BIG DATA ANALYTICS USING HADOOP TOOLS

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ABSTRACT OF THE THESIS

Big Data Analytics Using Hadoop Tools
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Big data technologies continue to gain popularity as large volumes of data are generated around us every minute and the demand to understand the value of big data grows. Big data means large volumes of complex data that are difficult to process with traditional data processing technologies. More organizations are using big data for better decision making, growth opportunities, and competitive advantages. Research is ongoing to understand the applications of big data in diverse domains such as e-Commerce, Healthcare, Education, Science and Research, Retail, Geoscience, Energy and Business.

As the significance of creating value from big data grows, technologies to address big data are evolving at a rapid pace. Specific technologies are emerging to deal with challenges such as capture, storage, processing, analytics, visualization, and security of big data. Apache Hadoop is a framework to deal with big data which is based on distributed computing concepts.

The Apache Hadoop framework has Hadoop Distributed File System (HDFS) and Hadoop MapReduce at its core. There are a number of big data tools built around Hadoop which together form the ‘Hadoop Ecosystem.’ Two popular big data analytical platforms built around Hadoop framework are Apache Pig and Apache Hive. Pig is a platform where large data sets can be analyzed using a data flow language, Pig Latin. Hive enables big data analysis using an SQL-like language called HiveQL. The purpose of this thesis is to explore big data analytics using Hadoop. It focuses on Hadoop’s core components and supporting analytical tools Pig and Hive.

TABLE OF CONTENTS

PAGE

ABSTRACT....................v
LIST OF FIGURES viii
ACKNOWLEDGEMENTS....................x
CHAPTER
1 INTRODUCTION 1
1.1 Big Data and Hadoop....................1
1.2 Thesis Organization 1
2 HADOOP ARCHITECTURE 3
2.1 Introduction....................3
2.2 Hadoop Architecture....................4
2.2.1 Hadoop Distributed File System (HDFS)....................5
2.2.1.1 NameNode and DataNode 5
2.2.1.2 File Write in HDFS....................6
2.2.1.3 File Read in HDFS....................7
2.2.2 MapReduce 8
2.2.2.1 YARN / MRv2....................9
2.2.2.2 Steps in MapReduce Job Execution....................10
3 SET UP SINGLE-NODE HADOOP CLUSTER USING CLOUDERA QUICKSTART VM....................12
3.1 Set Up Cloudera Quickstart VM....................12
3.1.1 HADOOP Configuration Files....................14
3.2 Running Wordcount Example....................15
4 MAPREDUCE PROGRAMMING 18
4.1 Use Case....................18
4.2 Source Code....................19
4.3 Execution 20
5 DATA ANALYSIS USING APACHE PIG....................24

5.1 Execution Modes 24
5.2 Using Pig For Data Analysis..24
5.3 Using Pig Editor In Hue..28
6 DATA ANALYSIS USING APACHE HIVE 31
6.1 Using Hive For Data Analysis 31
7 BIG DATA ANALYTICS ON AMAZON CLOUD...36
7.1 Amazon Web Services...36
7.2 Create An Emr Cluster...36
7.3 Connect To The Master Node..41
7.4 View Web Interfaces Hosted on the Master Node..44
7.5 Submit A Job To The Cluster 47
7.6 Using Hue On Amazon EMR 49
7.6.1 Using Hive Editor in Hue 50
8 SUMMARY AND FUTURE WORK 57
REFERENCES 59

LIST OF FIGURES

PAGE

Figure 2.1. Hadoop 2.x Components 5
Figure 2.2. File Write in HDFS 6
Figure 2.3. File Read in HDFS 7
Figure 2.4. Example to Illustrate How MapReduce Works..9
Figure 2.5. Steps in MapReduce Job Execution 10
Figure 3.1. Cloudera VM Listed in VMware Player 13
Figure 3.2. Browser in the Cloudera VM with Bookmark Links 14
Figure 3.3. Hadoop Configuration Files 14
Figure 3.4. Running wordcount Program 16
Figure 3.5. MapReduce Job Counters and Framework Details in the Execution Log............17
Figure 3.6. MapReduce Job Output 17
Figure 4.1. Executing MapReduce Application..21
Figure 4.2. Displaying the Output File 22
Figure 5.1. Execution Logs on the Console..26
Figure 5.2. Pig Script Output (Column 1: MovieID, Column 2: Title, Column 3: Average Rating)..27
Figure 5.3. Output of DUMP avg_rating..27
Figure 5.4. Pig Editor in Hue..28
Figure 5.5. Creating a Pig Script in Hue..29
Figure 5.6. Running a Pig Script in Hue..29
Figure 5.7. Displaying Pig Script Output in Hue..30
Figure 6.1. Hive Query Execution..34
Figure 6.2. Hive Query Output 35
Figure 7.1. AWS Console with Available Services..36
Figure 7.2. Create Cluster - Quick Options 37
Figure 7.3. Create Cluster - Software Configuration..38
Figure 7.4. Create Cluster - Hardware Configuration..38
Figure 7.5. Create Cluster - General Options 39

Figure 7.6. Create Cluster - Security Options 39
Figure 7.7. Cluster in Starting State 40
Figure 7.8. Cluster in Waiting State 40
Figure 7.9. PuTTYgen 41
Figure 7.10. Converting Private Key to .ppk Format 42
Figure 7.11. Public DNS Name of Cluster Master Node Displayed in EMR Console 43
Figure 7.12. Setting up an SSH Tunnel to the Master Node Using Dynamic Port Forwarding 44
Figure 7.13. Instructions to Setup Web Connection 45
Figure 7.14. Web Links for the Web Interfaces Hosted on the Cluster 47
Figure 7.15. Upload MapReduce Program Jar File to S3 47
Figure 7.16. Upload Input File to S3 47
Figure 7.17. Add Step to a Running Cluster 48
Figure 7.18. Add Step to Execute a Custom Jar File 48
Figure 7.19. Output Folder in S3 49
Figure 7.20. Hue Login Screen 49
Figure 7.21. Using WinSCP to Copy Files to Master Node 50
Figure 7.22. Provide Private Key File for Authentication 51
Figure 7.23. Create Database Using Metastore Manager 52
Figure 7.24. Create Tables Using Metastore Manager 53
Figure 7.25. Create a New Table From a File - Choose File 53
Figure 7.26. Create a New Table From a File - Choose Delimiter 54
Figure 7.27. Create a New Table From a File - Define Columns 54
Figure 7.28. 'ratings' Table Created 55
Figure 7.29. Executing a Hive Query 55
Figure 7.30. Hive Query and Result to Calculate Average Movie Rating 56

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CHAPTER 1

INTRODUCTION

Data is growing at a rate we never imagined. Large volumes of digital data are generated at a rapid rate by sources like social media sites, mobile phones, sensors, web servers, multimedia, medical devices and satellites, leading to a data explosion. The importance of capturing this data and creating value out of it has become more important than ever in every sector of the world economy. While the potential of creating meaningful insights out of big data in various domains like Business, Health Care, Public Sector Administration, Retail and Manufacturing are being studied, data science related technologies are expanding to capture, store and analyze big data efficiently.

1.1 Big Data and Hadoop

Apache Hadoop is the most popular open source framework to deal with big data. It makes use of distributed computing concepts at the data storage level using Hadoop Distributed File System (HDFS), and at the data processing level using MapReduce framework. In MapReduce, a large programming task is divided into a ‘Map’ phase which is performed in a distributed fashion and a ‘Reduce’ phase where the consolidation occurs. There are Hadoop related data analytical technologies like Pig which uses a data flow language called Pig Latin and Hive which helps users to analyze big data using SQL-like Hive queries.

The aim of this thesis is to understand the Hadoop framework and data analysis using MapReduce, Hive and Pig, and communicate typical usage of these technologies to a reader. This document can be used for self-study of Hadoop, Pig and Hive and will be shared on SDSU website. There are no texts or other sources that provide the step by step usage examples found in this document for these technologies, using the same presentation style and level of detail.

1.2 Thesis Organization

The initial chapters discuss the Hadoop framework, followed by data analysis using MapReduce, Hive and Pig on sample use cases. Big data analysis using Amazon Elastic MapReduce (Hadoop on Amazon cloud) is also explained in detail.

Chapter 2 focuses on the Hadoop architecture. Chapter 3 explains the Hadoop setup using Cloudera QuickStart VM. In Chapter 4, MapReduce is explained using a data analytics use case. Chapter 5 and Chapter 6 explain Apache Pig and Apache Hive respectively and show how these technologies can be used for solving data analysis problems. Chapter 7 explains big data analytics using Amazon Web Services (AWS). Chapter 8 concludes the study.

CHAPTER 2

HADOOP ARCHITECTURE

Apache Hadoop is an open-source framework which allows distributed storage and processing of large volumes of structured or unstructured data across clusters of commodity hardware.

2.1 Introduction

One of the early big data problems was faced by web search engines where millions of web pages had to be indexed in a fraction of second in a cost-effective way. Hadoop was created by Doug Cutting and originated in Apache Nutch, a web search engine project initiated by Doug Cutting and Mike Cafarella [1]. In 2005, Apache Nutch became an independent subproject of Apache Lucene, a text search engine library created by Doug Cutting. Nutch's implementation of distributed file system and MapReduce were inspired by Google's white papers [2] on Google's distributed file system (GFS) and MapReduce [3] respectively, which described the distributed file system and distributed computing architecture Google used for intensive data processing needs. Nutch's distributed file system and MapReduce implementations were moved to Apache Hadoop as an independent subproject of Apache Lucene in 2006 to build a generic framework to solve various big data problems.

