CHAPTER 5

MapReduce Details for Multimachine Clusters

Organizations run Hadoop Core to provide MapReduce services for their processing needs. They may have datasets that can't fit on a single machine, have time constraints that are impossible to satisfy with a small number of machines, or need to rapidly scale the computing power applied to a problem due to varying input set sizes. You will have your own unique reasons for running MapReduce applications.

To do your job effectively, you need to understand all of the moving parts of a MapReduce cluster and of the Hadoop Core MapReduce framework. This chapter will raise the hood and show you some schematics of the engine. This chapter will also provide examples that you can use as the basis for your own MapReduce applications.

Requirements for Successful MapReduce Jobs

For your MapReduce jobs to be successful, the mapper must be able to ingest the input and process the input record, sending forward the records that can be passed to the reduce task or to the final output directly, if no reduce step is required. The reducer must be able to accept the key and value groups that passed through the mapper, and generate the final output of this MapReduce step.

The job must be configured with the location and type of the input data, the mapper class to use, the number of reduce tasks required, and the reducer class and I/O types.

The TaskTracker service will actually run your map and reduce tasks, and the JobTracker service will distribute the tasks and their input split to the various trackers.

The cluster must be configured with the nodes that will run the TaskTrackers, and with the number of TaskTrackers to run per node. The TaskTrackers need to be configured with the JVM parameters, including the classpath for both the TaskTracker and the JVMs that will execute the individual tasks.

There are three levels of configuration to address to configure MapReduce on your cluster. From the bottom up, you need to configure the machines, the Hadoop MapReduce framework, and the jobs themselves.

We'll get started with these requirements by exploring how to launch your MapReduce jobs.

Tip A Hadoop job is usually part of a production application, which may have many steps, some of which are MapReduce jobs. Hadoop Core, as of version 0.19.0, provides a way of optimizing the data flows between a set of sequential MapReduce jobs. This framework for descriptively and efficiently running sequential MapReduce jobs together is called *chaining*, and uses the ChainMapper and the ChainReducer, as discussed in Chapter 8. An alternative is the cascading package, available from http://www.cascading.org/.

Launching MapReduce Jobs

Jobs within a MapReduce cluster can be launched by constructing a JobConf object (details on the JobConf object are provided in this book's appendix) and passing it to a JobClient object:

```
JobConf conf = new JobConf(MyClass.class);
/** Configuration setup deleted for clarity*/
/** Launch the Job by submitting it to the Framework. */
RunningJob job = JobClient.runJob(conf);
```
You can launch the preceding example from the command line as follows:

```
> bin/hadoop [-libjars jar1.jar,jar2.jar,jar3.jar] jar myjar.jar MyClass
```
The optional -libjars $jar1$. jar... specifications add JARs for your job. The assumption is that $MyClass$ is in the myjar. jar.

For this to be successful requires a considerable amount of runtime environment setup. Hadoop Core provides a shell script, bin/hadoop, which manages the setup for a job. Using this script is the standard and recommended way to start a MapReduce job. This script sets up the process environment correctly for the installation, including inserting the Hadoop JARs and Hadoop configuration directory into the classpath, and launches your application. This behavior is triggered by providing the initial command-line argument jar to the bin/hadoop script.

Hadoop Core provides several mechanisms for setting the classpath for your application:

- You can set up a fixed base classpath by altering hadoop-env. sh, via the HADOOP CLASSPATH environment variable (on all of your machines) or by setting that environment variable in the runtime environment for the user that starts the Hadoop servers.
- You may run your jobs via the bin/hadoop jar command and supply a -libjars argument with a list of JARs.
- The Distributed Cache object provides a way to add files or archives to your runtime classpath.

Tip The mapred, child, java, opts variable may also be used to specify non-classpath parameters to the child JVMs. In particular, the java. Library. path variable specifies the path for shared libraries if your application uses the Java Native Interface (JNI). If your application alters the job configuration parameter mapred.child.java.opts, it is important to ensure that the JVM memory settings are reset or still present, or your tasks may fail with out-of-memory exceptions.

The advantage of using the DistributedCache and -libjars is that resources, such as JAR files, do not have to already exist on the TaskTracker nodes. The disadvantages are that the resources must be unpacked on each machine and it is harder to verify which versions of the resources are used.

When launching an application, a number of command-line parameters may be provided. Table 5-1 lists some common command-line arguments. The class org. apache. hadoop.util. Generic Options Parser actually handles the processing of Table 5-1 arguments.

Flag	Description		
-libjars	A comma-separated list of JAR files to add to the classpath to the job being launched and to the map and reduce tasks run by the TaskTrackers. These JAR files will be staged into HDFS if needed and made available as local files in a temporary job area on each of the TaskTracker nodes.		
-archives	A comma-separated list of archive files to make available to the running tasks via the distributed cache. These archives will be staged into HDFS if needed.		
-files	A comma-separated list of files to make available to the running tasks via the distrib- uted cache. These files will be staged into HDFS if needed.		
-fs	Override the configuration default file system with the supplied URL, the parameter fs.default.name.		
-jt	Override the configuration default JobTracker with the supplied host port, the parameter mapred.job.tracker.		
-conf	Use this configuration in place of the conf/hadoop-default.xml and conf/hadoop-site.xml files.		
$-D$	Supply an additional job configuration property in key=value format. This argument may be provided multiple times. There must be white space between the -D and the key=value.		

Table 5-1. *Hadoop Standard Command-Line Arguments*

You can use hadoop jar to launch an application, as follows:

```
hadoop jar [-fs hdfs://host:port] [-jt host:port] [-conf hadoop-config.xml] \rightarrow\lceil-D prop1=value] \lceil-D prop2=value...] \lceil-libjars jar1\lceil,jar2,jar3]] \rightarrow[-files file1[,file2,file3]] [-archives archive1[,archive2,archive3]] →
applicationjar [main class if not supplied in jar] [arguments to main...]
```
When hadoop jar is used, the main method of $org.append$. hadoop.mapred. JobShell is invoked by the JVM, with all of the remaining command-line arguments. The JobShell in turn uses the class org.apache.hadoop.util.GenericOptionsParser to process the arguments, as described in Table 5-1.

There are two distinct steps in the argument processing of jobs submitted by the bin/ hadoop script. The first step is provided by the framework via the JobShell. The arguments after jar are processed by the JobShell, per Table 5-1. The first argument not in the set recognized by the JobShell must be the path to a JAR file, which is the job JAR file. If the job JAR file contains a main class specification in the manifest, that class will be the main class called after the first step of argument processing is complete. If the JAR file does not have a main class in the manifest, the next argument becomes required, and is used as main class name. Any remaining unprocessed arguments are passed to the main method of the main class as the arguments. The second step is the processing of the remaining command-line arguments by the user-specified main class.

Using Shared Libraries

Jobs sometime require specific shared libraries. For example, one of my jobs required a shared library that handled job-specific image processing. You can handle this in two ways:

- Pass the shared library via the Distributed Cache object. For example, using the command-line options -file libMyStuff.so would make libMyStuff.so available in the current working directory of each task. (The DistributedCache object is discussed shortly, in the "Using the Distributed Cache" section.)
- Install the shared library on every TaskTracker machine, and have the JVM library loader path java. library. path include the installation directory. The task JVM working directory is part of the java. Library, path for a task, and any file that is symbolic-linked may be loaded by the JVM.

Caution If you are manually loading shared libraries, the library name passed to System. loadLibrary() must not have the trailing .so. System. loadLibrary() first calls System. $mapLibraryName()$ and attempts to load the results. This can result in library load failures that are hard to diagnose.

MapReduce-Specific Configuration for Each Machine in a Cluster

For simplicity and ease of ongoing maintenance, this section assumes identical Hadoop Core installations will be placed on each of the machines, in the same location. The cluster-level configuration is covered in Chapter 3.

The following are the MapReduce-specific configuration requirements for each machine in the cluster:

- You need to install any standard JARs that your application uses, such as Spring, Hibernate, HttpClient, Commons Lang, and so on.
- It is probable that your applications will have a runtime environment that is deployed from a configuration management application, which you will also need to deploy to each machine.
- The machines will need to have enough RAM for the Hadoop Core services plus the RAM required to run your tasks.
- \bullet The conf/slaves file should have the set of machines to serve as TaskTracker nodes. You may manually start individual TaskTrackers by running the command bin/ hadoop-daemon.sh start tasktracker, but this is not a recommended practice for starting a cluster.

The hadoop-env.sh script has a section for providing custom JVM parameters for the different Hadoop Core servers, including the JobTracker and TaskTrackers. As of Hadoop 0.19.0, the classpath settings are global for all servers. The hadoop-env. sh file may be modified and distributed to the machines in the cluster, or the environment variable HADOOP JOBTRACKER OPTS may be set with JVM options before starting the cluster via the $bin/start$ -all. Sheommand or bin/start-mapred.sh command. The environment variable HADOOP TASKTRACKER OPTS may be set to provide per TaskTracker JVM options. It is much better to modify the file, as the changes are persistent and stored in a single Hadoop-specific location.

When starting the TaskTrackers via the start- $*$, sh scripts, the environment variable HADOOP TASKTRACKER OPTS may be set in the hadoop-env. sh file in the MapReduce conf directory on the TaskTracker nodes, or the value may be set in the login shell environment so that the value is present in the environment of commands started via \sinh . The start- $*$, sh scripts will ssh to each target machine, and then run the bin/hadoop-daemon.sh start tasktracker command.

Using the Distributed Cache

The DistributedCache object provides a programmatic mechanism for specifying the resources needed by the mapper and reducer. The job is actually already using the Distributed Cache object to a limited degree, if the job creates the Job Conf object with a class as an argument: new JobConf(MyMapper.class). You may also invoke your MapReduce program using the bin/hadoop script and provide arguments for -libjars, -files, or -archives.

The downloadable code for this book (available from this book's details page on the Apress web site, http://www.apress.com) includes several source files for the DistributedCache examples: Utils.java, DistributedCacheExample.java, and DistributedCacheMapper.java.

Caution The paths and URIs for DistributedCache items are stored as comma-separated lists of strings in the configuration. Any comma characters in the paths will result in unpredictable and incorrect behavior.

Adding Resources to the Task Classpath

Four methods add elements to the Java classpath for the map and reduce tasks. The first three in the following list add archives to the classpath. The archives are unpacked in the job local directory of the task. You can use the following methods to add resources to the task classpath:

JobConf.setJar(String jar): Sets the user JAR for the MapReduce job. It is on the JobConf object, but it manipulates the same configuration keys as the Distributed Cache. The file jar will be found, and if necessary, copied into the shared file system, and the full path name on the shared file system stored under the configuration key mapred. jar.

JobConf.setJarByClass (Class cls): Determines the JAR that contains the class cls and calls JobConf.setJar (jar) with that JAR.

