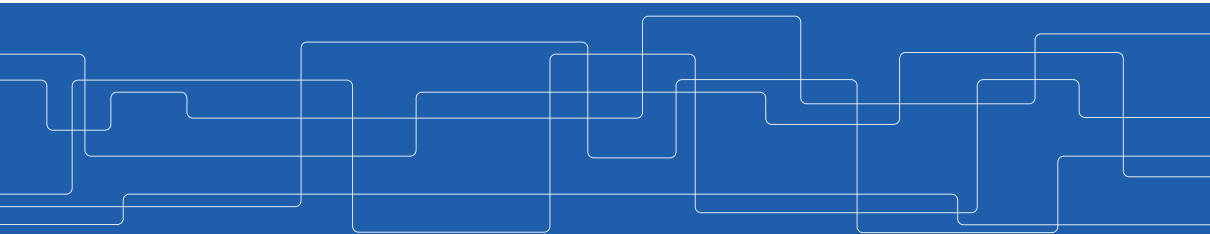




Parallel Processing - MapReduce and FlumeJava

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2020-09-08



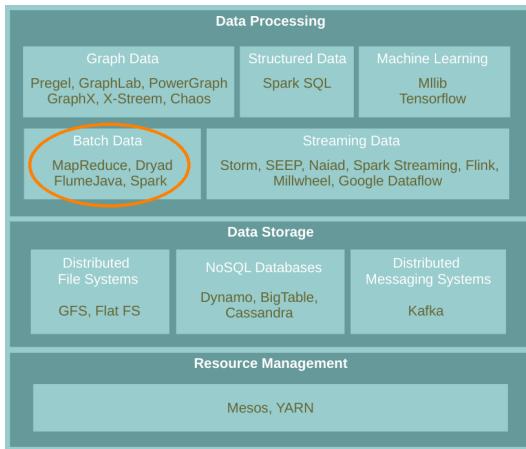


The Course Web Page

<https://id2221kth.github.io>

<https://tinyurl.com/y4qph82u>

Where Are We?



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

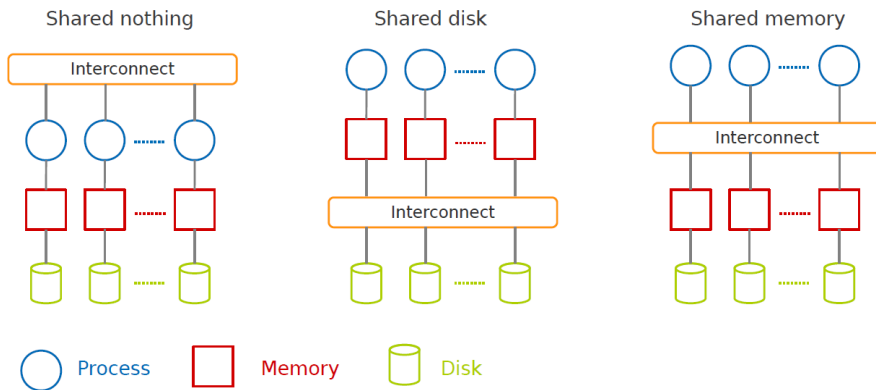


Scale Up vs. Scale Out

- ▶ 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**.

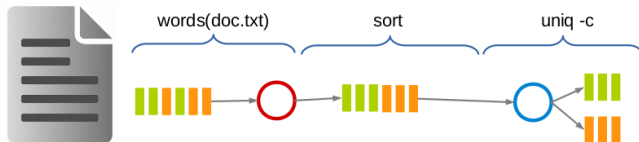
Programming Model

hello world



Word Count

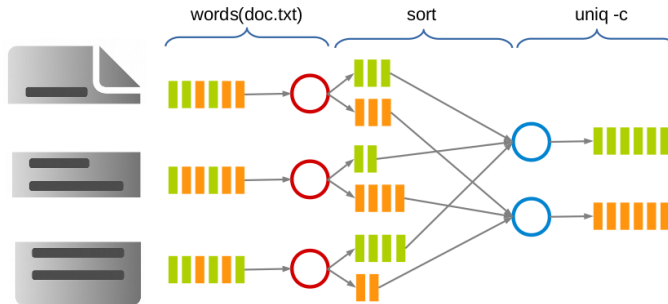
- ▶ Count the number of times each **distinct word** appears in the file
- ▶ If the file **fits in memory**: `words(doc.txt) | sort | uniq -c`



- ▶ If not?