One of the main design features of Hadoop is its high scalability in data storage and processing capability that can be achieved by adding more nodes to the cluster. It also enables cost effectiveness as it does not demand high-end servers, instead using inexpensive commodity machines. Since it uses ordinary hardware which fails more often than high-end machines, data is replicated for fault tolerance.

Hadoop use cases are vast and cover almost all sectors of the world economy like Politics, Data Storage, Financial Services, Health Care, Human Sciences, Telecoms, Travel, Energy, Retail and Logistics [4]. For example, use of big data and cloud computing using Amazon Web Services for election campaigns played an important role in Team Obama's win in the 2012 U.S. presidential election. In the financial domain, banks use Hadoop solutions for maintaining data accuracy and compliance with regulations, and this was more complex and time consuming before Hadoop. In health care, it is used for storage, processing and analysis of millions of medical records and claims, and for capturing and analyzing massive volumes of medical sensor data. In Telecom, large volumes of mobile call records can be stored and processed in real time. In energy, insights on household energy usage can be made by processing large volumes of energy usage data and potential energy saving plans can be derived. A list of companies using Hadoop and the related use cases can be found at Hadoop wiki [5].

2.2 Hadoop Architecture

Hadoop's underlying principle is distributed data storage and computation. Data transfer speed of hard drives is not growing proportionally with storage capacities, which slows down read and write operations. One feasible solution to this is distributed computing, where data is distributed over multiple disks and data is read and written in parallel. Since failure of one disk should not result in data loss, data must be replicated. Hadoop's file system, called Hadoop Distributed File System (HDFS), is based on this principle. When data is distributed, it's processing needs to be done in a distributed fashion. Hadoop's MapReduce framework takes care of this. In MapReduce programming model, the processing is done in two steps: in 'Map' phase, data is processed locally and in 'Reduce' phase, the results are consolidated. This also makes use of the principle that moving computation closer to data is cheaper than moving data closer to computation, especially when the size of the dataset is huge.

HDFS and MapReduce layers in Hadoop 2.x are shown below. The data storage layer consists of a NodeManager (one per cluster) and DataNodes (one per slave node). The data computation layer consists of a ResourceManager (one per cluster) and NodeManagers (one per slave node). These components are explained in detail in the coming sections.

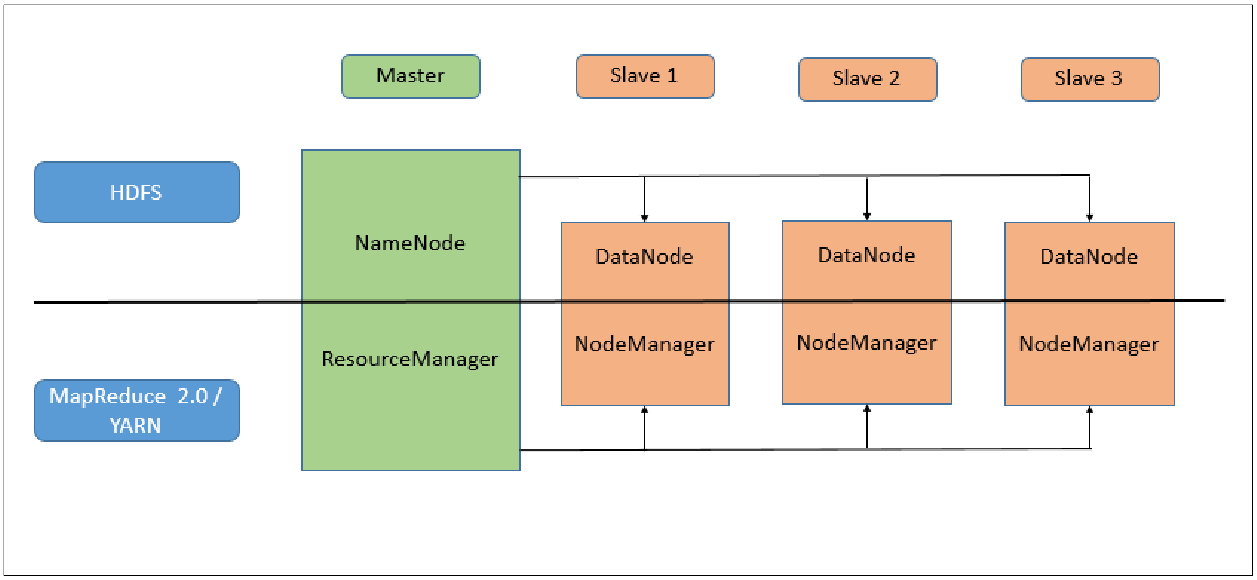


Figure 2.1. Hadoop 2.x Components

2.2.1 Hadoop Distributed File System (HDFS)

In HDFS [6] [7], files are split into blocks. The default block size is 128 MB in Hadoop 2.x generation. (In Hadoop 1.x, it was 64 MB). In a filesystem, a block is the minimum size of data that can be read or written from disk. Each block of data is replicated by a replication factor which has a default value of three and then stored on data nodes. Both block size and replication factor are configurable per file.

2.2.1.1 NameNode and DataNode

HDFS follows master-slave architecture. A cluster consists of a NameNode (master) and a set of DataNodes (slaves). NameNode and DataNodes are Java processes running on master and slave machines, respectively. Master is usually a server-grade machine and slaves are commodity machines. NameNode stores the file system metadata in persistent mode and controls file access by clients. File system metadata is stored persistently in FsImage file on NameNode’s local disk. EditLog logs changes made to the file system metadata (such as creation of new files, changing file replication factor, etc.) and is also stored persistently on the NameNode’s local disk. When the NameNode starts, it loads the FsImage into RAM and applies the transactions from the EditLog. It then creates a new persistent FsImage file creating a checkpoint. The old EditLog is cleared at this point.

The data blocks are stored on DataNodes. These service data read and write operations of data blocks from clients. DataNode periodically sends its block list to NameNode and NameNode stores blocks to DataNode mapping in memory.

An HDFS cluster may span multiple racks in the same or different data centers. Data centers may exist in geographically different locations. Determining on which nodes the replicas are to be placed is important in HDFS, since write operations on a remote rack are more expensive than those on local racks. HDFS follows the following replica placement policy by default: The first replica is placed on the same node as the client node. If the client is outside the cluster, a random node is chosen. The second and third replicas are placed on different nodes on a rack other than the first one. The remaining replicas are placed on random nodes and no single node should contain more than one replica and no single rack should contain more than two replicas.

2.2.1.2 File Write in HDFS

The sequence of steps in a file write operation in HDFS is explained below [8].

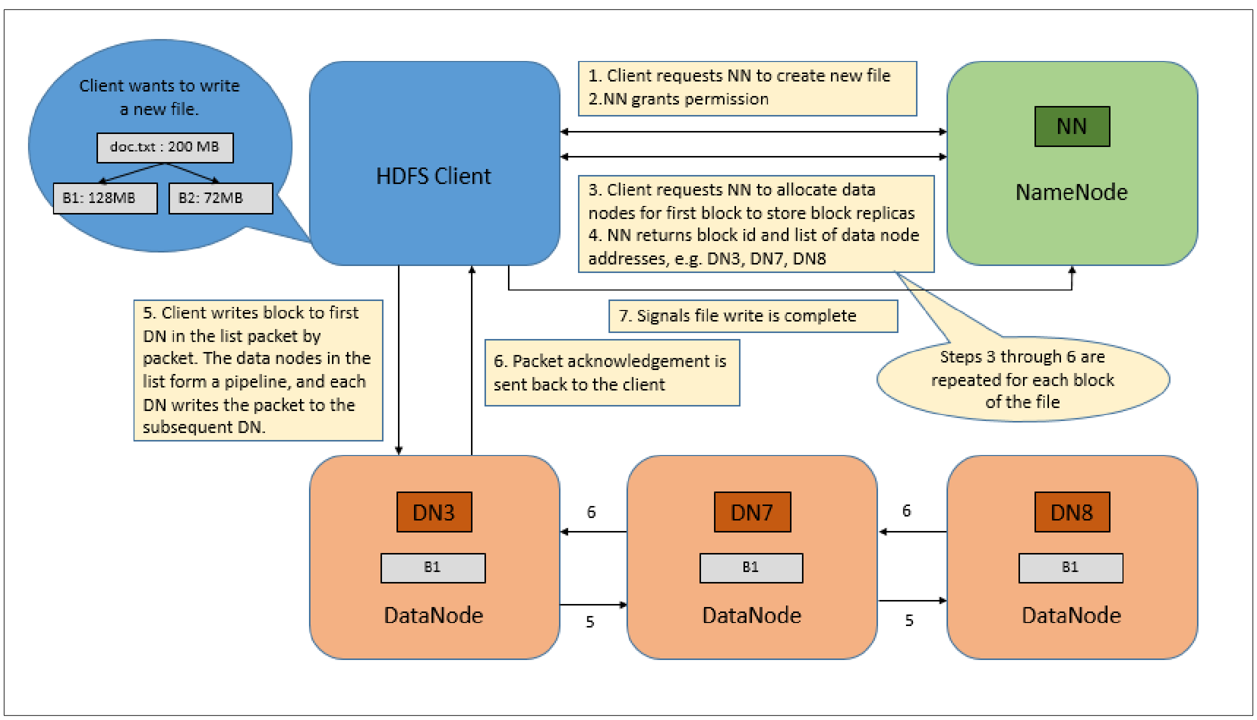


Figure 2.2. File Write in HDFS

1. Client requests NameNode to create a new file.

2. NameNode checks for client permission and duplicates and grants a lease for writing the file.
3. Client requests a list of data nodes to store block replicas.
4. NameNode returns a unique block id and a list of data node addresses.
5. The DataNodes form a pipeline and data is pushed as a sequence of packets. Client writes the packets to the first DataNode and each DataNode forwards it to the subsequent one in the pipeline. Along with the data, the checksum for each block is also sent to the DataNodes and gets stored in a metadata file.
6. For each received packet, an acknowledgement is sent back.