DistributedCache.addArchiveToClassPath(Path archive, Configuration conf): Adds an archive path to the current set of classpath entries. This is a static method, and the archive (a zip or JAR file) will be made available to the running tasks via the classpath of the JVM. The archive is also added to the list of cached archives. The contents will be unpacked in the local job directory on each TaskTracker node. The archive path is stored in the configuration under the key mapred. job. classpath. archives, and the URI constructed from archive.make0ualified(conf).toUri() is stored under the key mapred. job. classpath. archives. If the path component of the URI does not exactly equal archive, archive will not be placed in the classpath of the task correctly.

Caution The archive path must be on the JobTracker shared file system, and must be an absolute path. Only the path /user/hadoop/myjar.jar is correct; hdfs://host:8020/user/hadoop/myjar.jar will fail, as will hadoop/myjar.jar or myjar.jar.

DistributedCache.addFileToClassPath(Path file, Configuration conf): Adds a file path to the current set of classpath entries. It adds the file to the cache as well. This is a static method that makes the file available to the running tasks via the classpath of the JVM. The file path is stored under the configuration key mapred. job.classpath. files, and the URI constructed from file.make0ualified(conf).toUri() is stored under the key mapred.cache. files. If file is not exactly equal to the path portion of the constructed URI, file will not be added to the classpath of the task correctly.

Caution The file path added must be an absolute path on the JobTracker shared file system, and be only a path. /user/hadoop/myfile is correct; hdfs://host:8020/user/hadoop/myfile will fail, as will hadoop/myfile or myfile.

Distributing Archives and Files to Tasks

In addition to items that become available via the classpath, two methods distribute archives and individual files: DistributedCache.addCacheArchive(URI uri, Configuration conf) and DistributedCache.addCacheFile(URI uri, Configuration conf). Local file system copies of these items are made on all of the TaskTracker machines, in the work area set aside for this job.

Distributing Archives

The DistributedCache.addCacheArchive(URI uri, Configuration conf) method will add an archive to the list of archives to be distributed to the jobs. The URI must have an absolute path and be on the JobTracker shared file system.

If the URI has a fragment, a symbolic link to the archive will be placed in the task working directory as the fragment. The URI hdfs://host:8020/user/hadoop/myfile#mylink will result in a symbolic link mylink in the task working directory that points to the local file system location that myfile was unpacked into at task start. The archive will be unpacked into the local working directory of the task.

The URI will be stored in the configuration under the key mapred.cache.archives.

Distributing Files

This DistributedCache.addCacheFile(URI uri, Configuration conf) method will make a copy of the file *uri* available to all of the tasks, as a local file system file. The URI must be on the JobTracker shared file system.

If the URI has a fragment, a symbolic link to the URI fragment will be created in the JVM working directory that points to the location on the local file system where the *uri* was unpacked into at task start. The directory where DistributedCache stores the local copies of the passed items is not the current working directory of the task JVM. This allows the items to be referenced by names that do not have any path components. In particular, executable items may be referenced as ./name.

To pass a script via the distributed cache, use DistributedCache.addCacheFile(new URI $("hdfs://host:8020/user/hadoop/myscript.pl")$, conf);. To pass a script so that it may be invoked via ./script, use DistributedCache.addCacheFile(new URI("hdfs://host:8020/ user/hadoop/myscript.pl#script"), conf);.

The URI is stored in the configuration key mapred.cache.files.

Accessing the DistributedCache Data

Three methods find the locations of the items that were passed to the task via the DistributedCache object: URI JobConf.getResource(name), public static Path[]getLocalCacheArchives (Configuration conf), and public static Path[] getLocalCacheFiles(Configuration conf).

Looking Up Names

The URI JobConf, getResource (name) method will look up name in the classpath. If name has a leading slash, this method will search for it in each location in the classpath, and return the URI.

If the job passed a file into Distributed Cache via the -files command or the DistributedCache.addFileToClassPath(Path file, conf) method, a getResource() call of the file name component, with a leading slash, will return the URI.

N**Note** The standard search rules for resources apply. The cache items will be the last items in the classpath. This does not appear to work for files that are added via DistributedCache.addFileToClassPath. The full path is available via the set of paths returned by $DistributedCache.getFileClassPaths()$.

The DistributedCache.addArchiveToClassPath(jarFileForClassPath, job) method actually stores the JAR information into the configuration. In the following example, U tils. setupArchiveFile builds a JAR file with ten files in it, in the default file system (HDFS in this case). Utils. make Absolute returns the absolute path.

```
Path jarFileForClassPath = Utils.makeAbsolute(Utils.setupArchiveFile(job, \rightarrow10, true),iob);
DistributedCache.addArchiveToClassPath(jarFileForClassPath, job);
```
Any file that is in the JAR may be accessed via the get Resource $()$ method of the configuration object. If there were a file myfile in the JAR, the call conf.getResource("/myfile"); would return the URL of the resource. The call conf. getConfResourceAsInputStream("/myfile"); would return an InputStream that, when read, would provide the contents of myfile from the JAR.

Looking Up Archives and Files

The public static Path []getLocalCacheArchives (Configuration conf) method returns a list of the archives that were passed via DistributedCache. The paths will be in the task local area of the local file system. Any archive passed via the command-line -libjars and -archives options, or the methods DistributedCache.addCacheArchive() and DistributedCache. addArchiveToClassPath() and the JobConf.setJar line, will have its path returned by this call.

It is possible that the file name portion of your archive will be changed slightly. DistributedCache provides the following method to help with this situation:

```
public static String makeRelative(URI cache, Configuration conf)
```
This takes an original archive path and returns the possibly altered file name component.

The public static Path \lceil] getLocalCacheFiles (Configuration conf) method returns the set of localized paths for files that are passed via DistributedCache.addCacheFile and DistributedCache.addFileToClassPath and the command-line option -files. The file name portions of the paths may be different from the original file name.

Finding a File or Archive in the Localized Cache

The Distributed Cache object may change the file name portion of the files and archives it distributes. This is usually not a problem for classpath items, but it may be a problem for nonclasspath items. The Utils.makeRelativeName() method, described in Table 5-2 provides a way to determine what the file name portion of the passed item was changed to. In addition to the file name portion, the items will be stored in a location relative to the working area for the task on each TaskTracker. Table 5-2 lists the methods provided in the downloadable code that

make working with the DistributedCache object simpler. These methods are designed to be used in the mapper and reducer methods.

Table 5-2. *Utility Methods Provided in the Examples for Working with the DistributedCache Object*

Method	Description
Utils.makeRelativeName(name, conf)	Returns the actual name DistributedCache will use for the passed-in name.
Utils.findClassPathArchive(name, conf)	Returns the actual path on the current ma- chine of the archive name that was passed via DistributedCache.addArchiveToClassPath.
Utils.findClassPathFile(name, conf)	Returns the actual path on the current ma- chine of the file name that was passed via Dist ributeCacheAddFileToClasspath.
Utils.findNonClassPathArchive(name, conf)	Returns the actual path on the current ma- chine of the archive name that was passed via DistributedCache.addCacheArchive.
Utils.findNonClassPathFile(name, conf)	Returns the actual path on the current machine of the file name that was passed via DistributedCache.addCacheFile.

Configuring the Hadoop Core Cluster Information

The JobConf object provides two basic and critical ways for specifying the default file system: the URI to use for all shared file system paths, and the connection information for the Job-Tracker server. These two items are normally specified in the $\text{conf/hadoop-site.xml}$ file, but they may be specified on the command line or by setting the values on the JobConf object.

Setting the Default File System URI

The default file system URI is normally specified with the $fs.default.name$ setting in the hadoop-site.xml file, as it is cluster-specific. The value will be hdfs://NamenodeHostname:PORT. The PORT portion is optional and defaults to 8020, as of Hadoop 0.18

 \blacksquare **Note** The default value for the file system URI is $file:///$, which stores all files on the local file system. The file system that is used must be a file system that is shared among all of the nodes in the cluster.

```
<property>
 <name>fs.default.name</name>
 <value>hdfs://NamenodeHostname:PORT</value>
</property>
```
The Hadoop tools, examples, and any application that uses the Generic Option Parser class to handle command-line arguments will accept a $-fs$ hdfs://NamenodeHostname:PORT command-line argument pair to explicitly set the fs. default. name value in the configuration. This will override the value specified in the hadoop-site. xml file.

Here's a sample command line for listing files on an explicitly specified HDFS file system:

```
bin/hadoop dfs -fs hdfs://AlternateClusterNamenodeHostname:8020 -ls /
```
You can also use the JobConf object to set the default file system:

```
conf.set( "fs.default.name", "hdfs://NamenodeHostname:PORT");
```
Setting the JobTracker Location

The JobTracker location is normally specified with the mapred. $\mathrm{job}.$ tracker setting in the hadoop-site. xml file, as it is cluster-specific. The value will be JobTrackerHostname: PORT. Through Hadoop 0.19, there is not a standard for the PORT. Many installations use a port one higher that the HDFS port.

Note The default value for the JobTracker location is local, which will result in the job being executed by the JVM that submits it. The value $local$ is ideal for testing and debugging new MapReduce jobs. It is important to ensure that any required Hadoop configuration files are in the classpath of the test jobs.

```
<property>
 <name>mapred.job.tracker</name>
 <value>JobtrackerHostname:PORT</value>
</property>
```
Here's a sample command line explicitly setting the JobTracker for job control for listing jobs:

```
bin/hadoop job -jt AlternateClusterJobtrackerHostname:8021 -list
```
And here's how to use the JobConf object to set the JobTracker information:

```
conf.set( "mapred.job.tracker", "JobtrackerHostname:PORT");
```
The Mapper Dissected

All Hadoop jobs start with a mapper. The reducer is optional. The class providing the map function must implement the org. apache. hadoop.mapred. Mapper interface, which in turn requires the interfaces org.apache.hadoop.mapred.JobConfigurable and org.apache.hadoop. io. Closeable. The Hadoop framework provides org. apache. hadoop. mapred. MapReduceBase from which to derive mapper and reducer classes. The JobConfigurable and Closable

implementations are empty methods. In the utilities supplied with this book's downloadable code is com.apress.hadoopbook.utils.MapReduceBase, which provides more useful implementations.

Note The interface org. apache. hadoop. io. Closeable will be replaced with java. io. Closeable in a later release.

This section examines the sample mapper class SampleMapperRunner. java, which is available with the rest of the downloadable code for this book. When run as a Java application, this example accepts all of the standard Hadoop arguments and may be run with custom bean context and definitions:

```
bin/hadoop jar hadoopprobook.jar\rightarrowcom.apress.hadoopbook.examples.ch5.SampleMapperRunner -D →
mapper.bean.context=mycontext.xml -D mapper.bean.name=mybean -files \rightarrowmycontext.xml -deleteOutput
```
where:

- bin/hadoop jar is the standard Hadoop program invocation.
- hadoopprobook.jar com.apress.hadoopbook.examples.ch5.SampleMapperRunnerspecifies the JAR file to use and the main class to run.
- -D mapper.bean.context=mycontext.xml and -D mapper.bean.name=mybean specify that the string mycontext. xml is stored in the configuration under the key mapper, bean, context, and that the string mybean is stored in the configuration under the key mapper.bean.name.
- \bullet -files mycontext. xml causes the file mycontext. xml to be copied into HDFS, and then unpacked and made available in the working directory of each task run by the job. The working directory is in the task classpath. m ycontext. xml may have a directory path component, and not be just a stand-alone file name. The path and file name provided must be a path that can be opened from the current working directory.

