CPSC 436C
Cloud Computing for Data Science

MapReduce

Simplified Data Processing on Large Clusters

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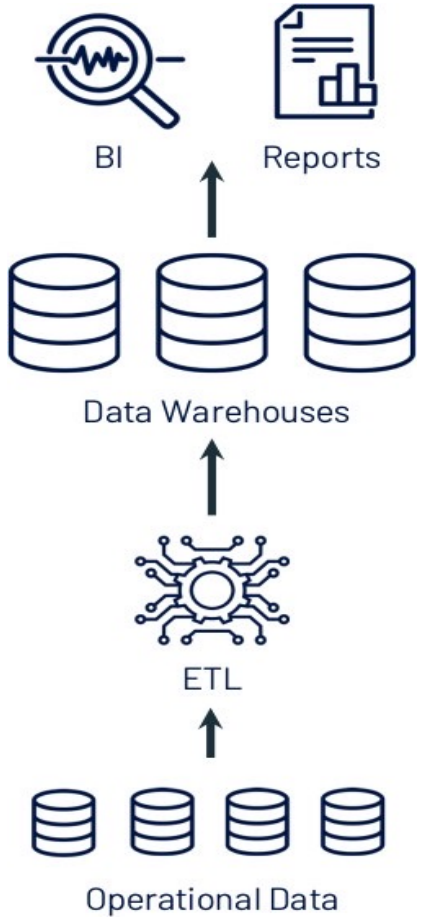
Last Class‘ Review

- Data Management Systems
  - Data Warehouse
  - Data Lake
  - Lake House

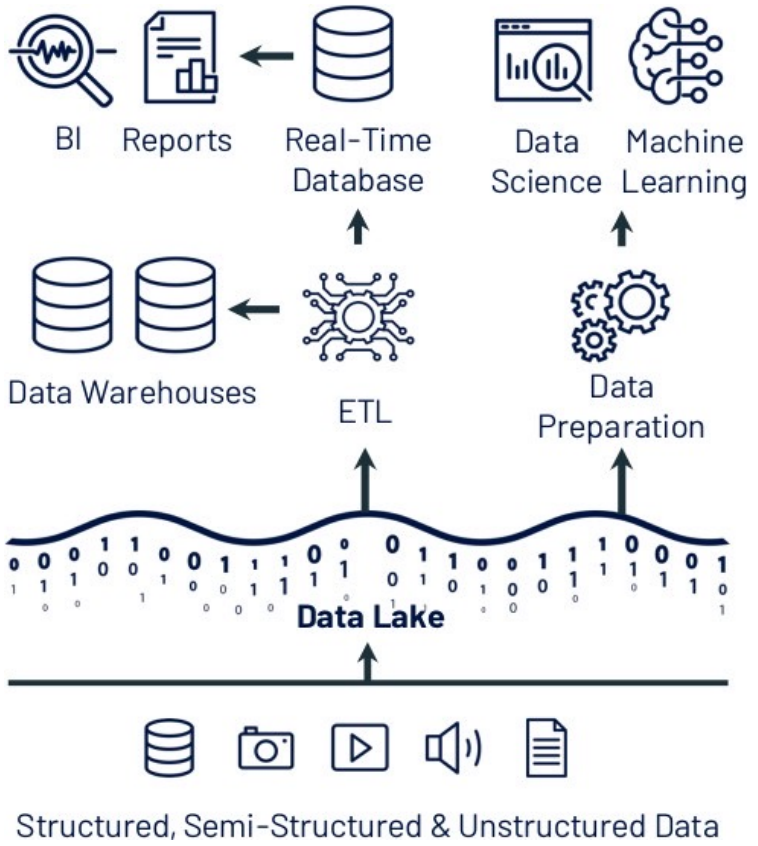
Data Warehouses (1980s)

- ETL (Extract, Transform, Load) data directly from operational database systems.
- Purpose-built for SQL analytics and BI: schemas, indexes, caching, etc.
- Powerful management features such as ACID transactions and time travel
- Data Warehouse defines the schema before data is stored (Schema on write).



Data Lakes (2010s)

- Low-cost storage to hold all raw data, e.g., Amazon S3, and HDFS.
- ETL jobs then load specific data into warehouses, possibly for further ELT.
- Directly readable in ML libraries (e.g., TensorFlow and PyTorch) due to open file format.



Raw Versus Conformed Data

- Raw data is information stored in its original format
  - For example, JSON stored as a document

- Conformed data is information that fits a specific schema, requiring transformation of raw data.

Data Warehouse and Data Lake

- Data warehouses
  - Store only conformed data
  - Transforms all data to a set schema as it is written
  - Performs additional tasks on the data, such as validation and metadata extraction.

- Data Lakes
  - Contain data in its raw format.
  - Performs the transformation on an as-needed basis, when the data is read by users.

- The trade-offs of conforming data include time and cost.

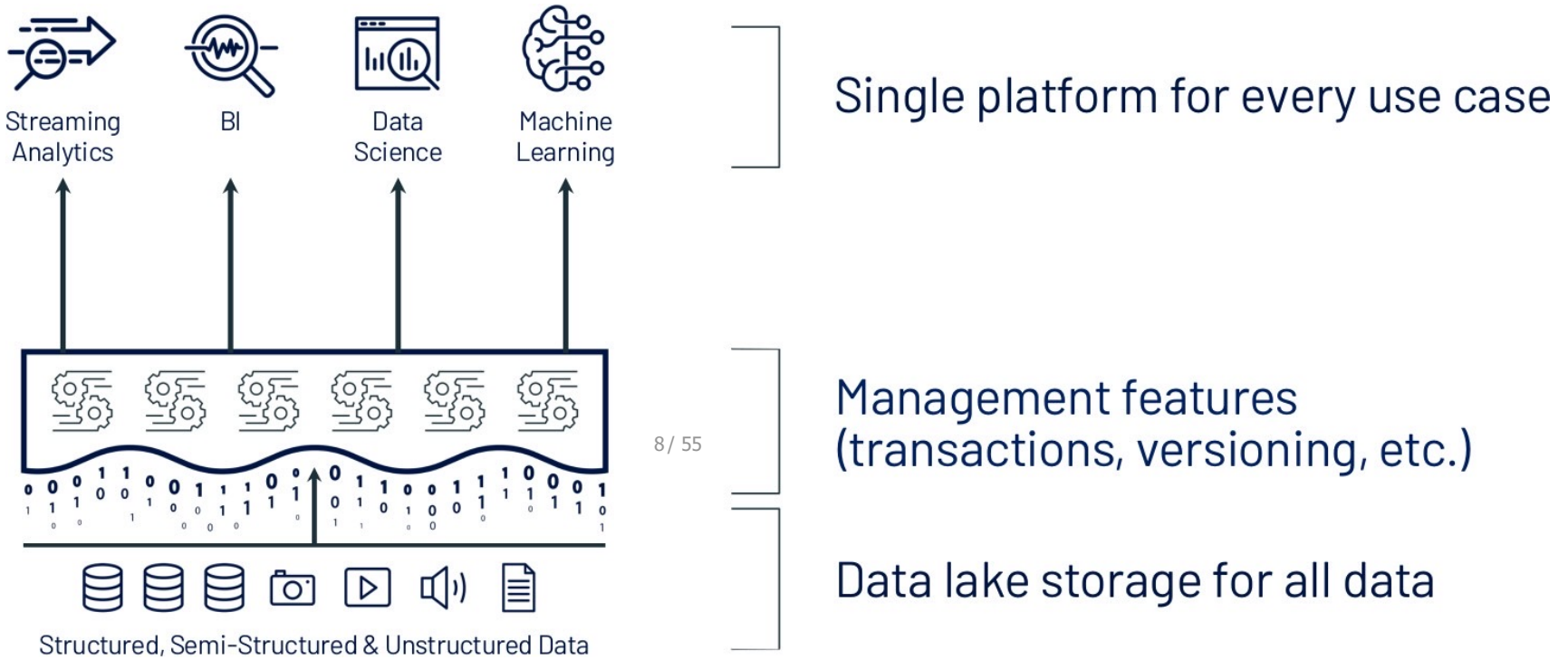
Schematization

- The trade-offs of ETL versus ELT systems is a difference in when the raw data is schematized.

- **Schema on read** is the paradigm of ELT systems, where raw data can be queried in its native format.

- **Schema on write** is the ETL paradigm, where the schema is applied when data is written into the data platform.

Lakehouse (2020)



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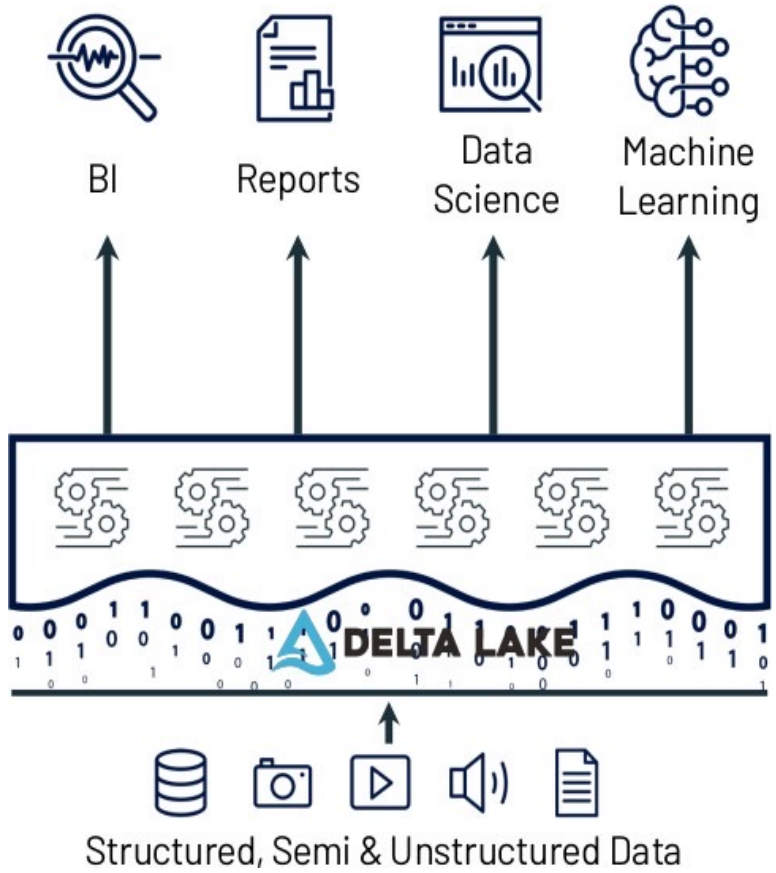
- Lakehouse combines the benefits of Data Warehouses and Data Lakes while simplifying enterprise data architectures.