2.2.1.3 File Read in HDFS

The sequence of steps in a file read operation in HDFS is explained below [8].

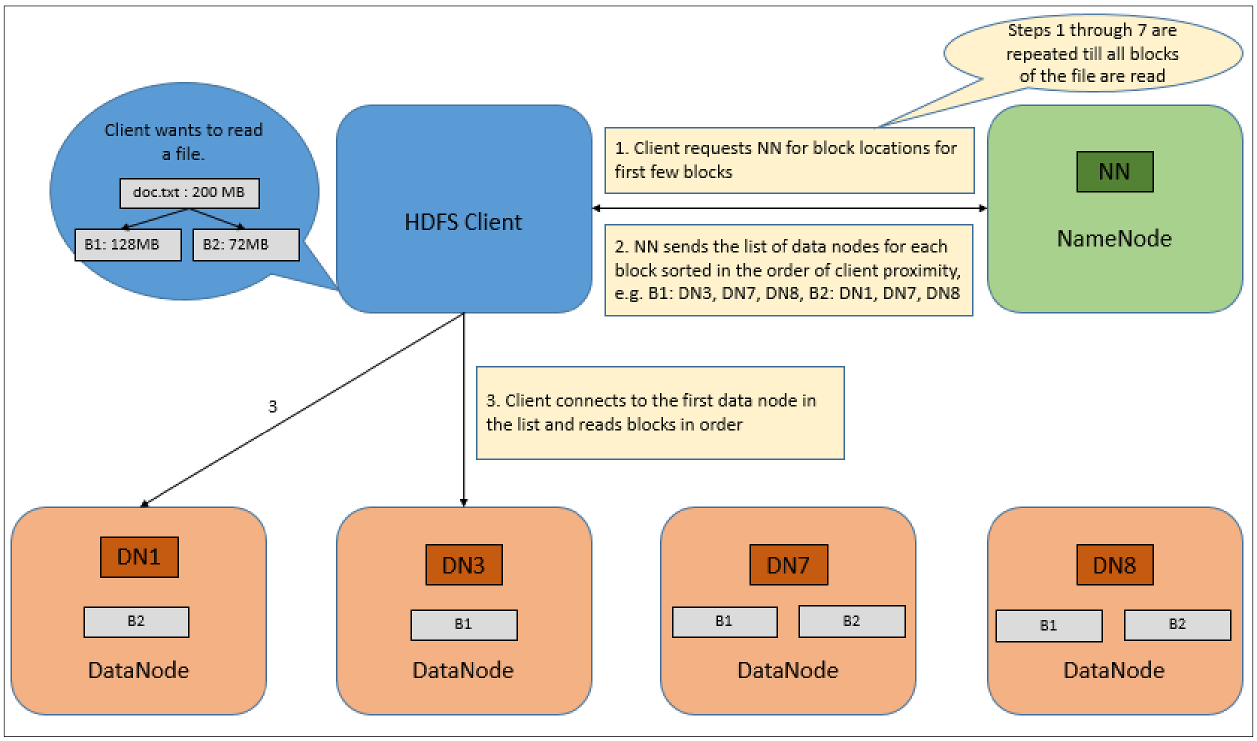


Figure 2.3. File Read in HDFS

1. Client requests the NameNode for the list of DataNodes where replicas are stored for each block of the file.
2. NameNode sends back the list of DataNode addresses sorted in the order of their distance from the client.
3. Client contacts the first DataNode in the list for each block and reads all the blocks in order. Along with the data, the block's checksum is also sent to the client and client calculates the checksum for the read data and checks if it is corrupted. If a read fails for a DataNode (DataNode is unavailable or data is corrupted), client goes to the next

DataNode in the list for block replica. The failed DataNodes will not be contacted for further block reads.

2.2.2 MapReduce

MapReduce [9] is a programming framework for distributed processing of large data sets on a cluster of computers. A MapReduce program typically consists of Map tasks and Reduce tasks. The initial input is split into smaller chunks called InputSplits, and processed by Map tasks in parallel. The output of Map tasks are then processed by Reduce tasks to produce the final output. The execution and monitoring of the tasks are handled by the framework itself. The framework typically schedules tasks local to the data and also handles re-execution of failed tasks.

InputFormat represents the input format for a MapReduce job. Default InputFormat is TextInputFormat. InputSplit represents the data to be processed by an individual Mapper. Default InputSplit is FileSplit. Default behavior of InputFormat is to split the input into byte-oriented logical input splits based on total input size with file system block size (default 128 MB in Hadoop 2.x) as the upper bound. The InputSplit is passed to a RecordReader which converts the byte-oriented input splits into record-oriented input splits. RecordReader reads InputSplit and generates <key, value> pairs. TextInputFormat uses LineRecordReader by default which returns a <key, value> pair with the key as the offset in file and value as the line.

One Mapper task is assigned for each InputSplit. Mapper takes input key-value pairs and transforms them into a set of intermediate key-value pairs. The transformation is performed by a map() method which is called for each key/value pair in the InputSplit. Intermediate outputs from Mapper are sorted and partitioned across the Reducers available. In the shuffle and sort step of the Reducer, relevant partitions are fetched and grouped based on the same key. In the reduce step of the Reducer, on each <key, (list of values)> pair in the input, reduce() method is called to produce the final output. Sometimes a Combiner is used which acts a local Reducer, which locally aggregates intermediate outputs from Mappers, thus reducing the data transfer from Mapper to Reducer.

MapReduce framework is illustrated by the word count example below:

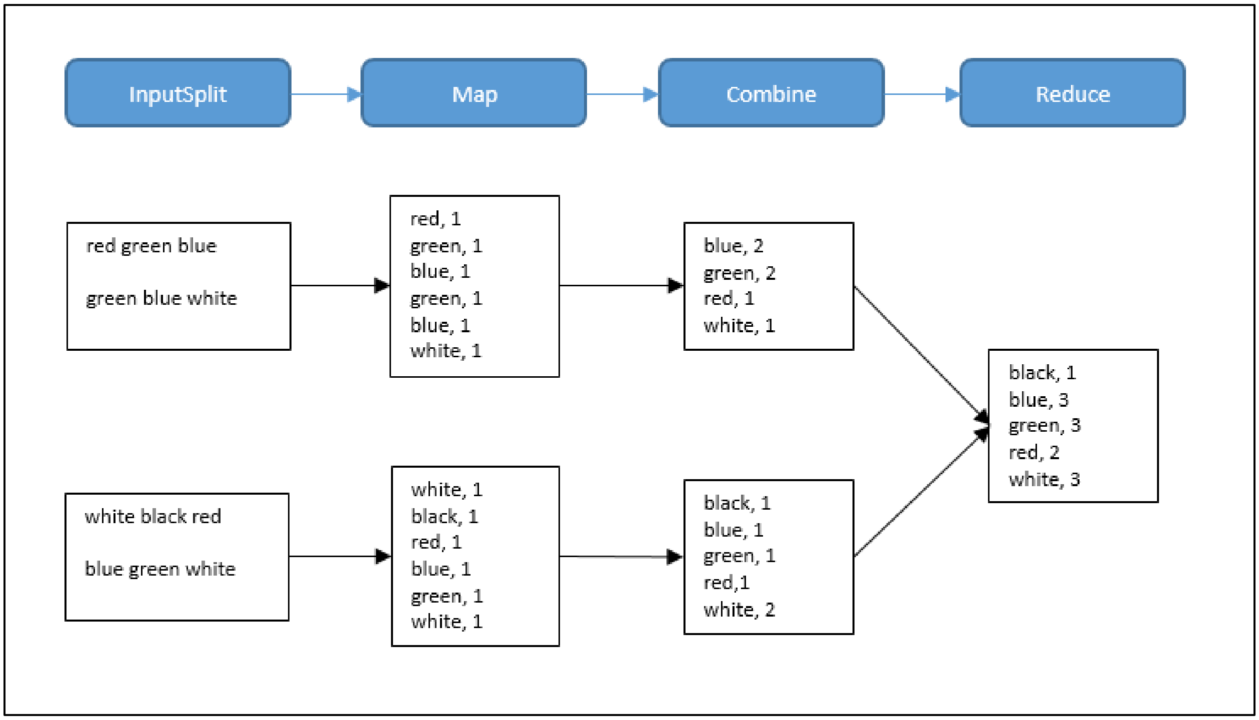


Figure 2.4. Example to Illustrate How MapReduce Works

There are two Mappers above which take each InputSplit and process it. Input to the map() function is each line and its offset in the file. The line is split into words and the intermediate outputs (<word>, 1) are generated. The combiner function which also runs locally to the Mapper, combines the count for the same word in the Mapper output. Finally, output is generated by a single Reducer where outputs from different combiners are fetched, sorted based on the key and processed to find the total count per word.

2.2.2.1 YARN / MRv2

MapReduce in Hadoop 2.x is called MapReduce 2.0 (MRv2) or YARN (Yet Another Resource Negotiator) [10]. MapReduce 1.0, the MapReduce in Hadoop 1.x, underwent many architectural changes in Hadoop 2.x.

