



# 6CS030 Lecture 5

Introduction to Hadoop  
Hadoop and Map Reduce



# Hadoop

- Open-source software framework used for distributed storage and processing of big datasets
- Can be set up over a cluster of computers built from normal, commodity hardware
- Many vendors offer their implementation of a Hadoop stack (e.g. Amazon, Cloudera, Dell, Oracle, IBM, Microsoft)

# History of Hadoop

- Key building blocks:
  - Google File System: a file system that could be easily distributed across commodity hardware, whilst providing fault tolerance
  - Google MapReduce: a programming paradigm to write programs that can be automatically parallelized and executed across a cluster of different computers
- Nutch web crawler prototype developed by Doug Cutting
  - Later renamed to Hadoop
- In 2008, Yahoo! open-sourced Hadoop as “Apache Hadoop”

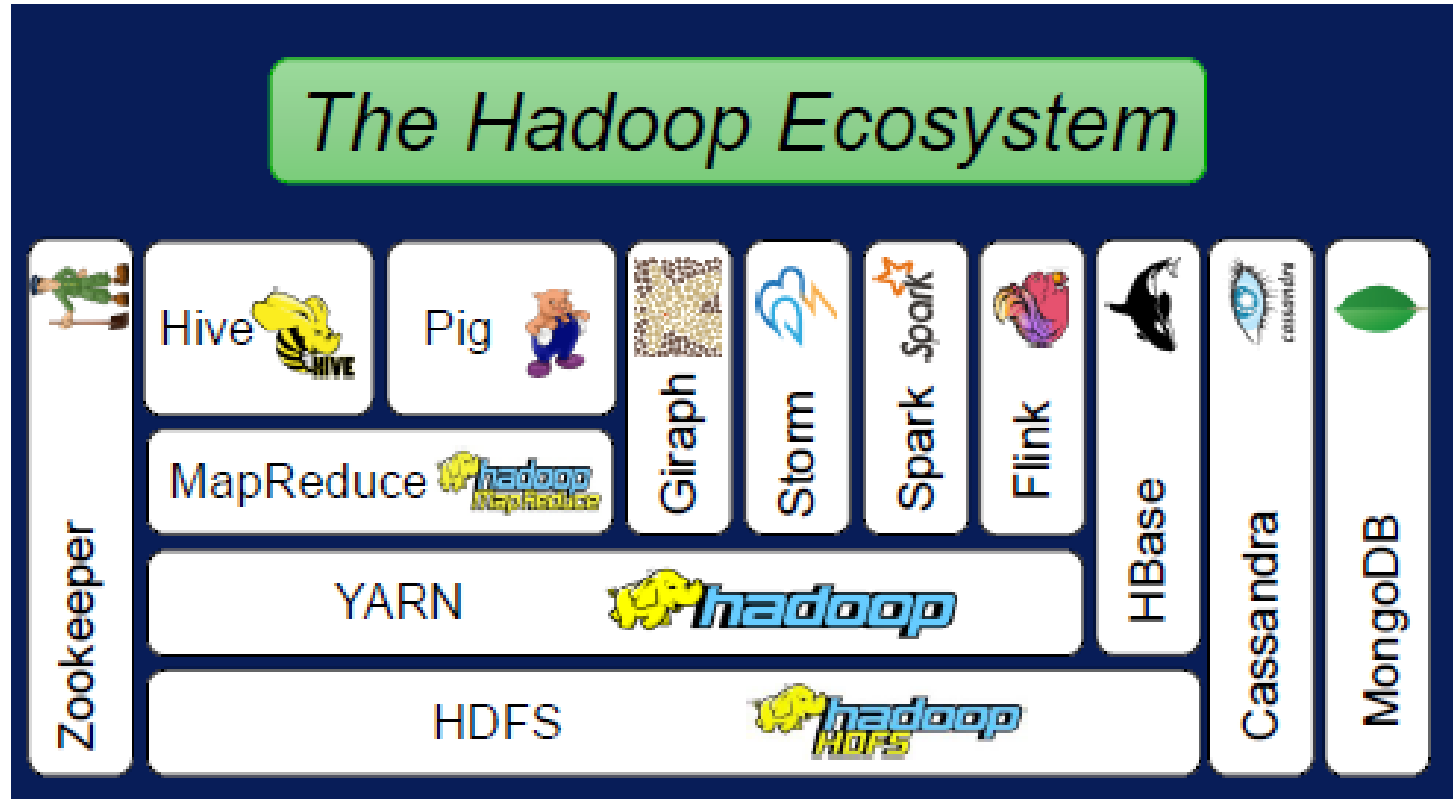
# The Hadoop Stack

## ■ Four modules:

- **Hadoop Common**: a set of shared programming libraries used by the other modules
- **Hadoop Distributed File System (HDFS)**: a Java-based file system to store data across multiple machines
- **MapReduce framework**: a programming model to process large sets of data in parallel
- **YARN (Yet Another Resource Negotiator)**: handles the management and scheduling of resource requests in a distributed environment

# Hadoop Ecosystem

- Lots of applications associated with Hadoop





# Hadoop Distributed File System (HDFS)

- Distributed file system to store data across a cluster of commodity machines
- High emphasis on fault-tolerance
- HDFS cluster is composed of a NameNode and various DataNodes

