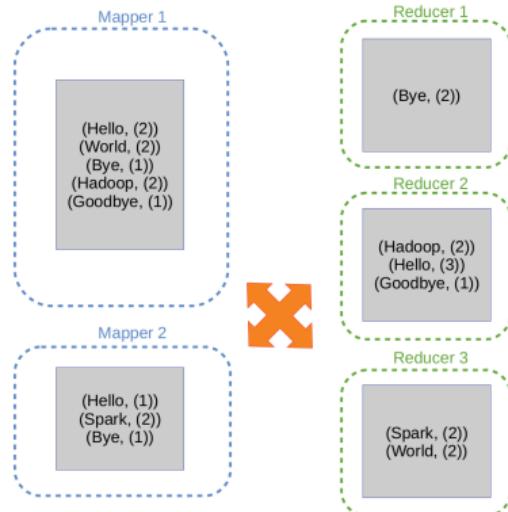
- ▶ What if we have multiple Reducer?



Sort (3/3)

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

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





FlumeJava



Motivation (1/2)

- ▶ It is easy in MapReduce:

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



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- ▶ It is easy in MapReduce:

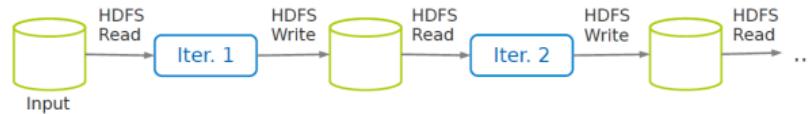
```
words(doc.txt) | sort | uniq -c
```

- ▶ What about this one?

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

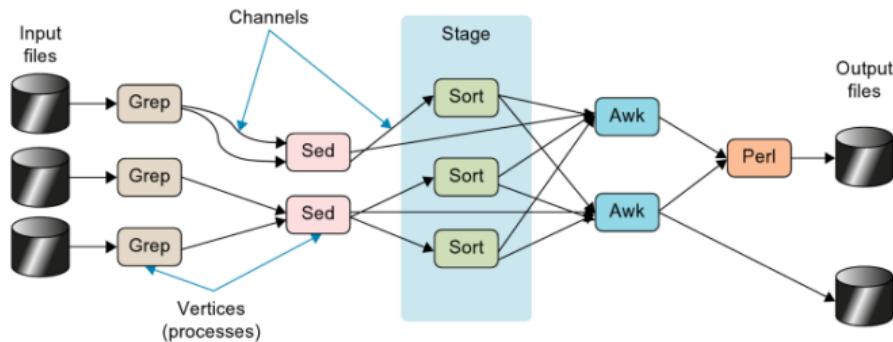
Motivation (2/2)

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



FlumeJava

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





Core Idea

- ▶ Providing a couple of **immutable parallel collections**
 - `PCollection<T>` and `PTable<K, V>`



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- ▶ Providing a number of **parallel operations** for processing the **parallel collections**
 - `parallelDo`, `groupByKey`, `combineValues` and `flatten`



Core Idea

- ▶ 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



Parallel Collections

- ▶ A few **classes** that represent **parallel collections** and abstract away the details of how data is represented.



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- ▶ **PCollection<T>**: an immutable bag of elements of type T.
- ▶ **PTable<K, V>**: an immutable multi-map with keys of type K and values of type V.

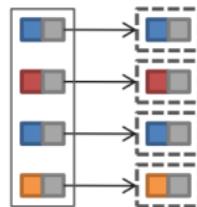


Parallel Collections

- ▶ A few **classes** that represent **parallel collections** and abstract away the details of how data is represented.
- ▶ **PCollection<T>**: an immutable bag of elements of type T.
- ▶ **PTable<K, V>**: an immutable multi-map with keys of type K and values of type V.
- ▶ The main way to manipulate these collections is to invoke a **data-parallel operation** on them.

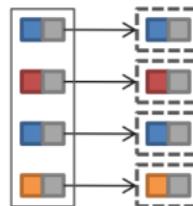
Parallel Operations (1/2)

- ▶ `parallelDo()`: elementwise computation over an input `PCollection<T>` to produce a new output `PCollection<S>`.

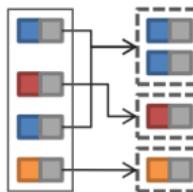


Parallel Operations (1/2)

- ▶ `parallelDo()`: elementwise computation over an input `PCollection<T>` to produce a new output `PCollection<S>`.



- ▶ `groupByKey()`: converts a multi-map of type `PTable<K, V>` into a uni-map of type `PTable<K, Collection<V>>`.





Parallel Operations (2/2)

- ▶ **combineValues()**: takes an input `PTable<K, Collection<V>>` and an associative combining function on `Vs`, and returns a `PTable<K, V>`, where each input collection of values has been combined into a single output value.



Parallel Operations (2/2)

- ▶ **combineValues()**: takes an input `PTable<K, Collection<V>>` and an associative combining function on `Vs`, and returns a `PTable<K, V>`, where each input collection of values has been combined into a single output value.
- ▶ **flatten()**: takes a list of `PCollection<T>s` and returns a single `PCollection<T>` that contains all the elements of the input `PCollections`.



Word Count in FlumeJava

```
public class WordCount {  
    public static void main(String[] args) throws Exception {  
        Pipeline pipeline = new MRPipeline(WordCount.class);  
  
        PCollection<String> lines = pipeline.readTextFile(args[0]);  
  
        PCollection<String> words = lines.parallelDo(new DoFn<String, String>() {  
            public void process(String line, Emitter<String> emitter) {  
                for (String word : line.split("\\s+")) {  
                    emitter.emit(word);  
                }  
            }  
        }, Writables.strings());  
  
        PTable<String, Long> counts = Aggregate.count(words);  
  
        pipeline.writeTextFile(counts, args[1]);  
  
        pipeline.done();  
    }  
}
```



Summary



Summary

- ▶ Scaling out: shared nothing architecture
- ▶ MapReduce
 - Programming model: Map and Reduce
 - Execution framework
- ▶ FlumeJava
 - Dataflow DAG
 - Parallel collection: PCollection and PTable
 - Transforms: ParallelDo, GroupByKey, CombineValues, Flatten

References

- ▶ J. Dean et al., "MapReduce: simplified data processing on large clusters", Communications of the ACM, 2008.
- ▶ C. Chambers et al., "FlumeJava: easy, efficient data-parallel pipelines", ACM Sigplan Notices, 2010.
- ▶ J. Lin et al., "Data-intensive text processing with MapReduce", Synthesis Lectures on Human Language Technologies, 2010.



Questions?