

This is the final output: the maximum global temperature recorded in each year.

The whole data flow is illustrated in [Figure 2-1](#). At the bottom of the diagram is a Unix pipeline, which mimics the whole MapReduce flow and which we will see again later in this chapter when we look at Hadoop Streaming.

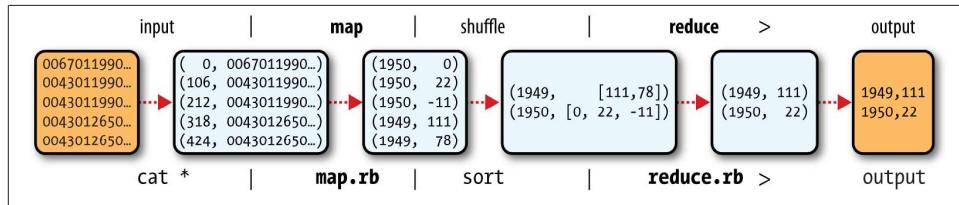


Figure 2-1. MapReduce logical data flow

Java MapReduce

Having run through how the MapReduce program works, the next step is to express it in code. We need three things: a map function, a reduce function, and some code to run the job. The map function is represented by the `Mapper` class, which declares an abstract `map()` method. [Example 2-3](#) shows the implementation of our map function.

Example 2-3. Mapper for the maximum temperature example

```

import java.io.IOException;

import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Mapper;

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) == '+') { // parseInt doesn't like leading plus signs
            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));
        }
    }
}

```

The Mapper class is a generic type, with four formal type parameters that specify the input key, input value, output key, and output value types of the map function. For the present example, the input key is a long integer offset, the input value is a line of text, the output key is a year, and the output value is an air temperature (an integer). Rather than using built-in Java types, Hadoop provides its own set of basic types that are optimized for network serialization. These are found in the org.apache.hadoop.io package. Here we use LongWritable, which corresponds to a Java Long, Text (like Java String), and IntWritable (like Java Integer).

The map() method is passed a key and a value. We convert the Text value containing the line of input into a Java String, then use its substring() method to extract the columns we are interested in.

The map() method also provides an instance of Context to write the output to. In this case, we write the year as a Text object (since we are just using it as a key), and the temperature is wrapped in an IntWritable. We write an output record only if the temperature is present and the quality code indicates the temperature reading is OK.

The reduce function is similarly defined using a Reducer, as illustrated in [Example 2-4](#).

Example 2-4. Reducer for the maximum temperature example

```

import java.io.IOException;

import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Reducer;

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));
    }
}

```

Again, four formal type parameters are used to specify the input and output types, this time for the reduce function. The input types of the reduce function must match the output types of the map function: `Text` and `IntWritable`. And in this case, the output types of the reduce function are `Text` and `IntWritable`, for a year and its maximum temperature, which we find by iterating through the temperatures and comparing each with a record of the highest found so far.

The third piece of code runs the MapReduce job (see [Example 2-5](#)).

Example 2-5. Application to find the maximum temperature in the weather dataset

```
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.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;

public class MaxTemperature {

    public static void main(String[] args) throws Exception {
        if (args.length != 2) {
            System.err.println("Usage: MaxTemperature <input path> <output path>");
            System.exit(-1);
        }

        Job job = new Job();
        job.setJarByClass(MaxTemperature.class);
        job.setJobName("Max temperature");

        FileInputFormat.addInputPath(job, new Path(args[0]));
        FileOutputFormat.setOutputPath(job, new Path(args[1]));

        job.setMapperClass(MaxTemperatureMapper.class);
        job.setReducerClass(MaxTemperatureReducer.class);

        job.setOutputKeyClass(Text.class);
        job.setOutputValueClass(IntWritable.class);

        System.exit(job.waitForCompletion(true) ? 0 : 1);
    }
}
```

A `Job` object forms the specification of the job and gives you control over how the job is run. When we run this job on a Hadoop cluster, we will package the code into a JAR file (which Hadoop will distribute around the cluster). Rather than explicitly specifying the name of the JAR file, we can pass a class in the `Job`'s `setJarByClass()` method, which Hadoop will use to locate the relevant JAR file by looking for the JAR file containing this class.

Having constructed a `Job` object, we specify the input and output paths. An input path is specified by calling the static `addInputPath()` method on `FileInputFormat`, and it can be a single file, a directory (in which case, the input forms all the files in that directory), or a file pattern. As the name suggests, `addInputPath()` can be called more than once to use input from multiple paths.

The output path (of which there is only one) is specified by the static `setOutputPath()` method on `FileOutputFormat`. It specifies a directory where the output files from the reduce function are written. The directory shouldn't exist before running the job because Hadoop will complain and not run the job. This precaution is to prevent data loss (it can be very annoying to accidentally overwrite the output of a long job with that of another).

