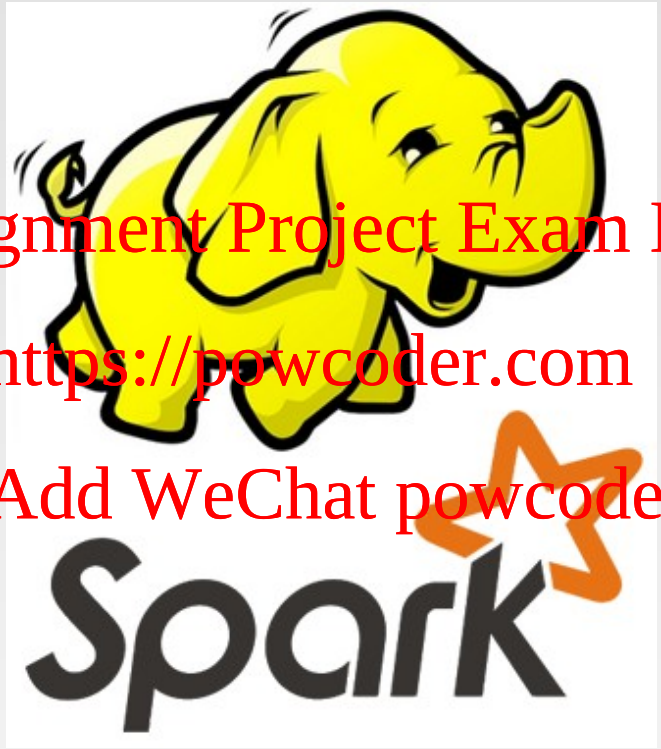
COMP9313: Big Data Management



Lecturer: Xin Cao

Course web site: http://www.cse.unsw.edu.au/~cs9313/

Chapter 2: MapReduce I

What is MapReduce

- Origin from Google, [OSDI'04]
  - MapReduce: Simplified Data Processing on Large Clusters
  - Jeffrey Dean and Sanjay Ghemawat
- Programming model for parallel data processing
- Hadoop can run MapReduce programs written in various languages: e.g. Java, Ruby, Python, C++
- For large-scale data processing
  - Exploits large set of commodity computers
  - Executes process in distributed manner
  - Offers high availability

Motivation for MapReduce

- A Google server room:

https://www.youtube.com/watch?t=3&v=avP5d16wEp0

Motivation for MapReduce

- Typical big data problem challenges:
  - How do we break up a large problem into smaller tasks that can be executed in parallel?
  - How do we assign tasks to workers distributed across a potentially large number of machines?
  - How do we ensure that the workers get the data they need?
  - How do we coordinate synchronization among the different workers?
  - How do we share partial results from one worker that is needed by another?
  - How do we accomplish all of the above in the face of software errors and hardware faults?

Motivation for MapReduce

- There was need for an abstraction that hides many system-level details from the programmer.

- MapReduce addresses this challenge by providing a simple abstraction for the developer, transparently handling most of the details behind the scenes in a ***scalable***, ***robust***, and ***efficient*** manner.

- MapReduce separates the ***what*** from the ***how***

Jeffrey (Jeff) Dean

- He is currently a Google Senior Fellow in the Systems and Infrastructure Group
- Designed MapReduce, BigTable, etc.
- One of the most genius engineer, programmer, computer scientist…
- Google “Who is Jeff Dean” and “Jeff Dean facts”

Jeff Dean Facts

- Kenton Varda created "Jeff Dean Facts" as a Google-internal April Fool's joke in 2007.
  - *The speed of light in a vacuum used to be about 35 mph. Then Jeff Dean spent a weekend optimizing physics*
  - *Jeff Dean once bit a spider, the spider got super powers and C readability*
  - *Jeff Dean puts his pants on one leg at a time, but if he had more than two legs, you would see that his approach is actually O(log n)*
  - *Compilers don't warn Jeff Dean. Jeff Dean warns compilers*
  - *The rate at which Jeff Dean produces code jumped by a factor of 40 in late 2000 when he upgraded his keyboard to USB2.0*

Typical Big Data Problem

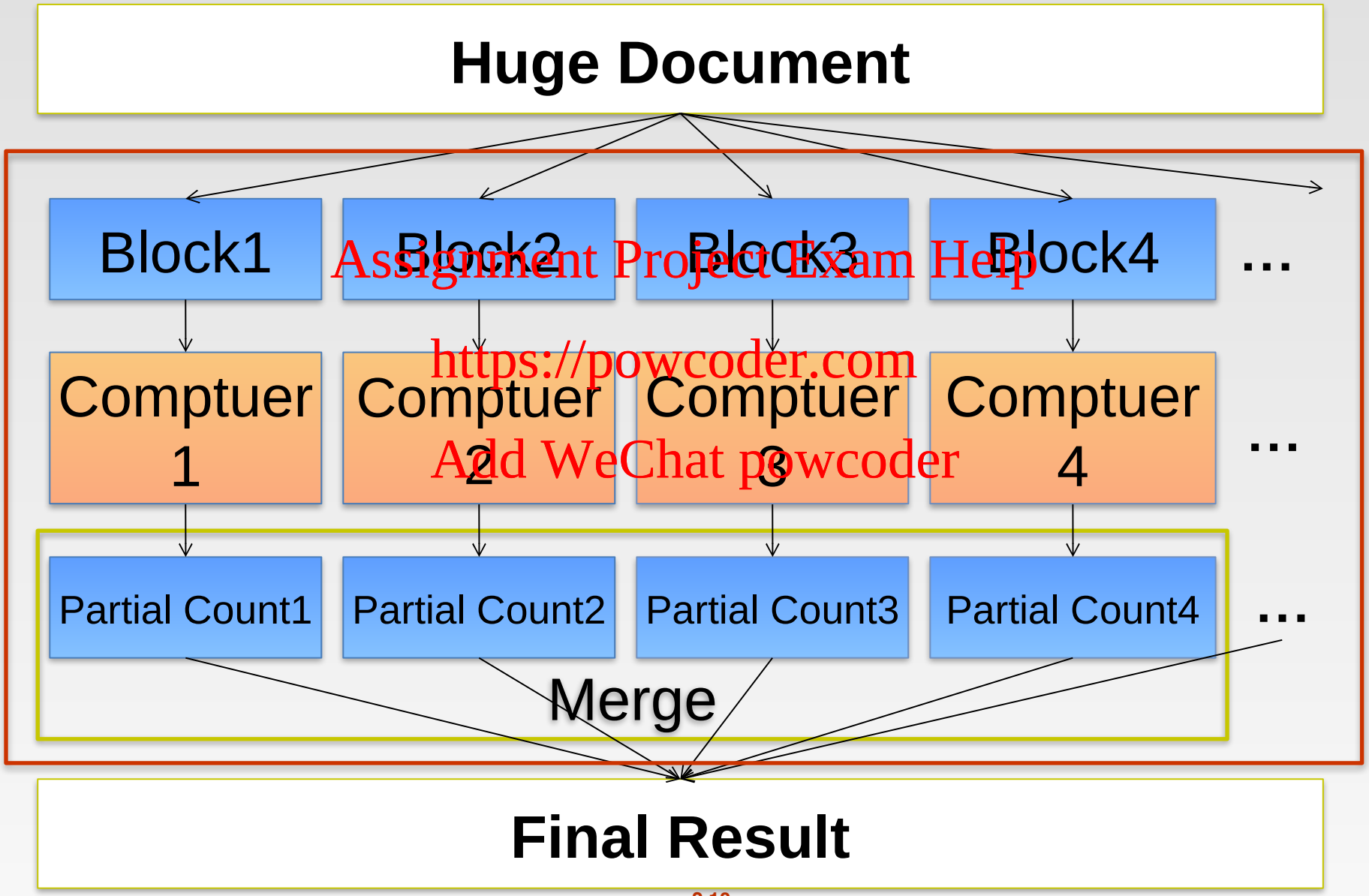
- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