# Hadoop Distributed File System (HDFS)

## ■ NameNode

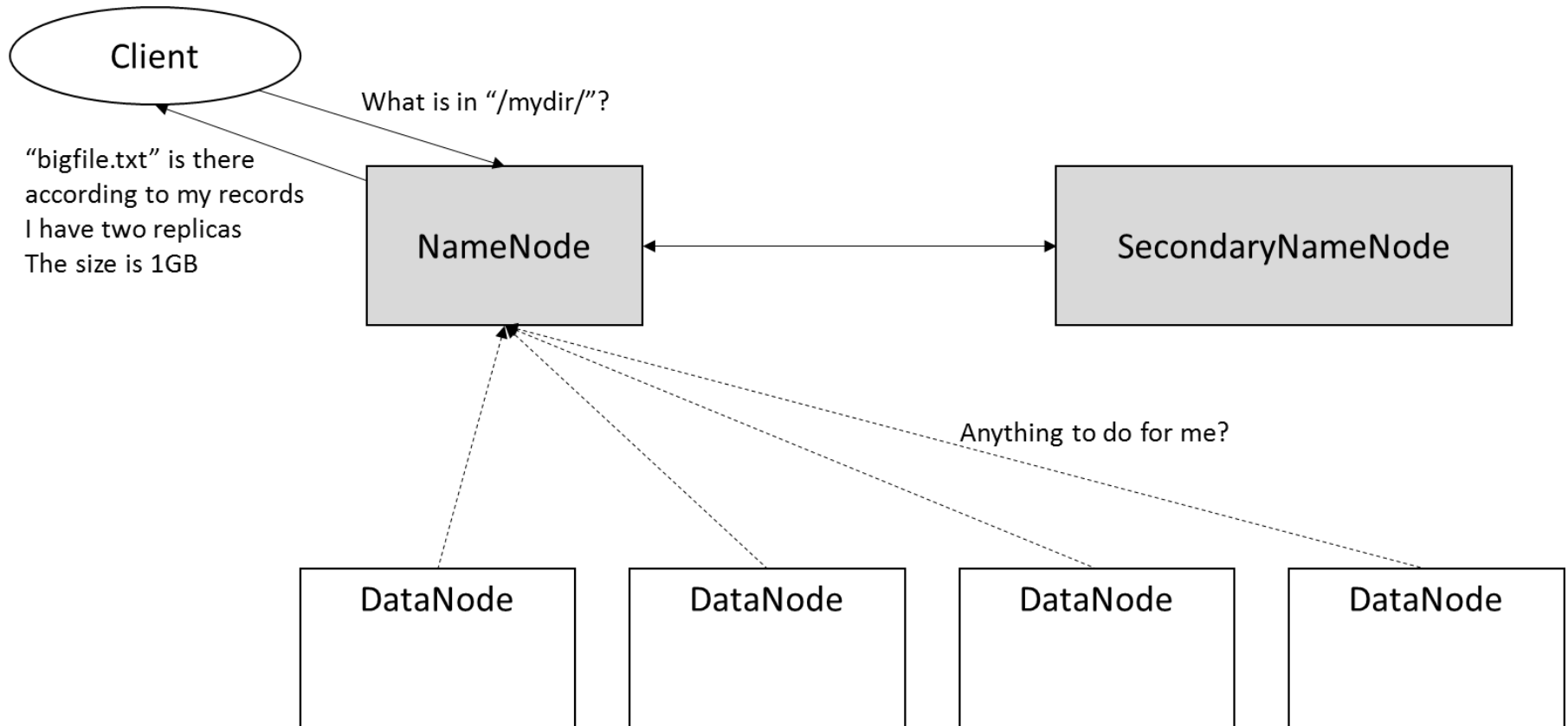
- a server which holds all the metadata regarding the stored files
- manages incoming file system operations
- maps data blocks (parts of files) to DataNodes

## ■ DataNode

- handles file read and write requests
- create, delete and replicate data blocks amongst their disk drives
- continuously loop, asking the NameNode for instructions.

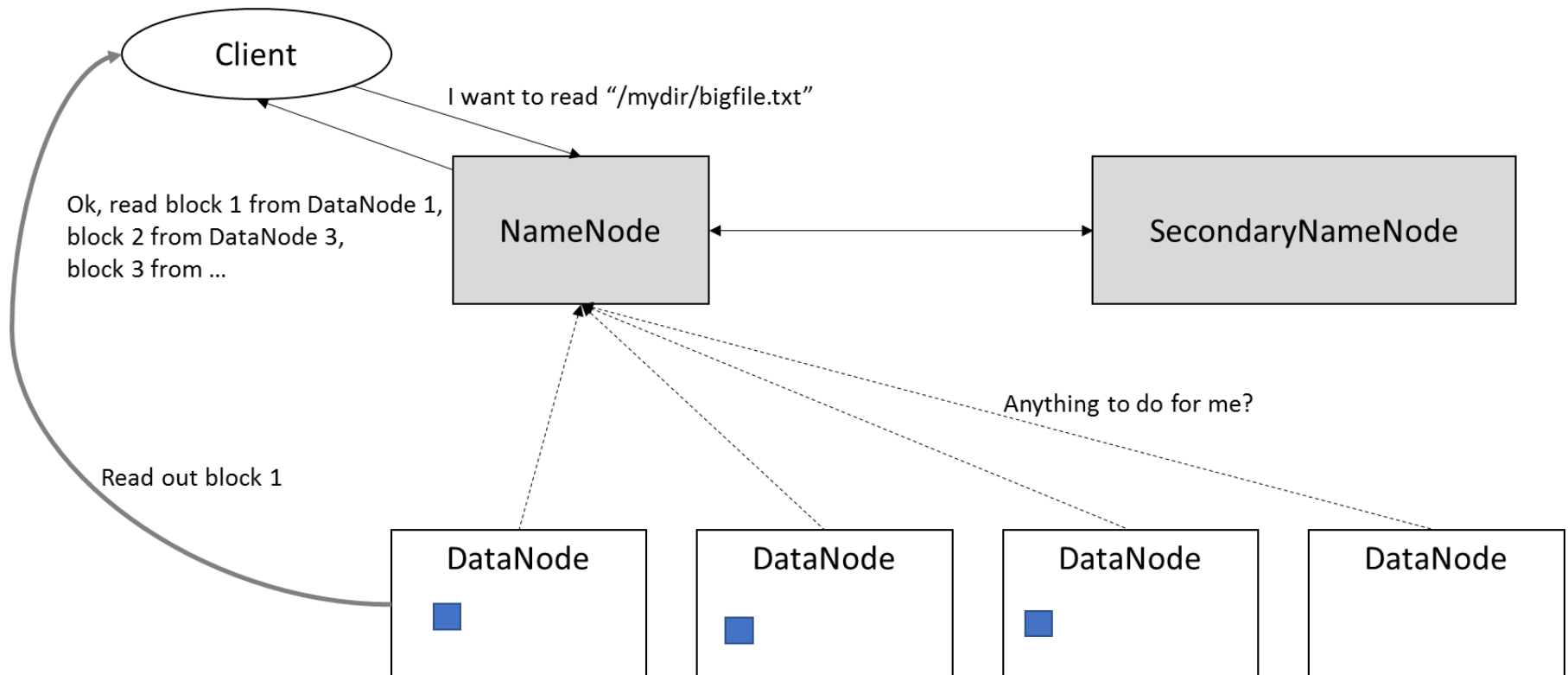
■ Note: size of 1 data block is typically 64 megabytes