Next, we specify the map and reduce types to use via the `setMapperClass()` and `setReducerClass()` methods.

The `setOutputKeyClass()` and `setOutputValueClass()` methods control the output types for the reduce function, and must match what the Reduce class produces. The map output types default to the same types, so they do not need to be set if the mapper produces the same types as the reducer (as it does in our case). However, if they are different, the map output types must be set using the `setMapOutputKeyClass()` and `setMapOutputValueClass()` methods.

The input types are controlled via the input format, which we have not explicitly set because we are using the default `TextInputFormat`.

After setting the classes that define the map and reduce functions, we are ready to run the job. The `waitForCompletion()` method on `Job` submits the job and waits for it to finish. The single argument to the method is a flag indicating whether verbose output is generated. When `true`, the job writes information about its progress to the console.

The return value of the `waitForCompletion()` method is a Boolean indicating success (`true`) or failure (`false`), which we translate into the program's exit code of `0` or `1`.



The Java MapReduce API used in this section, and throughout the book, is called the “new API”; it replaces the older, functionally equivalent API. The differences between the two APIs are explained in [Appendix D](#), along with tips on how to convert between the two APIs. You can also find the old API equivalent of the maximum temperature application there.

A test run

After writing a MapReduce job, it's normal to try it out on a small dataset to flush out any immediate problems with the code. First, install Hadoop in standalone mode (there are instructions for how to do this in [Appendix A](#)). This is the mode in which Hadoop

runs using the local filesystem with a local job runner. Then, install and compile the examples using the instructions on the book's website.

Let's test it on the five-line sample discussed earlier (the output has been slightly reformatted to fit the page, and some lines have been removed):

```
% export HADOOP_CLASSPATH=hadoop-examples.jar
% hadoop MaxTemperature input/ncdc/sample.txt output
14/09/16 09:48:39 WARN util.NativeCodeLoader: Unable to load native-hadoop
library for your platform... using builtin-java classes where applicable
14/09/16 09:48:40 WARN mapreduce.JobSubmitter: Hadoop command-line option
parsing not performed. Implement the Tool interface and execute your application
with ToolRunner to remedy this.
14/09/16 09:48:40 INFO input.FileInputFormat: Total input paths to process : 1
14/09/16 09:48:40 INFO mapreduce.JobSubmitter: number of splits:1
14/09/16 09:48:40 INFO mapreduce.JobSubmitter: Submitting tokens for job:
job_local26392882_0001
14/09/16 09:48:40 INFO mapreduce.Job: The url to track the job:
http://localhost:8080/
14/09/16 09:48:40 INFO mapreduce.Job: Running job: job_local26392882_0001
14/09/16 09:48:40 INFO mapred.LocalJobRunner: OutputCommitter set in config null
14/09/16 09:48:40 INFO mapred.LocalJobRunner: OutputCommitter is
org.apache.hadoop.mapreduce.lib.output.FileOutputCommitter
14/09/16 09:48:40 INFO mapred.LocalJobRunner: Waiting for map tasks
14/09/16 09:48:40 INFO mapred.LocalJobRunner: Starting task:
attempt_local26392882_0001_m_000000_0
14/09/16 09:48:40 INFO mapred.Task: Using ResourceCalculatorProcessTree : null
14/09/16 09:48:40 INFO mapred.LocalJobRunner:
14/09/16 09:48:40 INFO mapred.Task: Task:attempt_local26392882_0001_m_000000_0
is done. And is in the process of committing
14/09/16 09:48:40 INFO mapred.LocalJobRunner: map
14/09/16 09:48:40 INFO mapred.Task: Task 'attempt_local26392882_0001_m_000000_0'
done.
14/09/16 09:48:40 INFO mapred.LocalJobRunner: Finishing task:
attempt_local26392882_0001_m_000000_0
14/09/16 09:48:40 INFO mapred.LocalJobRunner: map task executor complete.
14/09/16 09:48:40 INFO mapred.LocalJobRunner: Waiting for reduce tasks
14/09/16 09:48:40 INFO mapred.LocalJobRunner: Starting task:
attempt_local26392882_0001_r_000000_0
14/09/16 09:48:40 INFO mapred.Task: Using ResourceCalculatorProcessTree : null
14/09/16 09:48:40 INFO mapred.LocalJobRunner: 1 / 1 copied.
14/09/16 09:48:40 INFO mapred.Merger: Merging 1 sorted segments
14/09/16 09:48:40 INFO mapred.Merger: Down to the last merge-pass, with 1
segments left of total size: 50 bytes
14/09/16 09:48:40 INFO mapred.Merger: Merging 1 sorted segments
14/09/16 09:48:40 INFO mapred.Merger: Down to the last merge-pass, with 1
segments left of total size: 50 bytes
14/09/16 09:48:40 INFO mapred.LocalJobRunner: 1 / 1 copied.
14/09/16 09:48:40 INFO mapred.Task: Task:attempt_local26392882_0001_r_000000_0
is done. And is in the process of committing
14/09/16 09:48:40 INFO mapred.LocalJobRunner: 1 / 1 copied.
14/09/16 09:48:40 INFO mapred.Task: Task attempt_local26392882_0001_r_000000_0
```

```

is allowed to commit now
14/09/16 09:48:40 INFO output.FileOutputCommitter: Saved output of task
'attempt...local26392882_0001_r_000000_0' to file:/Users/tom/book-workspace/
hadoop-book/output/_temporary/0/task_local26392882_0001_r_000000
14/09/16 09:48:40 INFO mapred.LocalJobRunner: reduce > reduce
14/09/16 09:48:40 INFO mapred.Task: Task 'attempt_local26392882_0001_r_000000_0'
done.
14/09/16 09:48:40 INFO mapred.LocalJobRunner: Finishing task:
attempt_local26392882_0001_r_000000_0
14/09/16 09:48:40 INFO mapred.LocalJobRunner: reduce task executor complete.
14/09/16 09:48:41 INFO mapreduce.Job: Job job_local26392882_0001 running in uber
mode : false
14/09/16 09:48:41 INFO mapreduce.Job: map 100% reduce 100%
14/09/16 09:48:41 INFO mapreduce.Job: Job job_local26392882_0001 completed
successfully
14/09/16 09:48:41 INFO mapreduce.Job: Counters: 30
    File System Counters
        FILE: Number of bytes read=377168
        FILE: Number of bytes written=828464
        FILE: Number of read operations=0
        FILE: Number of large read operations=0
        FILE: Number of write operations=0
    Map-Reduce Framework
        Map input records=5
        Map output records=5
        Map output bytes=45
        Map output materialized bytes=61
        Input split bytes=129
        Combine input records=0
        Combine output records=0
        Reduce input groups=2
        Reduce shuffle bytes=61
        Reduce input records=5
        Reduce output records=2
        Spilled Records=10
        Shuffled Maps =1
        Failed Shuffles=0
        Merged Map outputs=1
        GC time elapsed (ms)=39
        Total committed heap usage (bytes)=226754560
    File Input Format Counters
        Bytes Read=529
    File Output Format Counters
        Bytes Written=29