Per-cluster ResourceManager manages resources across the cluster. Per-application ApplicationMaster is responsible for the individual MapReduce job execution and monitoring. It coordinates the Map and Reduce tasks for each MapReduce application. Per-node NodeManager is responsible for launching and monitoring the containers running in each node and reporting their status back to the ResourceManager. Containers run ApplicationMaster and MapReduce tasks with certain allocated computation resources.

2.2.2.2 Steps in MapReduce Job Execution

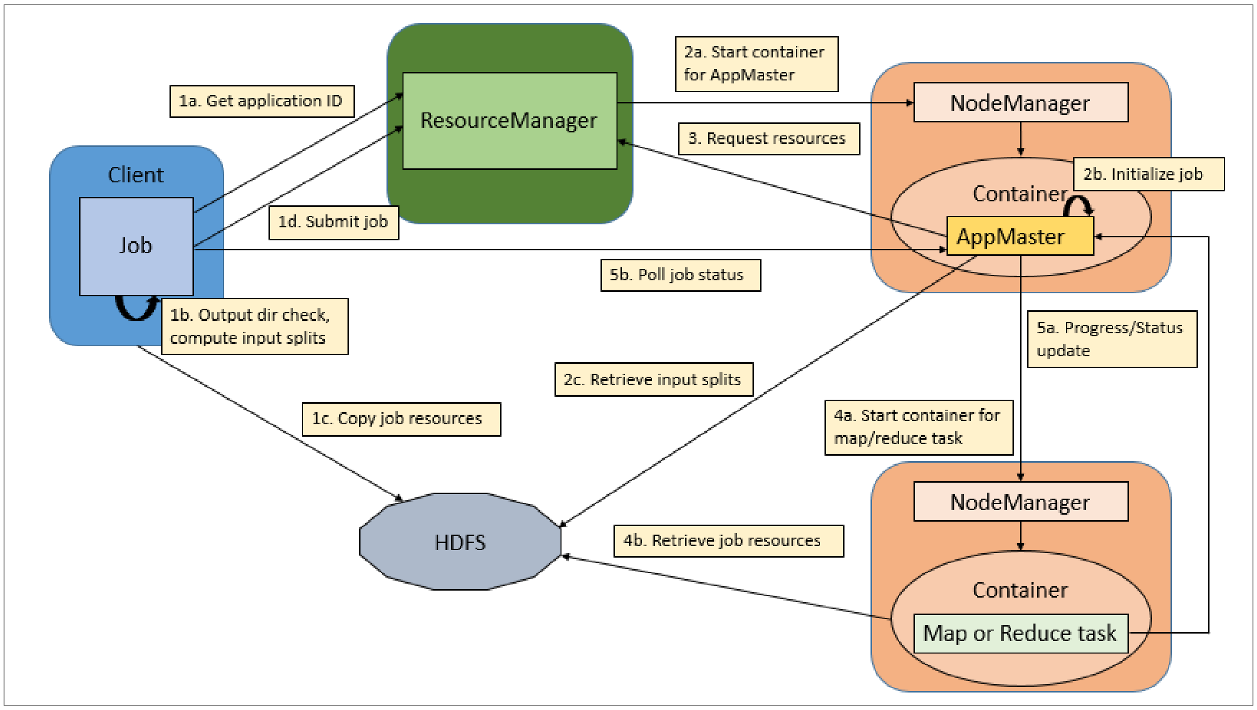


Figure 2.5. Steps in MapReduce Job Execution [8] [11]

1. Job Submission

   1.1. Client asks for an application ID from the ResourceManager.

   1.2. Check if output directory is specified and does not already exist. Checks input files are specified and calculates input splits.

   1.3. Copy resources like job jar file, configuration file and input splits to HDFS.

   1.4. Submit the job to ResourceManager.

2. Job Initialization

   2.1. ResourceManager's scheduler allocates container for ApplicationMaster and starts the container by contacting the NodeManager.

   2.2. ApplicationMaster initializes the job by creating the objects required for job progress tracking.

   2.3. ApplicationMaster retrieves the input splits from filesystem and creates map task for each input split. It also creates the required number of reducer tasks.

3. Task Assignment

   ApplicationMaster requests resources for map and reduce tasks to ResourceManager's scheduler. Scheduler tries to allocate map task on nodes where the data (input split) is already stored.

4. Task Execution

4.1. ApplicationMaster contacts the NodeManagers and asks to start the containers for map and reduce tasks.

4.2. Resources are retrieved from the filesystems.

Map/Reduce tasks are executed.

5. Job Progression and Completion

5.1. Map and reduce tasks send the progress (how much data is processed), status (running, completed, failed) updates and a set of counter values to the ApplicationMaster every three seconds. Thus ApplicationMaster gets notified when the job is finished.

5.2. Client polls ApplicationMaster for job status and learns when job is finished.

CHAPTER 3

SET UP SINGLE-NODE HADOOP CLUSTER USING CLOUDERA QUICKSTART VM

Specialized Hadoop vendors such as Cloudera, HortonWorks, and MapR provide data management and analytical platforms packaged around Apache Hadoop. Commercialized Hadoop solutions are also available from well-known enterprises like Microsoft (Microsoft HDInsight on Microsoft cloud (Microsoft Azure), IBM (IBM BigInsights on IBM cloud (IBM SmartCloud), Amazon (Amazon Elastic MapReduce (EMR) on Amazon cloud (Amazon Web Services (AWS)). A complete list of companies who provide products that include Apache Hadoop or derivative works and commercial support can be found in Hadoop wiki [12]. The enterprise users make use of the support and services provided by these vendors to avoid complications related to Hadoop setup and maintenance and to solve their business challenges more efficiently. Cloudera's Hadoop distribution [13], CDH (Cloudera Distribution Including Apache Hadoop), comes in many flavors. Cloudera QuickStart VM provides a single-node Hadoop cluster setup and makes it easy for beginners to gain hands-on experience on Hadoop from their local machines.

3.1 Set Up Cloudera QuickStart VM

Below are the system requirements:

- 64-bit host OS
- Player 4.x or higher (Windows) or Fusion 4.x or higher (Mac)
- Minimum RAM requirement is 4GB. Allocate more memory for larger workloads.

Follow below steps to install Cloudera QuickStart VM:

1. Download VMware Player [14].
2. Download QuickStart VM from Cloudera web site for VMware format [15]. (Downloads are available for VMware, KVM, and VirtualBox formats as Zip archives.)
3. Unzip the package. (Cloudera recommends using 7-Zip to extract files)

4. Open VMware Player and click on ‘Open a Virtual Machine’. Browse to the extracted folder and select the file cloudera-quickstart-vm-<version>-vmware.vmx (VMware virtual machine configuration file). Cloudera VM will be listed as below.

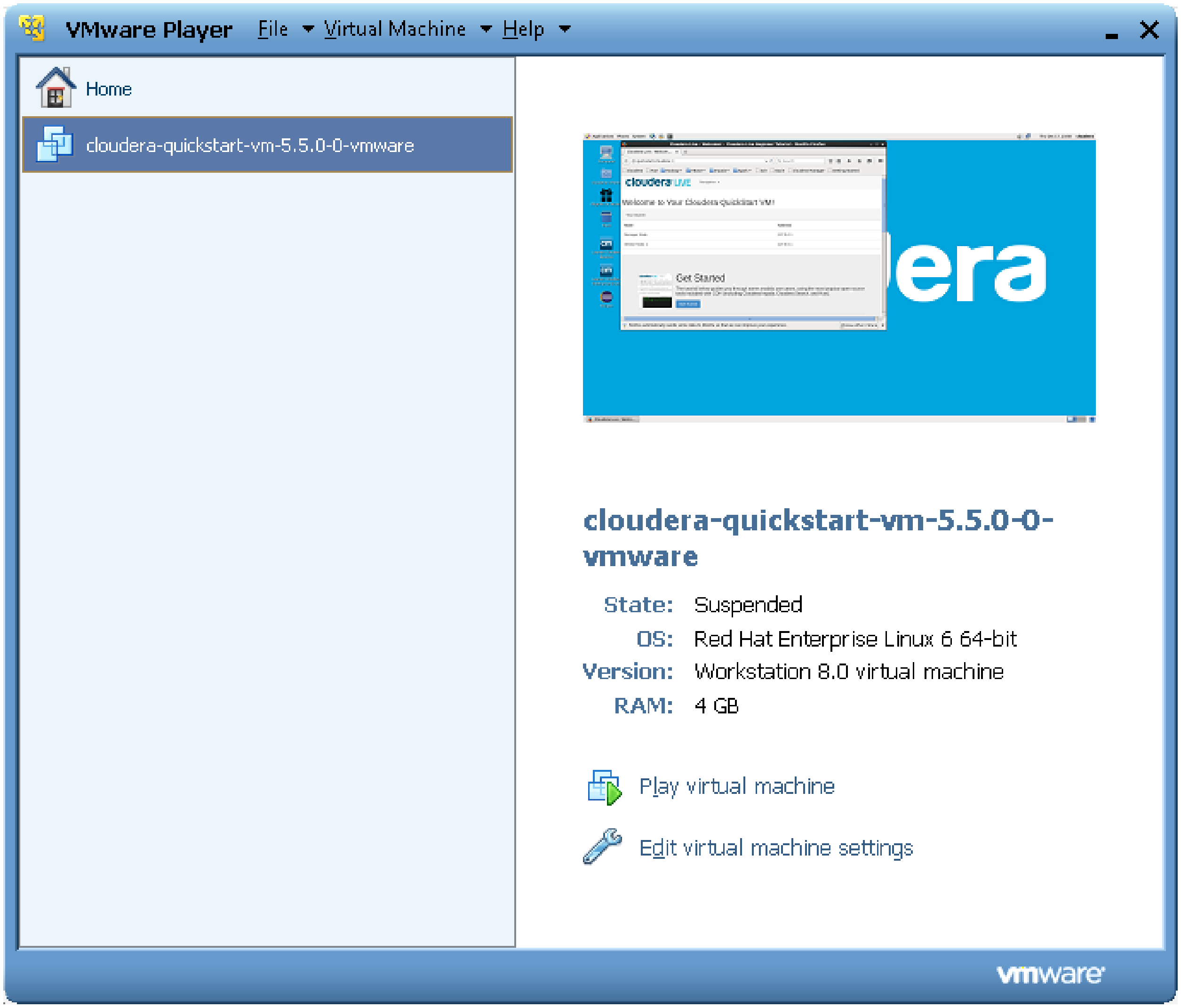


Figure 3.1. Cloudera VM Listed in VMware Player

5. Select the VM and click on ‘Play virtual machine’. (If Virtualization Support is not enabled on your Windows host machine, related errors may pop up. This can be solved by enabling Virtualization Technology in BIOS setting.) The VM runs CentOS 6.4. The VM starts and the user is automatically logged in as the cloudera user (both username and password are ‘cloudera’). A browser opens up as below with useful links to various Hadoop tools on the Bookmarks bar.