# Hadoop Distributed File System (HDFS)

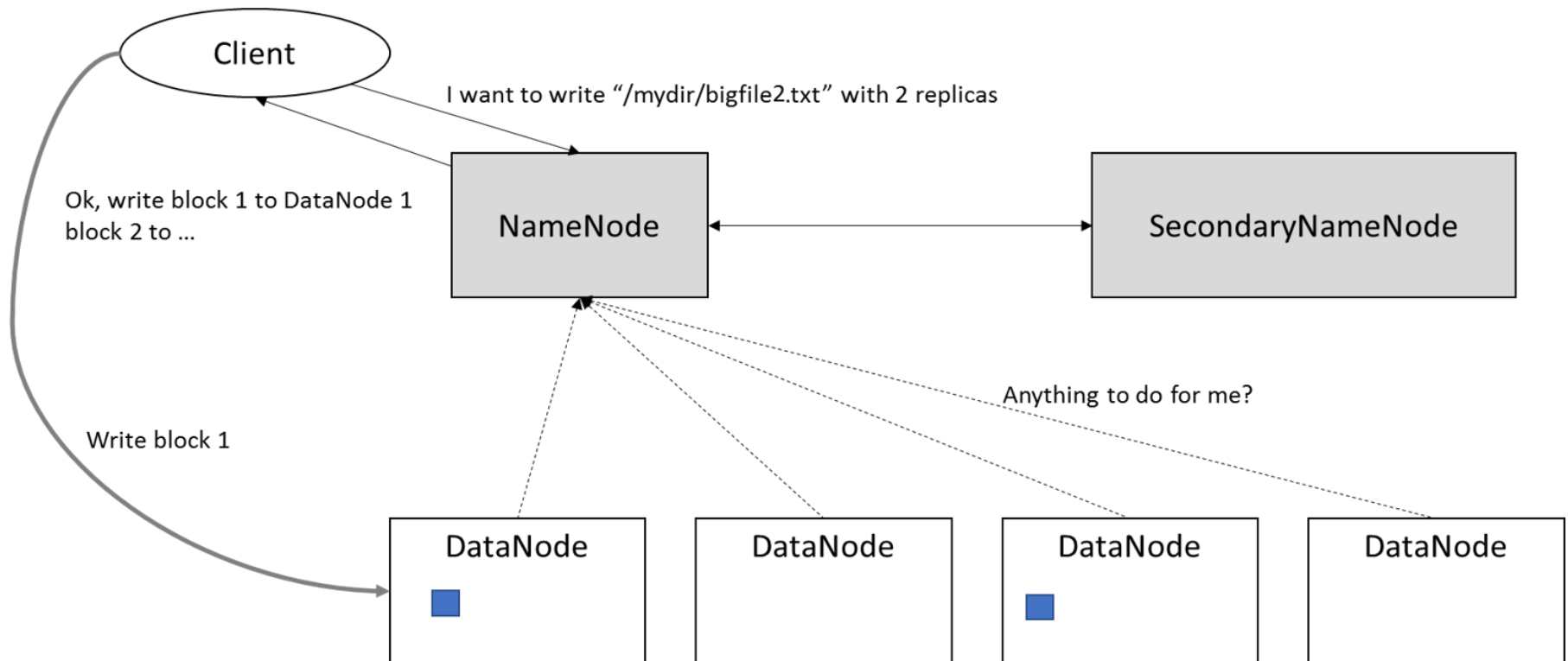




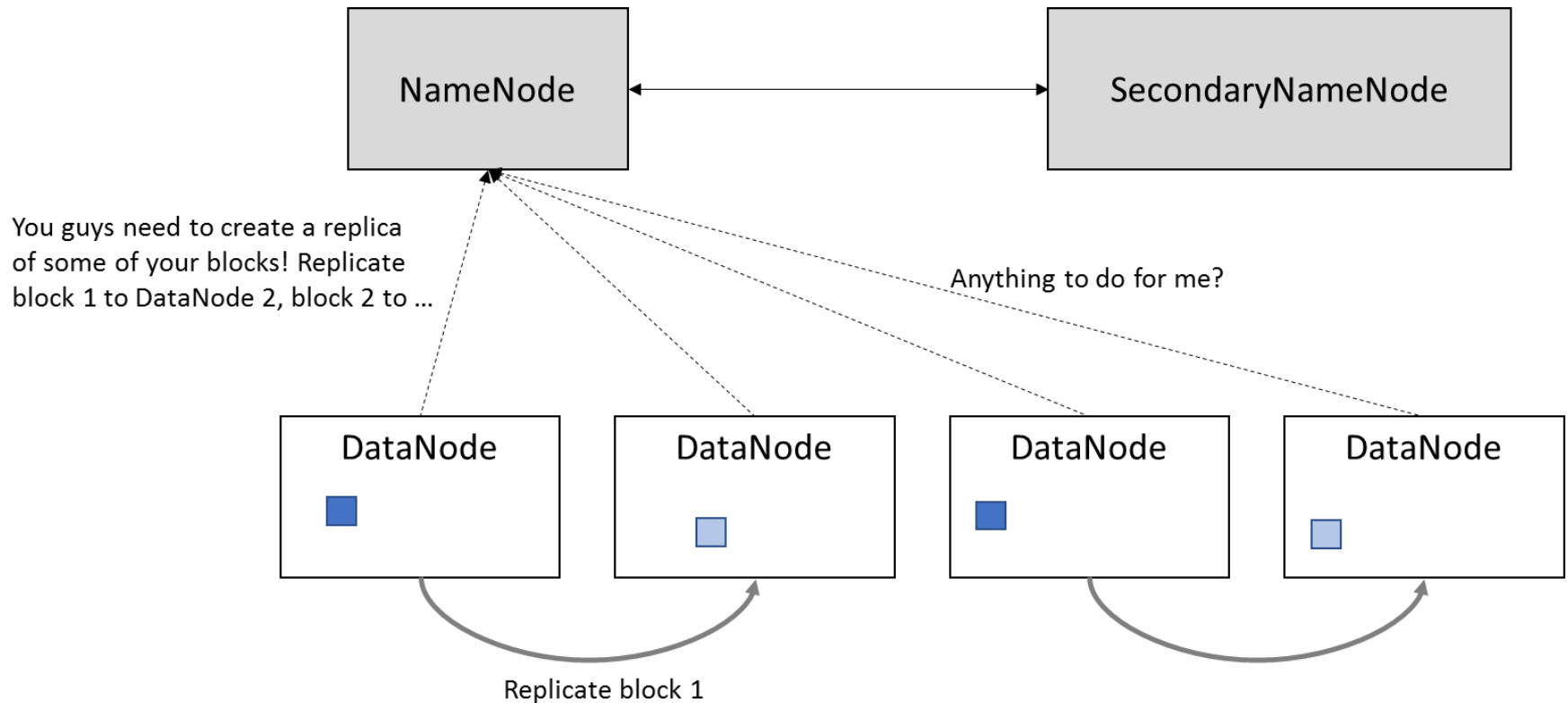
# Hadoop Distributed File System (HDFS)