```

When the `hadoop` command is invoked with a classname as the first argument, it launches a Java virtual machine (JVM) to run the class. The `hadoop` command adds the Hadoop libraries (and their dependencies) to the classpath and picks up the Hadoop configuration, too. To add the application classes to the classpath, we've defined an environment variable called `HADOOP_CLASSPATH`, which the `hadoop` script picks up.



When running in local (standalone) mode, the programs in this book all assume that you have set the `HADOOP_CLASSPATH` in this way. The commands should be run from the directory that the example code is installed in.

The output from running the job provides some useful information. For example, we can see that the job was given an ID of `job_local26392882_0001`, and it ran one map task and one reduce task (with the following IDs: `attempt_local26392882_0001_m_000000_0` and `attempt_local26392882_0001_r_000000_0`). Knowing the job and task IDs can be very useful when debugging MapReduce jobs.

The last section of the output, titled “Counters,” shows the statistics that Hadoop generates for each job it runs. These are very useful for checking whether the amount of data processed is what you expected. For example, we can follow the number of records that went through the system: five map input records produced five map output records (since the mapper emitted one output record for each valid input record), then five reduce input records in two groups (one for each unique key) produced two reduce output records.

The output was written to the `output` directory, which contains one output file per reducer. The job had a single reducer, so we find a single file, named `part-r-00000`:

```
% cat output/part-r-00000
1949 111
1950 22
```

This result is the same as when we went through it by hand earlier. We interpret this as saying that the maximum temperature recorded in 1949 was 11.1°C, and in 1950 it was 2.2°C.

Scaling Out

You’ve seen how MapReduce works for small inputs; now it’s time to take a bird’s-eye view of the system and look at the data flow for large inputs. For simplicity, the examples so far have used files on the local filesystem. However, to scale out, we need to store the data in a distributed filesystem (typically HDFS, which you’ll learn about in the next chapter). This allows Hadoop to move the MapReduce computation to each machine hosting a part of the data, using Hadoop’s resource management system, called YARN (see [Chapter 4](#)). Let’s see how this works.

Data Flow

First, some terminology. A MapReduce *job* is a unit of work that the client wants to be performed: it consists of the input data, the MapReduce program, and configuration