Map

Reduce

Key idea: provide a functional abstraction for these two operations

Distributed Word Count



The Idea of MapReduce

- Inspired by the map and reduce functions in functional programming
- We can view map as a transformation over a dataset
  - This transformation is specified by the function *f*
  - Each functional application happens in isolation
  - The application of *f* to each element of a dataset can be parallelized in a straightforward manner
- We can view reduce as an aggregation operation
  - The aggregation is defined by the function *g*
  - Data locality: elements in the list must be "brought together"
  - If we can group elements of the list, also the reduce phase can proceed in parallel
- The framework coordinates the map and reduce phases:
  - Grouping intermediate results happens in parallel

Data Structures in MapReduce

- Key-value pairs are the basic data structure in MapReduce
  - Keys and values can be: integers, float, strings, raw bytes
  - They can also be arbitrary data structures

- The design of MapReduce algorithms involves
  - Imposing the key-value structure on arbitrary datasets
    - E.g.: for a collection of Web pages, input keys may be URLs and values may be the HTML content
  - In some algorithms, input keys are not used (e.g., wordcount), in others they uniquely identify a record
  - Keys can be combined in complex ways to design various algorithms

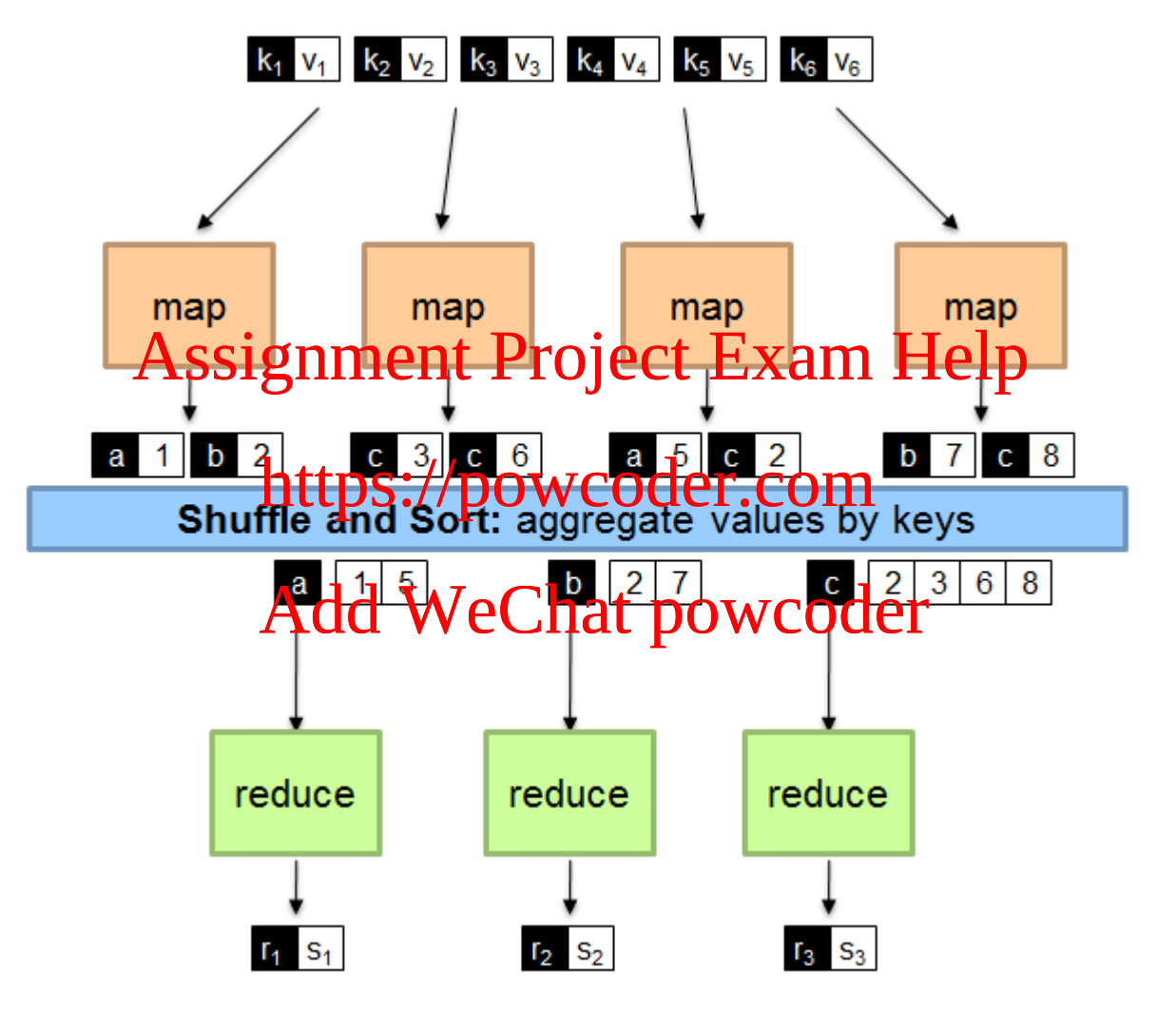
Map and Reduce Functions

- Programmers specify two functions:
  - **map** $(k_1, v_1) \rightarrow$ list $[<k_2, v_2>]$
    - Map transforms the input into key-value pairs to process
  - **reduce** $(k_2,$ list $[v_2]) \rightarrow [<k_3, v_3>]$
    - Reduce aggregates the list of values for each key
    - All values with the same key are sent to the same reducer
  - list $[<k_2, v_2>]$ will be grouped according to key k_2 as $(k_2,$ list $[v_2])$
- The MapReduce environment takes in charge of everything else…
- A complex program can be decomposed as a succession of Map and Reduce tasks

Everything Else?

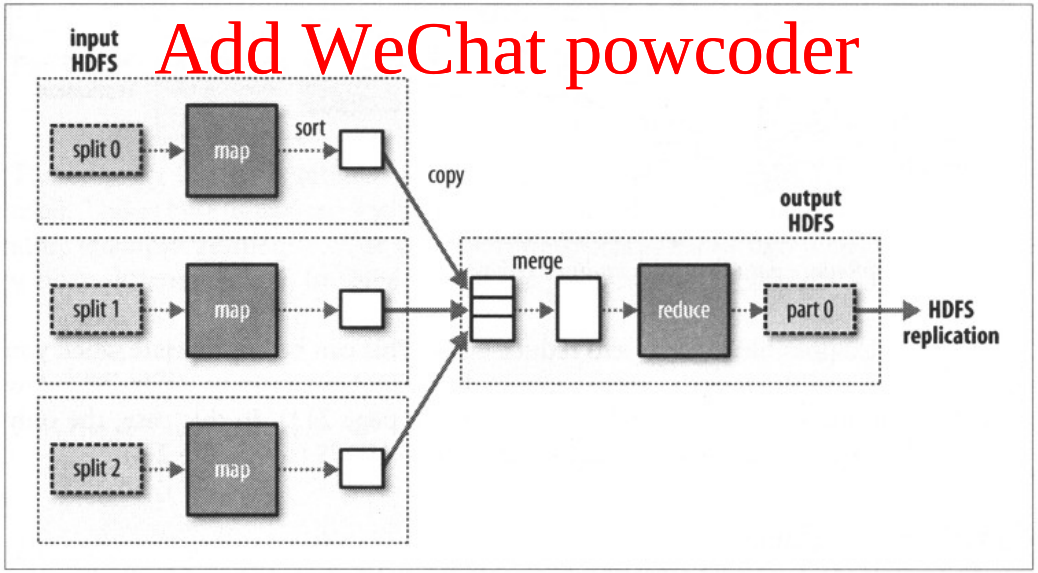
- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles “data distribution”
  - Moves processes to data
- Handles synchronization
  - Gathers, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects worker failures and restarts
- Everything happens on top of a distributed file system (HDFS)
- You don’t know:
  - Where mappers and reducers run
  - When a mapper or reducer begins or finishes
  - Which input a particular mapper is processing
  - Which intermediate key a particular reducer is processing