Lakehouse = Data Lake + Delta Lake

- Delta Lake is an open source storage layer that brings **reliability** to Data Lakes.
- Provides ACID transactions.
- Provides time travel and versioning.
- Unifies streaming and batch data processing.



How to Choose the Best trade-off

- The best trade-off is selected based on the requirements and the downstream processing needs of the application:
  - Performance
  - Cost
  - Complexity
  - Data quality
  - Type of ingested data
  - Frequency of ingested data
  - Type of analysis on target data

What Data Management System is the Best Fit?

- **Scenario 1: E-commerce Sales Analytics**

What Data Management System is the Best Fit?

- **Scenario 1: E-commerce Sales Analytics**

- ***Data Warehouse***

A traditional data warehouse is the best choice for this scenario. It's suitable for structured data, such as sales transactions, customer data, and inventory, which are common in e-commerce.

What Data Management System is the Best Fit?

- **Scenario 2: Real-time Social Media Analytics**

What Data Management System is the Best Fit?

- **Scenario 2: Real-time Social Media Analytics**

- ***Data Lake***

A data lake is the ideal choice in this scenario. Social media data often comes in various formats and is unstructured. Data lakes can efficiently handle raw, unstructured data and support real-time analytics and sentiment analysis.

What Data Management System is the Best Fit?

- **Scenario 3: Healthcare and Medical Research Data**

What Data Management System is the Best Fit?

- **Scenario 3: Healthcare and Medical Research Data**

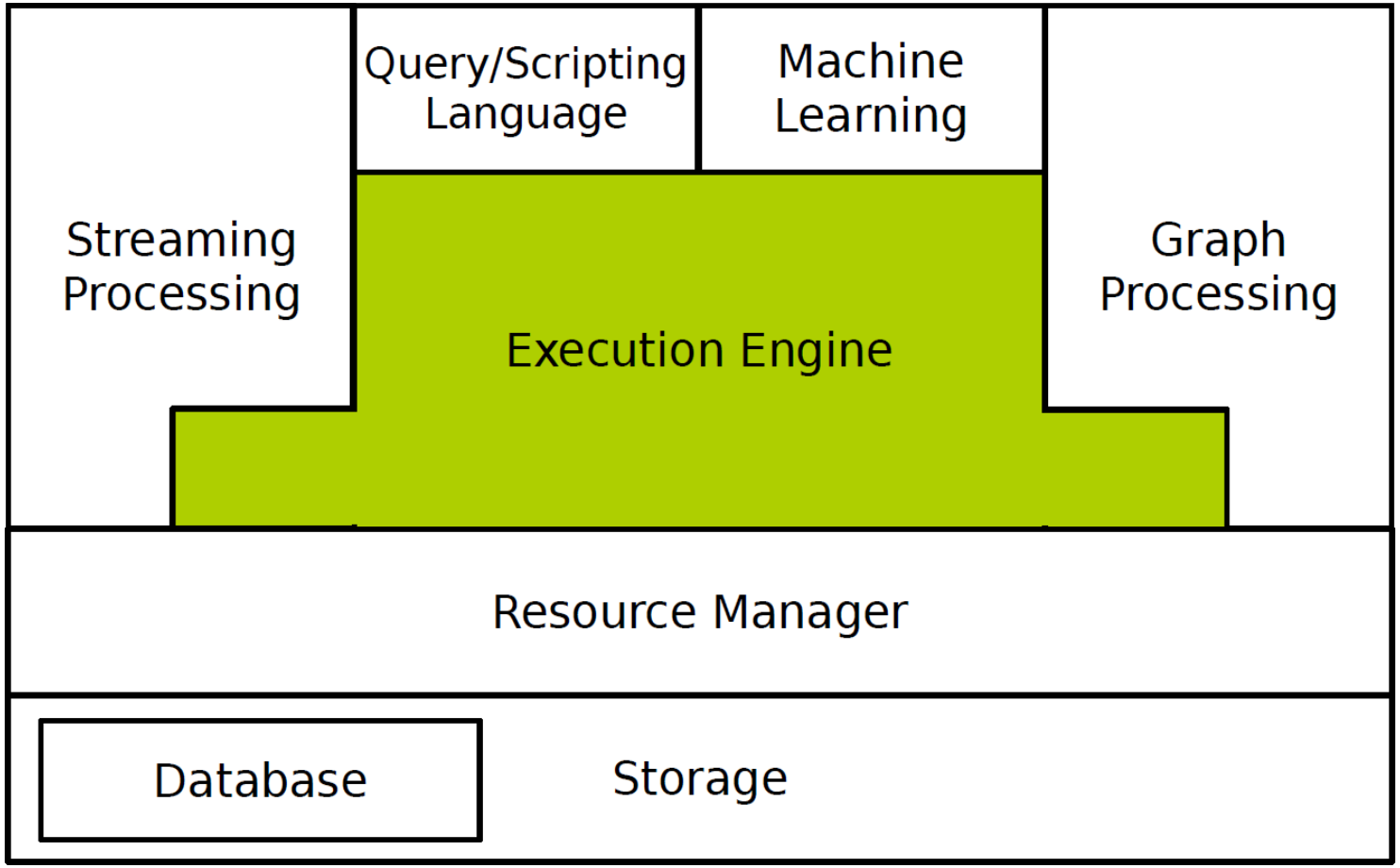
- ***Lakehouse***

A lakehouse architecture is a strong candidate in this scenario. Healthcare data can be a mix of structured electronic health records (EHRs), unstructured medical images, and genomic data. A lakehouse can provide the structure needed for EHR data while accommodating the flexibility required for genomic and image data. It's essential for real-time patient monitoring, research, and historical analysis.

Today's topic:

Data Processing - MapReduce

Data Processing



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.

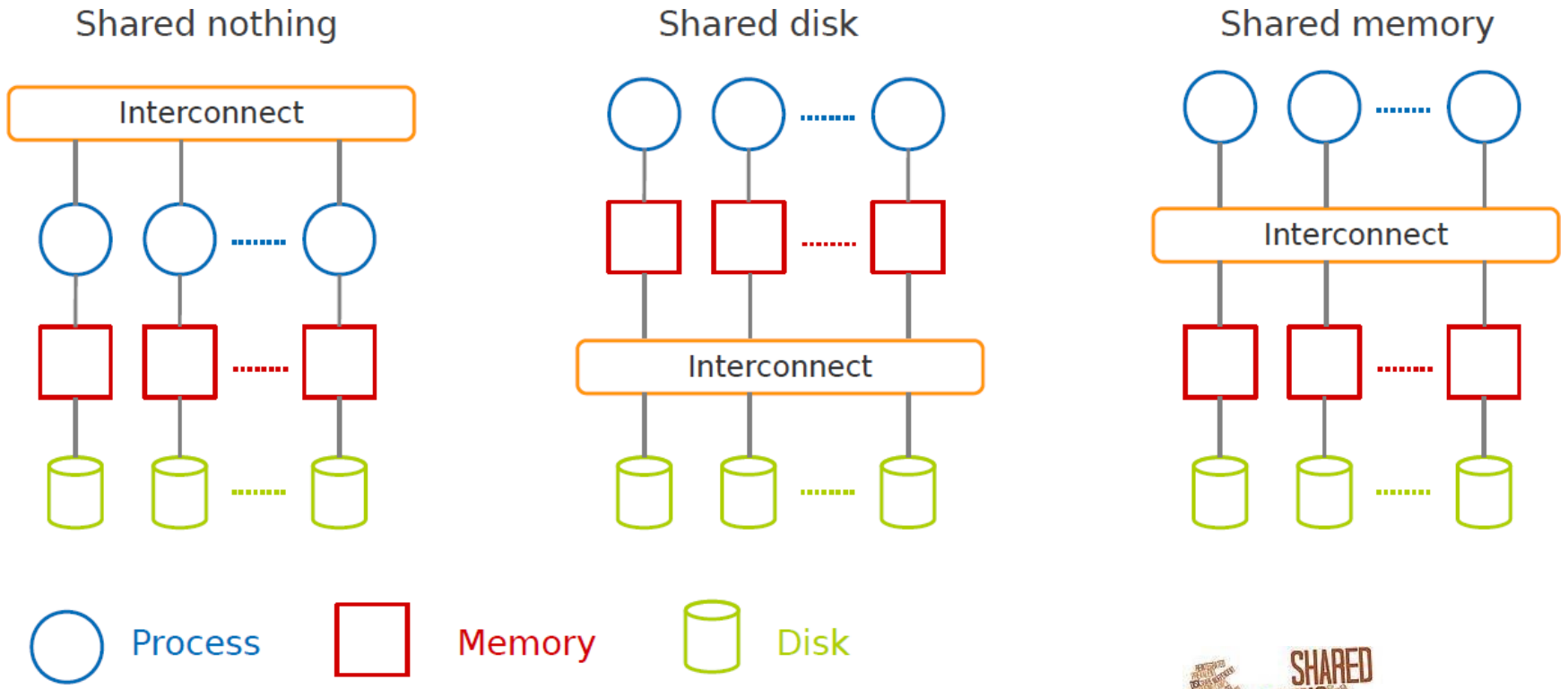
Scale Up vs. Scale Out

- Scale up: more expensive than scaling out.
- Scale out: more challenging for fault tolerance and software development.

Challenges

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

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.

MapReduce Resolves the Challenges

- Provides
  - data distribution
  - fault tolerance
  - load balancing

- Hides system-level details from programmers.

How MapReduce Resolves the Challenges?