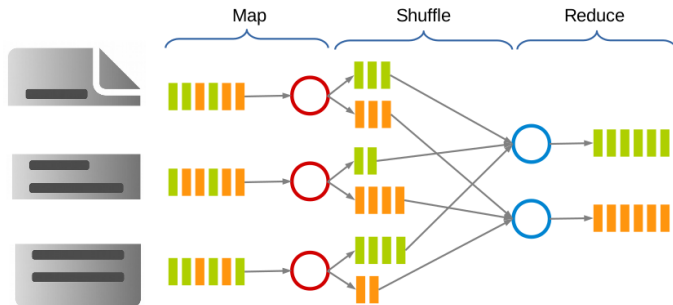
Data-Parallel Processing (1/2)

- Parallelize the data and process.



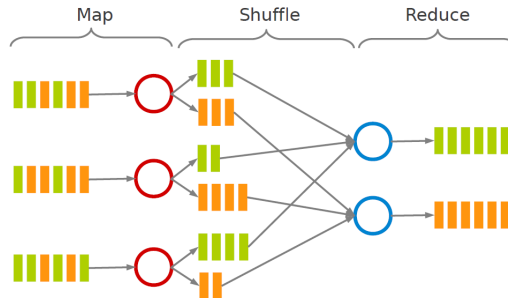
Data-Parallel Processing (2/2)

► MapReduce



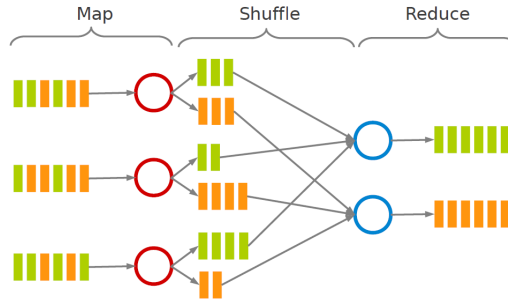
MapReduce Stages - Map

- ▶ 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**.



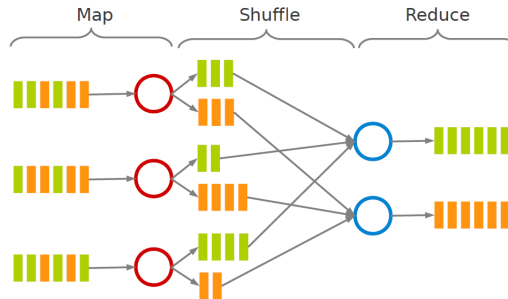
MapReduce Stages - Shuffle and Sort

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

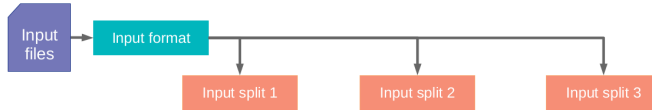


MapReduce Stages - Reduce

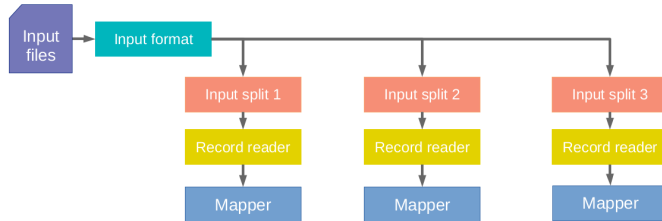
- ▶ Each **Reduce task** operates on all **intermediate values** associated with the **same intermediate key**.
- ▶ Produces the **final output**.