Note If you are using the value local as the value of the mapred. task. tracker configuration key, using the DistributedCache object is less effective, as the task cannot change working directories.

• --delete0utput, which must be the last argument, causes the output directory to be deleted before the job is started. This is convenient when running the job multiple times.

Mapper Methods

For the mapper, the framework will call three methods:

- configure() method, defined in the Configurable interface
- map() method, defined in the Mapper interface
- close() method, defined in the Closable interface

The following sections discuss these methods in detail.

Note The framework uses the static method org.append . apache . hadoop.util. ReflectionUtils.<T>newIn stance (Class<T> the Class, Configuration conf) to create instances of objects that need a copy of the configuration. This will create the instance using the no-argument constructor. If the class is an instance of Configurable, new Instance will call the set Confinethod with the supplied configuration. If the class is an instance of JobConfiguration, newInstance will call the configure method. Any exceptions that are thrown during the construction or initialization of the instance are rethrown as RuntimeExceptions.

The configure() Method

The void JobConfigurable.configure(JobConf job) method, defined in org.apache.hadoop. conf. Configurable, is called exactly one time per map task as part of the initialization of the Mapper instance. If an exception is thrown, this task will fail. The framework may attempt to retry this task on another host if the allowable number of failures for the task has not been $exceded.$ The methods JobConf.getMaxMapAttempts() and JobConf.setMaxMapAttempts(int n) control the number of times a map task will be retried if the task fails. The default is four times.

It is considered good practice for any Mapper implementation to declare a member variable that the configure $()$ method uses to store a reference to the passed-in JobConf object. The $\text{configure}()$ method is also used for loading any Spring application context or initializing resources that are passed via DistributedCache.

Listing 5-1 shows the configure () method used in $SampleMaperRunner.java$ (the example available with the downloadable code for this chapter).

Listing 5-1. *configure Method from SampleMapperRunner.java*

```
/** Sample Configure method for a map/reduce class.
```
- * This method assumes the class derives from {@link MapReduceBase}
- * and saves a copy of the JobConf object, the taskName
- $*$ and the taskId into member variables.
- * and makes an instance of the output key and output value
- * objects as member variables for the
- * map or reduce to use.

```
\ast
```

```
* If this method fails the Tasktracker will abort this task.
 * @param job The Localized JobConf object for this task
 * /
public void configure(JobConf job) {
    super.configure(job);
    LOG.info("Map Task Configure");
    this.conf = job;
   try {
        taskName = conf.getJobName();taskId = TaskAttemptID.forName(conf.get("mapred.task.id"));
        if (taskName == null || taskName.length() == 0) {
            /** if the job name is essentially unset make something up. */
            taskName = taskId.isMap() ? "map." : "reduce."+ this.getClass().getName();
        \mathcal{E}/*** These casts are safe as they are checked by the framework
         * earlier in the process.
        *outputKey = (K2) conf.getMapOutputKeyClass().newInstance();
        outputValue = (V2) conf.getMapOutputValueClass().newInstance();
    } catch (RuntimeException e) {
        LOG.error("Map Task Failed to initialize", e);
        throw e;
    \} catch (InstantiationException e) {
        LOG_error("Failed to instantiate the key or output value class",
                e);
        through the Example Exception (e);} catch (IllegalAccessException e) {
        LOG.error(
 "Failed to run no argument constructor for key or output value objects",
\mathsf{e});
        through the Example Exception (e);\mathcal{F}LOG.info(taskId.isMap() ? "Map" : "Reduce" + " Task Configure complete");
```
 \mathcal{L}

In this example, K2 is the map output key type, which defaults to the reduce output key type, which defaults to LongWritable. V2 is the map output value key type, which defaults to the reduce output value type, which defaults to Text.

This configure () method saves a copy of the JobConf object taskId and taskName into member variables. This method also instantiates a local instance of the key and value classes, to be used during the map() method calls. By using the is Map method on the taskId, you can take different actions for map and reduce tasks in the configure() and close) methods. This becomes very useful when a single class provides both a map method and a reduce method.

The map() Method

A call to the void map(K1 key, V1 value, OutputCollector < K2, V2> output, Reporter reporter) throws IOException method, defined in org.apache.hadoop.mapred.Mapper, will be made for every record in the job input. No calls will be made to the map() method in an instance before the configure () method completes.

If the job is configured for running multithreaded map tasks, as follows, there may be multiple simultaneous calls to the $map()$ method.

```
jobConf.setMapRunnerClass(MultithreadedMapRunner.class);
jobConf.setInt("mapred.map.multithreadedrunner.threads", 10);
```
When running multithreaded, each $map()$ call will have a different key and value object. The output and reporter objects are shared. The default number of threads for a multithreaded map task is ten.

The contents of the key object and the contents of the value object are valid only during the $map()$ method call. The framework will reset the object contents with the next key/value pair prior to the next call to $map()$.

The class converting the input into records is responsible for defining the types of $K1$ and V1. The standard textual input format, KeyValueTextInput, defines K1 and V1 to be of type Text.

K2 and V2 are defined by the JobConf.setMapOutputKeyClass(clazz) and JobConf. setMapOutputValueClass(clazz) methods. The types of K2 and V2 default to the classes set for the reduce key and value output classes. The reduce key and value output classes are set by JobConf.setOutputKeyClass(clazz) and JobConf.setOutputValueClass(clazz). The defaults for K2 and V2 are LongWritable and Text, respectively. You can explicitly configure the map output key and value classes, as follows:

```
jobConf.setMapOutputKeyClass(MyMapOutputKey.class);
jobConf.setMapOutputValueClass(MyMapOutputValue.class)
```
If a map output class is set, the corresponding reduce input class is also set to the class. If the map output key class is changed to BytesWritable, the Reducer. reduce's key type will be BytesWritable.

The close() Method

The void close() method, defined in $java.io.close$, is called one time after the last call to the map() method is made by the framework. This method is the place to close any open files or perform any status checking. Unless your configure $()$ method has saved a copy of the JobConf object, there is little interaction that can be done with the framework. The close) method example in Listing 5-2 checks the task status based on the ratio of exceptions to input keys.

```
Listing 5-2. close Method from SampleMapperRunner.java
```

```
/* Sample close method that sets the task status based on how
 * many map exceptions there were.
 * This assumes that the reporter object passed into the map method was saved and
 * that the JobConf object passed into the configure method was saved.
 *public void close() throws IOException {
    super.close():
    LOG.info("Map task close");
    if (reporter != null) {
        1*** If we have a reporter we can perform simple checks on the
         * completion status and set a status message for this task.
         * /
        Counter mapExceptionCounter = reporter.getCounter(taskName,
                "Total Map Failures");
        Counter mapTotalKeys = reporter.getCounter(taskName,
                "Total Map Keys");
        if (mapExceptionCounter.getCounter() == mapTotalKeys
                .getCounter() {
            reporter.setStatus("Total Failure");
        } else if (mapExceptionCounter.getCounter() != 0) {
            reporter.setStatus("Partial Success");
        \} else \{/* Use the Spring set bean to show we did get the values. */
 reporter.incrCounter(taskName, getSpringSetString(), getSpringSetInt());
            reporter.setStatus("Complete Success");
        \mathcal{E}\mathcal{L}7*** Ensure any HDFS files are closed here, to force them to be
     * committed to HDFS.
     * /
\mathcal{L}
```
The $close()$ method in Listing 5-2 will report success or failure status back to the framework, based on an examination of the job counters. It assumes that the map ϕ method reported an exception under the counter, Total Map Failure, in the counter group taskName, and the number of keys received is in the counter, Total Map Keys, in the counter group taskName.

If there are no exceptions, the method will report the task status as "Complete Success." If there are some exceptions, the status is set to "Partial Success," If the exception count equals the key count, the status is set to "Total Failure."

This example also logs to counters with the values received from the Spring initialization. I found the Spring value-based counters useful while working out how to initialize map class member variables via the Spring Framework, as described after the discussion of the mapper class declaration and member fields.

Mapper Class Declaration and Member Fields

It is a best practice to capture the JobConf object passed in the configure() method into a member variable. It is also a good practice to instantiate member variables, or thread local variables, for any key or value that would otherwise be created in the body of the map() method. Having the TaskAttemptId available is also useful, as it is easy to determine if this is the map phase or the reduce phase of a job.

It is convenient to capture the output collector and the reporter into member fields so that they may be used in the close $()$ method. This has a downside in that they can be captured only in the map() method, requiring extra code in that inner loop.

Listing 5-3 shows an example that declares a number of local variables, which are initialized by the configure () method for use by the $map()$ and close() methods.

Listing 5-3. *Class and Member Variable Declarations from SampleMapperRunner.java*

```
/*** Sample Mapper shell showing various practices
\ast* K1 and V1 will be defined by the InputFormat. K2 and V2 will be the
 * {@link JobConf#getOutputKeyClass()} and
 * {@link JobConf#getOutputValueClass()}, which by default are LongWritable
 * and Text. K1 and V1 may be explicitly set via
 * {@link JobConf#setMapOutputKeyClass(Class)} and
 * {@link JobConf#setMapOutputValueClass(Class)}. If K1 and V1 are
 * explicitly set, they become the K1 and V1 for the Reducer.
\ast* @author Jason
 &
 * /
public static class SampleMapper<K1, V1, K2, V2> extends MapReduceBase
        implements Mapper<K1, V1, K2, V2> {
    /*** Create a logging object or you will never know what happened in your
     * task.
     */** Used in metrics reporting. */String taskName = null;
    /*** Always save one of these away. They are so handy for almost any
     * interaction with the framework.
     *JobConf conf = null;/*** These are nice to save, but require a test or a set each pass through
     * the map method.
     *
```

```
Reporter reporter = null;/** Take this early, it is handy to have. */TaskAttemptID taskId = null;7*** If we are constructing new keys or values for the output, it is a
 * best practice to generate the key and value object once, and reset
 * them each time. Remember that the map method is an inner loop that
 * may be called millions of times. These really can't be used without
 * knowing an actual type
 *K2 outputKey = null;V2 outputValue = null;
```
Initializing the Mapper with Spring

Many installations use the Spring Framework to manage the services employed by their applications. One of the more interesting issues is how to use Spring in environments where Spring does not have full control over the creation of class instances. Spring likes to be in full control of the application and manage the creation of all of the Spring bean objects. In the Hadoop case, the Hadoop framework is in charge and will create the object instances. The examples in this section demonstrate how to use Spring to initialize member variables in the mapper class. The same techniques apply to the reducer class.