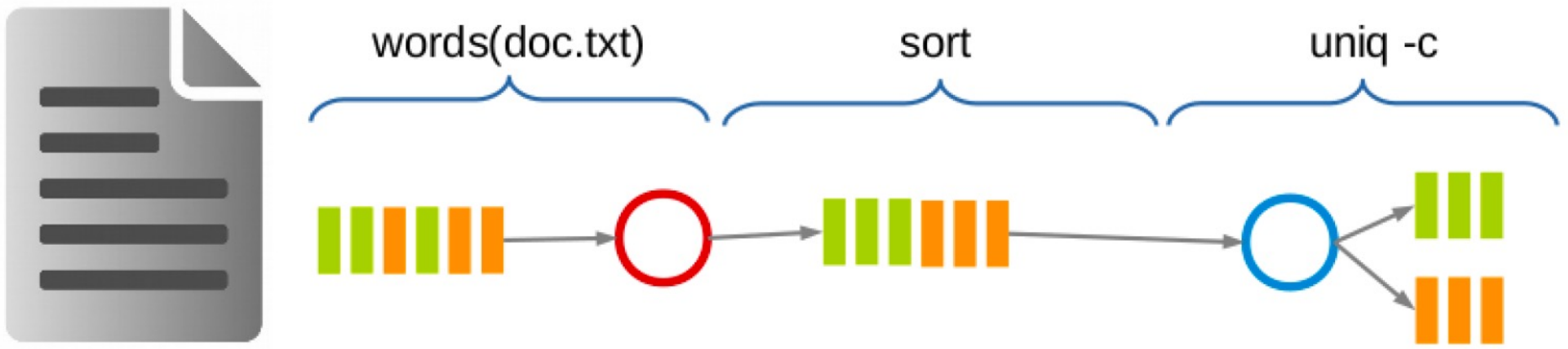
- A programming model: to batch process large data sets (inspired by functional programming).

- An execution framework: to run parallel algorithms on clusters of commodity hardware.

Programming Model

Word Count

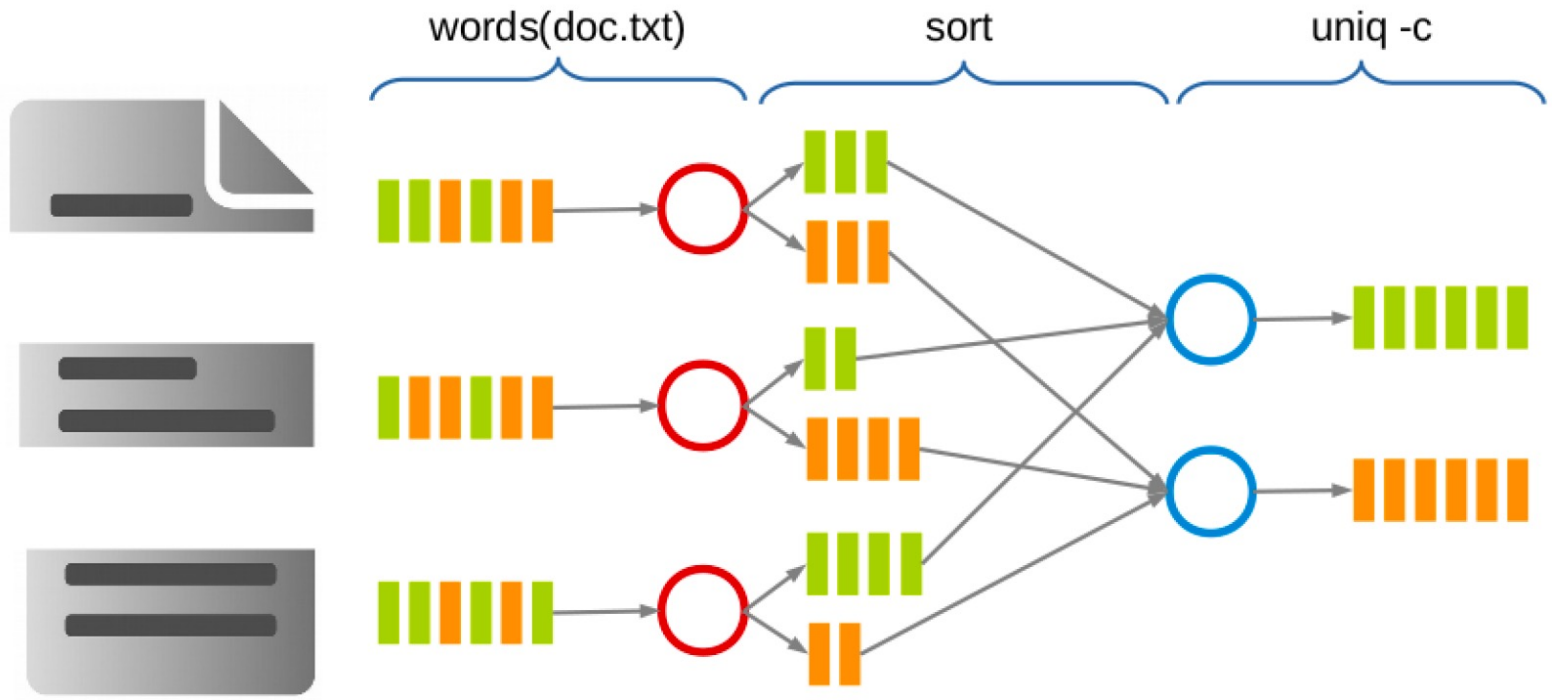
- Count the number of times each distinct word appears in the file
- If the file fits in memory: `words(doc.txt) | sort | uniq -c`



- If not?