# Hadoop Distributed File System (HDFS)



# Hadoop Distributed File System (HDFS)



# Hadoop Distributed File System (HDFS)

- HDFS provides a native Java API to allow for writing Java programs that can interface with HDFS

```
String filePath = "/data/all_my_customers.csv";
Configuration config = new Configuration();
org.apache.hadoop.fs.FileSystem hdfs =
    org.apache.hadoop.fs.FileSystem.get(config);
org.apache.hadoop.fs.Path path = new
    org.apache.hadoop.fs.Path(filePath);
org.apache.hadoop.fs.FSDataInputStream inputStream = hdfs.open(path);
byte[] received = new byte[inputStream.available()];
inputStream.readFully(received);

// ...
org.apache.hadoop.fs.FSDataInputStream inputStream = hdfs.open(path);
byte[] buffer = new byte[1024]; // Only handle 1KB at once
int bytesRead;
while ((bytesRead = in.read(buffer)) > 0) {
    // Do something with the buffered block here
}
```

# Hadoop Distributed File System (HDFS)

<code>hdfs dfs -mkdir mydir</code>	Create a directory on HDFS
<code>hdfs dfs -ls</code>	List files and directories on HDFS
<code>hdfs dfs -cat myfile</code>	View a file's content
<code>hdfs dfs -put myfile mydir</code>	Store a file on HDFS
<code>hdfs dfs -rm myfile</code>	Delete a file on HDFS
<code>hdfs dfs -touchz myfile</code>	Create an empty file on HDFS
<code>hdfs dfs -stat myfile</code>	Check the status of a file (file size, owner, ...)
<code>hdfs dfs -test -e myfile</code>	Check if file exists on HDFS
<code>hdfs dfs -test -z myfile</code>	Check if file is empty on HDFS
<code>hdfs dfs -test -d myfile</code>	Check if myfile is a directory on HDFS
<code>hdfs dfs -du</code>	Check disk space usage on HDFS

The commands in blue are the key ones you will most likely use



# MapReduce

- Programming paradigm made popular by Google and subsequently implemented by Apache Hadoop
- Focus on scalability and fault tolerance
- A map-reduce pipeline starts from a series of values and maps each value to an output using a given mapper function

# MapReduce

- A MapReduce pipeline in Hadoop starts from a list of key-value pairs, and maps each pair to one or more output elements
- The output elements are also key-value pairs
- Next, the output entries are grouped so all output entries belonging to the same key are assigned to the same worker (e.g. physical machine)
- These workers then apply the reduce function to each group, producing a new list of key-value pairs
- The resulting, final outputs can then be sorted

# MapReduce

- Reduce-workers can already get started on their work even although not all mapping operations have finished yet
- Implications:
  - the reduce function should output the same key-value structure as the one emitted by the map function
  - the reduce function itself should be built in such a way so it provides correct results, even if called multiple times



# Map Reduce Algorithm

- Map–reduce: a programming pattern for analysing streams or sets of data
- The computation takes a set of input key/value pairs, and produces a set of output key/value pairs. The user of the MapReduce library expresses the computation as two functions: **Map** and **Reduce**.
- **Map** takes an input pair and produces a set of intermediate key/value pairs. The MapReduce library groups together all intermediate values associated with the same intermediate key  $k$  and passes them to the Reduce function.
- Reduce accepts an intermediate key  $k$  and a set of values for that key.
  - It merges together these values to form a possibly smaller set of values.
  - Typically just zero or one output value is produced per Reduce invocation.
  - The intermediate values are supplied to the user's reduce function via an iterator.
  - This allows us to handle lists of values that are too large to manage in memory.