A Brief View of MapReduce



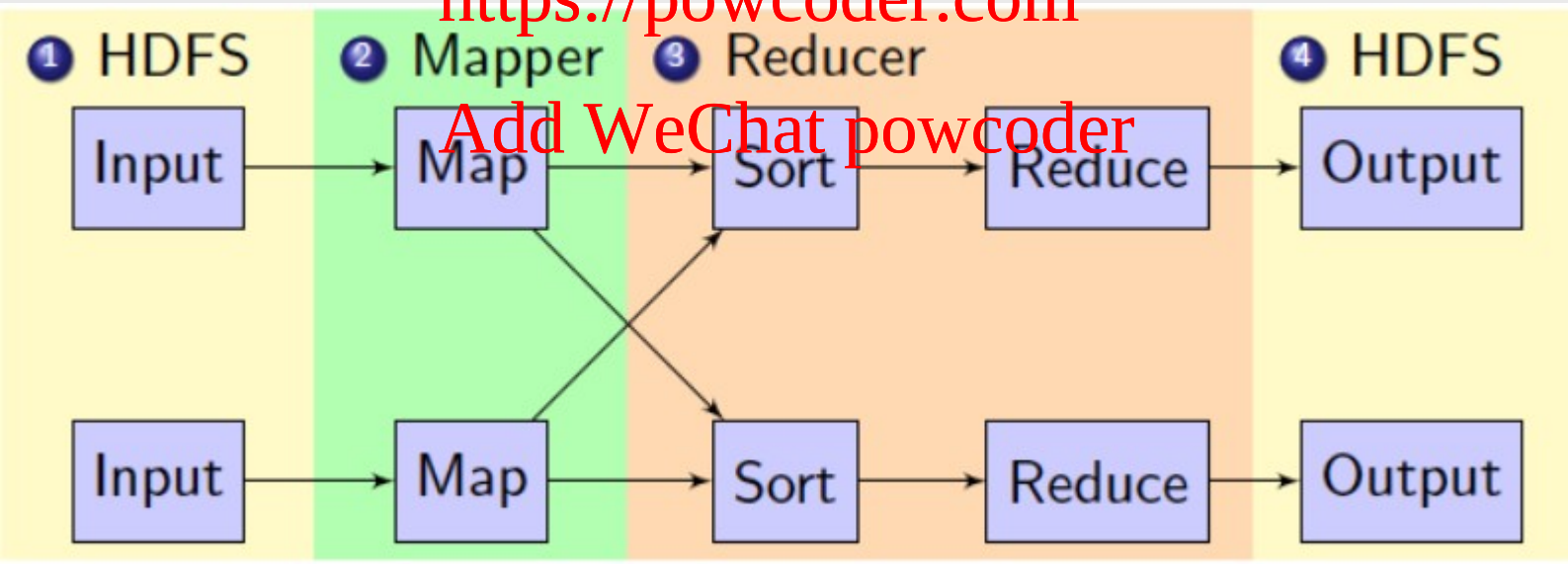
Shuffle and Sort

- Shuffle
  - Input to the Reducer is the sorted output of the mappers. In this phase the framework fetches the relevant partition of the output of all the mappers, via HTTP.
- Sort
  - The framework groups Reducer inputs by keys (since different Mappers may have output the same key) in this stage.
- Hadoop framework handles the Shuffle and Sort step .



Hadoop MapReduce Brief Data Flow

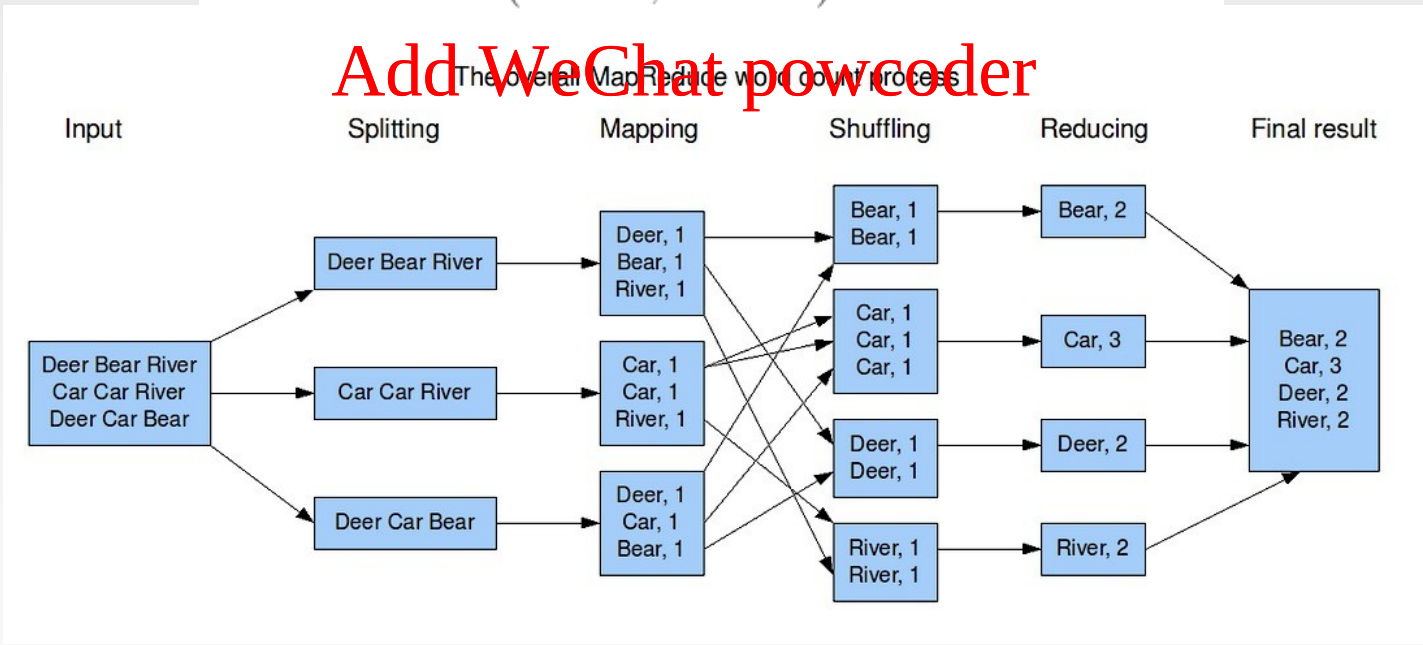
- 1. Mappers read from HDFS
- 2. Map output is partitioned by key and sent to Reducers
- 3. Reducers sort input by key
- 4. Reduce output is written to HDFS
- Intermediate results are stored on local FS of Map and Reduce workers



"Hello World" in MapReduce

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         for all term t ∈ doc d do
4:             Emit(term t, count 1)

1: class Reducer
2:     method Reduce(term t, counts [c1, c2, ...])
3:         sum ← 0
4:         for all count c ∈ counts [c1, c2, ...] do
5:             sum ← sum + c
6:         Emit(term t, count s)
```

“Hello World” in MapReduce

- Input:
  - Key-value pairs: (docid, doc) of a file stored on the distributed filesystem
  - docid : unique identifier of a document
  - doc: is the text of the document itself
- Mapper:
  - Takes an input key-value pair, tokenize the line
  - Emits intermediate key-value pairs: the word is the key and the integer is the value
- The framework:
  - Guarantees all values associated with the same key (the word) are brought to the same reducer
- The reducer:
  - Receives all values associated to some keys
  - Sums the values and writes output key-value pairs: the key is the word and the value is the number of occurrences

Coordination: Master

- Master node takes care of coordination:
  - Task status: (idle, in-progress, completed)
  - Idle tasks get scheduled as workers become available
  - When a map task completes, it sends the master the location and sizes of its R intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Dealing with Failures

- Map worker failure
  - Its task is reassigned to another map worker
  - Reduce workers are notified when task is rescheduled on another worker
- Reduce worker failure
  - Its task is reassigned to another reduce worker
  - Reduce task is restarted (usually require restarting mapper tasks as well)
- Master failure
  - MapReduce task is aborted and client is notified
- Robust
  - Google's experience: lost 1600 of 1800 machines once!, but finished fine

Where the Magic Happens

- Implicit between the map and reduce phases is a parallel "group by" operation on intermediate keys
  - Intermediate data arrive at each reducer in order, sorted by the key
  - No ordering is guaranteed across reducers

- Output keys from reducers are written back to HDFS
  - The output may consist of *r* distinct files, where *r* is the number of reducers

  - Such output may be the input to a subsequent MapReduce phase

- Intermediate keys (used in shuffle and sort) are transient:
  - They are not stored on the distributed filesystem
  - They are "spilled" to the local disk of each machine in the cluster

Write Your Own WordCount in Java?

MapReduce Program

- A MapReduce program consists of the following 3 parts:
  - Driver → main (would trigger the map and reduce methods)
  - Mapper
  - Reducer
  - It is better to include the map, reduce and main methods in 3 different classes

- Check detailed information of all classes at: https://hadoop.apache.org/docs/r2.7.2/api/allclasses-noframe.html

Mapper

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

Mapper Explanation

- Maps input key/value pairs to a set of intermediate key/value pairs.