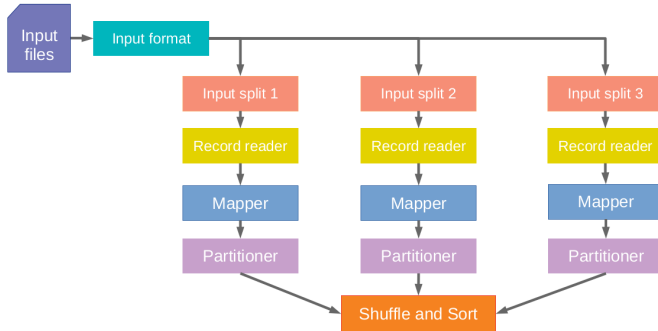
MapReduce Data Flow (1/5)



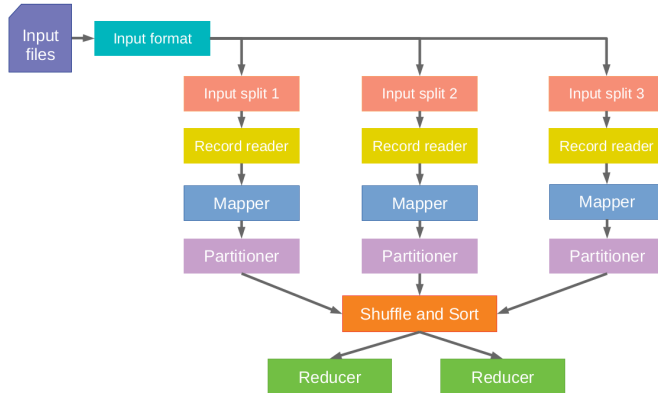
MapReduce Data Flow (2/5)



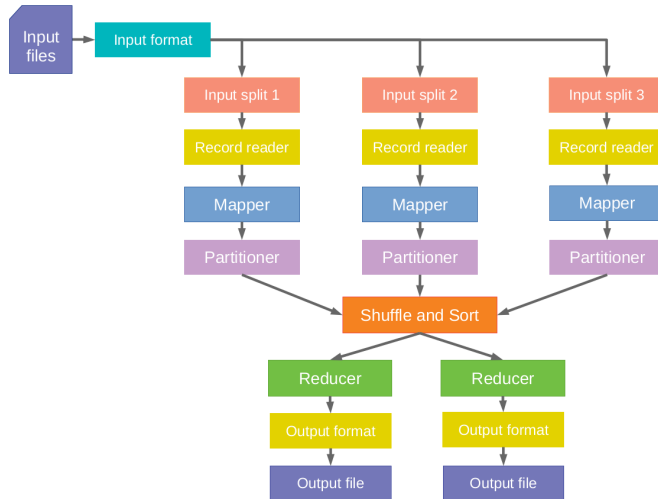
MapReduce Data Flow (3/5)



MapReduce Data Flow (4/5)

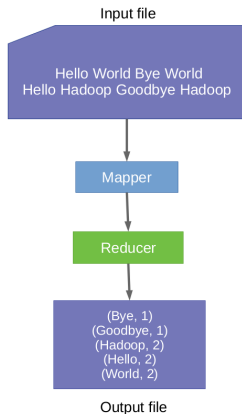


MapReduce Data Flow (5/5)