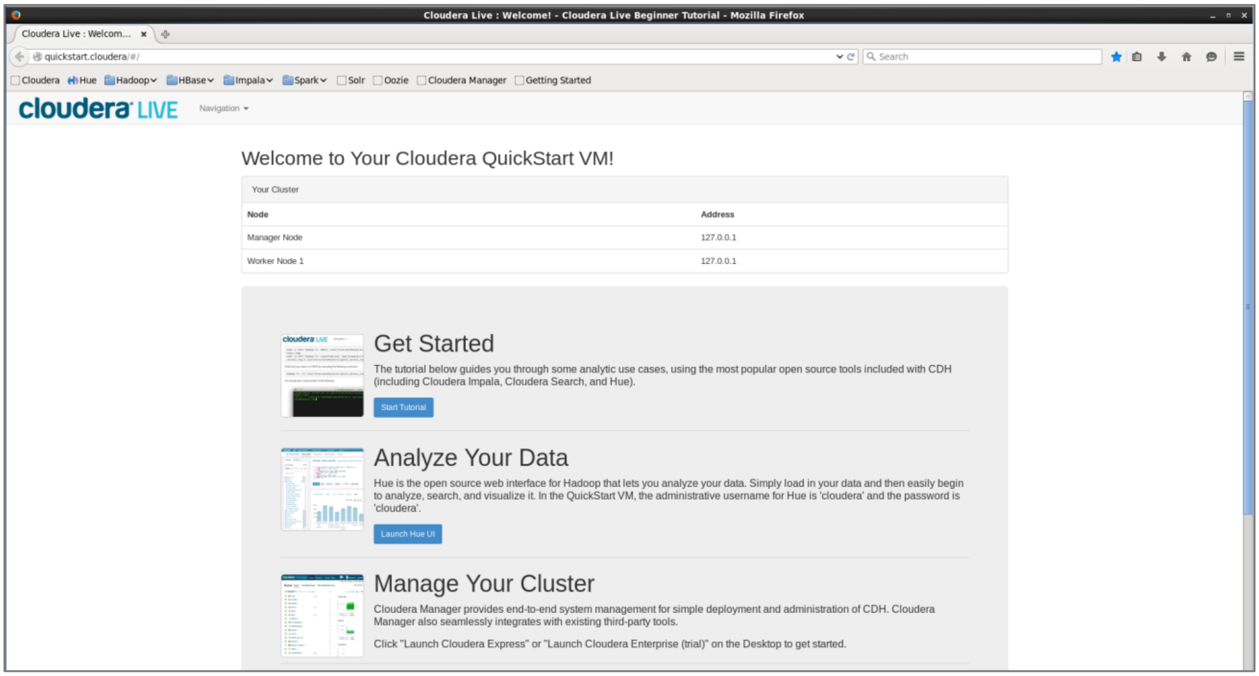


Figure 3.2. Browser in the Cloudera VM with Bookmark Links

6. Open Terminal and go to /usr/bin. Hadoop, Pig, Hive, HBase, Sqoop, Flume etc. are installed under the directories with the respective names.

3.1.1 HADOOP Configuration Files

The configuration files can be found under etc/Hadoop directory in Hadoop installation directory.

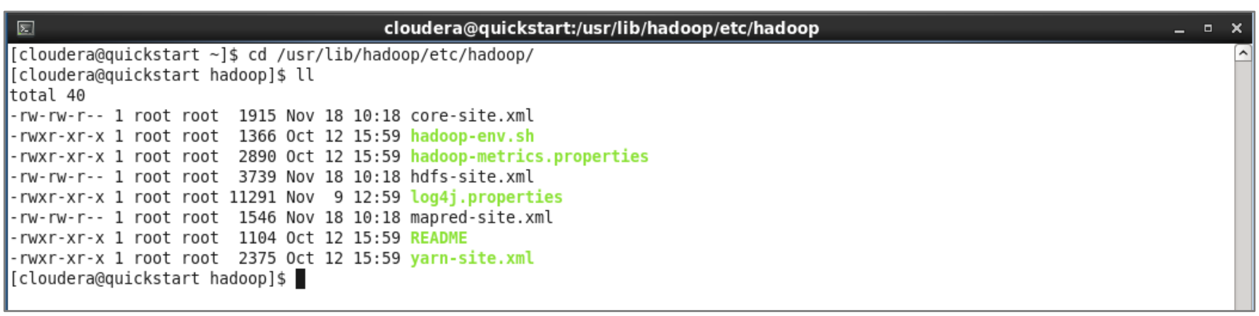


Figure 3.3. Hadoop Configuration Files

- hadoop-env.sh
- Environment settings for Hadoop scripts found in bin directory of Hadoop distribution
- core-site.xml
- Settings common to HDFS and MapReduce

- hdfs-site.xml
- Configurations for NameNode and DataNode
- yarn-site.xml
- Configurations for ResourceManager and NodeManager
- mapred-site.xml
- Configurations for MapReduce Applications and MapReduce JobHistory Server

3.2 Running Wordcount Example

Hadoop distribution comes with MapReduce examples jar file which has a number of example MapReduce programs. We will see how to execute the wordcount program from this jar. The word count problem was explained in section 2.2.2 and the same sample data is used here.

1. To display all the programs available within hadoop-mapreduce-examples.jar:

```
$ cd /usr/lib/hadoop-mapreduce
$ hadoop jar hadoop-mapreduce-examples.jar
```

2. Create input files for the wordcount program. Create files input1.txt and input2.txt on Desktop.

```
[cloudera@quickstart ~]$ cat /home/cloudera/Desktop/input1.txt
red green blue
blue green white

[cloudera@quickstart ~]$ cat /home/cloudera/Desktop/input2.txt
white black red
blue green white
```

3. Copy the input files to HDFS. Create an input folder under /user/cloudera/in and copy the input files.

```
[cloudera@quickstart ~]$ $ hdfs dfs -mkdir /user/cloudera/in

[cloudera@quickstart ~]$ $ hdfs dfs -copyFromLocal /home/cloudera/Desktop/input1.txt
/user/cloudera/in

[cloudera@quickstart ~]$ $ hdfs dfs -copyFromLocal /home/cloudera/Desktop/input2.txt
/user/cloudera/in

[cloudera@quickstart ~]$ hdfs dfs -ls /user/cloudera/in
Found 2 items
-rw-r--r--   1 cloudera cloudera         32 2015-12-29 22:50
/user/cloudera/in/input1.txt
-rw-r--r--   1 cloudera cloudera         33 2015-12-29 22:51
/user/cloudera/in/input2.txt
```

Note: The user can interact with HDFS using HDFS shell, which can be invoked by *hdfs dfs <command> <args>*. 'args' are file path URIs. URI format is *scheme://authority/path*. If the scheme and authority are not specified, the default values from configuration will be used. For example, *hdfs://host/path* and */path* are identical, if the configuration is set to point to *hdfs://host/*. [16]

4. Run wordcount program. Make sure the output folder does not exist already.

```
[cloudera@quickstart ~]$  hadoop jar hadoop-mapreduce-examples.jar wordcount
/user/cloudera/in/input /user/cloudera/output
```