```
//Map class header
public static class TokenizerMapper
        extends Mapper<Object, Text, Text, IntWritable>{
```

- Class Mapper<KEYIN,VALUEIN,KEYOUT,VALUEOUT>
  - KEYIN,VALUEIN -> (k1, v1) -> (docid, doc)
  - KEYOUT,VALUEOUT ->(k2, v2) -> (word, 1)


```
// IntWritable: A serializable and comparable object for integer
private final static IntWritable one = new IntWritable(1);
//Text: stores text using standard UTF8 encoding. It provides methods to
serialize, deserialize, and compare texts at byte level
private Text word = new Text();
//hadoop supported data types for the key/value pairs, in package
org.apache.hadoop
```

What is Writable?

- Hadoop defines its own “box” classes for strings (Text), integers (IntWritable), etc.

- All values must implement interface Writable

- All keys must implement interface WritableComparable

- Writable is a serializable object which implements a simple, efficient, serialization protocol

Mapper Explanation (Cont')

//Map method header

public void map(Object key, Text value, Context context) throws IOException, InterruptedException

- Object key/Text value: Data type of the input Key and Value to the mapper
- Context: An inner class of Mapper, used to store the context of a running task. Here it is used to collect data output by either the Mapper or the Reducer, i.e. intermediate outputs or the output of the job
- Exceptions: IOException, InterruptedException
- This function is called once for each key/value pair in the input split. Your application should override this to do your job.

Mapper Explanation (Cont')

```
//Use a string tokenizer to split the document into words
StringTokenizer itr = new StringTokenizer(value.toString());
//Iterate through each word and a form key value pairs
while (itr.hasMoreTokens()) {
//Assign each word from the token iterator (of String type) to a Text 'word'
        word.set(itr.nextToken());
//Form key value pairs for each word as <word, one> using context
        context.write(word, one);
}
```


- Map function produces Map.Context object
  - Map.context() takes *(k, v)* elements
- Any *(WritableComparable, Writable)* can be used

Reducer

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

      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);
      }
}
```

Reducer Explanation

```
//Reduce Header similar to the one in map with different key/value data type
public static class IntSumReducer
      extends Reducer<Text, IntWritable, Text, IntWritable>
//data from map will be <"word",{1,1,..}>, so we get it with an Iterator and thus we
can go through the sets of values
public void reduce(Text key, Iterable<IntWritable> values,
Context context) throws IOException, InterruptedException{
//Initaize a variable 'sum' as 0
            int sum = 0;
//Iterate through all the values with respect to a key and sum up all of them
            for (IntWritable val : values) {
                  sum += val.get();
            }
// Form the final key/value pairs results for each word using context
            result.set(sum);
            context.write(key, result);
```

Main (Driver)

```
public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
}
```

Main(The Driver)

- Given the Mapper and Reducer code, the short main() starts the MapReduction running
- The Hadoop system picks up a bunch of values from the command line on its own
- Then the main() also specifies a few key parameters of the problem in the Job object
- Job is the primary interface for a user to describe a map-reduce job to the Hadoop framework for execution (such as what Map and Reduce classes to use and the format of the input and output files)
- Other parameters, i.e. the number of machines to use, are optional and the system will determine good values for them if not specified
- Then the framework tries to faithfully execute the job as-is described by Job

Main Explanation

```
//Creating a Configuration object and a Job object, assigning a job name for identification purposes
Configuration conf = new Configuration();
Job job = Job.getInstance(conf, "word count");
```

- Job Class: It allows the user to configure the job, submit it, control its execution, and query the state. Normally the user creates the application, describes various facets of the job via Job and then submits the job and monitor its progress.


```
//Setting the job's jar file by finding the provided class location
job.setJarByClass(WordCount.class);
//Providing the mapper and reducer class names
job.setMapperClass(TokenizerMapper.class);
job.setReducerClass(IntSumReducer.class);
//Setting configuration object with the Data Type of output Key and Value for map and reduce
job.setOutputKeyClass(Text.class);
job.setOutputValueClass(IntWritable.class);
```

Main Explanation (Cont')

```
//The hdfs input and output directory to be fetched from the command line
FileInputFormat.addInputPath(job, new Path(args[0]));
FileOutputFormat.setOutputPath(job, new Path(args[1]));
//Submit the job to the cluster and wait for it to finish.
System.exit(job.waitForCompletion(true) ? 0 : 1);
```

Make It Running !

- Configure environment variables

```
export JAVA_HOME=…
export PATH=${JAVA_HOME}/bin:${PATH}
export HADOOP_CLASSPATH=${JAVA_HOME}/lib/tools.jar
```

- Compile WordCount.java and create a jar:

```
$ hadoop com.sun.tools.javac.Main WordCount.java
$ jar cf wc.jar WordCount*.class
```

- Put files to HDFS

```
$ hdfs dfs –put YOURFILES input
```

- Run the application

```
$ hadoop jar wc.jar WordCount  input output
```

- Check the results

```
$ hdfs dfs –cat output/*
```



```
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 {

  public static class TokenizerMapper
       extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    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);
      }
    }
  }

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

    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);
    }
  }

  public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
```

Make It Running !

- Given two files:
  - file1: Hello World Bye World
  - file2: Hello Hadoop Goodbye Hadoop
- The first map emits:
  - < Hello, 1> < World, 1> < Bye, 1> < World, 1>
- The second map emits:
  - < Hello, 1> < Hadoop, 1> < Goodbye, 1> < Hadoop, 1>
- The output of the job is:
  - < Bye, 1> < Goodbye, 1> < Hadoop, 2> < Hello, 2> < World, 2>

Mappers and Reducers

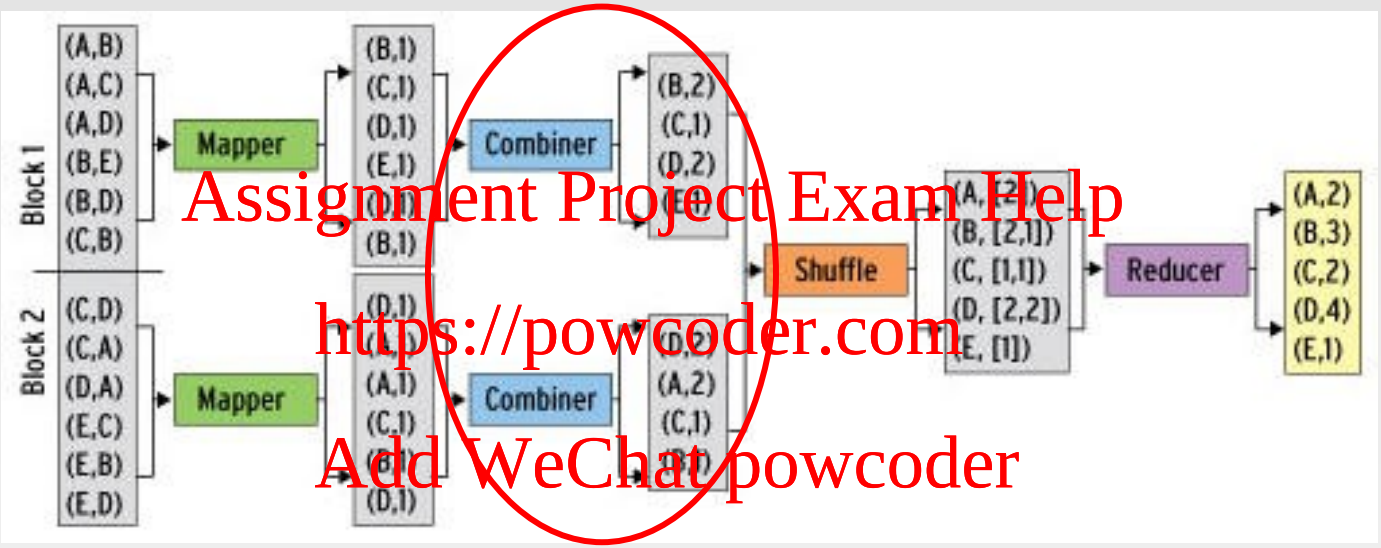
- Need to handle more data? Just add more Mappers/Reducers!
- No need to handle multithreaded code ☺
  - Mappers and Reducers are typically single threaded and deterministic
    - Determinism allows for restarting of failed jobs
  - Mappers/Reducers run entirely independent of each other
    - In Hadoop, they run in separate JVMs