# Map Reduce Count Example

Step 0: file is stored in HDFS

Map generates key-value pairs

Pairs with same key moved to same node

Adds values for same keys

Input	Splitting	Mapping	Shuffling	Reducing	Write to file
<div>Hello Mike Hello John John is good Mike is Tall</div>	<div>Hello Mike</div> <div>Hello John</div> <div>John good</div> <div>Mike Tall</div>	<div>Hello , 1 Mike , 1</div> <div>Hello , 1 John , 1</div> <div>John , 1 good , 1</div> <div>Mike , 1 Tall , 1</div>	<div>good , 1</div> <div>Hello , 1 Hello , 1</div> <div>John , 1 John , 1</div> <div>Mike , 1 Mike , 1</div>	<div>good , 1</div> <div>Hello , 2</div> <div>John , 2</div> <div>Mike , 2</div>	<div>good , 1 Hello , 2 John , 2 Mike , 2</div>

# MapReduce

- In Hadoop, MapReduce tasks are written in Java

- Can also use Python, but is converted to Java

- To run a MapReduce task, a Java program is packaged as a JAR archive and launched as:

```
hadoop jar myJarFile.jar myJavaClass [args...]
```

- You first need to compile the Java file:

```
javac -classpath $(hadoop classpath) -d myClassDir  
myJavaClass.java
```

- Then produce the Jar file:

```
cd myClassDir      # cd to where the class files are  
jar cf myJarFile.jar classesRequired*.class # note there  
can be a number of classes produced
```

# MapReduce Example – Word Count

- Word Count is the “Hello World” of Hadoop!
- This Java example counts the appearance of a word in a file:

```
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;

public class WordCount {
    // Following fragments will be added here
}
```

[https://hadoop.apache.org/docs/stable/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html#Inputs and Outputs](https://hadoop.apache.org/docs/stable/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html#Inputs_and_Outputs)

# MapReduce - Mapper

- Define mapper function as a class extending the built-in mapper class:  
`Mapper<KeyIn, ValueIn, KeyOut, ValueOut>`
- Need to indicate which type of key-value input pair we expect and which type of key-value output pair our mapper will emit

# MapReduce

```
public class WordCount {  
    public static class TokenizerMapper  
        extends Mapper<Object, Text, Text, IntWritable> {  
        private final static IntWritable one = new IntWritable(1);  
        private Text word = new Text();
```

Can't use standard Java types  
such as String, so use Text for  
String type data

"context" is used to  
emit output values

```
        public void map(Object key, Text value, Context context )  
            throws IOException, InterruptedException {  
            StringTokenizer itr = new StringTokenizer(value.toString());  
            while (itr.hasMoreTokens()) {  
                word.set(itr.nextToken());  
                context.write(word, one);  
            }  
        }  
    }  
}
```

# MapReduce

Input key-value pairs	
Key <Object>	Value <Text>
0	This is the first line
23	And this is the second line, and this is all



Mapped key-value pairs	
Key <Text>	Value <IntWritable>
this	1
is	1
the	1
first	1
line	1
and	1
...	...

# MapReduce

- The reducer function is specified as a class extending the built-in class:

```
Reducer<KeyIn, ValueIn, KeyOut,  
ValueOut>
```



# MapReduce

```
public static class IntSumReducer extends Reducer  
    <Text, IntWritable, Text, IntWritable> {  
    private IntWritable result = new IntWritable();
```

IntWritable used for  
numeric types

```
    public void reduce(Text key,  
        Iterable<IntWritable> values, Context context )  
        throws IOException, InterruptedException {  
        int sum = 0;  
        for (IntWritable val : values) {  
            sum += val.get(); }  
        result.set(sum);  
        context.write(key, result);  
    }  
}
```

Summarises the results  
so far

Outputs a (word, sum)  
pair

# MapReduce

Mapped key-value pairs	
Key <Text>	Value <IntWritable>
this	1
is	1
the	1
first	1
line	1
and	1
this	1
is	1

Mapped key-value pairs for “this”	
Key <Text>	Value <IntWritable>
this	1
this	1



Reduced key-value pairs for “this”	
Key <Text>	Value <IntWritable>
this	1 + 1 = 2

# MapReduce

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

Sets up Map Reduce job with a short name

```
    job.setJarByClass(WordCount.class);  
    job.setMapperClass(TokenizerMapper.class);  
    job.setCombinerClass(IntSumReducer.class);  
    job.setReducerClass(IntSumReducer.class);  
    job.setOutputKeyClass(Text.class);  
    job.setOutputValueClass(IntWritable.class);
```

Tells Hadoop which JAR it needs to distribute to workers

Sets Mapper class

Sets Reducer class

Sets output classes

```
    FileInputFormat.addInputPath(job, new Path(args[0]));  
    FileOutputFormat.setOutputPath(job, new Path(args[1]));  
    System.exit(job.waitForCompletion(true) ? 0 : 1);
```

```
}
```

The program expects two arguments, the first one is the input directory on HDFS and second the output directory

# MapReduce

- Before the program can be run you need to compile it first:  
`javac -classpath $(hadoop classpath) -d classDir WordCount.java`
- Then produce the Jar file:  
`cd classDir # cd to where the class files are`  
`jar cf wordcount.jar Word*.class`
- Use vi or nano to create 2 testfiles:  
testfile1:  
    A long time ago in a galaxy far far away  
testfile2:  
    Another episode of Star Wars
- Put these in the hdfs input area.
- By default you have an `input` directory already created. Use `–put` to save the files there:  
`hdfs dfs –put testfile? /user/yourStudentNo/input`
- The output directory must not exist already. If you have already run the program it can be deleted first using `–rm`:  
`hdfs dfs –rm –R /user/yourStudentNo/output_dir`