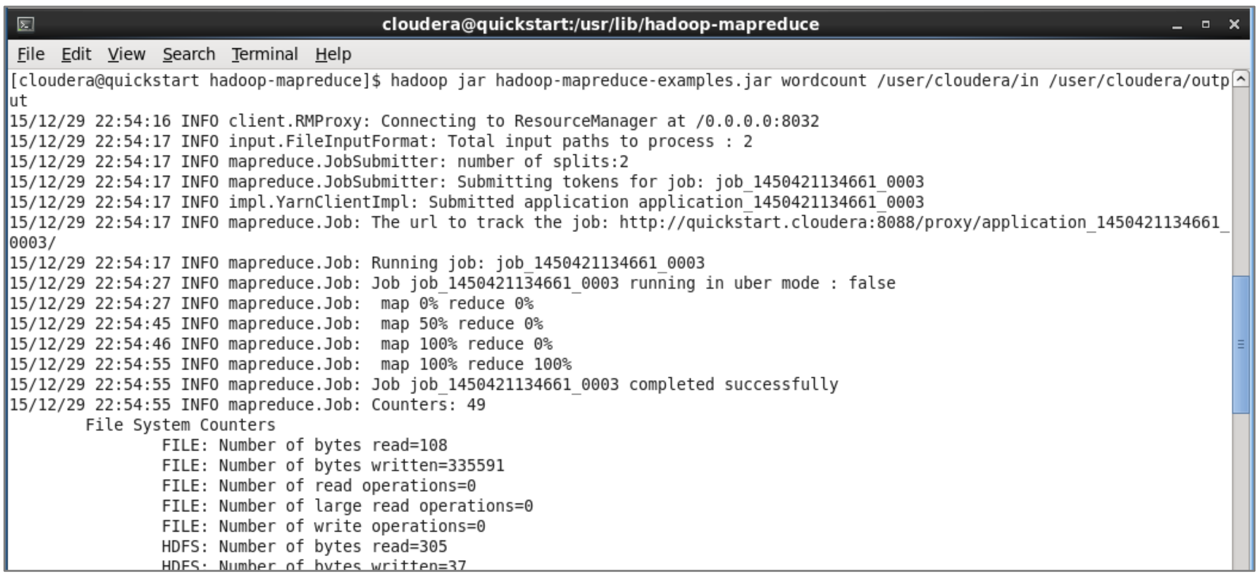
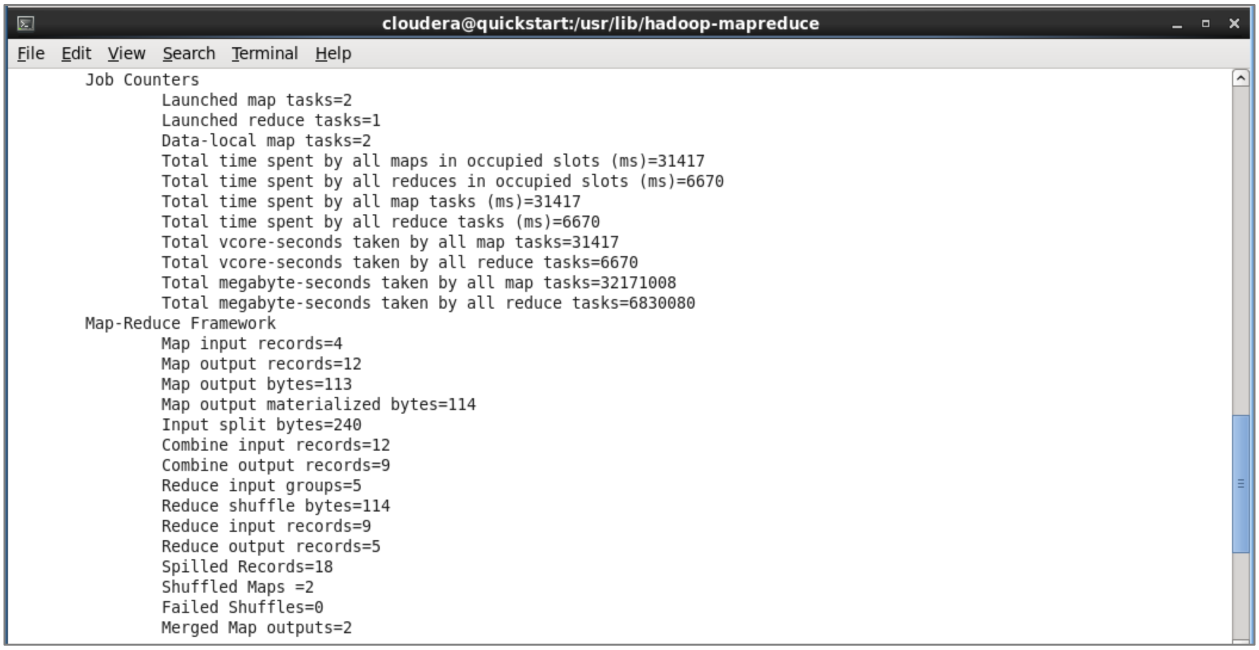


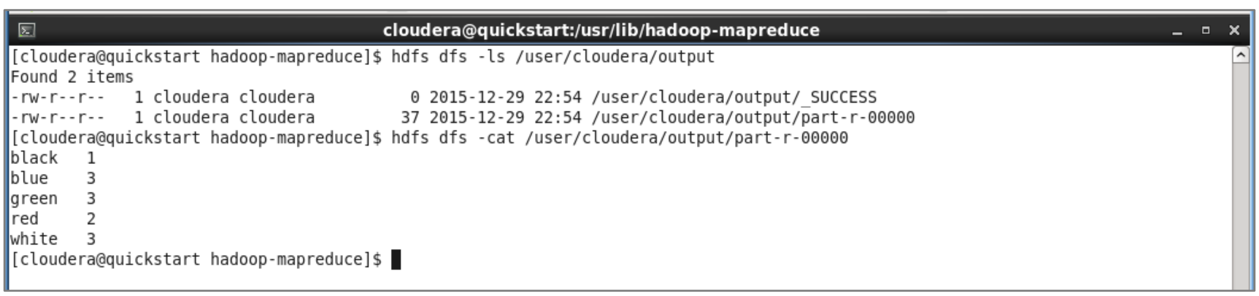
Figure 3.4. Running wordcount Program



```
cloudera@quickstart:/usr/lib/hadoop-mapreduce
File  Edit  View  Search  Terminal  Help
        Job Counters
                Launched map tasks=2
                Launched reduce tasks=1
                Data-local map tasks=2
                Total time spent by all maps in occupied slots (ms)=31417
                Total time spent by all reduces in occupied slots (ms)=6670
                Total time spent by all map tasks (ms)=31417
                Total time spent by all reduce tasks (ms)=6670
                Total vcore-seconds taken by all map tasks=31417
                Total vcore-seconds taken by all reduce tasks=6670
                Total megabyte-seconds taken by all map tasks=32171008
                Total megabyte-seconds taken by all reduce tasks=6830080
        Map-Reduce Framework
                Map input records=4
                Map output records=12
                Map output bytes=113
                Map output materialized bytes=114
                Input split bytes=240
                Combine input records=12
                Combine output records=9
                Reduce input groups=5
                Reduce shuffle bytes=114
                Reduce input records=9
                Reduce output records=5
                Spilled Records=18
                Shuffled Maps =2
                Failed Shuffles=0
                Merged Map outputs=2
```

Figure 3.5. MapReduce Job Counters and Framework Details in the Execution Log

5. Verify output.



```
cloudera@quickstart:/usr/lib/hadoop-mapreduce
[cloudera@quickstart hadoop-mapreduce]$ hdfs dfs -ls /user/cloudera/output
Found 2 items
-rw-r--r--   1 cloudera cloudera          0 2015-12-29 22:54 /user/cloudera/output/_SUCCESS
-rw-r--r--   1 cloudera cloudera         37 2015-12-29 22:54 /user/cloudera/output/part-r-00000
[cloudera@quickstart hadoop-mapreduce]$ hdfs dfs -cat /user/cloudera/output/part-r-00000
black   1
blue    3
green   3
red     2
white   3
[cloudera@quickstart hadoop-mapreduce]$ 
```

Figure 3.6. MapReduce Job Output

CHAPTER 4

MAPREDUCE PROGRAMMING

In this chapter, we will see how to develop a MapReduce program using eclipse as the development environment.

4.1 Use Case

The dataset used is the MovieLens 1M Dataset [17] provided by GroupLens Research. The dataset is obtained by GroupLens from MovieLens, a movie recommendation website. This data set contains 10000054 ratings and 95580 tags applied to 10681 movies by 71567 users in three files, movies.dat, ratings.dat and tags.dat.

Movies.dat files contains movie information with format MovieID::Title::Genres (sample row: 1356::Star Trek: First Contact (1996)::Action|Adventure|Sci-Fi). Ratings.dat file contains movie rating given by users with format UserID::MovieID::Rating::Timestamp (sample row: 2::647::3::978299351).

We will develop a MapReduce application to find the average movie rating using rating.dat file.

- First copy the input files to HDFS.

```
cloudera@quickstart ~]$  hdfs dfs –mkdir /user/cloudera/input

[cloudera@quickstart ~]$  hdfs dfs -copyFromLocal /home/cloudera/Desktop/ratings.dat
/user/cloudera/input
```

- In the Cloudera VM, open eclipse. Create a new java project. Add dependencies jars. Right click on the project -> Build Path -> Configure Build Path. On Libraries tab, select Add External Jars. Browse and add the jars under /usr/lib/Hadoop/client-0.20.

4.2 Source Code

```
// MovieAvgRating.java
import java.io.IOException;
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.FloatWritable;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
public class MovieAvgRating {
	public static class Map extends
			Mapper<LongWritable, Text, Text, IntWritable> {
		public void map(LongWritable key, Text value, Context context)
				throws IOException, InterruptedException {
			String[] tokens = value.toString().split("::");
			String movie = tokens[1];
			int rating = Integer.parseInt(tokens[2]);
			context.write(new Text(movie), new IntWritable(rating));
		}
	}
	public static class Reduce extends
			Reducer<Text, IntWritable, Text, FloatWritable> {
		public void reduce(Text key, Iterable<IntWritable> values,
				Context context) throws IOException, InterruptedException {
			int counter = 0; int sum = 0;
			for (IntWritable val : values) {
				sum += val.get();
				counter++;
			}
			float avg = sum / counter;
			context.write(key, new FloatWritable(avg));
		}
	}
```

```
        public static void main(String[] args) throws Exception {
                Configuration conf = new Configuration();
                Job job = Job.getInstance(conf, "movie rating");
                job.setJarByClass(MovieAvgRating.class);
                job.setMapperClass(Map.class);
                job.setReducerClass(Reduce.class);
                job.setOutputKeyClass(Text.class);
                job.setMapOutputValueClass(IntWritable.class);
                job.setOutputValueClass(FloatWritable.class);
                FileInputFormat.addInputPath(job, new Path(args[0]));
                FileOutputFormat.setOutputPath(job, new Path(args[1]));
                System.exit(job.waitForCompletion(true) ? 0 : 1);
            }
        }
}
```

A MapReduce application typically implements map and reduce methods of Mapper and Reduce classes, respectively. Here the map method processes the input file line by line, splits the lines based on the given delimiter "::" and creates the mapper output key-value pair as (MovieID, Rating). The reduce method calculates the average of values (ratings) for each key (MovieID) and gives the output key-value pair (MovieID, Average Rating).

