

# Big Data Processing - The MapReduce Programming Model

Hong-Linh Truong
Department of Computer Science
<a href="mailto:linh.truong@aalto.fi">linh.truong@aalto.fi</a>, <a href="https://rdsea.github.io">https://rdsea.github.io</a>

## MapReduce Programming Model



## MapReduce programming model

- MapReduce is a programming model from Google
  - Various implementations/frameworks support MapReduce
    - Apache Hadoop (<a href="https://hadoop.apache.org">https://hadoop.apache.org</a>)

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- Support batch data processing for very large datasets
- Suitable for batch jobs in big data, e.g.,
  - Web search, document processing, ecommerce information
  - Extract, transform, data wrangling, and data cleansing tasks



#### Common needs

- Thinking if we have data that can be represented as record=(key,value)
  - o e.g., key="aalto", value="1000" (1000 likes in linkedin)
  - potentially millions of records, with millions of keys

#### Operations

- data analytics like summarization/aggregation/filtering
  - **■** *count, min, max, average, etc.*
- ojoining data from big data set
- ocollecting data and shuffling the data to the right tasks



## Map & Reduce

- Map: map data into (key, value)
  - Receives <key,value>
  - Outputs <key,value> new set of <key,value>
- Reduce: compute results from the same key
  - Receives <key, Iterable[value]>
  - Outputs <key,value>



## **Example of a real data**

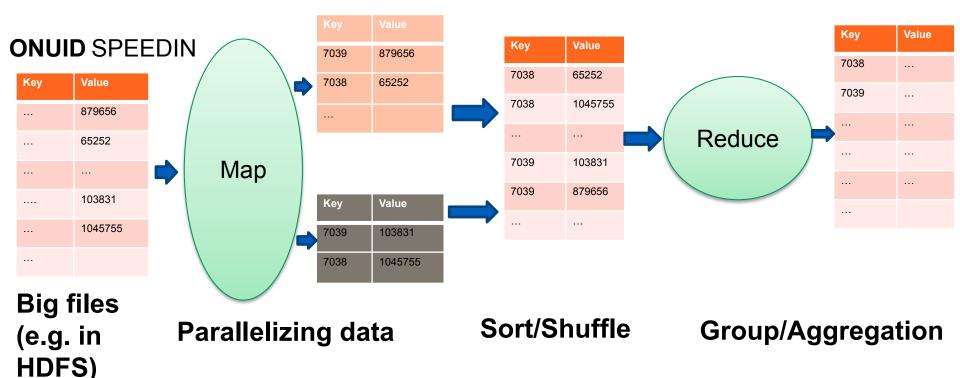
#### Look at the network monitoring data

PROVINCECODE, DEVICEID, IFINDEX, FRAME, SLOT, PORT, ONUINDEX, ONUID, TIME, SPEEDIN, SPEEDOUT XXN, 10XXXXXX023, 26XXXXXX8, 1, 2, 7, 39, 100XXXXXXX2310207039, 01/08/2019 00:04:07, 148163, 49018 XXN, 10XXXXXX023, 26XXXXXX8, 1, 2, 7, 38, 100XXXXXXX2310207038, 01/08/2019 00:04:07, 1658, 1362 XXN, 10XXXXXXX023, 26XXXXXX8, 1, 2, 7, 9, 100XXXXXXX2310207009, 01/08/2019 00:04:07, 6693, 5185

Sample: https://github.com/rdsea/bigdataplatforms/tree/master/data/onudata



# Understand the MapReduce programming model





## **Key ideas of MapReduce**

- A kind of divide-and-conquer paradigm
- Data can be divided by "Map" operators
  - data processing tasks extract "intermediate results"
- Intermediate results can be aggregated through "Reduce" operators
  - data processing tasks produce a result from "intermediate results"
- We can glue "Map" and "Reduce" operators into a multi-stage data flow model
- Other possible operators:
  - o Combiner: performs "Reduce" at local nodes
  - Partitioner: decides key/value for Reduce



## Key ideas of MapReduce

#### Key points for the developers

 should write only the main "logic": Map and Reduce operators

#### The runtime framework will

- handle data movement and input/output management for Map/Reduce tasks
- parallelizing tasks in multiple nodes