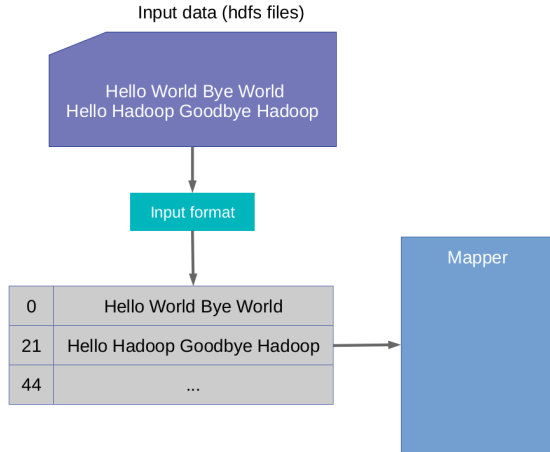


Word Count in MapReduce

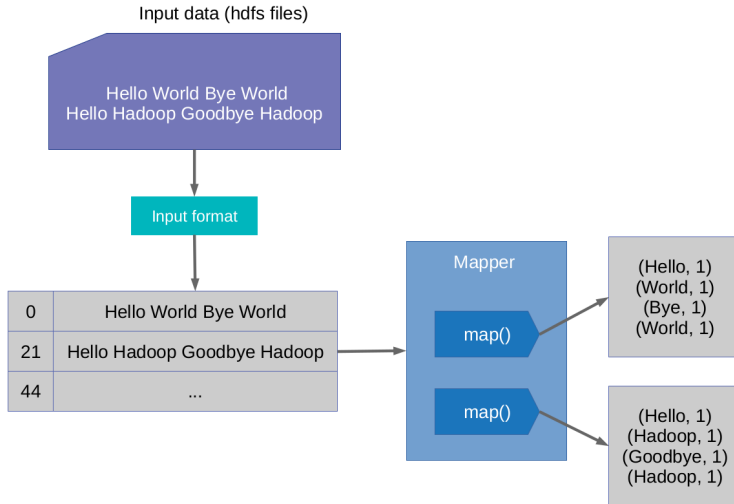
- Consider doing a **word count** of the following file using **MapReduce**



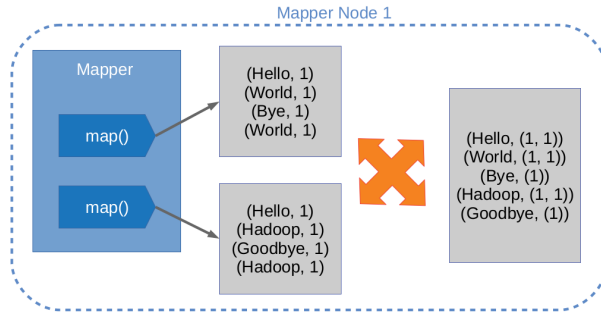
Word Count in MapReduce - Map (1/2)



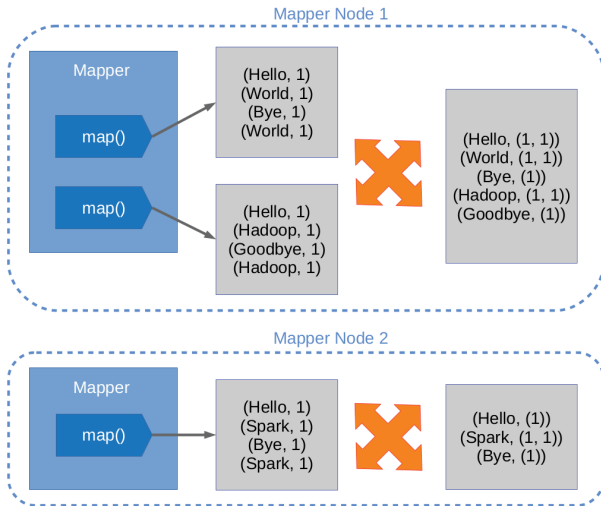
Word Count in MapReduce - Map (2/2)



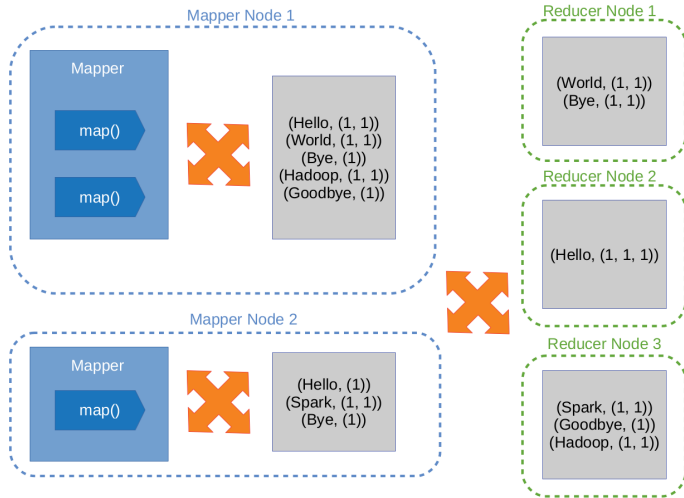
Word Count in MapReduce - Shuffle and Sort (1/3)