Listing $5-4$ shows the bean file used in the Spring example. The file mapper bean context. xml in the downloadable examples $src/config$ directory is the actual file used.

Listing 5-4. *Simple Bean Resource File for the Spring-Initialized Task*

```
<?xml version="1.0" encoding="UTF-8"?>
<beans xmlns="http://www.springframework.org/schema/beans"
   xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
   xmlns:context="http://www.springframework.org/schema/context"
   xsi:schemaLocation="http://www.springframework.org/schema/beans \rightarrowhttp://www.springframework.org/schema/beans/spring-beans.xsd
        http://www.springframework.org/schema/context →
        http://www.springframework.org/schema/context/spring-context.xsd">
   <bean id="SampleMapperJob.mapper.bean.name"
       class="com.apress.hadoopbook.examples.ch5.SampleMapperRunner.SampleMapper"
       lazy-init="true"
       scope="singleton">
       <description> Simple bean definition to provide an example for
       using Spring to initialize context in a Mapper class.</description>
       <property name="springSetString"><value>SetFromDefaultFile</value></property>
       <property name="springSetInt"><value>37</value></property>
 \langle/hean\rangle</heans>
```
Creating the Spring Application Context

To create an application context, you need to provide Spring with a resource set from which to load bean definitions. Being very JobConf-oriented, I prefer to pass the names of these resources, and possibly the resources themselves, to my tasks via the JobConf and DistributedCache objects.

The example in Listing 5-5 extracts the set of resource names from the JobConf object, and if not found, will supply a default set of resource names. This follows the Hadoop style of using comma-separated elements to store multiple elements in the configuration. The set of resources names are unpacked and passed to the Spring Framework. Each of these resources must be in the classpath, which includes the task working directory.

At the very simplest, the user may specify the specific Spring configuration files on the command line via the -files argument, when the Generic Options Parser is in use. The mapper class will need to determine the name of the file passed in via the command line. For the example, set up the Spring initialization parameters on the application command line as follows:

```
hadoop jar appJar main-class -files spring1.xml,spring2,xml,spring3.xml \rightarrow-D mapper.bean.context=spring1.xml
```
Note In the command-line specification, the -D mapper.bean.context=value argument must come after the main class reference to be stored in the job configuration. If it comes before the jar argument, it will become a Java system property.

The example in Listing 5-5 copies $spring1.xml$, $spring2.xml$, and $spring3.xml$ from the local file system into HDFS, and then copies them to the task local directory and creates symbolic links from the local copy to the task working directory. The configuration parameter mapper.bean.context tells the map task which bean file to load. In the example, SampleMapperRunner looks up the configuration entry mapper.bean.context to determine which bean files to use when creating the application context.

Listing 5-5. *Extracting the Resource File Names from the JobConf Object and Initializing the Spring Application Context (from utils.Utils.java)*

```
^{1**}* Initialize the Spring environment. This is of course completely
 * optional.
\ast* This method picks up the application context from a file, that is in
 * the classpath. If the file items are passed through the
 * {@link DistributedCache} and symlinked
 * they will be in the classpath.
\ast
```

```
* @param conf The JobConf object to look for the Spring config file names.
* If this is null, the default value is used.
* @param contextConfigName The token to look under in the config for the names
* @param defaultConfigString A default value
* @return TODO
&
*public static ApplicationContext initSpring(JobConf conf, String contextConfigName,
       String defaultConfigString) {
   7*** If you are a Spring user, you would initialize your application
    * context here.
    * /
   /** Look up the context config files in the JobConf, provide a default value. */
   String applicationContextFileNameSet =
       conf == null defaultConfigString :
            conf.get( contextConfigName, defaultConfigString);
   LOG.info("Map Application Context File "
            + applicationContextFileNameSet);
   /** If no config information was found, bail out. */if (applicationContextFileNameSet==null) {
       LOG.error( "Unable to initialize Spring configuration using "
         + applicationContextFileNameSet );
       return null;
   \mathcal{F}/** Attempt to split it into components using the config
     * standard method of comma separators. */
   String[] components = StringUtils.split(applicationContextFileNameSet, ",");
   /** Load the configuration. */ApplicationContext applicationContext =
       new ClassPathXmlApplicationContext( components);
   return applicationContext;
\}
```
Using Spring to Autowire the Mapper Class

Once the Spring application context has been created, the task may instantiate beans. The confusing issue is that the mapper class has already been instantiated, so how can Spring be forced to initialize/autowire that class?

Accomplishing this autowiring requires two things. The first is that the bean definition to be used must specify lazy initialization, to prevent Spring from creating an instance of the bean when the application context is created. The second is to know the bean name/ID of the mapper class.

The example in Listing 5-6 makes some assumptions about how application contexts and task beans are named, and can be easily modified for your application.

Listing 5-6. *Example of a Spring Task Initialization Method*

```
/** Handle Spring configuration for the mapper.
* The bean definition has to be <code>lazy-init="true"</code>
 * as this object must be initialized.
 * This will fail if Spring weaves a wrapper class for AOP around
 * the configure bean.
\ast* The bean name is extracted from the configuration as
 * mapper.bean.name or reducer.bean.name
 * or defaults to taskName.XXXX.bean.name
\ast* The application context is loaded from mapper.bean.context
 * or reducer.bean.context and may be a set of files
 * The default is jobName.XXX.bean.context
\ast* @param job The JobConf object to look up application context \rightarrowfiles and bean names in
 * @param RuntimeException if the application context can not be \rightarrowloaded or the initializtion requires delegation of the task object.
 *void springAutoWire(JobConf job) {
    String springBaseName = taskId.isMap()? "mapper.bean": "reducer.bean";
    /* Construct a bean name for this class using the configuration
      * or a default name. */String beanName = conf.get(springBaseName + ".name",taskName + "." + springBaseName + ".name" );
    LOG.info("Bean name is " + beanName);applicationContext = Utils.initspring(job, springBaseName)+ ".context", springBaseName + ".context.xml");
    if (applicationContext==null) {
        throw new RuntimeException(
 "Unable to initialize spring configuration for " + springBaseName);
    \mathcal{F}AutowireCapableBeanFactory autowire =
  applicationContext.getAutowireCapableBeanFactory();
    Object mayBeWrapped = autowire.configureBean( this, beanName);
    if (mayBeWrapped != this) {
        throw new RuntimeException( "Spring wrapped our class for " + beanName);
    \mathcal{F}\mathcal{F}
```
In Listing 5-6, a base name is constructed for looking up information in the configuration via the following:

String springBaseName = taskId.isMap()? "mapper.bean": "reducer.bean";

The example builds a context file name key, which will be mapper, bean, context in the case of a map, to look up the application context information in the configuration. If a value is found, it is treated as a comma-separated list of bean resource files to load. The application context is loaded and saved in the member variable applicationContext:

```
applicationContext = SpringUtils.initspring(job, springBaseName)+ ".context", springBaseName + ".context.xml");
```
A default bean file is used if no value is found. In this example, the file is mapper.bean.context.xml.

A bean name key mapper.bean.name, with a default value of mapper.bean.name, is looked up in the configuration. This is the bean that will be used to configure the task. The following line constructs the bean name to use:

```
String beanName = conf.get(springBaseName + ".name", taskName + "."+ springBaseName + ".name" );
```
An autowire-capable bean factory is extracted from the application context via the following:

```
AutowireCapableBeanFactory autowire =
  applicationContext.getAutowireCapableBeanFactory();
```
The following line actually causes Spring to initialize the task:

Object mayBeWrapped = autowire.configureBean(this, beanName);

The code must ensure that Spring did not return a delegator object when it was initializing the task from the bean definition:

```
if (mayBeWrapped != this) {
    throw new RuntimeException( "Spring wrapped our class for " + beanName);
\mathcal{L}
```
N**Note** This example does not handle the case where Spring returns a delegator object for the task. To handle this case, the $map()$ method would need to be redirected through the delegated object.

Partitioners Dissected

A core part of the MapReduce concept requires that map outputs be split into multiple streams called *partitions*, and that each of these partitions is fed to a single reduce task. The reduce contract specifies that each reduce task will be given as input the fully sorted set of keys

and their values in a particular partition. The entire partition is the input of the reduce task. For the framework to satisfy this contract, a number of things have to happen first. The outputs of each map task are partitioned and sorted. The partitioner is run in the context of the map task.

The Hadoop framework provides several partitioning classes and a mechanism to specify a class to use for partitioning. The actual class to be used must implement the org. apache. hadoop.mapred.Partitioner interface, as shown in Listing 5-7. The piece that provides a partition number is the getPartition() method:

```
int getPartition(K2 key, V2 value, int numPartitions)
```
Note that both the key and the value are available in making the partition choice.

Listing 5-7. *The Partitioner Interface in Hadoop 0.19.0*

```
/*** Partitions the key space.
\ast* <p><code>Partitioner</code> 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. Hence this controls
* which of the <code>m</code> reduce tasks the intermediate key (and hence the
* record) is sent for reduction.</p>
\ast* @see Reducer
* /
public interface Partitioner<K2, V2> extends JobConfigurable {
 7*** Get the partition number for a given key (hence record) given the total
  * number of partitions i.e. number of reduce tasks for the job.
\ast* <p>Typically a hash function on a all or a subset of the key.</p>
\overline{\phantom{a}}* @param key the key to be paritioned.
   * @param value the entry value.
  * @param numPartitions the total number of partitions.
  * @return the partition number for the <code>key</code>.
  * /
 int getPartition(K2 key, V2 value, int numPartitions);
y
```
The key and value will be streamed into the partition number that this function returns. Each key/value pair output by the $map()$ method has the partition number determined and is then written to that map local partition. Each of these map local partition files is sorted in key order by the class returned by the JobConf.getOutputKeyComparator() method.

For each reduce task, the framework will collect all the reduce task's partition pieces from each of the map tasks and merge-sort those pieces. The results of the merge-sort are then fed to the reduce() method. The merge-sort is also done by the class returned by the JobConf.getOutputKeyComparator() method.

The output of a reduce task will be written to the part-*XXXXX* file, where the *XXXXX* corresponds to the partition number.

The Hadoop framework provides the following partitioner classes:

- HashPartitioner, which is the default
- TotalOrderPartitioner, which provides a way to partition by range
- KeyFieldBasedPartitioner, which provides a way to partition by parts of the key

The following sections describe each of these partitioners.

The HashPartitioner Class

The default partitioner, $org.append$.hadoop.mapred.lib.HashPartitioner, simply uses the hash code value of the key as the determining factor for partitioning. Listing 5-8 shows the actual code from the default partitioner used by Hadoop. The partition number is simply the hash value of the key modulus the number of partitions.