It is important to give the correct types for input and output key-value pairs. For example, since the average rating calculated is a float value, the type of output value of Reduce method is given as FloatWritable.

In the main method, the MapReduce job configuration is created via Job instance. Mapper, Reducer, key/value types, input files and output paths can be configured in a Job. job.waitForCompletion submits the job and monitors its progress.

4.3 Execution

1. For debugging, the program can be executed in eclipse using a sample input file. In this case, Hadoop runs in LocalJobRunner mode, where all daemons run in a single JVM. The built-in debug features of eclipse can be handy at this stage. Also, the input and output files will be in local file path, not HDFS.

2. Create a sample input file data.txt with a few lines of data from ratings.dat within the project folder.
3. Next create a Run Configuration for the application. Go to Run -> Run Configuration -> Java Application, right click and select New. In the arguments tab, enter the input file data.txt and name of output folder which will be created inside the project folder for the program output. Click on Run and verify the output.
4. To run the program in the cluster mode, the project needs to be exported into a jar file. Right click on the project and select Export. Select Java -> Jar File -> Enter the export destination (say home/cloudera/Desktop/movierating.jar) -> Next -> Next. For ‘Select the class of the application entry point’, click on Browse and select the class name MovieAvgRating and click on Finish.
5. On the terminal, go to Desktop and enter the following command to execute the MapReduce application.

```
cloudera@quickstart ~]$  hadoop jar movierating.jar /user/cloudera/input/ratings.dat
/user/cloudera/output
```

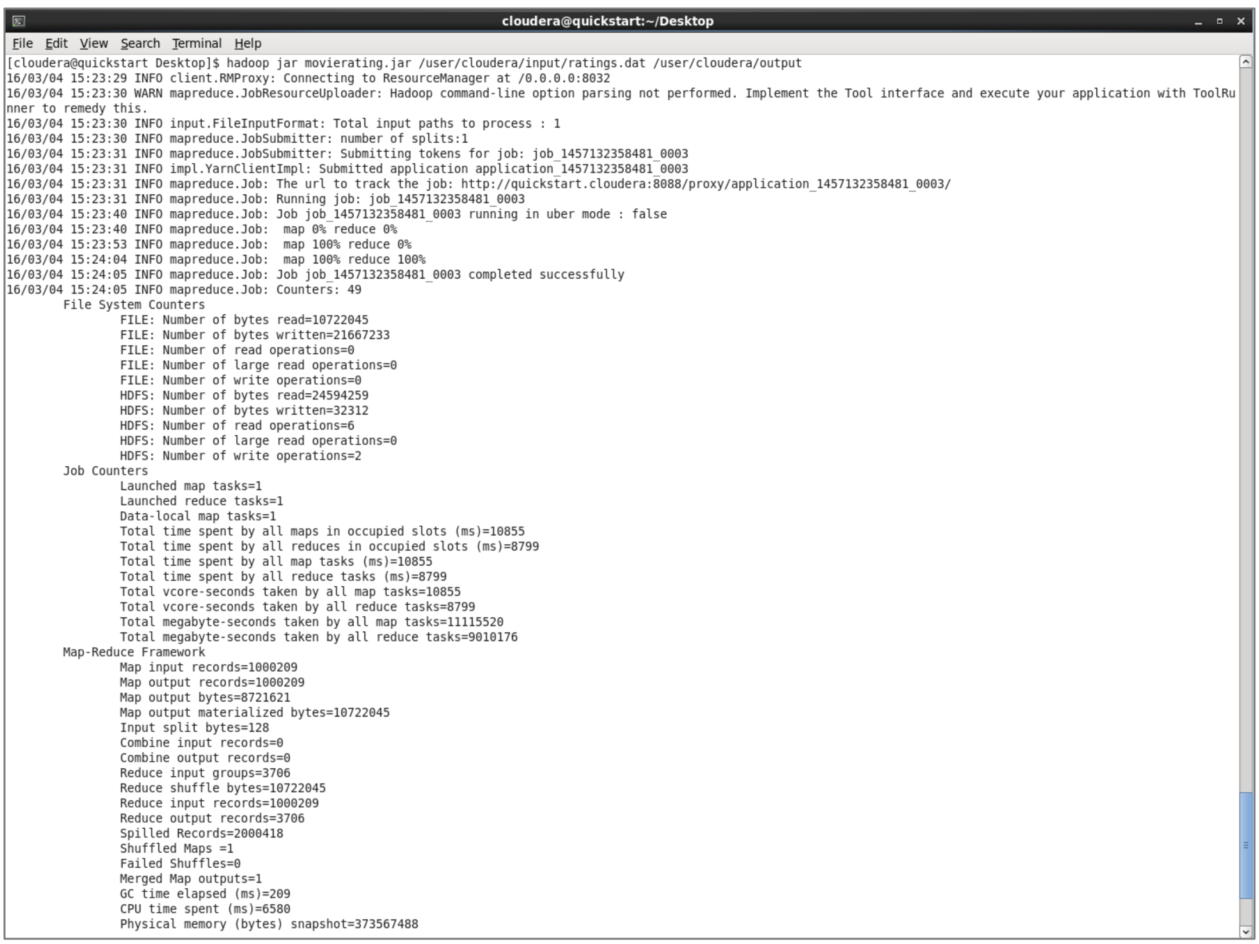


Figure 4.1. Executing MapReduce Application

If the application entry point was not set with the class name in the jar, the main class name needs to be specified during the execution as below:

```
cloudera@quickstart ~]$  hadoop jar movierating.jar MovieAvgRating
/user/cloudera/data/rating.dat /user/cloudera/output
```

6. Verify output.

```
[cloudera@quickstart ~]$ hdfs dfs -ls /user/cloudera/output
Found 2 items
-rw-r--r--   1 cloudera cloudera          0 2016-01-31 00:13
/user/cloudera/output/_SUCCESS
-rw-r--r--   1 cloudera cloudera      32221 2016-01-31 00:13
/user/cloudera/output/part-r-00000
[cloudera@quickstart ~]$ hdfs dfs -cat /user/cloudera/output/part-r-00000
```

Figure 4.2. Displaying the Output File

7. Output can be copied from HDFS to local file path and opened in a file editor or shared as needed.

```
[cloudera@quickstart ~]$ hdfs dfs –copyToLocal /user/cloudera/output/ part-r-00000
/home/cloudera/Desktop
```

CHAPTER 5

DATA ANALYSIS USING APACHE PIG

Pig [18] is a data analysis platform for big data which runs on top of Hadoop. Pig uses a procedural language called Pig Latin and Pig compiler converts it into a sequence of MapReduce jobs. Pig allows the user to perform complex data analysis easily without the need to write the equivalent MapReduce programs in Java.

5.1 Execution Modes

Pig can be run either in interactive mode or batch mode. To run in interactive mode, invoke Grunt shell using ‘pig’ command and then enter the Pig commands and statements interactively in the Grunt shell. Pig can be run in batch mode using Pig scripts. Pig script is a group of Pig commands and statements put into a single file. The pig script files usually use .pig extension, though it is not mandatory.

Interactive mode or batch mode can be run either in local or MapReduce mode. In local mode, there is no distributed execution; rather it uses the local host and file system where Pig is running.

$ pig -x local

In MapReduce mode, which is the default mode, the execution is done in a distributed fashion on the Hadoop cluster.

$ pig Or $ pig -x mapreduce

5.2 Using Pig For Data Analysis

The dataset used is the MovieLens 1M Dataset [14] mentioned earlier in chapter 4. We will write a pig script to compute the average movie rating using movies.dat and ratings.dat files.

1. PigStorage, the built-in default load function is used here to load the input files. Since it takes only a single character as field delimiter, we are doing a simple preprocessing of input files to change the delimiter form ‘::’ to ‘:’. (Another option would be to write a user-defined load function to load input in a specific format.)