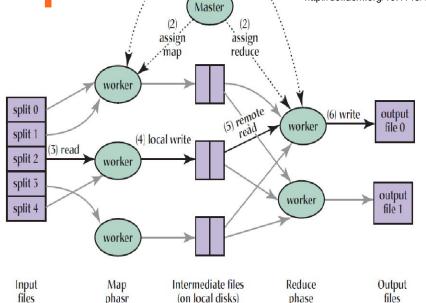


MapReduce concept in the original paper

Figures source: Jeffrey Dean and Sanjay Ghemawat. 2008. MapReduce: simplified data processing on large clusters. Commun. ACM 51, 1 (January 2008), 107-113. DOI=10.1145/1327452.1327492 http://doi.acm.org/10.1145/1327452.1327492

```
map(String key, String value):
    // key: document name
    // value: document contents
    for each word w in value:
        EmitIntermediate(w, "1");

reduce(String key, Iterator values):
    // key: a word
    // values: a list of counts
    int result = 0;
    for each v in values:
        result += ParseInt(v);
    Emit(AsString(result));
```



User

Program

(1) fork

Key point: parallelize workers to process a lot of input files and produce a lot of output files



## Tasks and their dependencies

- A task (Map or Reduce) is stateless
  - executed as an individual process
- Acyclic graph of tasks as a workflow
  - can be executed using a batch job scheduler
  - o files as the exchange medium among tasks



## Hadoop MapReduce

- Hadoop supports the MapReduce programming model
  - Use cluster nodes for data processing tasks
  - Access data in HDFS files and partitions in different nodes
  - Hadoop runtime automatically creates parallel tasks
  - YARN is used to run jobs of MapReduce applications
- Data management (HDFS) and data processing (MapReduce) are aligned nicely
  - $\circ$  Run in the same nodes  $\Rightarrow$  data locality optimization



# Map/Reduce tasks and data/node partitions

#### A Map task can handle a data partition in the same node

- e.g., a Map task handles a HDFS data block ⇒ local data optimization: no data movement - local processing
- Results from a Map task are intermediate ⇒ to where a task will store them?
- what if a Map task fails?

#### Reduce Task

 $\circ$  to deal with data produced from different Map tasks  $\Rightarrow$  where to run the Reduce tasks?



```
Examples - Map
                                                                  Output
                                          Input
public static class SpeedInMapper 🚄 💮
    extends Mapper<Object, Text, LongWritable , AverageWritable>[
 private LongWritable id =new LongWritable();
 private AverageWritable averagecount = new AverageWritable();
 public void map(Object key, Text value, Context putput)
     throws IOException, InterruptedException {
     String valueString = value.toString();
                                                               Parse the data to
     String[] record = valueString.split(",");
     id.set(Long.parseLong(record[7]));
                                                               get ONUID and
     averagecount.setAverage(Float.parseFloat(record[9]));
                                                               SPEEDIN
     averagecount.setCount(1);
     output.write(id,averagecount);
                                          Map (ONUID, (SPEEDIN, count))
```



## **Example - Reduce Input**

#### Output

```
public static class SpeedInAverageReducer
    extends Reducer LongWritable, AverageWritable, LongWritable, FloatWritable> {
 private FloatWritable new result = new FloatWritable();
 public void reduce(LongWritable key, Iterable<AverageWritable> values,
                   Context context
                   ) throws IOException, InterruptedException {
   float avg = 0;
   int count = 0:
   for (AverageWritable val : values) {
                                                     Simple way to
       float current avg =val.getAverage();
       int current count =val.getCount();
                                                     determine the
       avg = avg + (current avg*current count);
       count = count + current count;
                                                     average as
                                                     "Reduce" operator
  new result.set(avg/count);
  context.write(key, new_result);
                                                           Reduce (ONUID, AVG)
```