Listing 5-8. *The HashCode Partitioner from Hadoop 0.19.0*

```
/** Partition keys by their {@link Object#hashCode()}. */
public class HashPartitioner<K2, V2> implements Partitioner<K2, V2> {
  public void configure(JobConf job) \{\}/** Use {@link Object#hashCode()} to partition. */
  public int getPartition(K2 key, V2 value,
                          int numReduceTasks) \{napportion (key.hashCode() & Integer.MAX VALUE) % numReduceTasks;
  \}
```
y

The hash value is converted to a positive value, $(key.\text{hashCode}()$ & Integer. MAX VALUE), to ensure that the partition will be a positive integer. The resulting number has modulus the number of reduce tasks applied, % numReduceTasks, and the result returned. This produces a positive number between 0 and one less than the number of partitions.

The TotalOrderPartitioner Class

The TotalOrderPartitioner, org.apache.hadoop.mapred.lib.TotalOrderPartitioner, relies on a file that provides the class with range information. With this information, the partitioner is able to determine which range a key/value pair belongs in and route it to the relevant partition.

Note The TotalOrderParitioner grew out of the TetraSort example package. Jim Gray introduced a contest called the TeraByteSort, which was a benchmark to sort one terabyte of data and write the results to disk. In 2008, Yahoo! produced a Hadoop version of the test that completed in 209 seconds (http:// developer.yahoo.net/blogs/hadoop/2008/07/apache hadoop wins terabyte sort benchmark. html). The code is included with the Hadoop examples as $bin/hadoop$ ar hadoop-*-examples. jar terasort in-dir out-dir. The class file is org.apache.hadoop.examples.terasort.TeraSort.

Building a Range Table

The $org.append$.hadoop.mapred.lib.InputSampler class is used to generate a range partitioning file for arbitrary input sets. This class will sample the input to build an approximate range table.

This sampling strategy will take no more than the specified number of samples total from the input. The user may specify a maximum number of input splits to look in as well. The actual number of records read from each input split varies based on the number of splits and the number of records in the input split.

The Hadoop framework controls how the input is split based on the number of input files, the input format, the input file size, and the minimum split size and the HDFS block size. Let's look at a few examples of running InputSampler from the command line.

In the following example, the argument set -splitSample 1000 10 will sample a total of 1,000 input records out of no more than 10 input splits.

```
bin/hadoop jar hadoop-0.19.0-core.jar org.apache.hadoop.mapred.lib.InputSampler \rightarrow-inFormat org.apache.hadoop.mapred.KeyValueTextInputFormat →
-keyClass org.apache.hadoop.io.Text -r 15 -splitSample 1000 10 csvin csvout
```
If there are 10 or more input splits, each of which has more than 100 records, the first 100 records from each input split will be used for samples. The input is loaded from the directory csvin, and is parsed by the KeyValueTextInputFormat class. The range file is written to csvout, and the argument set $-r-15$ sets up the output for a job with 15 output partitions. The input splits are examined in the order in which they are returned by InputFormat.

The next example takes 1,000 samples from roughly 10 input splits. The input splits are sampled in a random order, and the records from each split read are sequentially.

```
\mathit{bin/hadoop} jar hadoop-0.19.0-core.jar org.apache.hadoop.mapred.lib.InputSampler ➡
-inFormat org.apache.hadoop.mapred.KeyValueTextInputFormat \rightarrow-keyClass org.apache.hadoop.io.Text -r 15 -splitRandom .1 1000 10 csvin csvout
```
Each record has a 0.1% chance of being selected. The -splitRandom .1 1000 10 argument set specifies the percentage, the total samples, and the maximum splits to sample. If the 1,000 samples are not selected after processing the recommended number of splits, more splits will be sampled. The index is set up for 15 reduce tasks, and the input comes from csvin. The index is written to csvout. The splits to examine are selected randomly.

In the final example, the argument set -splitInterval .01 10 will examine no more than 10 input splits and take one record in 100 from each split.

```
bin/hadoop jar hadoop-0.19.0-core.jar org.apache.hadoop.mapred.lib.InputSampler \rightarrow-inFormat org.apache.hadoop.mapred.KevValueTextInputFormat →
-keyClass org.apache.hadoop.io.Text -r 15 -splitInterval .01 10 csvin csvout
```
The frequency parameter defines how many records will be sampled. For a frequency of 0.1, as in this example, one record in 10 will be used. For a frequency of 0.01, one record in 100 will be used. The index is set up for 15 reduce tasks. The input comes from csvin, and the $index$ is written to $cosu$.

Using the TotalOrderPartitioner

Once an index is generated, a job may be set up to use the TotalOrderPartitioner and the index. Three configuration settings are required for this to work:

- The partitioner must be set to TotalOrderPartitioner in the JobConf object via conf.se tPartitionerClass(TotalOrderPartitioner).
- The partitioning index must be specified via the configuration key total.order.partitioner.path:

conf.set("total.order.partitioner.path", "csvout");

• The sort type for the keys must also be specified. If the binary representation of the keys is the correct sorting, the Boolean field total.order.partitioner.natural.order should be set to true in the configuration. If the binary representation of the keys is not the correct sort, the Boolean field total.order.partitioner.natural.order must be set to false. This Boolean field is set as follows:

```
conf.setBoolean("total.order.partitioner.natural.order");
```
 If the binary representation of the key is the correct sort order, a binary trie (an ordered tree structure; see http://en.wikipedia.org/wiki/Trie) will be constructed and used for searching; otherwise, a binary search based on the output key comparator will be used.

Here's an example of how to put all this together:

```
TotalOrderPartitioner.setPartitionFile(conf,"csvout");
conf.setPartitionerClass(TotalOrderPartitioner.class);
conf.set("total.order.partitioner.natural.order",false);
conf.setNumReduceTasks (15);
```
In this example, csvin is the input file, and csvout is the index file. The csvout file was set up for 15 reduce tasks, and requires the comparator rather than binary comparison.

The KeyFieldBasedPartitioner Class

The KeyFieldBasedPartitioner, org.apache.hadoop.mapred.lib.KeyFieldBasedPartitioner, provides the job with a way of using only parts of the key for comparison purposes. The primary concept is that the keys may be split into pieces based on a piece separator string. Each piece is then numbered from 1 to *N*, and each character of each piece numbered from 1 to *M*.

The separator string is defined by the configuration key map.output.key.field.separator and defaults to the tab character. It may be set to another string, str, as follows:

```
conf.set(map.output.key.field.separator, str);
```
This is functionally equivalent to using the String, split (Pattern, quote (str)) call on each key and treating the resulting array as if indexes were one-based instead of zero-based.

If the separator is X and the key is oneXtwoXthree, the pieces will be 1) one, 2) two, 3) three. Referencing individual characters within the pieces is also one-based rather than zerobased, with the index 0 being the index of the last character of the key part. For the first key

piece in the preceding example, the string one, the characters will be 1) $(0, 2)$ n, 3) $(e, 0)$ e. Note that both 3 and 0 refer to e, which is the last character of the key piece.

N**Note** In addition to the one-based ordinal position within the key piece, the last character of the key piece may also be referenced by o.

The key pieces to compare are specified by setting the key field partition option, via the following:

```
conf. setKeyFieldPartitionerOptions(str).
```
The str format is very similar to the key field-based comparator.

The Javadoc from Hadoop 0.19.0 for KeyFieldBasedPartitioner provides the following definition:

Defines a way to partition keys based on certain key fields (also see KeyFieldBasedComparator). The key specification supported is of the form -k pos1[,pos2], where, pos is of the form f[.c][opts], where f is the number of the key field to use, and c is the number of the first character from the beginning of the field. Fields and character posns are numbered starting with 1; a character position of zero in pos2 indicates the field's last character. If '.c' is omitted from pos1, it defaults to 1 (the beginning of the field); if omitted from pos2, it defaults to 0 (the end of the field).

In plain English, $-k\#$ selects piece $\#$ for the comparison, and $-k\#1, \#2$ selects the pieces from #1 through #2. In the preceding example, $-k1$ selects oneX as the portion of the key to use for comparison, and $-k1$, 1 selects one as the portion of the key to use for comparison.

There is also the facility to select a start and stop point within an individual key. The option $-k1$, 2 , 1 is equivalent to $-k1$, 2 , 1 , 0 , and selects ne from the one for comparison.

You may also span key pieces. $-k1.2, 3.2$ selects eXtwoXth as the comparison region from the sample key. It means to start with key piece 1, character 2 and end with key piece 3 character 2.

N**Note** If your key specification may touch the last key piece, it is important to terminate with the last character of the key. Otherwise, the current code (as of Hadoop 0.19.0) will generate an ArrayIndexOutOfBoundsException as it tries to use the missing separator string. In this section's example, $-k3,3$ would work, but $-k3$ would throw the exception.

The Reducer Dissected

The reducer has a very similar shape to the mapper. The class may provide configure $()$ and close) methods. All of the mapper good practices of saving the JobConf object and making instances of the output key and output value objects apply to the reducer as well.

The key difference is in the reduce () method. Unlike the map () method, which is given a single key/value pair on each invocation, each reduce() method invocation is given a key and all of the values that share that key.

The reducer is an operator on groups. The default is to define a group as all values that share a key. Common uses for reduce tasks are to suppress duplicates in datasets or to segregate ranges and order output of large datasets.

In the example shown in Listing $5-9$, notice that the signature of the reduce() method contains an Iterator < V>, an iterator over the values that share key. The identity reducer simply outputs each value in the iterator.

Listing 5-9. *The Identity Reducer from Hadoop Core 0.19.0*

```
/** Performs no reduction, writing all input values directly to the output. */
public class IdentityReducer<K, V>
    extends MapReduceBase implements Reducer<K, V, K, V> {
  /** Writes all keys and values directly to output. */public void reduce(K1 key, Iterator<V1> values,
                     OutputCollector<K2, V2> output, Reporter reporter)
   throws IOException \{while (values.hasNext()) {
      output.collect(key, values.next());
    \mathcal{F}\}
```
 \mathcal{F}

The configure $()$ and $close()$ methods have the same requirements and suggested usage as the corresponding mapper methods.

It is generally recommended that you do not make a copy of all of the value objects, as there may be very many of these objects.

N**Note** In one of my early applications, I assumed that there would never be more than a small number of values per key. The reduce tasks started experiencing out-of-memory exceptions. It turned out that there were often more than 150,000 values per key!

It is possible to simulate a secondary sort/grouping of the values by setting the output value grouping. To do this requires the cooperation of the Output Comparator, OutputPartitioner, and OutputValueGroupingComparator. See this book's appendix for more information.

By default, the input key and value types are the same as the output key and value types, and are set by the conf.setOutputKeyClass(class) and conf.setOutputValueClass(class) methods. The defaults are LongWritable and Text, respectively.

If the map output keys must be different, using $\text{conf}\cdot\text{setMapOutputKeyClass}$ (class) and $\text{conf.setMapOutputValueClass}$ (class) will also change the expected input key and value for the reduce task.

A Simple Transforming Reducer

Listing 5-10 shows the simple transformational reducer, SimpleReduceTransformingReducer. java, used in this chapter's SimpleReduce. java example.