# MapReduce

Needs to contain the input files

Must **not** exist beforehand

```
hadoop jar wordcount.jar WordCount /user/myDir/input_wc /user/myDir/output_wc
```

```
testuser2@sml:~/java/classDir$ hadoop jar wordcount.jar WordCount /user/testuser2/input_wc /user/testuser2/output_wc
2019-03-04 17:39:00,884 INFO client.RMPProxy: Connecting to ResourceManager at localhost/127.0.0.1:8050
2019-03-04 17:39:01,364 WARN mapreduce.JobResourceUploader: Hadoop command-line option parsing not performed. Implement the Tool interface and execute your application with ToolRunner to remedy this.
2019-03-04 17:39:01,376 INFO mapreduce.JobResourceUploader: Disabling Erasure Coding for path: /tmp/hadoop-yarn/staging/testuser2/.staging/job_1551235767797_0068
2019-03-04 17:39:01,565 INFO input.FileInputFormat: Total input files to process : 2
2019-03-04 17:39:01,606 INFO mapreduce.JobSubmitter: number of splits:2
2019-03-04 17:39:01,731 INFO mapreduce.JobSubmitter: Submitting tokens for job: job_1551235767797_0068
2019-03-04 17:39:01,733 INFO mapreduce.JobSubmitter: Executing with tokens: []
2019-03-04 17:39:01,897 INFO conf.Configuration: resource-types.xml not found
2019-03-04 17:39:01,898 INFO resource.ResourceUtils: Unable to find 'resource-types.xml'.
2019-03-04 17:39:01,958 INFO impl.YarnClientImpl: Submitted application application_1551235767797_0068
2019-03-04 17:39:01,992 INFO mapreduce.Job: The url to track the job: http://sml:8088/proxy/application_1551235767797_0068/
2019-03-04 17:39:01,993 INFO mapreduce.Job: Running job: job_1551235767797_0068
2019-03-04 17:39:08,084 INFO mapreduce.Job: Job job_1551235767797_0068 running in uber mode : false
2019-03-04 17:39:08,085 INFO mapreduce.Job: map 0% reduce 0%
2019-03-04 17:39:12,142 INFO mapreduce.Job: map 100% reduce 0%
2019-03-04 17:39:17,175 INFO mapreduce.Job: map 100% reduce 100%
2019-03-04 17:39:17,187 INFO mapreduce.Job: Job job_1551235767797_0068 completed successfully
2019-03-04 17:39:17,285 INFO mapreduce.Job: Counters: 53
  File System Counters
    FILE: Number of bytes read=156
    FILE: Number of bytes written=646457
    FILE: Number of read operations=0
    FILE: Number of large read operations=0
    FILE: Number of write operations=0
    HDFS: Number of bytes read=310
    HDFS: Number of bytes written=94
    HDFS: Number of read operations=11
    HDFS: Number of large read operations=0
    HDFS: Number of write operations=2
```

If successful, will see above, plus many more lines of output....

# MapReduce

- To see what is in your output directory:

```
hdfs dfs -ls /user/testuser2/output_wc
```

- Should output:

Found 2 items

```
-rw-r--r--  1 testuser2 hadoop      0 2019-03-04 17:39
/user/testuser2/output_wc/_SUCCESS
-rw-r--r--  1 testuser2 hadoop    94 2019-03-04 17:39
/user/testuser2/output_wc/part-r-00000
```

- To see what is in the output file:

```
hdfs dfs -cat /user/testuser2/output_wc/part-r-00000
```

- Sample output:

- Sample input:

A long time ago in a galaxy far far away  
Another episode of Star Wars

```
A 1
Another 1
Star 1
Wars 1
a 1
ago 1
away 1
episode 1
far 2
galaxy 1
in 1
long 1
of 1
time 1
```



# MapReduce

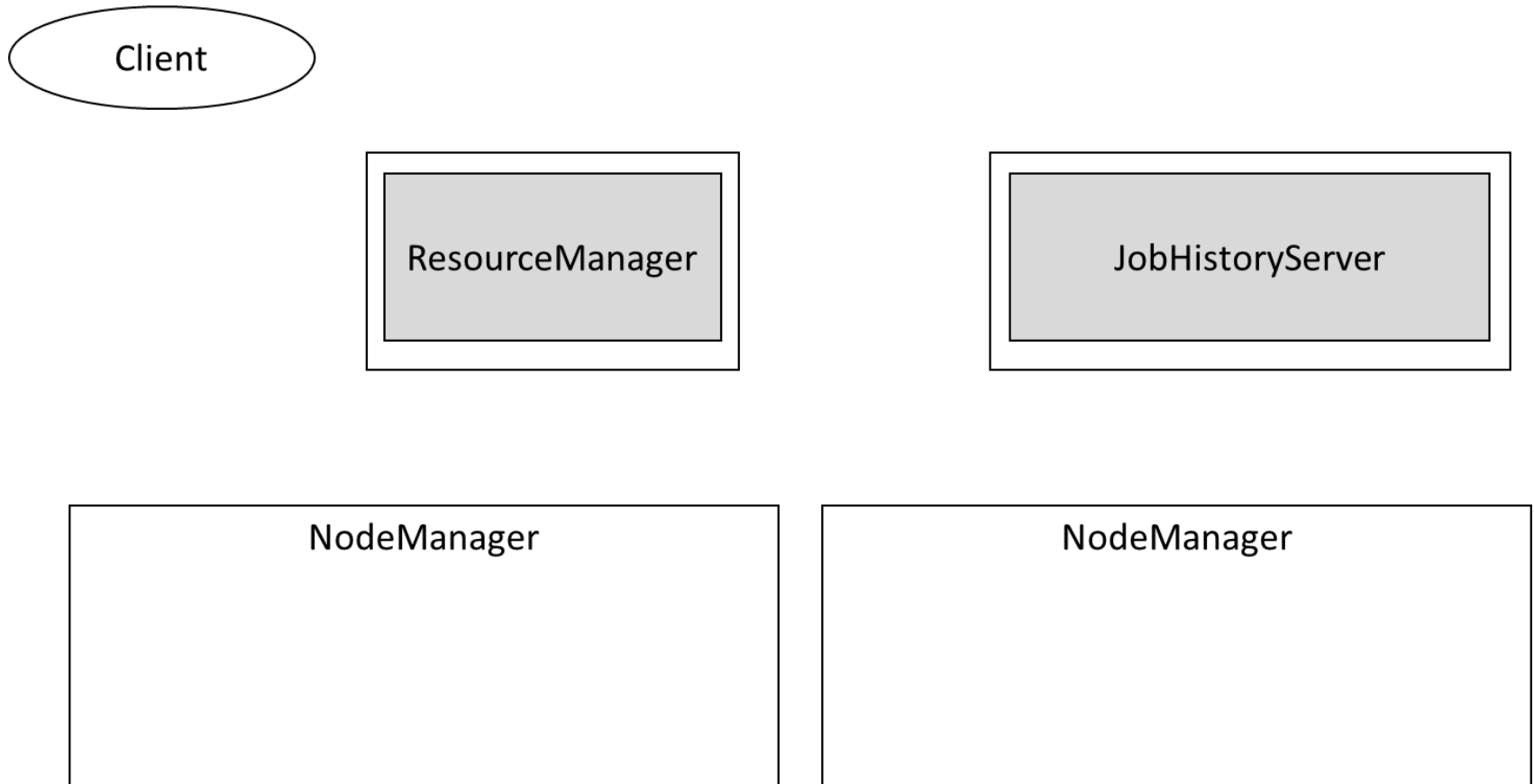
- Constructing MapReduce programs requires a certain skillset in terms of programming
- Tradeoffs in terms of speed, memory consumption, and scalability