Combiners

- Often a Map task will produce many pairs of the form $(k,v_1), (k,v_2), \ldots$ for the same key k
  - E.g., popular words in the word count example
- Combiners are a general mechanism to reduce the amount of intermediate data, thus saving network time
  - They could be thought of as "mini-reducers"
- Warning!
  - The use of combiners must be thought carefully
    - Optional in Hadoop: the correctness of the algorithm cannot depend on computation (or even execution) of the combiners
    - A combiner operates on each map output key. It must have the same output key-value types as the Mapper class.
    - A combiner can produce summary information from a large dataset because it replaces the original Map output
  - Works only if reduce function is commutative and associative
    - In general, reducer and combiner are not interchangeable

Combiners in WordCount

- Combiner combines the values of all keys of a single mapper node (single machine):



- Much less data needs to be copied and shuffled!
- If combiners take advantage of all opportunities for local aggregation we have at most $m \times V$ intermediate key-value pairs
  - m: number of mappers
  - V: number of unique terms in the collection
- Note: not all mappers will see all terms

Combiners in WordCount

- In WordCount.java, you only need to add the follow line to Main:

  job.setCombinerClass(IntSumReducer.class);

  - This is because in this example, Reducer and Combiner do the same thing
  - Note: Most cases this is not true!
  - You need to write an extra combiner class
- Given two files:
  - file1: Hello World Bye World
  - file2: Hello Hadoop Goodbye Hadoop
- The first map emits:
  - < Hello, 1> < World, 2> < Bye, 1>
- The second map emits:
  - < Hello, 1> < Hadoop, 2> < Goodbye, 1>

Partitioner

- Partitioner controls the partitioning of the keys of the intermediate map-outputs.
  - The key (or a subset of the key) is used to derive the partition, typically by a *hash function*.
  - The total number of partitions is the same as the number of reduce tasks for the job.
    - This controls which of the m reduce tasks the intermediate key (and hence the record) is sent to for reduction.
- System uses HashPartitioner by default:
  - hash(key) mod R
- Sometimes useful to override the hash function:
  - E.g., ***hash(hostname(URL)) mod R*** ensures URLs from a host end up in the same output file
    - https://www.unsw.edu.au/faculties and https://www.unsw.edu.au/about-us will be stored in one file
- Job sets Partitioner implementation (in Main)

MapReduce: Recap

- Programmers must specify:
  - map $(k_1, v_1) \rightarrow [(k_2, v_2)]$
  - reduce $(k_2, [v_2]) \rightarrow [<k_3, v_3>]$
  - All values with the same key are reduced together
- Optionally, also:
  - combine $(k_2, [v_2]) \rightarrow [<k_3, v_3>]$
    - Mini-reducers that run in memory after the map phase
    - Used as an optimization to reduce network traffic
  - partition $(k_2$, number of partitions$) \rightarrow$ partition for k_2
    - Often a simple hash of the key, e.g., hash(k_2) mod n
    - Divides up key space for parallel reduce operations
- The execution framework handles everything else…

MapReduce: Recap (Cont')

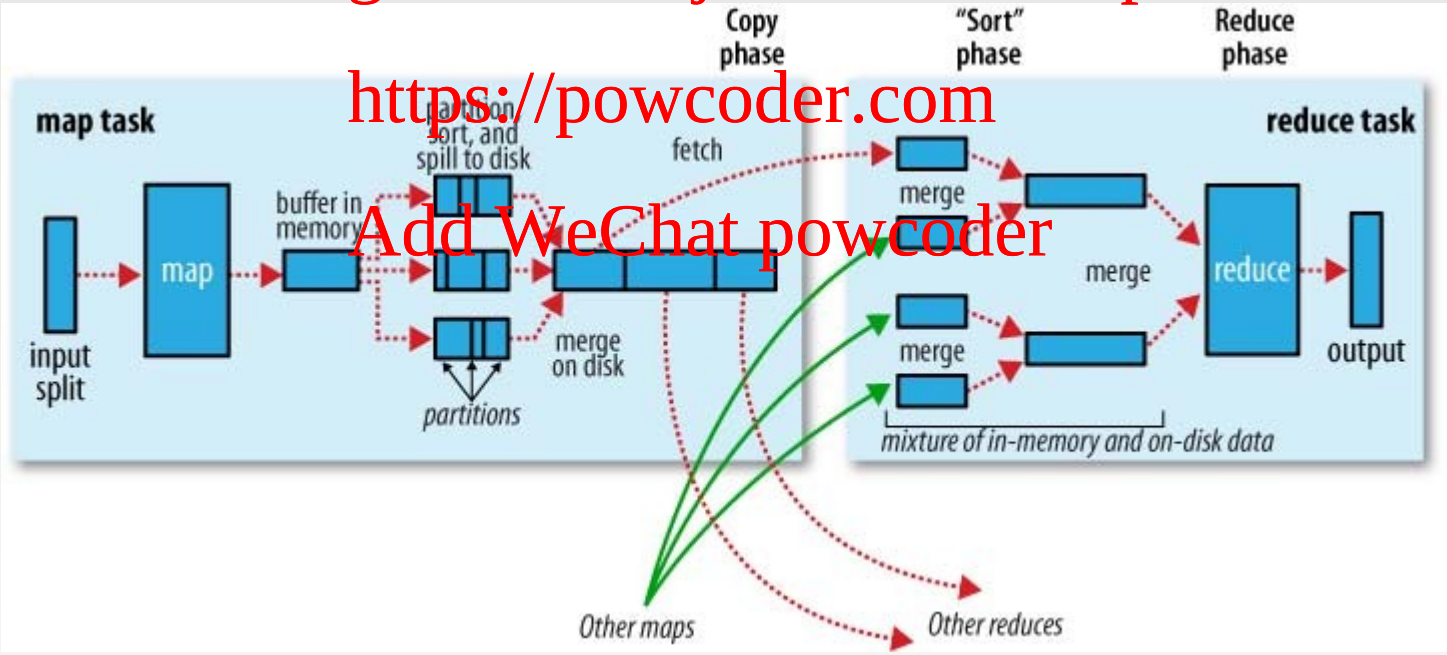
- Divides input into fixed-size pieces***, input splits***
  - Hadoop creates one map task for each split
  - Map task runs the user-defined map function for each *record* in the split
- Size of splits
  - Small size is better for load-balancing: faster machine will be able to process more splits
  - But if splits are too small, the overhead of managing the splits dominate the total execution time
  - For most jobs, a good split size tends to be the size of a HDFS block, 64MB(default)
- Data locality optimization
  - Run the map task on a node where the input data resides in HDFS
  - This is the reason why the split size is the same as the block size

MapReduce: Recap (Cont')