Listing 5-10. *Transformational Reducer in SimpleReduceTransformingReducer.java*

```
/* Demonstrate some aggregation in the reducer
\ast* Produce output records that are the key, the average, the count,
* the min, max and diff
\ast* @author Jason
&
*public class SimpleReduceTransformingReducer extends MapReduceBase implements
       Reducer<LongWritable, LongWritable, Text, Text> {
   /** Save object churn. */Text outputKey = new Text();
   Text outputValue = new Text();
   /* Used in building the textual representation of the output key and values. */
   StringBuilder sb = new StringBuilder();Formatter fmt = new Formatter(sb);
```

```
@Override
    public void reduce(LongWritable key, Iterator<LongWritable> values,
             OutputCollector<Text, Text> output,
             Reporter reporter) throws IOException {
        /** This is a bad practice, the transformation of
          * the key should be done in the map. */reporter.incrCounter("Reduce Input Keys", "Total", 1);
        try {
             long total = 0;
             long count = 0;
             long min = Long.MAX VALUE;long max = 0;
             /** Examine each of the values that grouped with this key. */while (values.hasNext()) {
                 final long value = values.next().get();
                 if (value>max) \{max = value;\{\hspace{.8cm},\hspace{.8cm}\}if (value<min) {
                     min = value;\{\hspace{.8cm},\hspace{.8cm}\}total += value;
                 count++;
y ya kunane a Marekani ya Afrika Ingila. Marekani ya kunane a Marekani ya Afrika Ingila. Marekani ya Afrika In
             sb.setLength(0);fmt.format("%12d %3d %12d %12d %12d", total/count,
                          count, min, max, max-min);
             fmt.flush();
             outputValue.set(sb.toString());sb.setLength(0);
             fmt.format("%4d", key.get());
             outputKey.set(sb.toString());
             reporter.incrCounter("Reduce Output Keys", "Total", 1);
             output.collect(outputKey, outputValue);
        \} catch( Throwable e) {
             reporter.incrCounter("Reduce Input Keys", "Exception", 1);
             if (e instance of IOException) {
                 throw (IOException) e;
y
```

```
if (e instance of Runtime Exception) {
                 throw (RuntimeException) e;
\qquad \qquad \}throw new IOException(e);
\}\}\mathcal{L}
```
It begins by establishing several member variables that will be used in the reduce() method to save object generation:

```
/** Save object churn. */Text outputKey = new Text();
    Text outputValue = new Text();
    /* Used in building the textual representation of the output key and values. */
    StringBuilder sb = new StringBuilder();Formatter fmt = new Formatter(sb);
```
The working body of the reduce () method is within a try block that catches Throwables, and the input count, output count, and failure count are reported to the framework:

```
reporter.incrCounter("Reduce Input Keys", "Total", 1);
try \{****
    reporter.incrCounter("Reduce Output Keys", "Total", 1);
    output.collect(outputKey, outputValue);
```

```
\} catch( Throwable e) {
```

```
reporter.incrCounter("Reduce Input Keys", "Exception", 1);
```
In the body of the example in Listing 5-10, each value that is passed in is examined and aggregated:

```
/* Examine each of the values that grouped with this key. */
while (values.hasNext()) {
    final long value = values.next().get();
    if (value>max) {
         max = value;
    \mathcal{L}_{\mathcal{L}}if (value<min) {
         min = value;\mathcal{F}total += value;
    count++;y
```
Finally, the output key and value are constructed with the aggregated data:

```
sb.setLength(0);fmt.format("%12d %3d %12d %12d %12d", total/count, count, min, max, max-min);
fmt.flush();
outputValue.set(sb.toString());
sb.setLength(0);fmt.format("%4d", key.get());
```
 $outputKey.set(sb.toString())$;

The example that runs this reducer also uses an output grouping comparator that groups the records in sets of ten. The comparator Utils. GroupByLongGroupingComparator. java (supplied with the downloadable code for this chapter) handles grouping LongWritable values in sets of 10, 0–9, 10–19, and so on.

The following is the core code in SimpleReduce that sets up the job that runs SimpleReduceTransformingReducer:

```
job.setInputFormat(KeyValueTextInputFormat.class);
FileInputFormat.setInputPaths(job, inputDir);
```

```
job.setMapperClass(SimpleReduceTransformingMapper.class);
job.setMapOutputValueClass(LongWritable.class);
job.setMapOutputKeyClass(LongWritable.class);
```

```
/** Force the reduce to take text as the output value class,
  * instead of the default. */job.setOutputValueClass(Text.class);
```

```
job.setOutputKeyClass(Text.class);
```

```
job.setReducerClass(SimpleReduceTransformingReducer.class);
```

```
/** Cause the keys to be grouped by 10s. */
job.setOutputValueGroupingComparator(GroupByLongGroupingComparator.class);
job.setNumReduceTasks(1); \quad /** Ensure that all keys go to 1 reduce so
   * the group by is stable. */
```
The following command will run the SimpleReduce job (your output will vary slightly):

```
% HADOOP CLASSPATH=/misc/HadoopSource/commons-lang-2.4.jar →
bin/hadoop jar /misc/HadoopSource/hadoop-0.19.0/hadoopprobook.jar \rightarrowcom.apress.hadoopbook.examples.ch5.SimpleReduce -libjars →
/misc/HadoopSource/commons-lang-2.4.jar
```

```
Total input paths to process : 5
Running job: job 200902221346 0079
map 0% reduce 0%
map 20% reduce 0%
map 60% reduce 0%
map 80% reduce 0%
map 100% reduce 0%
map 100% reduce 100%
Job complete: job 200902221346 0079
Counters: 20
  File Systems
   HDFS bytes read=7103
   HDFS bytes written=2135
   Local bytes read=9006
    Local bytes written=18176
  Job Counters
    Launched reduce tasks=1
    Launched map tasks=5
   Data-local map tasks=5
 Map Input Keys
    Total=500Reduce Output Keys
    Total=35Map Output Keys
    Total=500
  Reduce Input Keys
    Total=35
 Map-Reduce Framework
    Reduce input groups=35
    Combine output records=0
   Map input records=500
    Reduce output records=35
   Map output bytes=8000
   Map input bytes=7103
   Combine input records=0
   Map output records=500
    Reduce input records=500
The Job is complete and successfull
```
Note how the output keys are multiples of tens. This is the result of the output value grouping. The actual output is the key, the average value, the number of values averaged, the minimum value, the maximum value, and the difference between the minimum and the maximum.

Now you can print the job output (key, average, count, min, max, difference), as follows:

% hadoop dfs -cat SampleReduce.ouput/part-00000

A Reducer That Uses Three Partitions

A variant of the SimpleReduce.java example, called TotalOrderSimpleReduce.java (available with the rest of this chapter's downloadable code), uses three partitions, rather than just one. This example demonstrates how to use the InputSampler class and the TotalOrderPartitioner

class, as well as some of the interesting errors that will occur if the partitioner and the OutputValueGroupingComparator do not coordinate fully.

In this example, the grouping operator groups by multiples of ten in the key space. The TotalOrderParititioner selects a random sample of the keys and creates three groups that are roughly even in size given the sample of keys. There is no guarantee that an entire group of keys will not be split into multiple partitions.

This application also requires a custom InputFormat, LongLongTextInputFormat, as the input key and the reduce key must be of the same type for the Input Sampler. In the previous version, the map input keys are Text and the reduce input keys are Long Writable. Listing 5-11 shows the core of the LongLongTextInputFormat, the RecordReader.next method.

Listing 5-11. *The RecordReader.next Method of the LongLongTextInputFormat*

```
/* Delegated next, read the textual values from the the data source
  * and convert them into LongWritables.
 * @param key The key object to fill with the next record's key
 * @param value The value object to fill with the next record's value
 * @return true if a record was read or false if at EOF
 * @throws IOException
 * @see org.apache.hadoop.mapred.RecordReader#next(java.lang.Object, \rightarrowjava.lang.Object)
 *public boolean next(LongWritable key, LongWritable value) throws IOException {
    /** Perform the real read. */final boolean res = realReader.next(this.key, this.value);
    if (!res) { /** If at eof, we are done. */return false;
    \mathcal{F}/** Attempt to convert the two text values read into LongWritables.
     * If there is an error, throw an IOException.
     */try \{key.set(Long.valueOf(this.key.toString()));
        value.set(Long.valueOf(this.value.toString()));
        return true;
    \} catch( NumberFormatException e) {
        throw new IOException("Invalid key, value " + key + ", " + value);
   \}\mathcal{F}
```
The code in Listing 5-12 sets up the JobConf object for the TotalOrderParitioner. Note that natural ordering is set to true. As the keys are long values, they are binary comparable. The call to runInputSampler computes the partitioning index and stores it in the file TotalOrderSimpleReduce.index.

```
Listing 5-12. TotalOrderPartition Setup, from TotalOrderSimpleReduce.java
```

```
job.setInputFormat(LongLongTextInputFormat.class);
FileInputFormat.setInputPaths(job, inputDir);
job.setMapOutputValueClass(LongWritable.class);
job.setMapOutputKeyClass(LongWritable.class);
/** Setup for a total order partitioning. */job.setPartitionerClass(TotalOrderPartitioner.class);
job.setBoolean("total.order.partitioner.natural.order", true);
/** Force reduce to take text as the output value class, instead of the default. */
job.setOutputValueClass(Text.class);
job.setOutputKeyClass(Text.class);
job.setReducerClass(SimpleReduceTransformingReducer.class);
/** Cause the keys to be grouped by 10s. */
job.setOutputValueGroupingComparator(GroupByLongGroupingComparator.class);
/** Ensure that all keys go to 3 reduce to demonstrate order based partitioning. */
```

```
job.setNumReduceTasks(3);
```

```
runInputSampler(job, inputDir.suffix(".index"));
```
The code in Listing 5-13 runs the InputSampler to compute and store the index in indexFile. The assumption here is that the JobConf object conf is already correctly set up with the InputPaths and InputReader. The sampling strategy is to randomly sample the records with a 0.1% chance that any record is chosen. No more than 100 samples and a suggested 10 input splits are to be read.