# Yet Another Resource Negotiator (YARN)

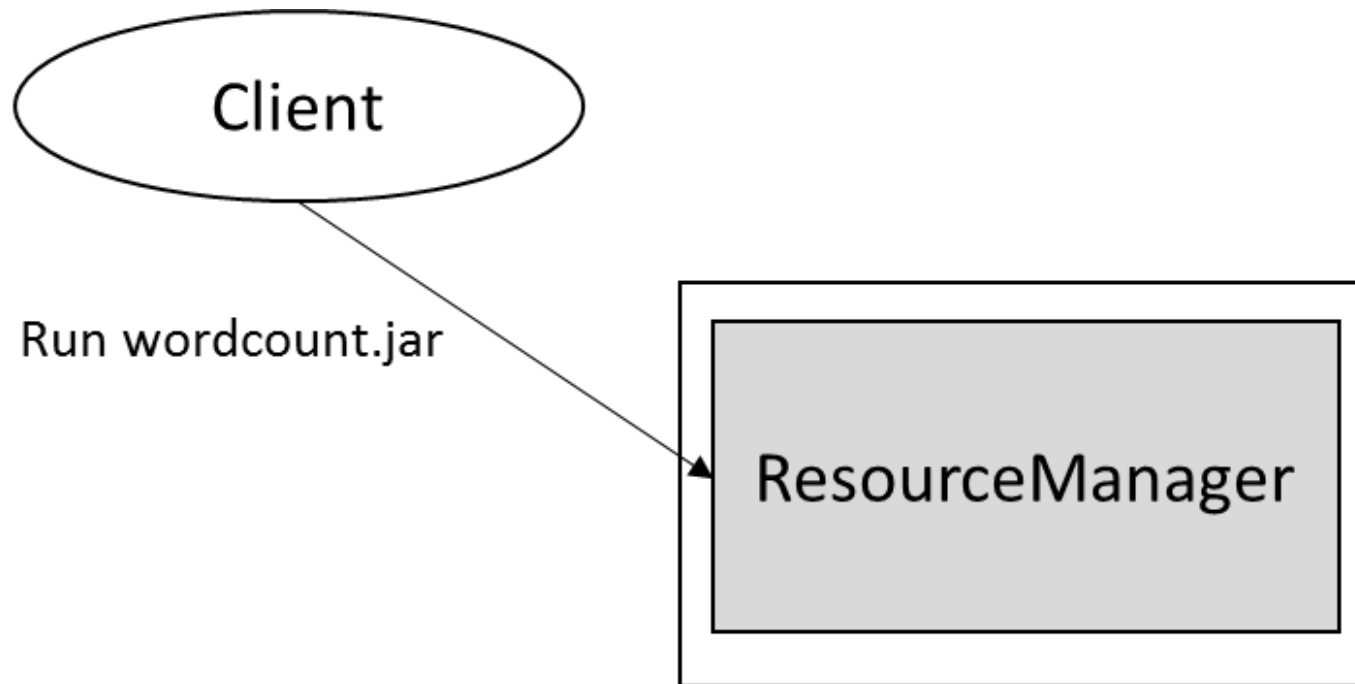
- Yet Another Resource Negotiator (YARN) distributes a MapReduce program across different nodes and takes care of coordination
- Three important services
  - **ResourceManager**: a global YARN service that receives and runs applications (e.g., a MapReduce job) on the cluster
  - **JobHistoryServer**: keeps a log of all finished jobs
  - **NodeManager**: responsible to oversee resource consumption on a node



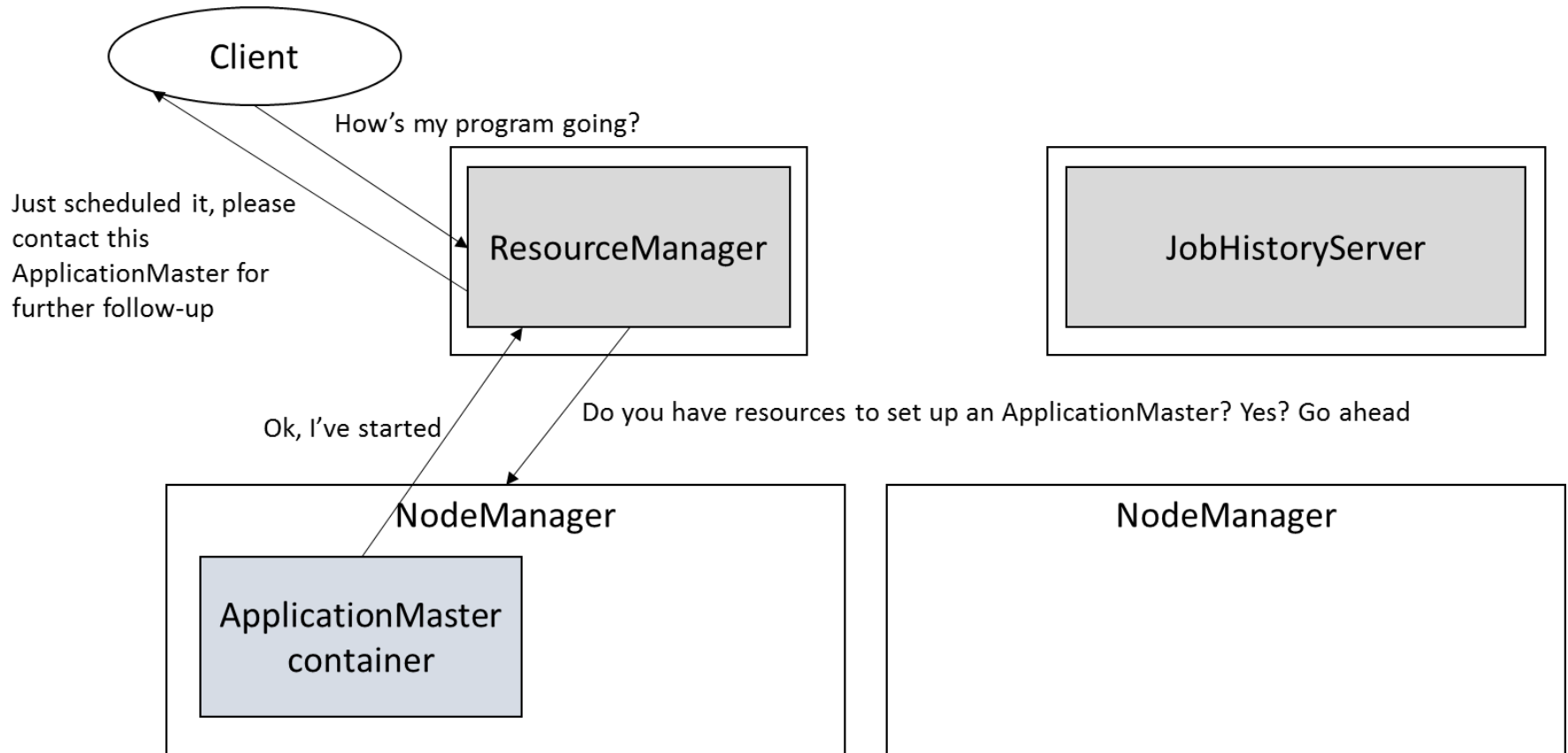
# Yet Another Resource Negotiator (YARN)