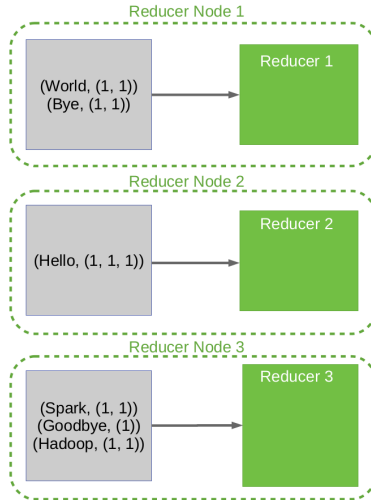
Word Count in MapReduce - Shuffle and Sort (2/3)



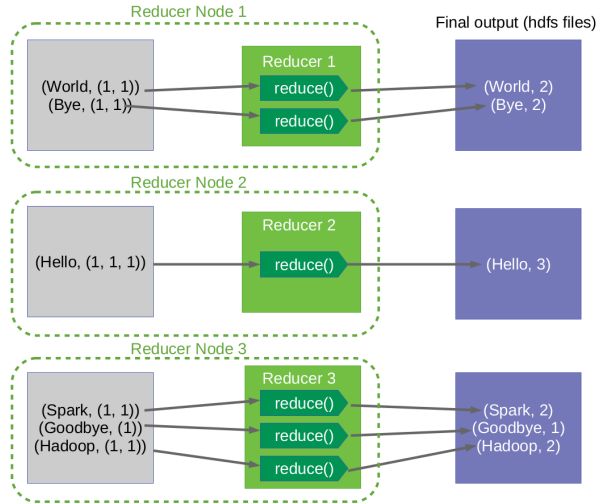
Word Count in MapReduce - Shuffle and Sort (3/3)



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) \Rightarrow **map()** \Rightarrow (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)

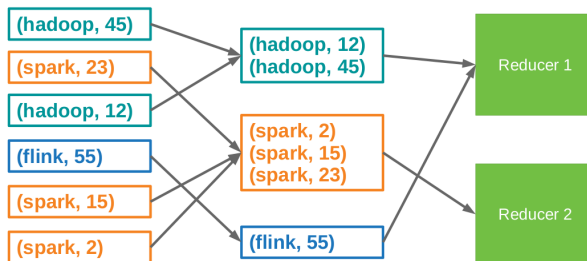
```
map(k, v) = foreach w in v emit (w, 1)
```

```
(21, Hello Hadoop Goodbye Hadoop) ⇒ map() ⇒ (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

$(\text{inter_k}, [\text{inter_v1}, \text{inter_v2}, \dots]) \Rightarrow \text{reduce}() \Rightarrow$
 $(\text{out_k}, \text{out_v1})$
 $(\text{out_k}, \text{out_v2})$
 \dots

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))
```

$(\text{KTH}, [5, 1, 12, 7]) \Rightarrow \text{reduce}() \Rightarrow (\text{KTH}, 12)$



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);
        }
    }
}
```

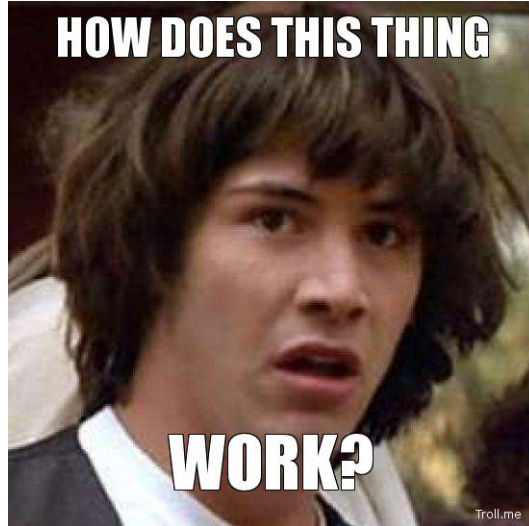


Example: Word Count - **reduce**