Listing 5-13. *Running the InputSampler*

```
/* Generate the TotalOrderPartitioner index file for our key space
\ast* This will sample the input paths set in conf, using the input format reader.
 * The index file location is written to conf.
\ast* @param conf The Configuration object to use
 * @param indexFile The index file to generate
 * @throws IOException
 *public void runInputSampler(final JobConf conf, Path indexFile) throws IOException {
    TotalOrderPartitioner.setPartitionFile(conf, indexFile);
    RandomSampler<LongWritable, LongWritable> sampler = new
    InputSampler.RandomSampler<LongWritable,LongWritable>(0.1, 100, 10);
    InputSampler.<LongWritable,LongWritable>writePartitionFile(conf, sampler);
\}
```
The following results show that the input for group 150 is split between partition 0 and partition 1, and that the group 220 is split between partition 2 and partition 3. Your results will differ, as random data generation and selection are occurring.

```
HADOOP CLASSPATH=/misc/HadoopSource/commons-lang-2.4.jar hadoop jar /misc →
/HadoopSource/hadoop-0.19.0/hadoopprobook.jar com.apress.hadoopbook.examples.ch5 \rightarrow.PotalOrderSimpleReduce -libjars /misc/HadoopSource/commons-lang-2.4.jar
```

```
The Job is complete and successfull
Counter Group: File Systems
   HDFS bytes read 8060
   HDFS bytes written 2257
   Local bytes read 9018
   Local bytes written 18488
Counter Group: Job Counters
   Launched reduce tasks \frac{3}{2}Launched map tasks 5
   Data-local map tasks 5
Counter Group: Reduce Output Keys
   Total 37
Counter Group: Reduce Input Keys
   Total 37
Counter Group: Map-Reduce Framework
   Reduce input groups 37
   Combine output records 0
   Map input records 500
   Reduce output records 37
   Map output bytes 8000
   Map input bytes 7135
   Combine input records 0
   Map output records 500
   Reduce input records 500
```
Let's examine the reduce output data:

for a in 0 1 2; do echo part-0000\$a; hadoop dfs -cat TotalOrderSimpleReduce \rightarrow $.k$ ouput/part-0000\$a; done

Combiners

A combiner is a mini-reducer. The purpose of a combiner is to reduce the volume of data that must be passed to the reducer from a map task by summarizing output records that share the same key. A combiner must implement the Reducer interface, and the reduce () method of the combiner will be called with each output key and all of the output values that share that key. The output of the combiner is what will be sent over the network to the actual reduce task for the job or written to the final output directory, if there is no reduce task configured. The combiner class $reduce()$ method must have the same input and output key/value types as the reducer class.

For each call to output. collect made by the $map()$ method, the framework will route the key/value pair to the applicable partition, based on the result of the Partitioner.getPartition

call. When all of the map task input has been processed, these partitions are sorted, and each one is passed as input to the combiner. The combiner's reduce $()$ method will be called once for each unique key in the partition, and the values will be the set of values that share that key. The output of the combiner will replace that set of original map outputs, ideally with fewer records or smaller records. This is suitable for jobs that are producing summary information from a large dataset.

Caution The combiner must not change the key values, as the map outputs are not re-sorted after the combiner runs. The reduce phase requires the map outputs to be sorted by key.

It is common for the same class that is used in the reduce task to be used for the combiner. However, this practice often leads to difficult-to-diagnose problems. The combiner must only aggregate values, in a manner that is suitable for processing by the actual reducer. The actual reducer has the larger job of producing the final job output. Problems occur when the reducer is modified to provide some change in the job output, and the person doing the modification is unaware that the reducer is also used as a combiner. It is very important that the combiner class not have side effects, and that the actual reducer be able to properly process the results of the combiner.

Tip It not always simple to build a correct combiner. If a job output has problems, try running the job without the combiner to see if the problem persists. If your actual $reduce()$ method is nontrivial, do not also use it as a combiner; instead, write a separate object to combine the map outputs.

The classic example of using a combiner is the org.apache.hadoop.examples.WordCount example. This MapReduce job reads a set of text input files and counts the frequency of occurrence of each word in the input files. The map phase outputs each word in the file as a key, with the count of 1. There will be one output record for each word in the file. The combiner will aggregate these into a set that contains one output record per unique word in the input, and the value is the number of times the word appeared in the input. Unless the writer has such a large vocabulary that no word is used more than once, the combiner will greatly reduce the number of records to be processed by the reduce phase.

Listings 5-14, 5-15, and 5-16 show the JobConf setup and the map $($ and reduce $($ methods from the WordCount.java example, The default InputFormat is TextInputFormat, which returns a LongWritable key, the input line number, and a Text value, which is the full line from the input file. The $map()$ method tokenizes the line and emits a record for each word of the input record, a Text and the value 1, an IntWritable. The reduce () method simply sums the values and outputs the word as Text and the sum of values, an IntWritable. By using the reduce() method as a combiner, there is a large reduction in the size of each map task output.

```
Listing 5-14. The JobConf Setup, from WordCount.java's run Method
```

```
conf.setJobName("wordcount");
\frac{1}{\sqrt{2}} the keys are words (strings)
conf.setOutputKeyClass(Text.class);
\frac{1}{\sqrt{2}} the values are counts (ints)
conf.setOutputValueClass(IntWritable.class);
```

```
conf.setMapperClass(MapClass.class);
conf.setCombinerClass(Reduce.class);
conf.setReducerClass(Reduce.class);
```
Listing 5-15. *The Core of the map Method, from WordCount.java*

```
public void map(LongWritable key, Text value,
               OutputCollector<Text, IntWritable> output,
               Reporter reporter) throws IOException {
String line = value.toString();StringTokenizer itr = new StringTokenizer(line);
while \text{(itr. hasMoreTokens())} {
  word.set(itr.nextToken());
  output.collect(word, one);
\mathcal{F}
```
Listing 5-16. *The Core of the reduce Method, from WordCount.java*

```
public void reduce(Text key, Iterator<IntWritable> values,
                  OutputCollector<Text, IntWritable> output,
                  Reporter reporter) throws IOException {
int sum = 0;while (values.hasNext()) {
  sum += values.next().get();
\mathcal{L}output.collect(key, new IntWritable(sum));
```
When the map task has completed and the partitions are sorted, the combiner may run over the partitions and aggregate values, reducing the total number of key/value pairs that must go over the network to the reduce task.

For example, suppose the map partition dataset originally contained the following:

After the combiner has completed, the map partition dataset would contain these keys and values:

It is fairly simply to shoot yourself in the foot with a combiner. The combiner must not cause the loss of any information that is needed by the actual reducer. The classic example of this is a reducer that computes the average of the values for each key. If that reducer is also used as a combiner, the information on the number of records involved computing the average will be lost, and the reduce tasks will see only the average values for each key; the final result will be the average of the averages, instead of the actual average. Combiners also must be idempotent, as they may be run an arbitrary number of times by the Hadoop framework over a given map task's output.

File Types for MapReduce Jobs

The Hadoop framework supports text files, binary (sequence) files, and map files, which are actually a pair of sequence files. Let's take a closer look at each of these file types.

Text Files

The Hadoop framework supports a number of textual input files and output files. The input formats support transparent decompression of input files if an input file name ends in one of the recognized compression format suffixes (.gz, .deflate, .lzo deflate, .lzo, and .bz2).

The following formats are available for text files:

TextInputFormat: This class reads each line of the input split and returns a record composed of the line number as a LongWritable key, and the line itself as a Text value. The workhorse class that actually produces the key/value pairs is $org.append$. hadoop.mapred.LineRecordReader. There is only one tunable parameter: the configuration key, mapred.linerecordreader.maxlength, which sets the maximum number of characters allowed in a line. The default value is Integer. MAX VALUE, essentially unlimited. The parameter may be adjusted using the $conf.setInt()$ method. For example, conf.setInt("mapred.linerecordreader.maxlength", 1024) limits the line length to 1,204 characters.

 $KeyValueTextInputFormat: This class reads each line and splits the line into a key/$ value pair on a tab character. The workhorse class is org. apache. hadoop. mapred. KeyValueLineRecordReader. The separator may be configured by setting the configuration key key value separator, in, input, line. The key and value are both Text. If there is no separator found, the value will be an empty string.

NLineInputFormat: This format is ideal for using the input data as control information. It guarantees that each input split will be *N* lines long, with one split being the remaining lines. The configuration key mapred. line. input. format. linespermap controls the number of lines of input per map task. The default value is 1. This may be changed using the $conf.setInt()$ method. For example, $conf.setInt("mapped.line.$ $input.formatuinespermap", 10) sets the value to 10. Under the covers, this uses$ org.apache.hadoop.mapred.LineRecordReader to read the input data and produce LongWritable, Text key/value pairs.

MultiFileInputFormat: This is an abstract class that provides a way for a single task to receive multiple input files as the task's input split. This is commonly done for performance tuning. There is substantial time involved in setting up and starting a task, as well as collecting the results. If the input split is small, a substantial portion of the job runtime may be in the setup and teardown of tasks. The developer is responsible for implementing the getRecordReader() method. The org.apache.hadoop.examples MultiFileWordCount provides an example of a RecordReader that handles reading from multiple files.

Text0utputFormat: This is the standard textual output format. It basically calls the to String method on each key and value, producing a single-line key SEPARATOR value ASCII newline for each output record. The SEPARATOR is specified by the value of the configuration key apred, textoutput format, separator, which defaults to TAB. If the value is null, no SEPARATOR and no value will be emitted. If key is null, SEPARATOR value is emitted. The end-of-record character is hard-coded as an ASCII newline character. Compression is supported if configured.

MultipleText0utputFormat: This format allows you to write output records to different files based on the key and value. The test case org. apache. hadoop. mapred. TestMultipleText0utputFormat provides a sample implementation. The Java source to this class is located in src/test/org/apache/hadoop/mapred/ TestMultipleTextOutputFormat.java in your Hadoop distribution. Using MultipleTextOutputFormat, the user has the option of interceding in the selection of an output file for each output key/value pair in several different ways by overriding different methods.

- For map-only jobs, a portion of the input file path may be included in the output path, by setting the value of the configuration key mapred.outputformat. numOfTrailingLegs, to a positive integer. The default is no components of the input file path are used. The value +1 worth of components from the right side of the input file are inserted in the output file path before the file name. This happens after the call to generate File Name For Key Value (). The actual key and value parameters may be modified by overriding the getActualKey() and getActualValue() methods.
- You can change the final file name or leaf name via the String generateLeafFileName(String name) method. The parameter name is the original leaf name. The leaf name is normally the part-*XXXXX*, where the *XXXXX* corresponds to the reduce ordinal number, or the map ordinal number if this is a map-only job. (Changing the leaf name is not commonly done.)
- You can change the path to the output file via the String generateFileNameForKeyValue(K key, V value, String name) method. The name parameter is the result of generate Leaffile Name. You can construct arbitrary paths out of the key, value, and name. This is the method commonly overridden by developers. The example in Listing 5-17 produces an output file name of the first letter of the key, a dash, and the partition number. If the key were akey, and the name were part-00000, this key/value pair would go to the file a -part-00000.

Listing 5-17. *Simple MultipleTextOutputFormat Output File Name Generator*

```
static class KeyBasedMultipleTextOutputFormat extends
     MultipleTextOutputFormat<Text, Text> {
  protected String generateFileNameForKeyValue(Text key, Text v, String name) {
    return key.toString().substring(0, 1) + "-" + name;
  \mathcal{E}\mathcal{F}
```
Caution It is critically important to minimize the number of HDFS files that are opened. HDFS, through at least Hadoop 0.19.0, is designed for small numbers of very large files. Opening many small files will bring your cluster to its knees, and may result in catastrophic failure of your job, as well as your HDFS. It is very easy to open hundreds of thousands of files with MultipleOutputFormats.

Sequence Files

Sequence files are a binary format for storing sets of serialized key/value pairs. Sequence files support compression, encapsulate the key and value types, and provide validity checksums. They are an ideal format to use for data that is expensive or complex to parse.