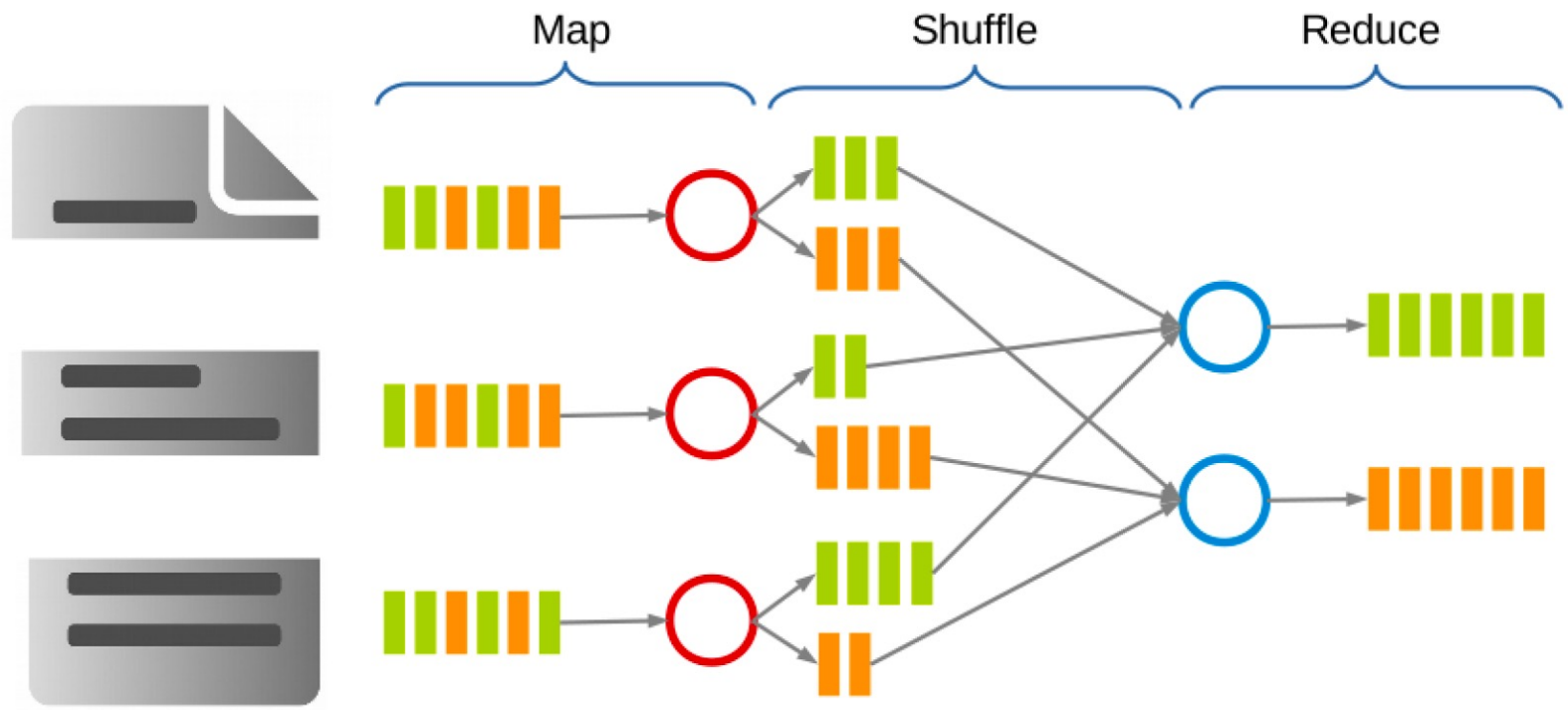
Data Parallel Processing

- Parallelizes data and processing



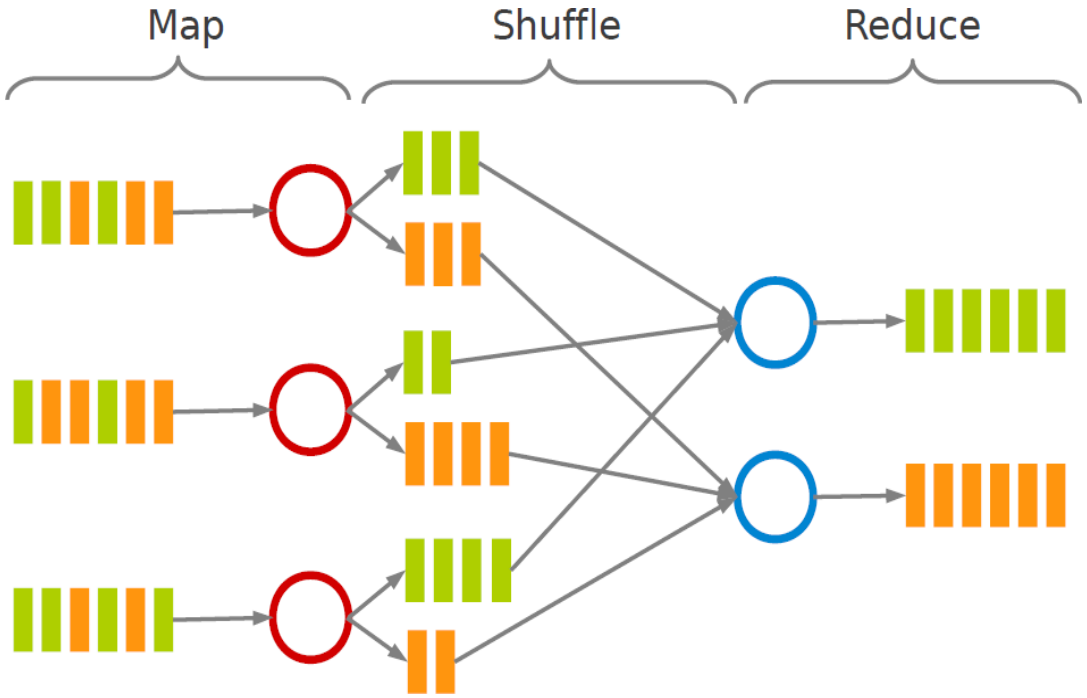
Data Parallel Processing

- MapReduce



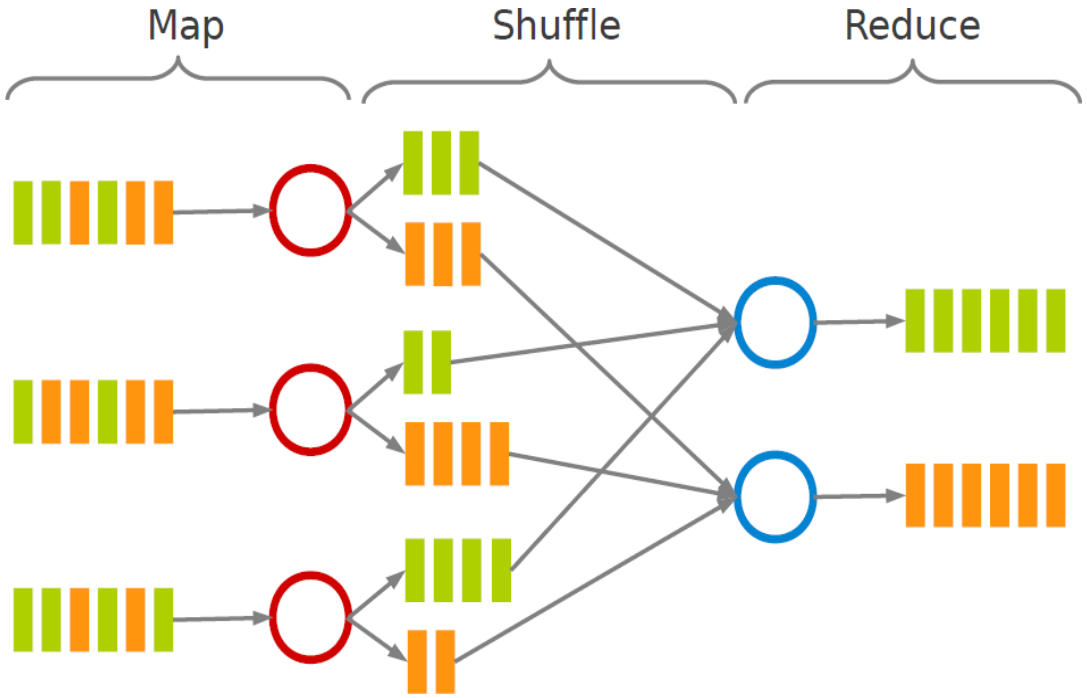
MapReduce Stages - Map

- 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

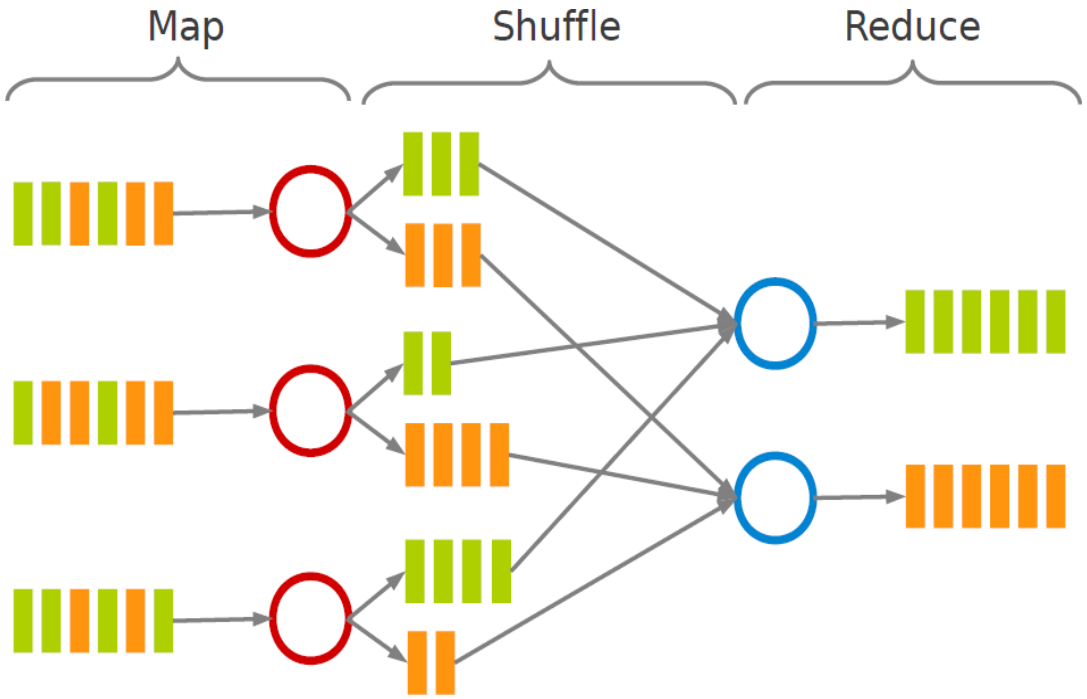
- Sorts and consolidates intermediate data from all mappers.
- Happens after all Map tasks are complete and before Reduce tasks start.



MapReduce Stages - Reduce

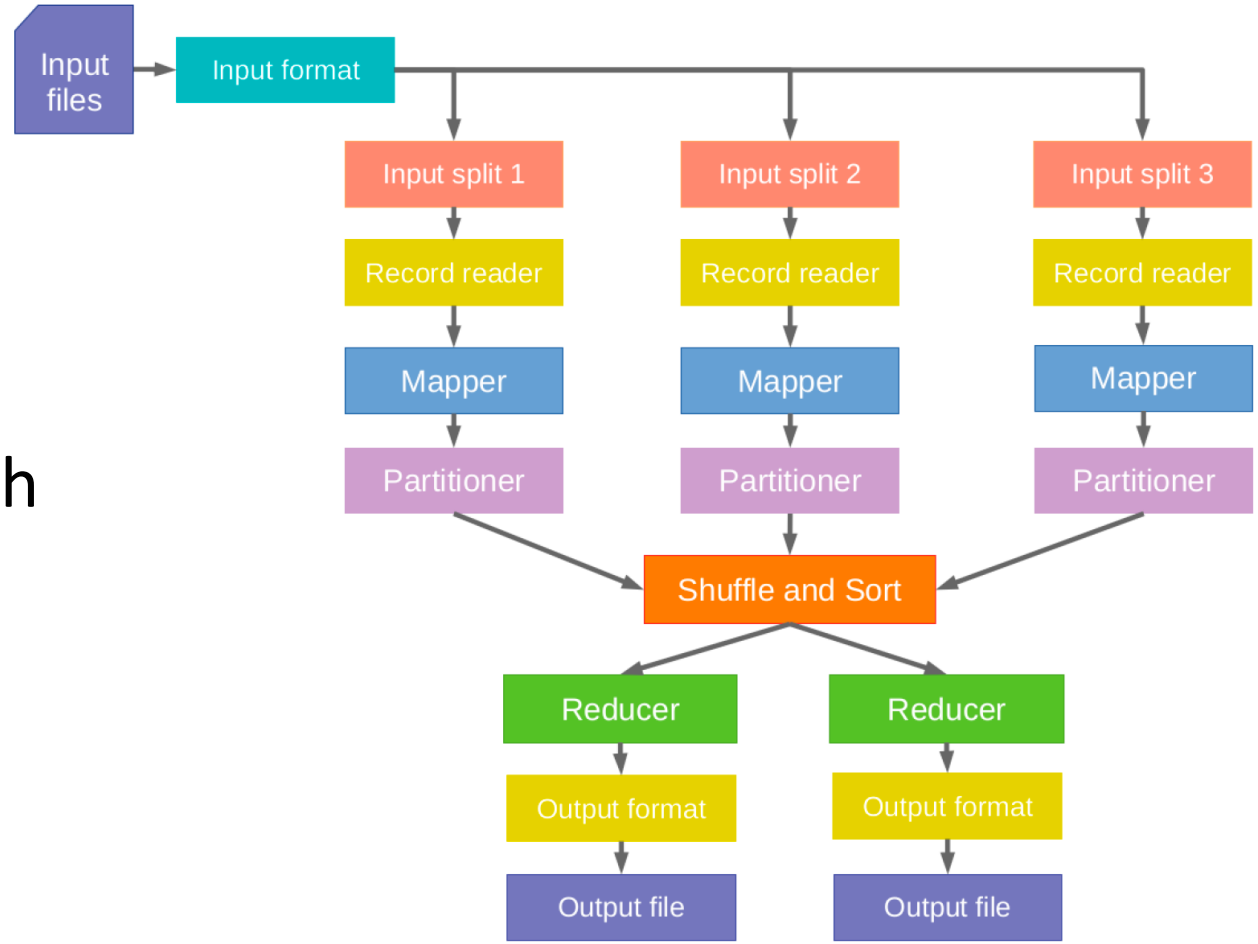
- Each Reduce task operates on all intermediate values associated with the same intermediate key.

- Produces the final output.



MapReduce Data Flow

- **map** function: processes data and generates a set of intermediate key/value pairs.
- **reduce** function: merges all intermediate values associated with the same intermediate key.