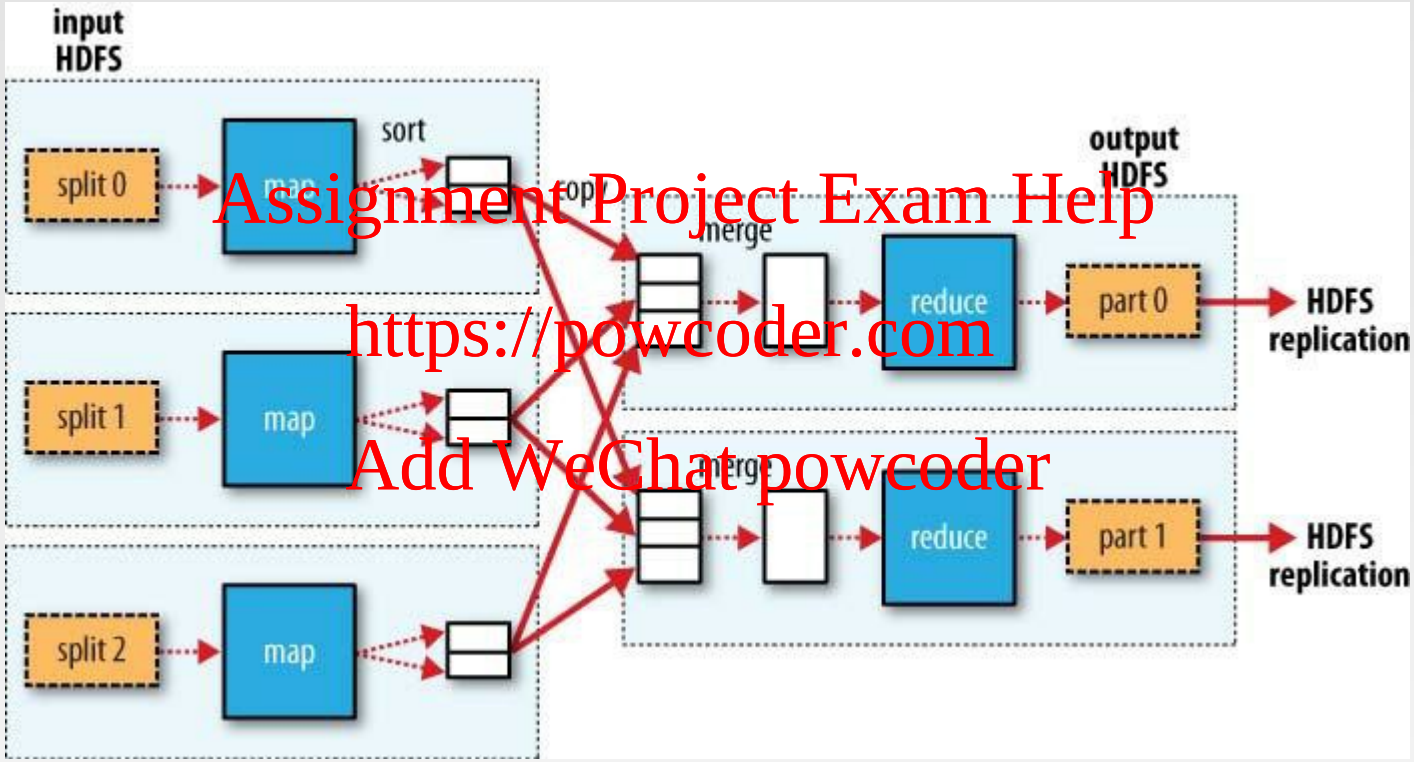
- Map tasks write their output to local disk (not to HDFS)
  - Map output is intermediate output
  - Once the job is complete the map output can be thrown away
  - So storing it in HDFS with replication would be overkill
  - If the node of map task fails, Hadoop will automatically rerun the map task on another node
- Reduce tasks don't have the advantage of data locality
  - Input to a single reduce task is normally the output from all mappers
  - Output of the reduce is stored in HDFS for reliability
- The number of reduce tasks is not governed by the size of the input, but is specified independently

MapReduce: Recap (Cont')

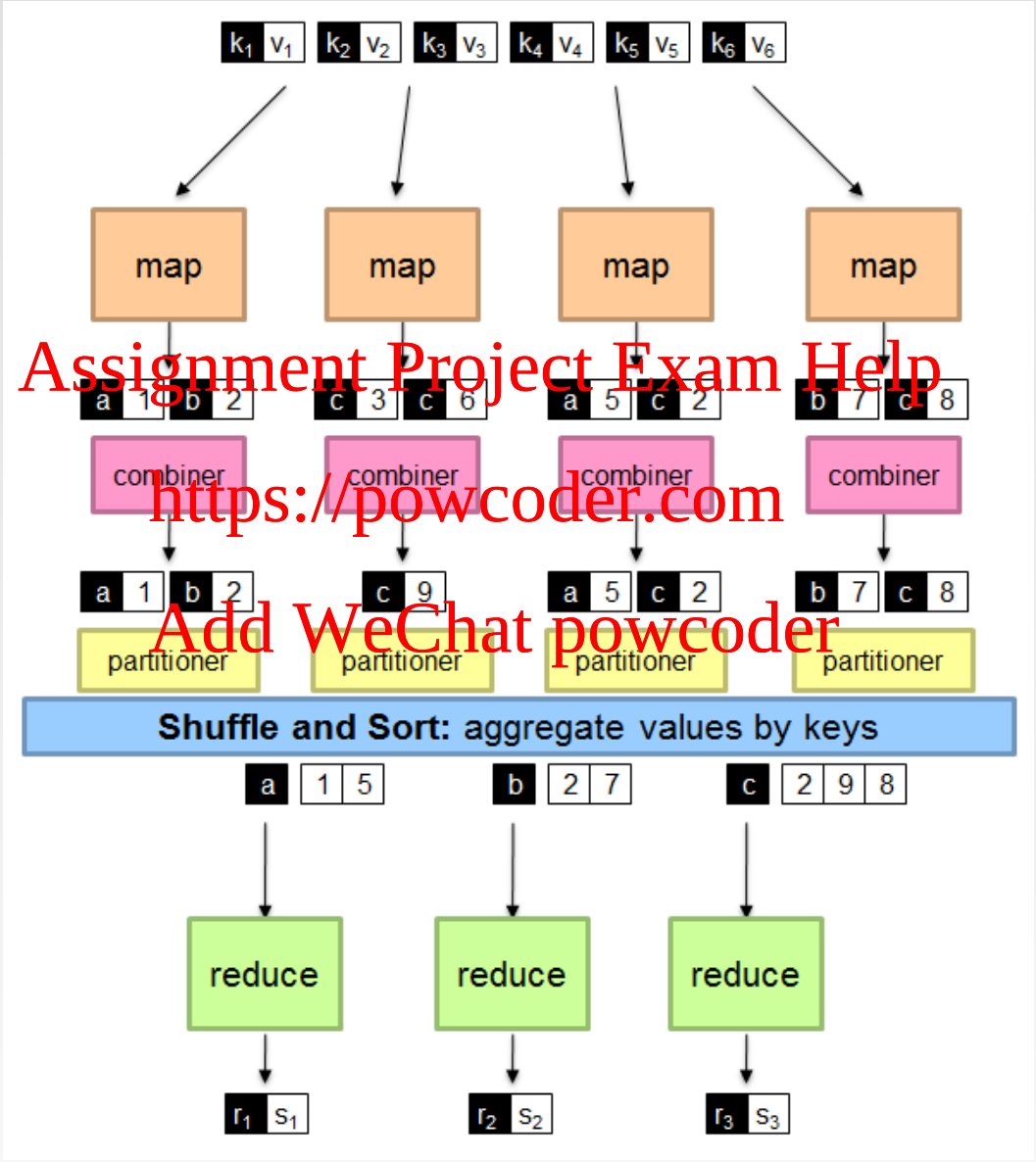
- When there are multiple reducers, the map tasks partition their output:
  - One partition for each reduce task
  - The records for every key are all in a single partition
  - Partitioning can be controlled by a user-defined partitioning function