## Driver: connect Map and Reduce operators

```
public static void main(String[] args) throws Exception {
   Configuration conf = new Configuration();
   Job job = Job.getInstance(conf, "simpleonuaverage");
   job.setJarByClass(SimpleAverage.class);
   job.setMapperClass(SpeedInMapper.class);
   job.setCombinerClass(SpeedInAverageCombiner.class);
   job.setReducerClass(SpeedInAverageReducer.class);
   job.setMapOutputKeyClass(LongWritable.class);
   job.setMapOutputValueClass(AverageWritable.class);
   job.setOutputKeyClass(LongWritable.class);
   job.setOutputValueClass(FloatWritable.class);
   FileInputFormat.addInputPath(job, new Path(args[0]));
   FileOutputFormat.setOutputPath(job, new Path(args[1]));
   System.exit(job.waitForCompletion(true) ? 0 : 1);
}
```



## **Example with Python using MRJob**

```
class ONUSpeedinAverage(MRJob):
    def mapper(self, _, entry):
        provincecode, deviceid, ifindex, frame, slot, port, onuindex, onuid, timestamp, speedin, speedout= entry.split(",")
        #average speed is speedin with count = 1
        vield (onuid, (float(speedin),1))
  ## recalculate the new speedin average through an array of speedin average values
    def recalculate avg(self, onuid, speedin avg values):
        current speedin total = 0
        new avg count = 0
        for speedin avg, avg count in speedin avg values:
            current speedin total = current speedin total +(speedin avg*avg count)
            new avg count = new avg count + avg count
        new speedin avg = current speedin total/new avg count
        return (onuid, (new speedin avg, new avg count))
    def combiner(self, onuid, speedin avg values):
        yield self. recalculate avg(onuid, speedin avg values)
    def reducer(self, onuid, speedin avg values):
        onuid. (speedin avg. avg count) = self. recalculate avg(onuid, speedin avg values)
        vield (onuid, speedin avg)
if name == ' main ':
    ONUSpeedinAverage.run()
```

Note: see code examples in our GIT



## Scheduling and monitoring

#### ■ A MapReduce program runs ⇒ MapReduce Job

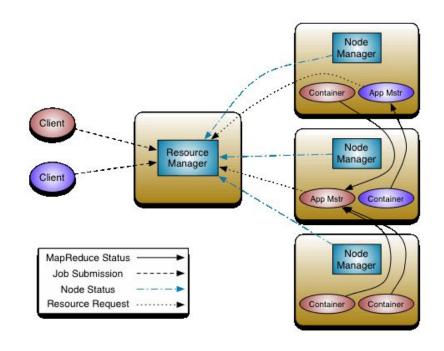
 includes many tasks (Map and Reduce processes + others)

#### JobTracker

 monitors the whole job (all tasks of a MapReduce program)

#### TaskTracker

- performs a task of the MapReduce applications
- informs JobTracker about the state of the tasks



#### Figure source:

http://hadoop.apache.org/docs/current/hadoop-yarn/hadoop-yarn-site/YARN.html



## Monitoring MapReduce Jobs



Logged in as: dr.who





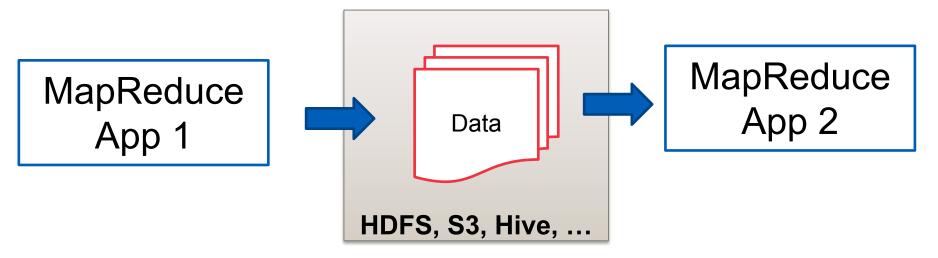
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Showing 1 to 1 of 1 entries

## **Connecting MapReduce applications**

#### **Build complex MapReduce pipelines**



Using big data storage/database as data exchange
We can use workflows to coordinate different MapReduce apps



## **Problems with MapReduce**

- Strict Map & Reduce tasks connection ⇒ limitation
- Need more flexible in processing big data workloads
  - batch data flows and streaming data flows
- Programming diversity support
  - software engineering productivity



#### Thanks!

Hong-Linh Truong
Department of Computer Science

rdsea.github.io