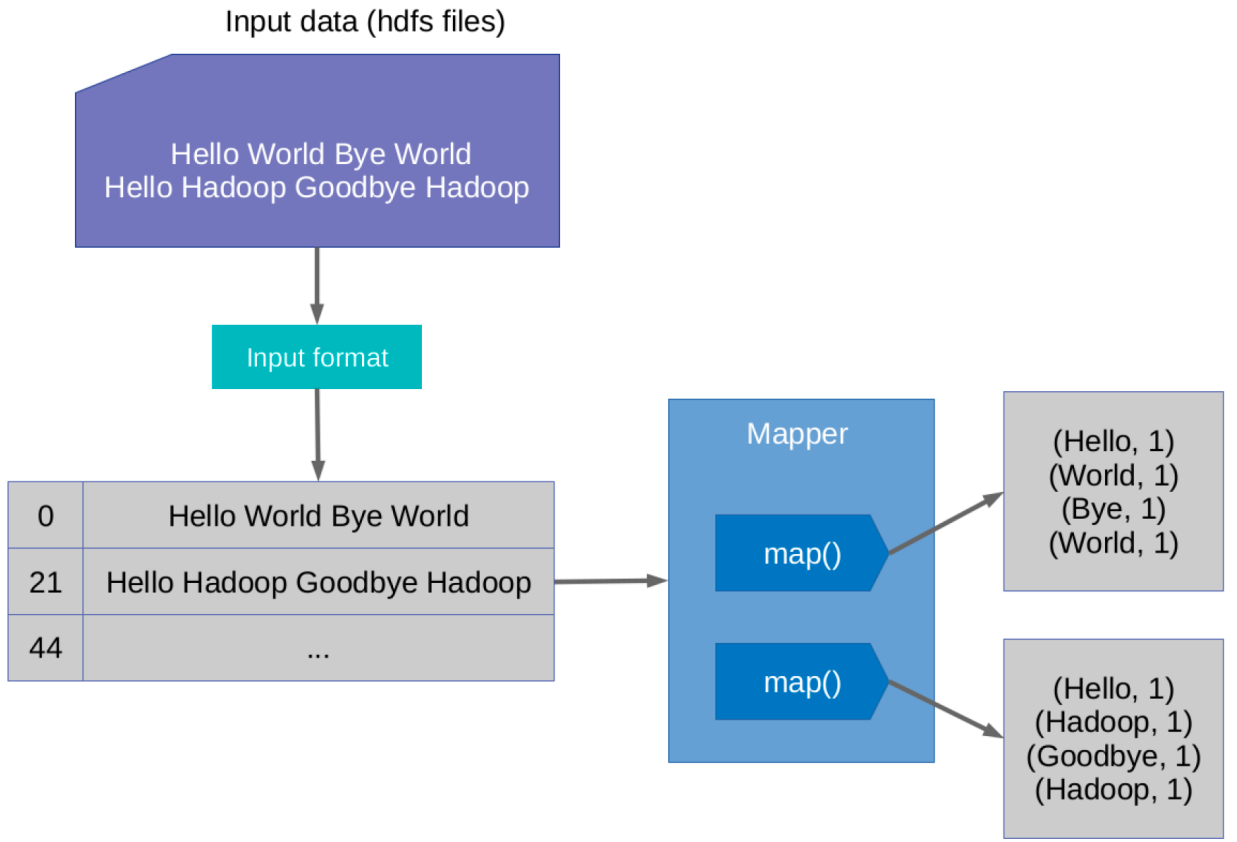


Example: Word Count

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

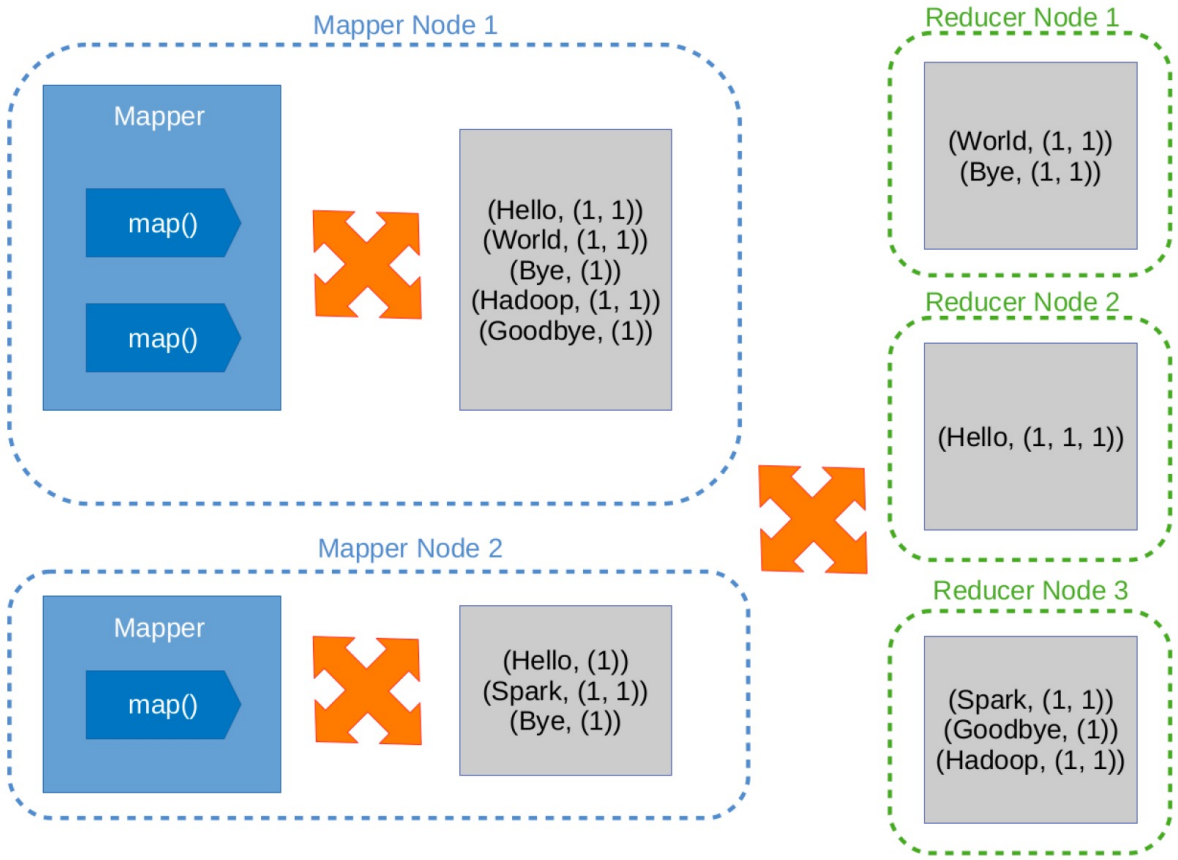
Example: Word Count - *Map*

- The map function reads in words one a time and outputs (word, 1) for each parsed input word.



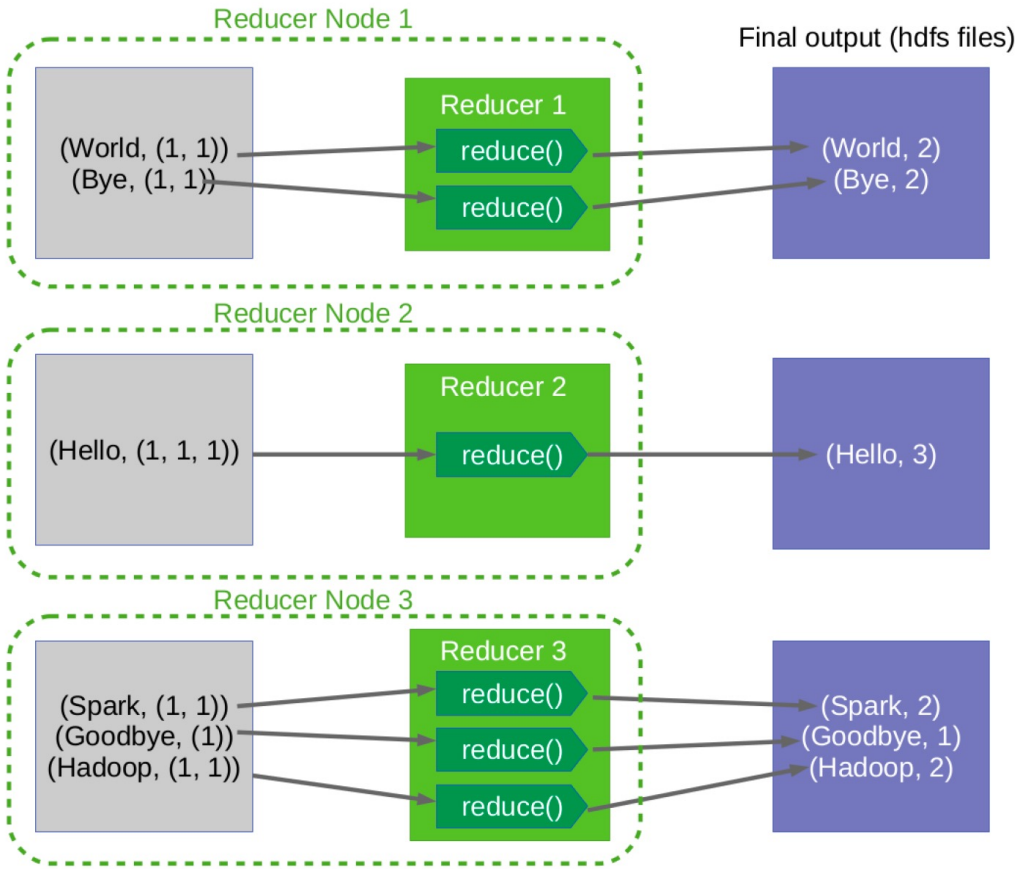
Example: Word Count - *Shuffle*

- The shuffle phase between map and reduce phase creates a list of values associated with each key.



Example: Word Count - *Reduce*

- The reduce function sums the numbers in the list for each key and outputs (word, count) pairs.