More Detailed MapReduce Dataflow

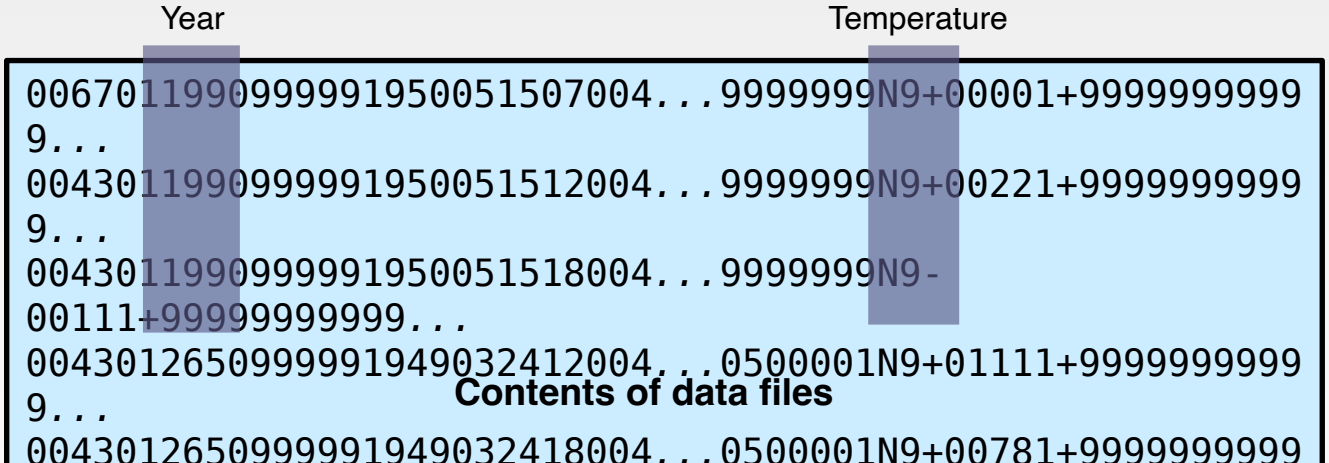


MapReduce: Recap



Another Example : Analysis of Weather Dataset

- Data from NCDC(National Climatic Data Center)
  - A large volume of log data collected by weather sensors: e.g. temperature
- Data format
  - Line-oriented ASCII format
  - Each record has many elements
  - We focus on the temperature element
  - Data files are organized by date and weather station
  - There is a directory for each year from 1901 to 2001, each containing a gzipped file for each weather station with its readings for that year
- Query
  - What's the highest recorded global temperature for each year in the dataset?



Contents of data files

```
% ls raw/1990 | head
010010-99999-1990.gz
010014-99999-1990.gz
010015-99999-1990.gz
010016-99999-1990.gz
010017-99999-1990.gz
010030-99999-1990.gz
010040-99999-1990.gz
010080-99999-1990.gz
010100-99999-1990.gz
010150-99999-1990.gz
```

List of data files

Analyzing the Data with Unix Tools

- To provide a performance baseline
- Use *awk* for processing line-oriented data
- Complete run for the century took **42 minutes** on a single EC2 High-CPU Extra Large Instance


```
#!/usr/bin/env bash
for year in all/*
do
  echo -ne `basename $year .gz`"\t"
  gunzip -c $year | \
    awk '{ temp = substr($0, 88, 5) + 0;
           q = substr($0, 93, 1);
           if (temp !=9999 && q ~ /[01459]/ && temp > max) max = temp }
         END { print max }'
done
```

```
% ./max_temperature.sh
1901    317
1902    244
1903    289
1904    256
1905    283
...
```

How Can We Parallelize This Work?

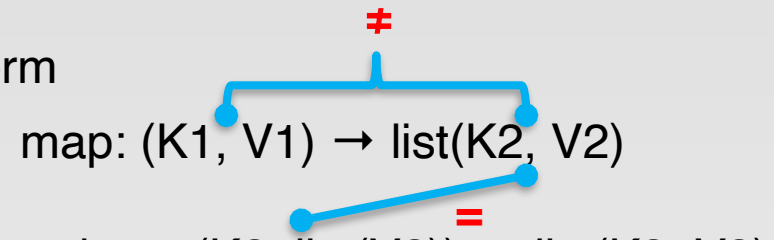
- To speed up the processing, we need to run parts of the program in **parallel**
- Challenges?
  - Divide the work into even distribution is not easy
    - File size for different years varies
  - Combining the results is complicated
    - Get the result from the maximum temperature for each chunk
  - We are still limited by the processing capacity of a single machine
    - Some datasets grow beyond the capacity of a single machine
- To use **multiple machines**, we need to consider a variety of complex problems
  - Coordination: Who runs the overall job?
  - Reliability: How do we deal with failed processes?
- **Hadoop** can take care of these issues

MapReduce Design

- We need to answer these questions:
  - What are the map input key and value types?
  - What does the mapper do?
  - What are the map output key and value types?
  - Can we use a combiner?
  - Is a partitioner required?
  - What does the reducer do?
  - What are the reduce output key and value types?
- And: What are the file formats?
  - For now we are using text files
  - We may use binary files

MapReduce Types

- General form



- Combine function

```
map: (K1, V1) → list(K2, V2)
combine: (K2, list(V2)) → list(K2, V2)
reduce: (K2, list(V2)) → list(K3, V3)
```


  - The same form as the reduce function, except its output types
  - Output type is the same as Map
  - The combine and reduce functions may be the same

- Partition function

```
partition: (K2, V2) → integer
```

  - Input intermediate key and value types
  - Returns the partition index

MapReduce Design

- Identify the input and output of the problem
  - Text input format of the dataset files (input of mapper)
    - Key: offset of the line (unnecessary)
    - Value: each line of the files (string)
  - Output (output of reducer)
    - Key: year (string or integer)
    - Value: maximum temperature (integer)
- Decide the MapReduce data types
  - Hadoop provides its own set of basic types
    - optimized for network serialization
    - org.apache.hadoop.io package
  - In WordCount, we have used Text and IntWritable
  - Key must implement interface WritableComparable
  - Value must implement interface Writable