```
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));  
    }  
}
```

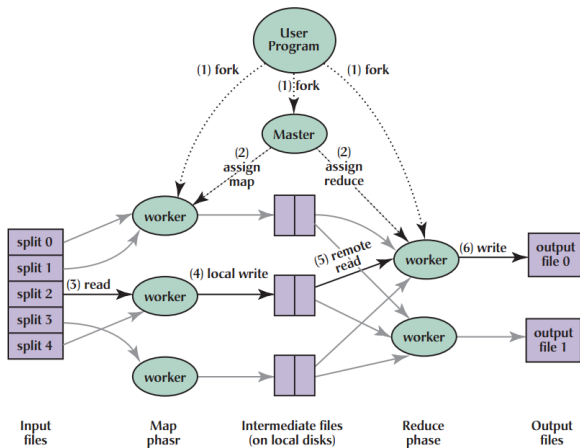
Example: Word Count - driver

```
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);  
}
```



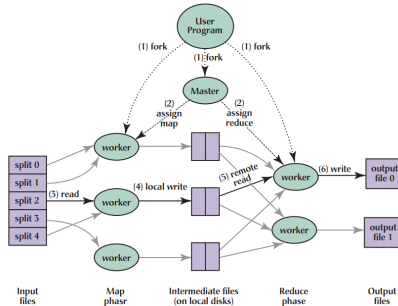
Implementation

Architecture



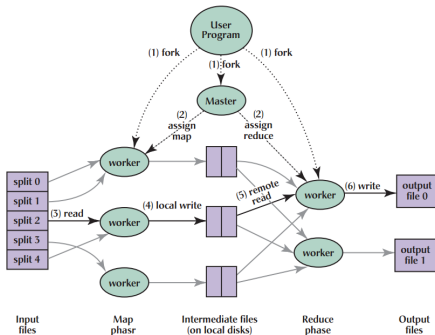
MapReduce Execution (1/7)

- ▶ 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.



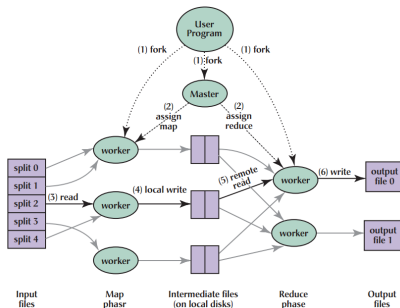
MapReduce Execution (2/7)

- ▶ 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.



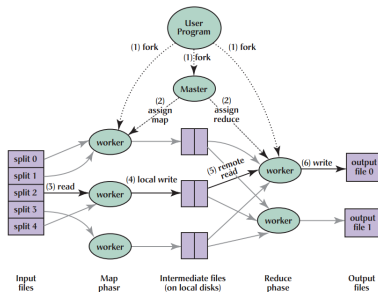
MapReduce Execution (3/7)

- ▶ 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**.



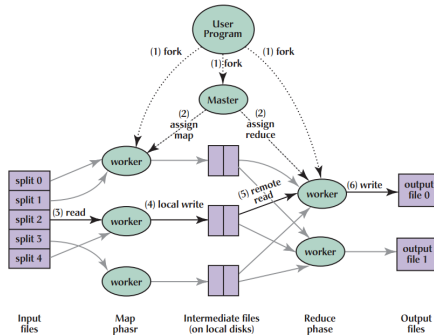
MapReduce Execution (4/7)

- ▶ 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**.



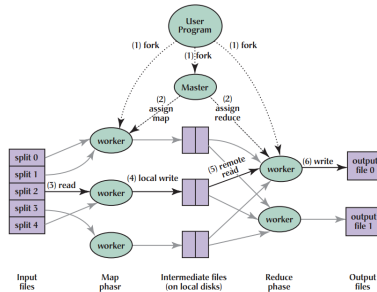
MapReduce Execution (5/7)

- ▶ 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**.



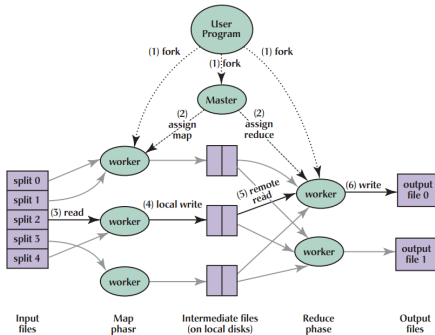
MapReduce Execution (6/7)

- ▶ 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.

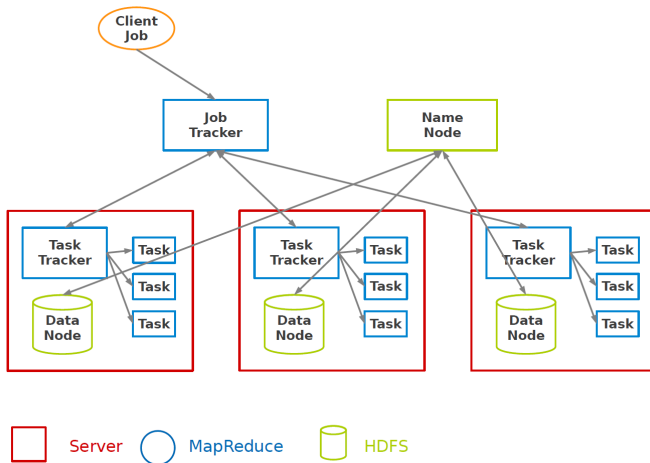


MapReduce Execution (7/7)

- 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

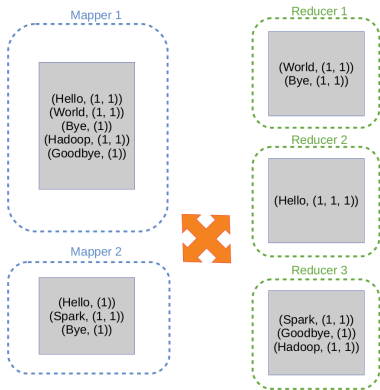


MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ Joining
- ▶ Sorting

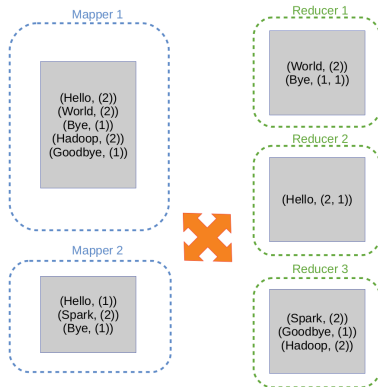
Local Aggregation - In-Map Combiner (1/2)

- 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.

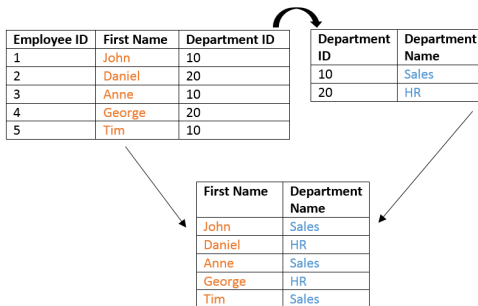




MapReduce Algorithm Design

- ▶ Local aggregation
- ▶ **Joining**
- ▶ Sorting

- ▶ Joins 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**.

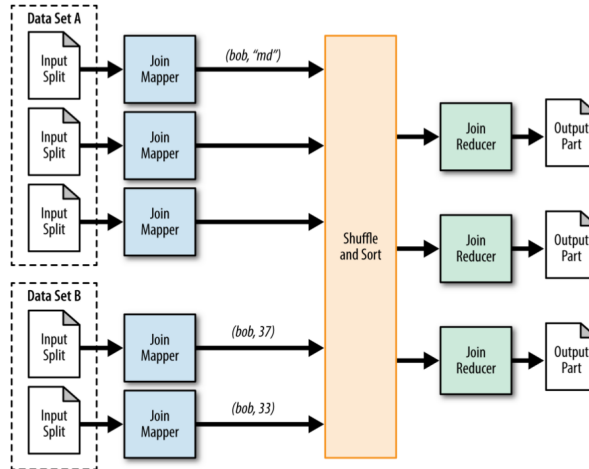




Joins - Two Strategies

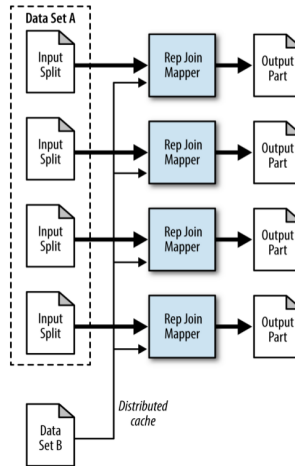
- ▶ Reduce-side join
 - Repartition join
 - When joining two or more large datasets together
- ▶ Map-side join
 - Replication join
 - When one of the datasets is small enough to cache

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.]

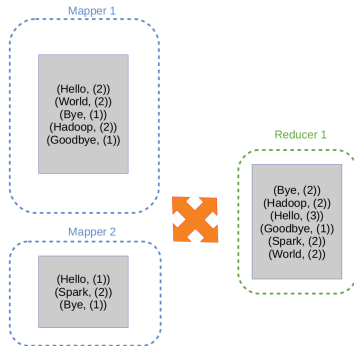


MapReduce Algorithm Design

- ▶ 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**.



-
- The diagram illustrates the MapReduce process. Two mappers (Mapper 1 and Mapper 2) send their output to three reducers (Reducer 1, Reducer 2, and Reducer 3). Mapper 1 outputs: (Hello, (2)), (World, (2)), (Bye, (1)), (Hadoop, (2)), (Goodbye, (1)). Mapper 2 outputs: (Hello, (1)), (Spark, (2)), (Bye, (1)). Reducer 1 receives: (World, (2)), (Bye, (2)). Reducer 2 receives: (Hello, (3)). Reducer 3 receives: (Spark, (2)), (Goodbye, (1)), (Hadoop, (2)).