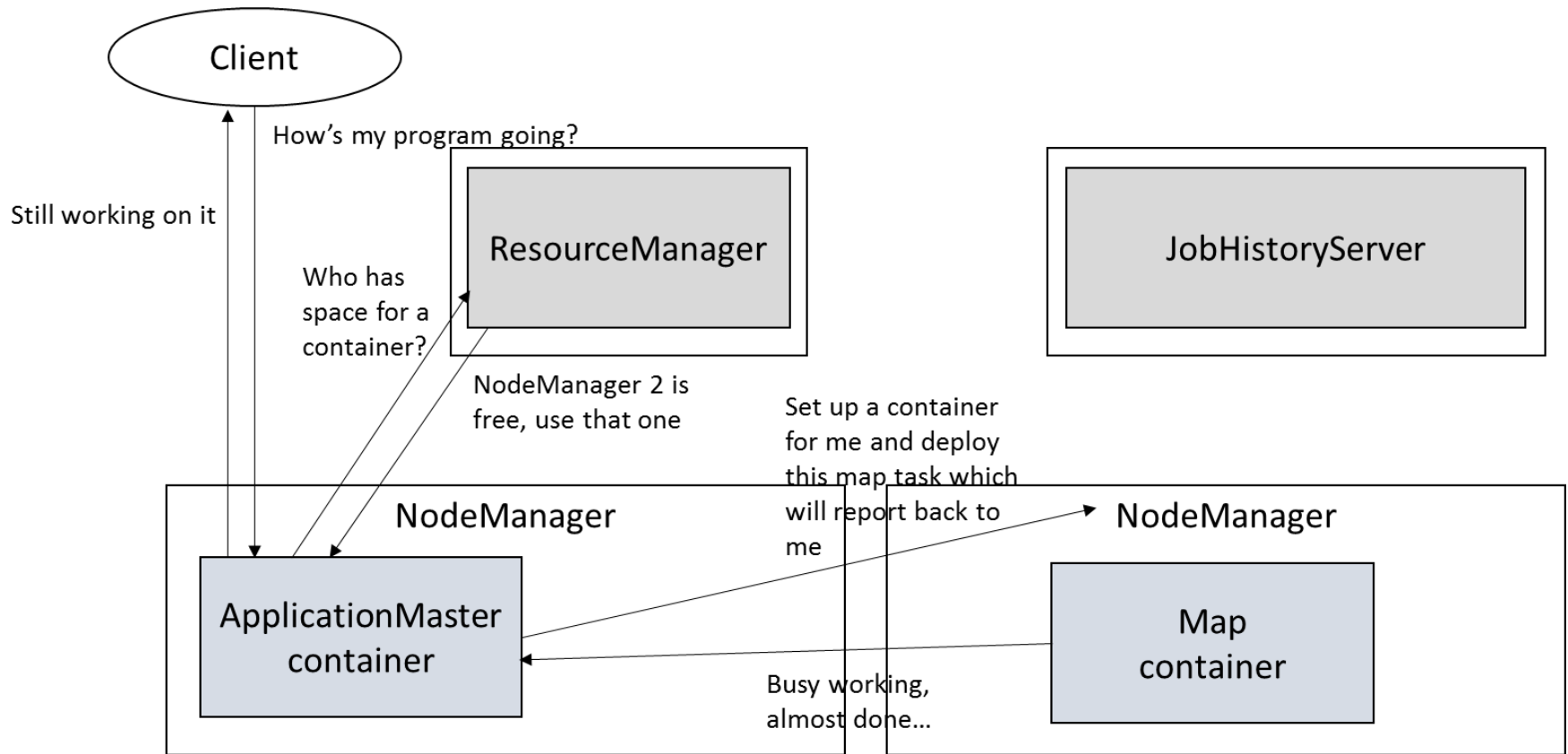
# Yet Another Resource Negotiator (YARN)



# Yet Another Resource Negotiator (YARN)



# Yet Another Resource Negotiator (YARN)





# Yet Another Resource Negotiator (YARN)

- Complex setup
- Allows to run programs and applications other than MapReduce

# Conclusion

## ■ This lecture has:

- ☐ Introduced Hadoop
- ☐ Looked at using Map Reduce with Hadoop
- ☐ See the Workshop material for some examples using Java and Python

## ■ Next week will look at:

- ☐ SQL on Hadoop
- ☐ Apache Spark