Example: Word count- *Map*

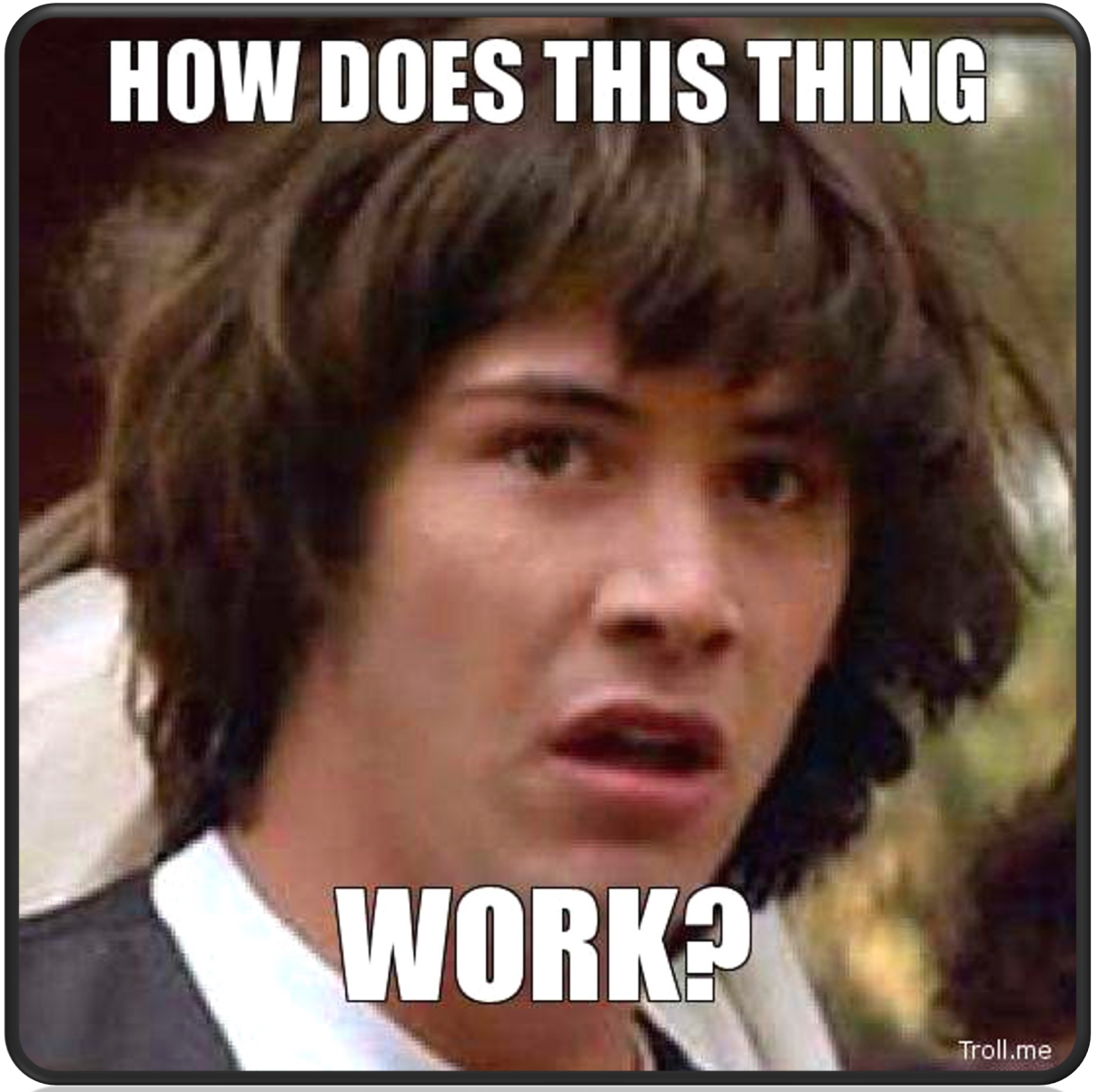
```
public static class MyMap extends Mapper<...> {
  private final static IntWritable one = new IntWritable(1); private Text
  word = new Text();

  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*

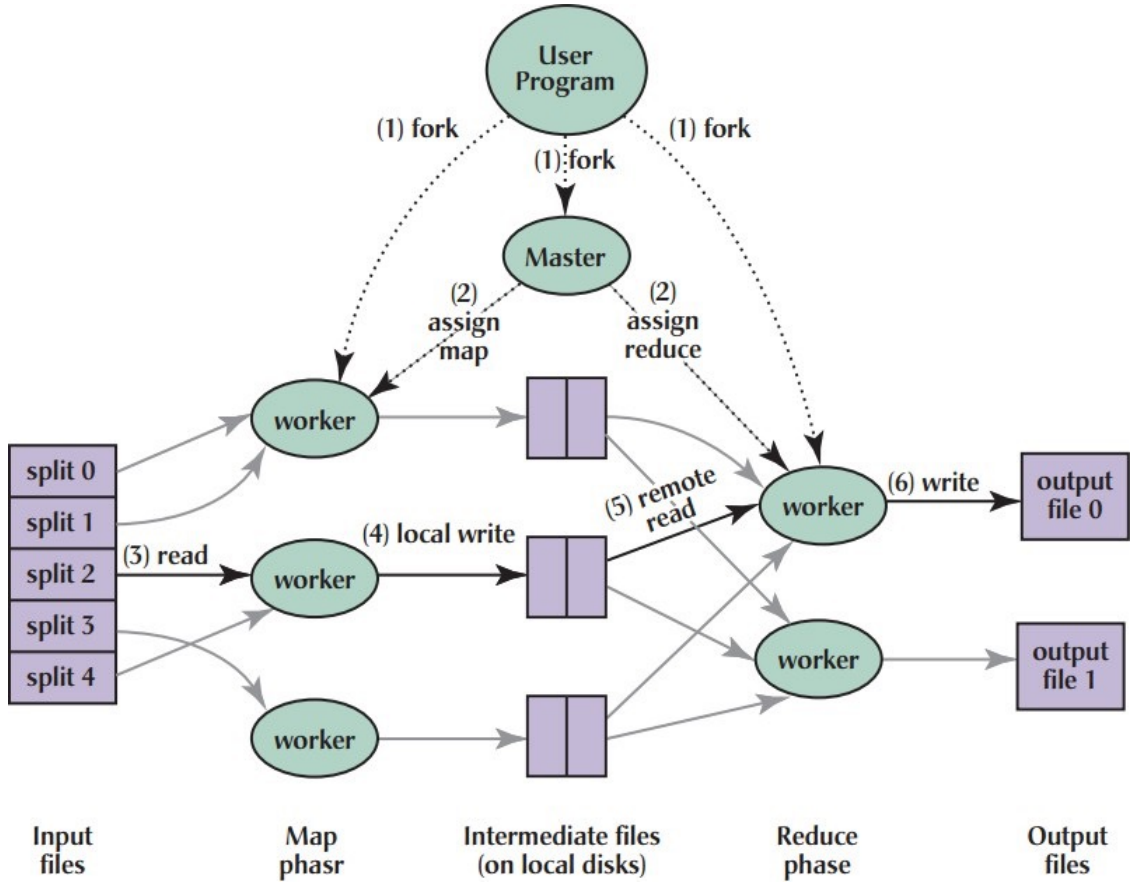
```
public static void main(String[] args) throws Exception {
  Configuration conf = new Configuration();
  Job job = new Job(conf, "wordcount");