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

FlumeJava



Motivation (1/2)

- ▶ It is easy in **MapReduce**:

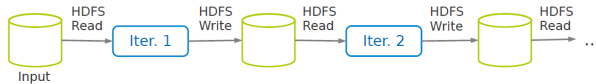
```
words(doc.txt) | sort | uniq -c
```

- ▶ What about this one?

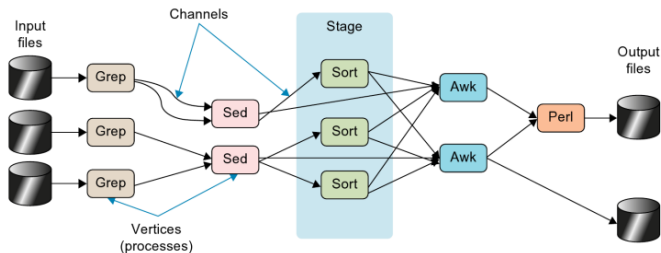
```
words(doc.txt) | grep | sed | sort | awk | perl
```

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** 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>`
- ▶ 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

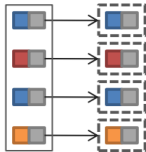


Parallel Collections

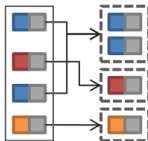
- ▶ A few **classes** that represent **parallel collections** and abstract away the details of how data is represented.
- ▶ **PCollection<T>**: an immutable bag of elements of type T.
- ▶ **PTable<K, V>**: an immutable multi-map with keys of type K and values of type V.
- ▶ The main way to manipulate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



- ▶ **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 `V`s, 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

- ▶ 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?