The following formats are available for sequence files:

SequenceFileInputFormat: The basic workhorse, this format supports splitting and provides the key and value types. If the input file is a map file (described in the next section), the data file is read.

SequenceFileAsBinaryInputFormat: This format returns the raw key and value bytes. It returns BytesWritable keys and values.

Sequence File As Text Input Format: This format returns the key and value as text. It calls the to String method on the key and value classes and returns the key/value pair as Text, Text.

Sequence File Input Filter: This format returns only specific records from the sequence file. It provides the static void setFilterClass(Configuration conf, Class filter Class) method, which supplies a class that is used to determine which records are returned by the next(key, value) method on the reader. The FilterClass must implement the SequenceFileInputFilter.Filter interface and provide a method boolean $accept(Object key)$. Three filters are provided:

- RegexFilter.setPattern(Configuration conf, String regex) provides the regular expression to filter keys.
- PercentFilter.setFrequency(Configuration conf, int frequency) provides the way of accepting one record in frequency records.
- MD5Filter.setFrequency(Configuration conf, int frequency) provides a way of selecting only those records that have an MD5 hash that is evenly divisible by frequency.

SequenceFileOutputFormat: This format writes the serialized key/value records as output. This is the standard sequence file output. The key and value types must be specified via the conf.setOutputKeyClass() and conf.setOutputValueClass() methods.

SequenceFileAsBinaryOutputFormat: This format writes the raw bytes. The key and value types must be BytesWritable, and these raw bytes are written as the records.

Map Files

Map files are a pair of sorted sequence files. If a map file named mymap is created, there will be a directory mymap in HDFS, and two files in mymap: index and data. The data sequence file contains the key/value pairs as records, where the records are sorted in key order. The index sequence file is key/location information, where location is the location in data where the first record containing a key is located.

Map files provide a way to find a particular key, or region of a sorted file, without having to read the entire file. The HBase project (http://hadoop.apache.org/hbase) provides a persistent distributed hash table stored in HDFS, using map files as the underlying storage.

When a map file is specified as a job input, the data file is used as the actual input. There is not a MapFileInputFormat class; the SequenceFileInputFormat class is used. The path specified is the path to the directory containing the index and data files. Sequence File Input Format will use the data file as the input source.

Tip For best performance, it is strongly suggested that all key lookups be performed in the sort order of the underlying map file. HDFS is highly optimized for streaming files sequentially, and does a very poor job of providing low-latency access to random locations within a file.

For the MapFileOutputFormat, the value of the configuration key io.map.index.interval determines how many records are written to the data sequence file between writes to the index sequence file. The default is one index entry for every 128 records.

Map files provide the following methods for looking up key/value pairs.

- void reset(): Resets the read position to the beginning of the file.
- WritableComparable midKey(): Returns the key roughly in the middle of the file.
- void finalKey(WritableComparable key): Reads the final key.
- boolean seek(WritableComparable key): Seeks to the key, or to the first key after it, if it does not exist.
- boolean next(WritableComparable key, Writable val): Reads the next key/value pair.
- Writable get(WritableComparable key, Writable val): Gets the value for key.
- WritableComparable getClosest(WritableComparable key, Writable val): Gets the closest match to the key, searching as seek.
- WritableComparable getClosest(WritableComparable key, Writable val, final boolean before): Works like the previously described getClosest() method, unless before is true—in which case the key before is returned.

Compression

The Hadoop framework supports several types of compression and several compression formats. The framework supports the gzip, zip, sometimes LZO, and bzip2 compression codecs. Native libraries are supplied for Linux i386 and x86_64 for gzip, zip, and LZO for some releases. The framework will transparently compress and uncompress most input and output files. Input files are uncompressed when the input file name has a suffix that maps to one of the known codecs, as shown in Table 5-3.

Note LZO is licensed under the GPL. It is incompatible with the Apache license and has been removed from some distributions. I sincerely wish that this will be resolved and that native LZO becomes a standard part of the Hadoop distribution.

Table 5-3. *Compression Codecs and Mapped File Name Suffixes*

Codec	Suffix	
GzipCodec	.gz	
DefaultCodec	deflate	
LzoCodec	.lzo deflate	
LzopCodec	. 170	
Bzip2Codec	,hz2	

Codec Specification

The Hadoop framework supports a number of codecs, with native implementations for a smaller number. GzipCodec, LzoCodec, and the DefaultCodec (zip) have native implementations. Bzip2Codec has a pure Java implementation. LzoCodec may not be available in some releases due to licensing issues. Bzip2Codec is available as of Hadoop 0.19.0.

The list of codecs is stored in the configuration under the key io. $composition.close$. In Hadoop 0.19, it has the following value:

```
org.apache.hadoop.io.compress.DefaultCodec,org.apache.hadoop.io.compress. →
GzipCodec, org.apache.hadoop.io.compress.BZip2Codec
```
If your environment requires additional codecs, the glue interface is org , apache, hadoop, io.compress.CompressionCodec. You would then add the class name to the list of codecs in the io.compression.codecs value. The selection of a compression codec is a choice between speed and compression rate. LZO is the fastest by far, and produces files about double the size of gzip. The bzip2 compression is the slowest—substantially slower than gzip—and produces files about one half the size of gzip.

Sequence File Compression

Sequence files are binary record-oriented files, where each record has a serialized key and serialized value. The Hadoop framework supports compressing and decompressing sequence files transparently.

Sequence files may be, and generally should be, compressed. The framework will transparently compress at the record level or the block level. The key io.seqfile.compression.type controls the record- or block-level compression for sequence files. A value of BLOCK requests block-level compression. A value of RECORD, the default, specifies record-level compression. A value of NONE disables compression.

In general, block-level compression is recommended, because it provides greater data reduction (at the expense of individual key access). The compression overhead is less, and the compression ratio is much greater. For sequence files that are being used as input to a map or reduce phase, block-level compression is ideal. Sequence files that were written using transparent compression may be divided into multiple input splits by the framework.

Many sites will set the default to BLOCK in their hadoop-site. xml file, as follows:

```
<property>
```

```
<name> io.segfile.compression.type</name>
 <value>BLOCK</value>
 <description>Force the default sequence file compression to
           be block compression for efficiency reasons
</value>
</property>
```
Map Task Output

The intermediate map task outputs are a set of sequence files, one per reduce task. As these files must be transferred across the network, a low-overhead compression type, such as gzip or LZO, can provide a substantial reduction in network traffic for little CPU cost. The blog entry at http://blog.oskarsson.nu/2009/03/hadoop-feat-lzo-save-disk-space-and.html has some interesting information about compression CPU and size reductions for different Hadoop codecs. Table 5-4 summarizes the compression speed results. For pretty decent compression LzoCodec provides high throughput.

Note I have spent some time running the same job with different compression codecs and RECORD or BLOCK set for compression, to determine which combination gave the overall performance for the job. At present, this must be done manually.

Compressor	Original Size	Compressed Size	Compression Speed	Decompression Speed	
bzip2	8.3 _{GB}	1.1GB	2.4MB/s	9.5MB/s	
gzip	8.3 _{GB}	1.8GB	17.5MB/s	58MB/s	
LZO best	8.3GB	2GB	4MB/s	60.6MB/s	
LZO	8.3 _{GB}	2.9GB	49.3MB/s	74.6MB/s	

Table 5-4. *Compression Timings for Hadoop Compression Codecs*

Map output block-level compression may be specified by the job or in the site configuration. If compressed, map output, destined for a reduce task, is always BLOCK compressed. Listing $5-18$ provides an XML block suitable for inclusion in the conf/hadoop-site. xml file to make LZO compression the default for the map task outputs.

Listing 5-18. *A hadoop-site.xml Specification for Map Output Level Compression with LZO*

```
<property>
 <name>mapred.compress.map.output</name>
 <value>true</value>
 \alphadescription>Should the outputs of the maps be compressed before being
               sent across the network. Uses SequenceFile compression.
 </description>
</property>
<property>
 <name>mapred.map.output.compression.codec</name>
 <value>org.apache.hadoop.io.compress.LzoCodec</value>
 \alphadescription>If the map outputs are compressed, how should they be
               compressed? Use Lzo fast even though not as good compression.
 </description>
</property>
```
Listing 5-19 demonstrates configuring a cluster to always use compression for final output files, and if the final output file is a sequence file, to use BLOCK compression.

Listing 5-19. *A hadoop-site.xml Specification for Final Output Files to be Compressed with LZO, and If Sequence Files, BLOCK-Compressed*

```
<property>
  <name>mapred.output.compress</name>
  <value>true</value>
  <description>Should the job outputs be compressed?
  </description>
</property>
```

```
<property>
 <name>mapred.output.compression.type</name>
 <value>BLOCK</value>
 <description>The type of compression to use for final
  output sequence files. May be BLOCK, RECORD or None.
 </description>
</property>
<property>
 <name>mapred.output.compression.codec</name>
 <value>org.apache.hadoop.io.compress.LzoCodec</value>
 \alphadescription>If the job outputs are compressed, how should they be
               compressed? Use Lzo fast even though not as good compression.
 </description>
</property>
```
Listings 5-20 and 5-21 demonstrate specifying the compression codec and type via settings on the JobConf object.

Listing 5-20. *Setting Intermediate Map Output Compression via the JobConf*

```
conf. setCompressMapOutput(true);
conf. setMapOutputCompressorClass(LzoCodec.class);
```
Listing 5-21. *Setting Final Output Compression via the JobConf*

```
FileOutputFormat.setOutputCompress (conf, true);
FileOutputFormat.setOutputCompressorClass(LzoCodec.class);
SequenceFileOutputFormat.setOutputCompressionType(conf,CompressionType.BLOCK);
```
JAR, Zip, and Tar Files

The Hadoop framework knows how to unpack JAR, zip, and tar files, but this is only automatically done for archives passed via the Distributed Cache object The class org. apache. hadoop. fs. File Util provides two static methods that may be used to unpack these files: $unTar()$ for tar files and $unzip()$ for zip files. The archives may be unpacked only onto the native file system, not into HDFS.

Summary

The Hadoop Core framework provides a rich set of tools to support a variety of use cases. As with most powerful tools, using them effectively requires training and experience. This chapter has provided a solid foundation for configuring jobs to run successfully and building classes that will actual perform the work for the job.

The effective use of counters in the map and reduce methods provides both the application writer and the organization with metrics for job performance. The DistributedCache object provides a way of distributing required data to all of the tasks, without needing to have the data already available on the TaskTracker nodes. You can choose from a variety of input and output formats. The use of compression can greatly reduce the wall clock runtime of a job, as can the use of a combiner. The KeyFieldBasedComparator and KeyFieldBasedPartitioner classes allow you to implement a secondary sort via the OutputValueGroupingComparator. Partitioning is a simple controllable process. You also know how to use MultipleTextOutputFormat, and the potential problems it can bring. It is now time to have fun writing MapReduce jobs!