  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);
}
```


HOW DOES THIS THING
WORK?
Troll.me

MapReduce Execution Engine

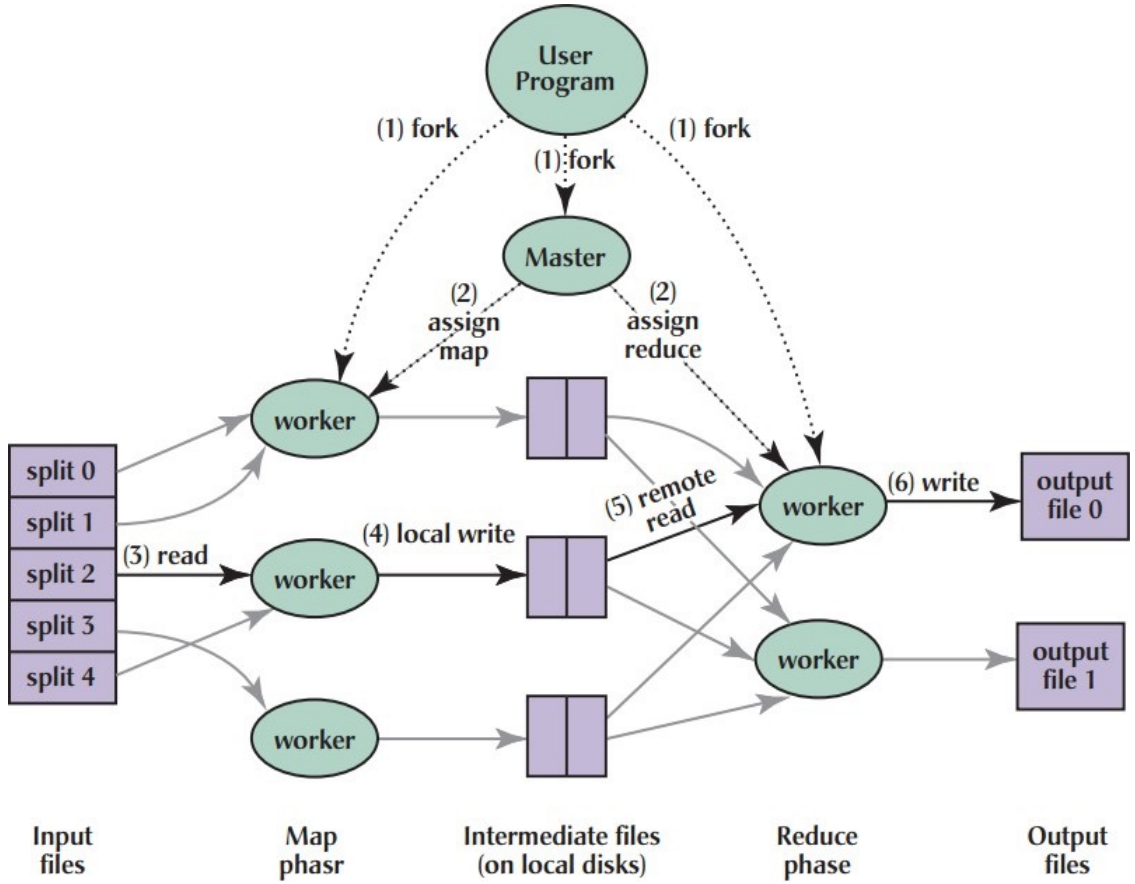
MapReduce Execution (1/7)

- The user program divides the input files into M splits.
  - A typical size of a split is the size of a HDFS block (64 -128MB).
  - Converts them to key/value pairs.
- It starts up many copies of the program on a cluster of machines.



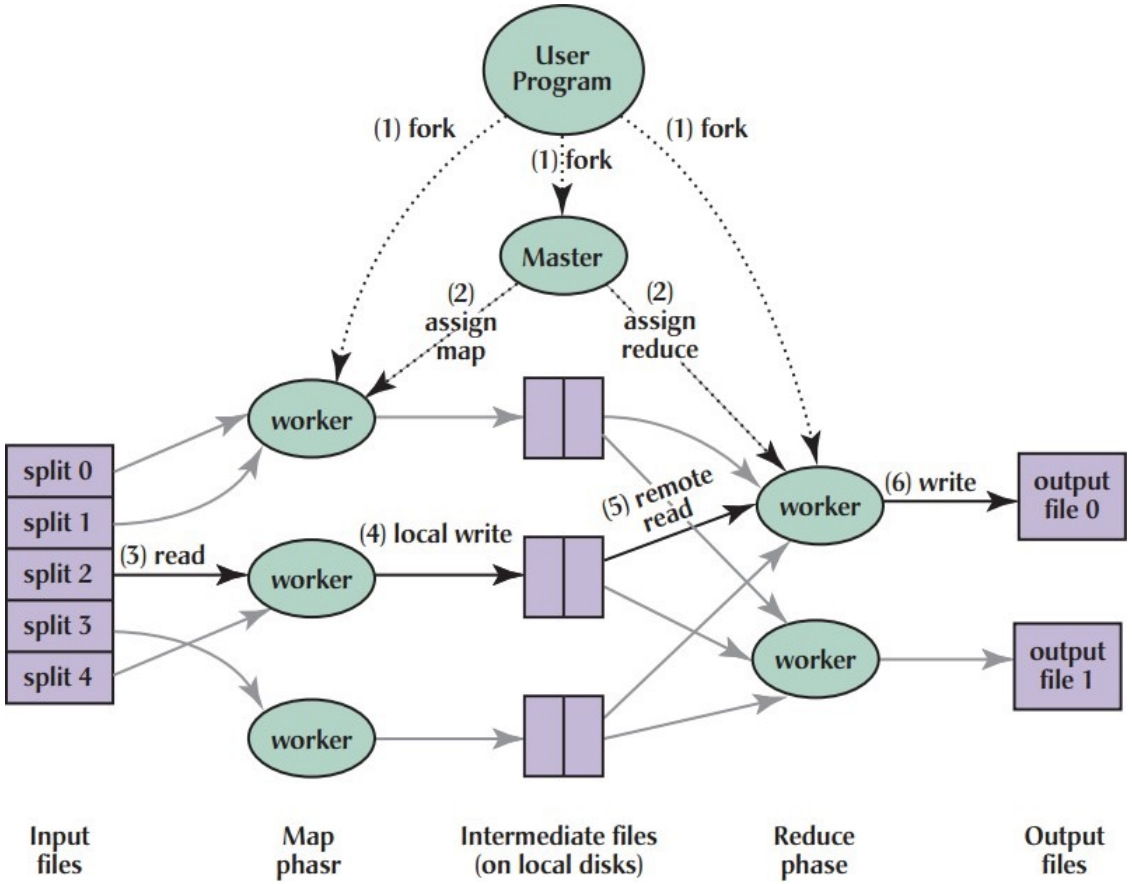
MapReduce Execution (2/7)

- 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.



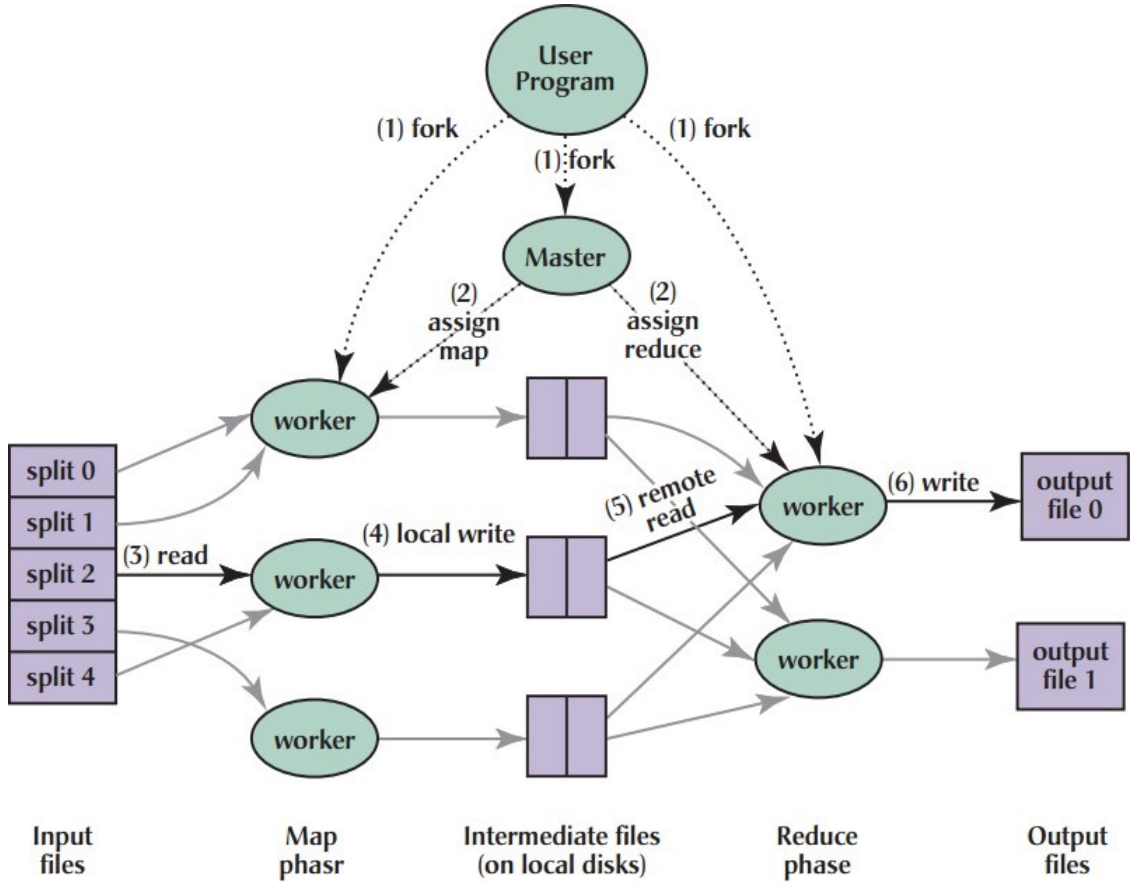
MapReduce Execution (3/7)

- 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 intermediate key/value pairs produced by the map function are buffered in memory.



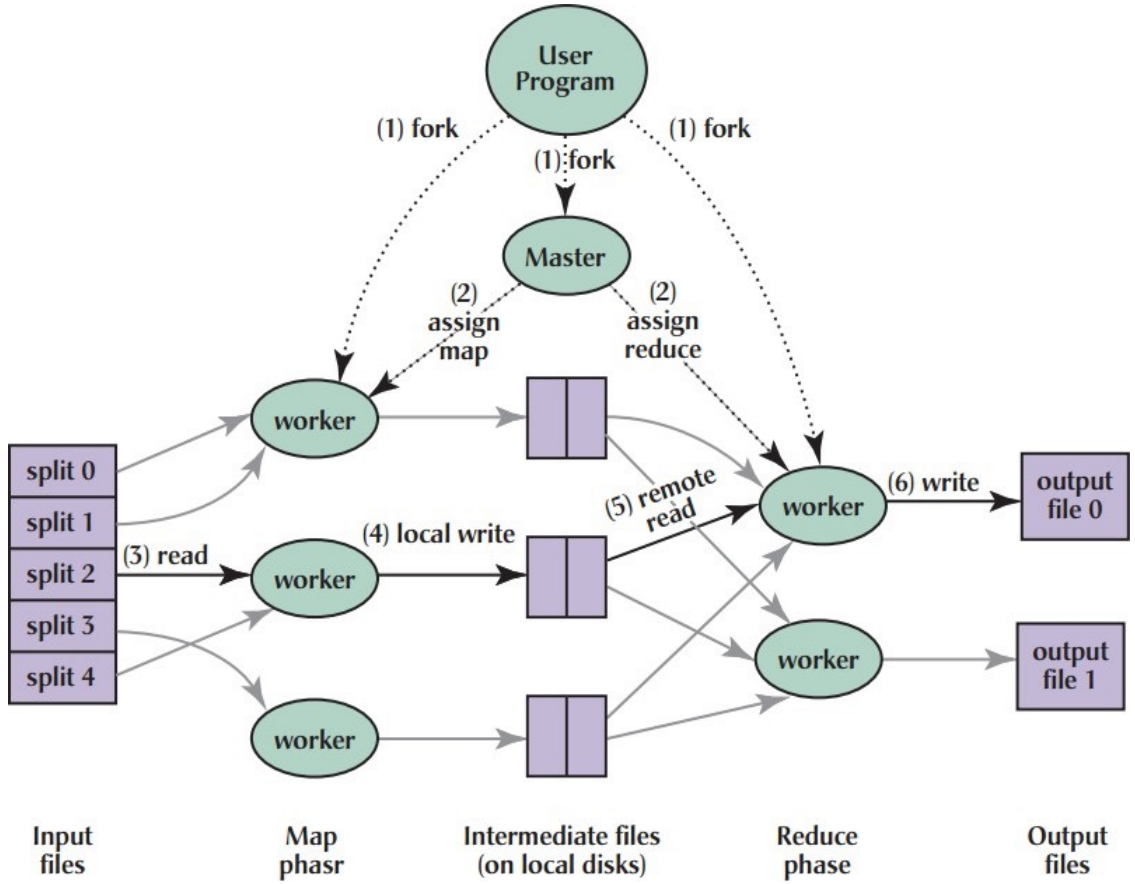