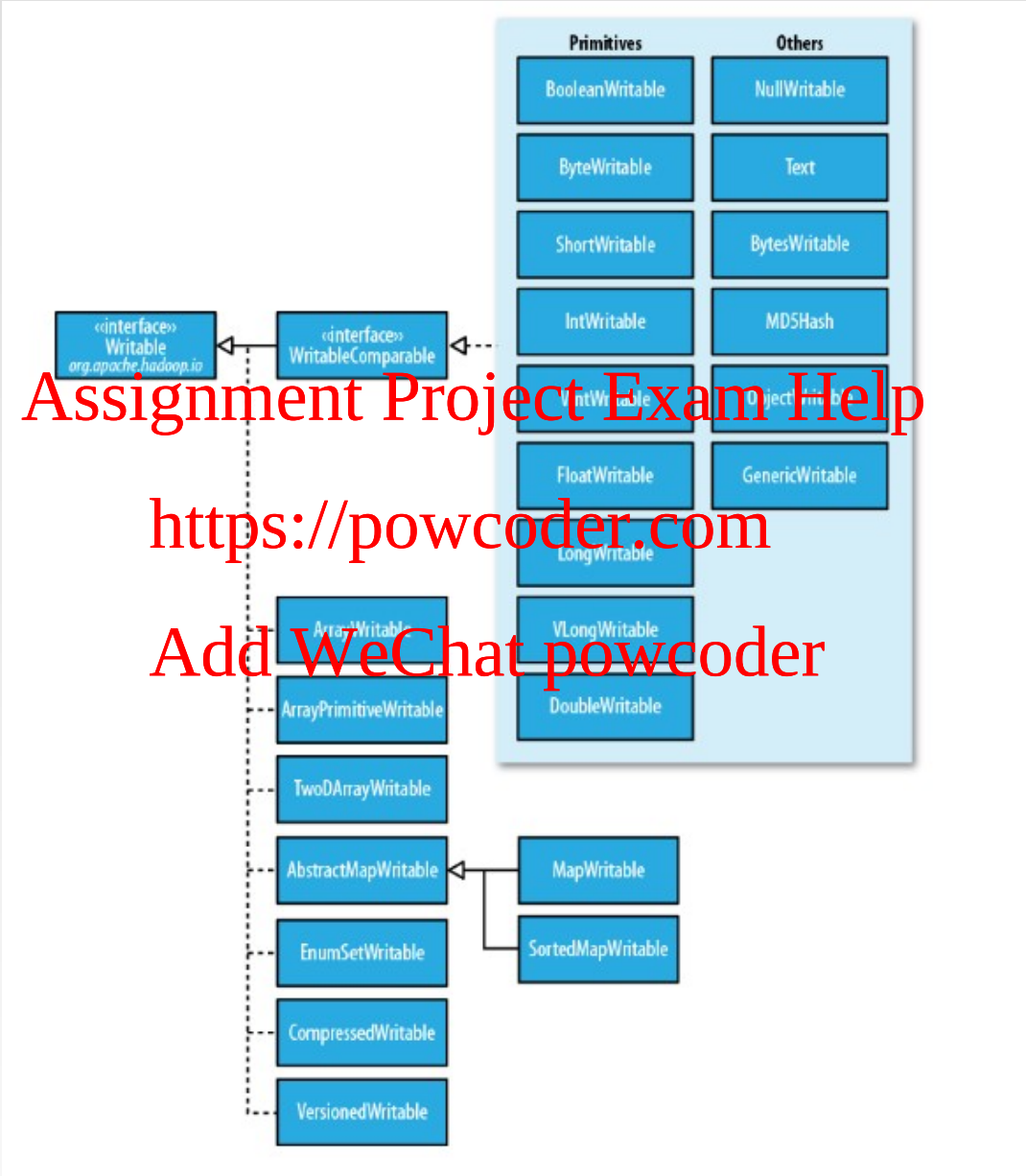
Writable Wrappers

Java primitive	Writable implementation
boolean	BooleanWritable
byte	ByteWritable
short	ShortWritable
int	IntWritable VIntWritable
float	FloatWritable
long	LongWritable VLongWritable
double	DoubleWritable

Java class	Writable implementation
String	Text
byte[]	BytesWritable
Object	ObjectWritable
null	NullWritable

Java collection	Writable implementation
array	ArrayWritable ArrayPrimitiveWritable TwoDArrayWritable
Map	MapWritable
SortedMap	SortedMapWritable
enum	EnumSetWritable

Writable Class Hierarchy



What does the Mapper Do?

- Pull out the year and the temperature
  - Indeed in this example, the map phase is simply data preparation phase
  - Drop bad records(filtering)

Input File

```
0067011990999991950051507004...9999999N9+00001+99999999999...
0043011990999991950051512004...9999999N9+00221+99999999999...
0043011990999991950051518004...9999999N9-00111+99999999999...
0043012650999991949032412004...0500001N9+01111+99999999999...
0043012650999991949032418004...0500001N9+00781+99999999999...
```


Input of Map Function (key, value)

```
(0, 0067011990999991950051507004...9999999N9+00001+99999999999...)
(106, 0043011990999991950051512004...9999999N9+00221+99999999999...)
(212, 0043011990999991950051518004...9999999N9-00111+99999999999...)
(318, 0043012650999991949032412004...0500001N9+01111+99999999999...)
(424, 0043012650999991949032418004...0500001N9+00781+99999999999...)
```

Map

Output of Map Function (key, value)

```
(1950, 0)
(1950, 22)
(1950, -11)
(1949, 111)
(1949, 78)
```

Map Input and Output

- Input
  - Key: offset of the line (unnecessary)
    - The dataset is quite large and contains a huge number of lines
    - LongWritable
  - Value: each line of the files (string)
    - Text
- Output
  - Key: year
    - Both string or integer format
    - Text/IntWritable
  - Value: temperature
    - Integer is already enough to store it
    - IntWritable
- Combiner and Partitioner?

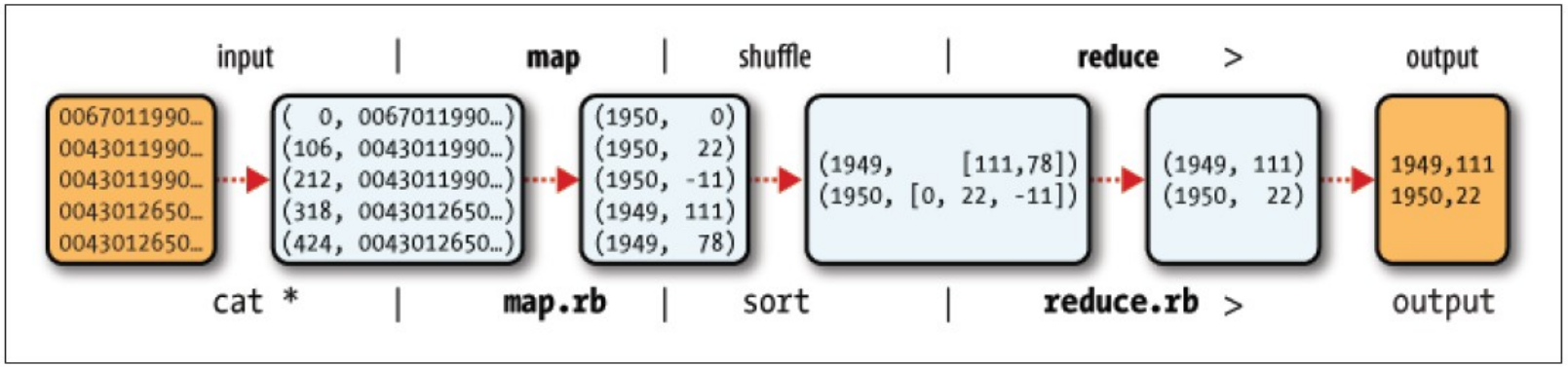
What does the Reducer Do?

- Reducer input
  - (year, [temperature1, temperature2, temperature3, …])
- Scan all values received for the key, and find out the maximum one
- Reducer output
  - Key: year
    - String/IntWritable
  - Value: maximum temperature
    - IntWritable

MapReduce Design of NCDC Example

- The output from the map function is processed by MapReduce framework
  - Sorts and groups the key-value pairs by key

- Reduce function iterates through the list and pick up the maximum value



Java Implementation of the Example

```
public class MaxTemperatureMapper extends Mapper<LongWritable, Text, Text, IntWritable> {
  private static final int MISSING = 9999;

  @Override
  public void map(LongWritable key, Text value, Context context) throws IOException, InterruptedException {
    String line = value.toString();
    String year = line.substring(15, 19);
    int airTemperature;
    if (line.charAt(87) == '+') {
      airTemperature = Integer.parseInt(line.substring(88, 92));
    } else {
      airTemperature = Integer.parseInt(line.substring(87, 92));
    }
    String quality = line.substring(92, 93);
    if (airTemperature != MISSING && quality.matches("[01459]")) {
      context.write(new Text(year), new IntWritable(airTemperature));
    }
  }
}
```

Java Implementation of the Example

```
public class MaxTemperatureReducer
             extends Reducer<Text, IntWritable, Text, IntWritable> {
  @Override
  public void reduce(Text key, Iterable<IntWritable> values,
      Context context) throws IOException, InterruptedException {
    int maxValue = Integer.MIN_VALUE;
    for (IntWritable value : values) {
      maxValue = Math.max(maxValue, value.get());
    }
    context.write(key, new IntWritable(maxValue));
  }
}
```

Java Implementation of the Example

```
public class MaxTemperatureWithCombiner {
//specify the usage of the job
  public static void main(String[] args) throws Exception {
    if (args.length != 2) {
      System.err.println("Usage: MaxTemperatureWithCombiner <input path> " + "<output path>");
      System.exit(-1);
    }
//Construct a job object to configure, control and run the job
    Job job = new Job();
    job.setJarByClass(MaxTemperatureWithCombiner.class);
    job.setJobName("Max temperature");
//Specify input and output paths
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
//Specify map and reduce classes, also a combiner
    job.setMapperClass(MaxTemperatureMapper.class);
    job.setCombinerClass(MaxTemperatureReducer.class);
    job.setReducerClass(MaxTemperatureReducer.class);
//Specify output type
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
//submit the job and wait for completion
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
}
```


Codes can be found here:
http://hadoopbook.com/code.html

References

- Chapter 2, Hadoop The Definitive Guide

End of Chapter2