MapReduce Execution (4/7)

- The buffered pairs are periodically written to local disk.
- They are partitioned into R regions (hash(key) mod 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.



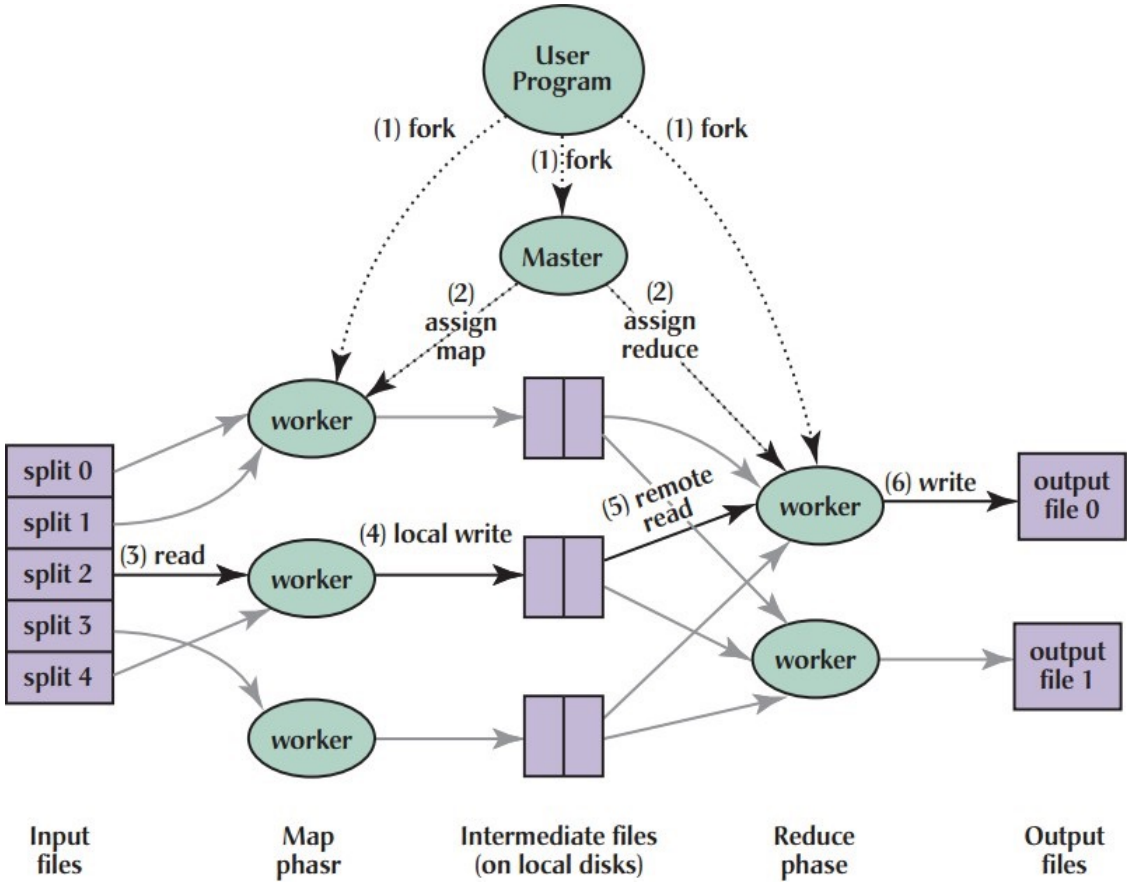
MapReduce Execution (5/7)

- 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.



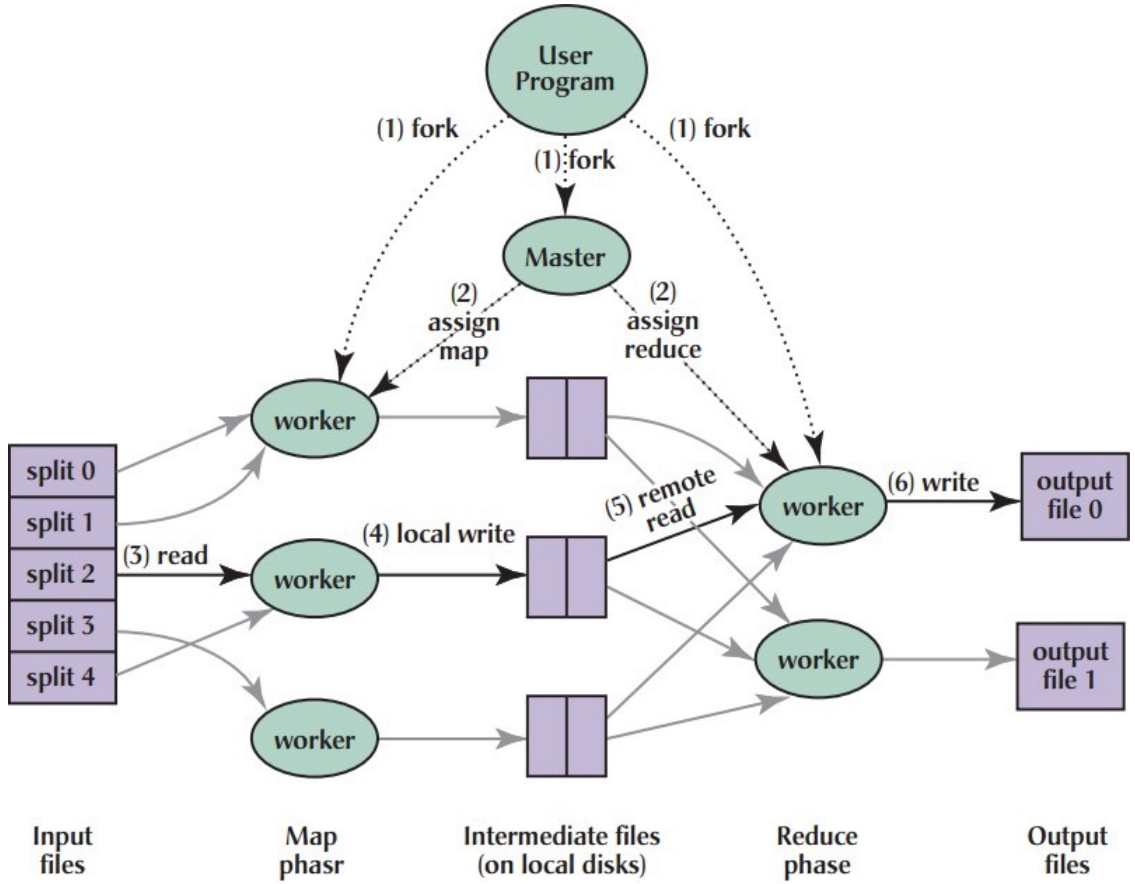
MapReduce Execution (6/7)

- 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.

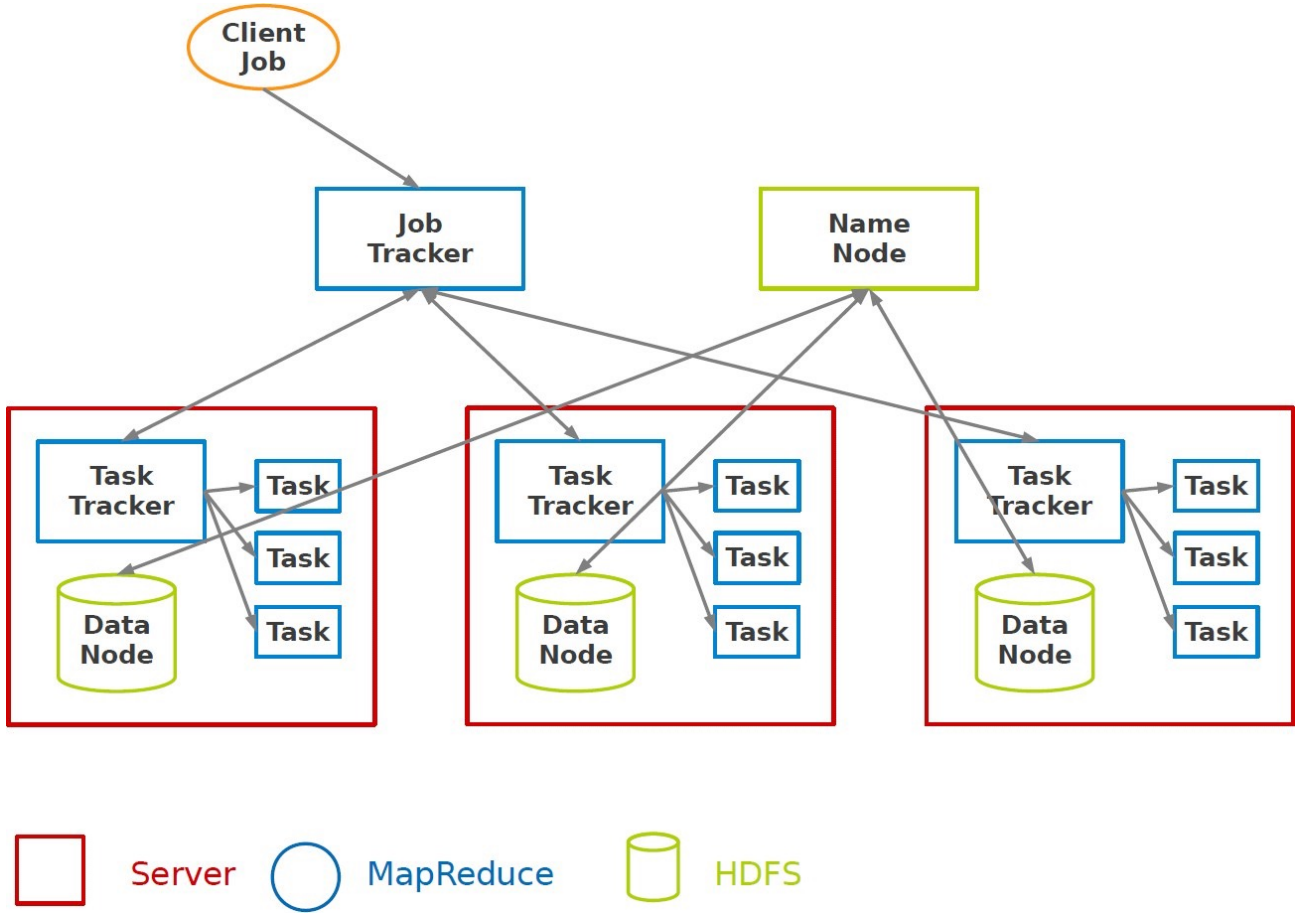


MapReduce Execution (7/7)

- 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.

Is MapReduce Applicable on Every Function?

- It is easy in MapReduce:

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

- What about this one?

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

Next class:

Spark Execution Engine