   $ sed -i 's/::/:/g' movies.dat ratings.dat

2. Copy the input files to HDFS.

```
cloudera@quickstart ~]$  hdfs dfs –mkdir /user/cloudera/data

cloudera@quickstart ~]$  hdfs dfs -copyFromLocal /home/cloudera/Desktop/movies.dat
/user/cloudera/data

cloudera@quickstart ~]$  hdfs dfs -copyFromLocal /home/cloudera/Desktop/ratings.dat
/user/cloudera/data
```

3. Create a pig script, named MovieRatings.pig, as below.

```
-- Load movies.dat
movies =  LOAD '/user/cloudera/data/movies.dat' USING PigStorage(':') As
(MovieID:chararray, Title:chararray, Genres:chararray);

-- Load ratings.dat
ratings = LOAD '/user/cloudera/data/ratings.dat' USING PigStorage(':') AS
(UserID:chararray, MovieID:chararray, Rating:float, Timestamp:chararray);

-- Group by MovieID and compute average rating per movie
grp_movies = GROUP ratings by (MovieID);
avg_rating = FOREACH grp_movies GENERATE group as MovieID,
ROUND(AVG(ratings.Rating)*100.0)/100.0 as Avg_Rating;

-- Join average ratings and movies based on MovieID to map the movie title to the
average rating
join_movies_avg_rating = JOIN movies by MovieID, avg_rating by MovieID;

-- Generate the final output and sort by average rating
movies_avg_rating = FOREACH join_movies_avg_rating GENERATE $0 as MovieID, $1 as
Title, $4 as Avg_Rating;


movies_avg_rating_sorted = ORDER movies_avg_rating BY Avg_Rating DESC;
STORE movies_avg_rating_sorted INTO '/user/cloudera/pig/out';
```

First, data is loaded from input files using LOAD operator to form relations ‘movies’ and ‘ratings’. Ratings are grouped by MovieID using GROUP operator and the average rating is then calculated for each Movie. Relations movies and avg_rating are joined based on the common field MovieID using JOIN operator so that movie title from movies relation can be mapped to the average rating from avg_rating relation. Final output is generated by picking the columns MovieID, Title and Avg_Rating. Output is sorted in descending order of average rating. STORE command is used to save the final output on HDFS.

4. Execute the pig script.

```
$ pig MovieRating.pig
```

```
cloudera@quickstart:~
File  Edit  View  Search  Terminal  Help

HadoopVersion   PigVersion      UserId  StartedAt       FinishedAt      Features
2.6.0-cdh5.5.0  0.12.0-cdh5.5.0 cloudera        2016-01-01 23:37:38     2016-01-01 23:40:10     HASH_JOIN,GROUP_BY,ORDER_BY

Success!

Job Stats (time in seconds):
JobId   Maps    Reduces MaxMapTime      MinMapTIme      AvgMapTime      MedianMapTime   MaxReduceTime   MinReduceTime   AvgReduc
eTime   MedianReducetime        Alias   Feature Outputs
job_1450421134661_0064  1       1       13      13      13      13      7       7       7       7       avg_rating,grp_movies,ra
tings   GROUP_BY,COMBINER
job_1450421134661_0065  2       1       12      11      12      12      8       8       8       8       join_movies_avg_rating,m
ovies,movies_avg_rating HASH_JOIN
job_1450421134661_0066  1       1       5       5       5       5       6       6       6       6       movies_avg_rating_sorted
SAMPLER
job_1450421134661_0067  1       1       5       5       5       5       6       6       6       6       movies_avg_rating_sorted
ORDER_BY        /user/cloudera/pig/out,

Input(s):
Successfully read 1000209 records (21593884 bytes) from: "/user/cloudera/pig/ratings.dat"
Successfully read 3883 records from: "/user/cloudera/pig/movies.dat"

Output(s):
Successfully stored 3706 records (123578 bytes) in: "/user/cloudera/pig/out"

Counters:
Total records written : 3706
Total bytes written : 123578
Spillable Memory Manager spill count : 0
Total bags proactively spilled: 0
Total records proactively spilled: 0
```

Figure 5.1. Execution Logs on the Console

5. Verify output.

```
[cloudera@quickstart ~]$ hdfs dfs -ls /user/cloudera/pig/out
Found 2 items
-rw-r--r--   1 cloudera cloudera          0 2016-01-31 23:40
/user/cloudera/pig/out/_SUCCESS
-rw-r--r--   1 cloudera cloudera      32221 2016-01-31 23:40
/user/cloudera/pig/out/part-r-00000
[cloudera@quickstart ~]$ hdfs dfs -cat /user/cloudera/pig/out/part-r-00000
```

```
138     Neon Bible, The (1995)  2.5
1773    Tokyo Fist (1995)       2.5
1782    Little City (1998)      2.5
2242    Grandview, U.S.A. (1984)        2.5
2200    Under Capricorn (1949)  2.5
3592    Time Masters (Les Ma�tres du Temps) (1982)      2.5
505     North (1994)    2.49
132     Jade (1995)     2.49
3579    I Dreamed of Africa (2000)      2.49
1592    Air Bud (1997)  2.49
2306    Holy Man (1998) 2.49
2373    Red Sonja (1985)        2.48
3453    Here on Earth (2000)    2.48
19      Ace Ventura     2.48
1887    Almost Heroes (1998)    2.48
2458    Armed and Dangerous (1986)      2.48
1359    Jingle All the Way (1996)       2.48
3162    Simpatico (1999)        2.48
415     Another Stakeout (1993) 2.48
2992    Rawhead Rex (1986)      2.48
3004    Bachelor, The (1999)    2.48
447     Favor, The (1994)       2.48
191     Scarlet Letter, The (1995)      2.47
489     Made in America (1993)  2.47
1520    Commandments (1997)     2.47
611     Hellraiser      2.47
3626    8 1/2 Women (1999)      2.47
```

Figure 5.2. Pig Script Output (Column 1: MovieID, Column 2: Title, Column 3: Average Rating)

6. DUMP command is useful for debugging. DUMP, unlike STORE, will not store the results persistently in the file system; rather it will display the results on the screen. You can create a relation and then 'DUMP' it to verify the correctness of the result.

For example, *DUMP avg_rating* will give the result below:

```
(3431,2.67)
(3432,2.26)
(3433,2.15)
(3434,2.26)
(3435,4.42)
(3436,2.79)
(3437,2.0)
(3438,2.68)
(3439,2.13)
(3440,1.92)
(3441,3.28)
(3442,2.31)
(3443,3.8)
(3444,3.23)
(3445,3.19)
(3446,3.41)
(3447,3.72)
(3448,3.73)
(3449,2.97)
(3450,3.42)
(3451,3.92)
(3452,3.14)
(3453,2.48)
(3454,2.7)
(3456,3.94)
(3457,2.99)
(3458,3.0)
```

Figure 5.3. Output of DUMP avg_rating

7. DESCRIBE is another useful operator. It is useful to understand the schema of a relation. For example, `DESCRIBE join_movie_avg_rating` will display the schema as:

```
join_movie_avg_rating: {movie::MovieID: chararray, movie::Title:
chararray, movie::Genres: chararray, avg_rating::MovieID: chararray,
avg_rating::Avg_Rating: double}
```

5.3 Using Pig Editor In Hue

Hue [19] provides a user friendly web interface for data analysis using Hadoop. Open Hue interface (http://quickstart.cloudera:8888/). If prompted for user/password, enter cloudera/cloudera.

1. Choose Query Editors -> Pig. 'Editor' screen is displayed. Previously created scripts can be managed from 'Scripts' screen. Previously executed jobs can be viewed on Dashboard screen.

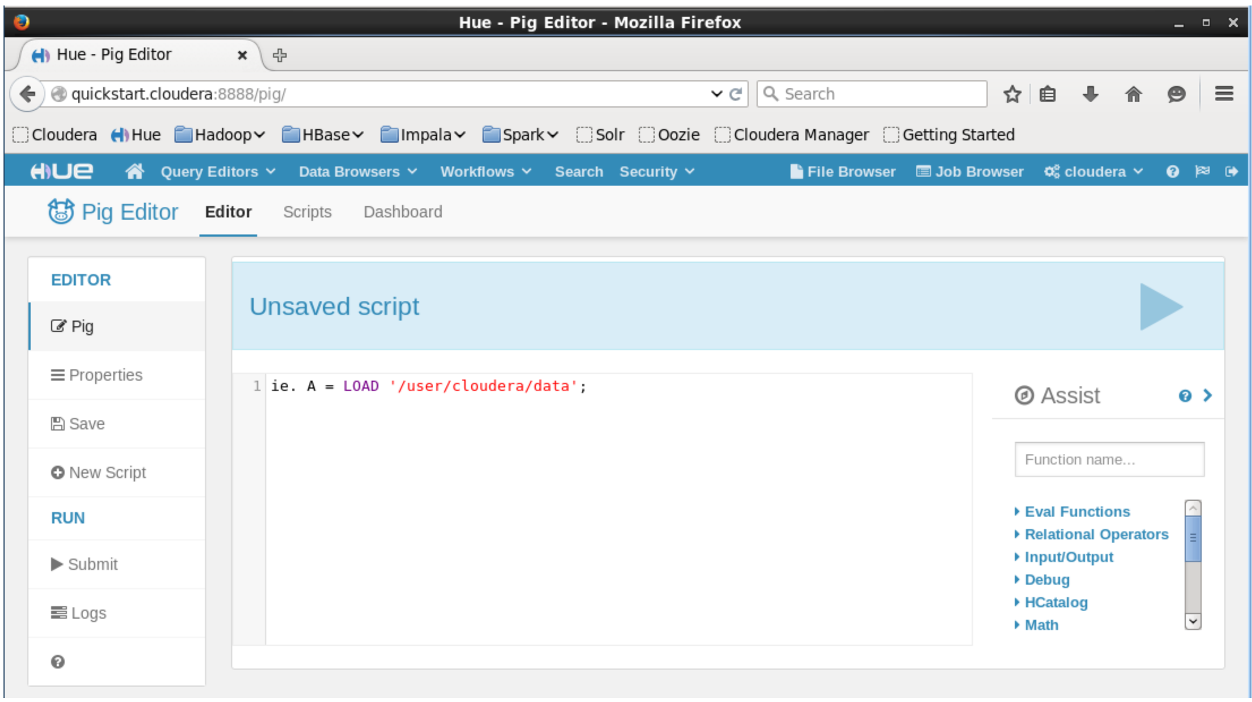


Figure 5.4. Pig Editor in Hue

2. Click on New Script on the left panel, create the script and save it by giving a name.

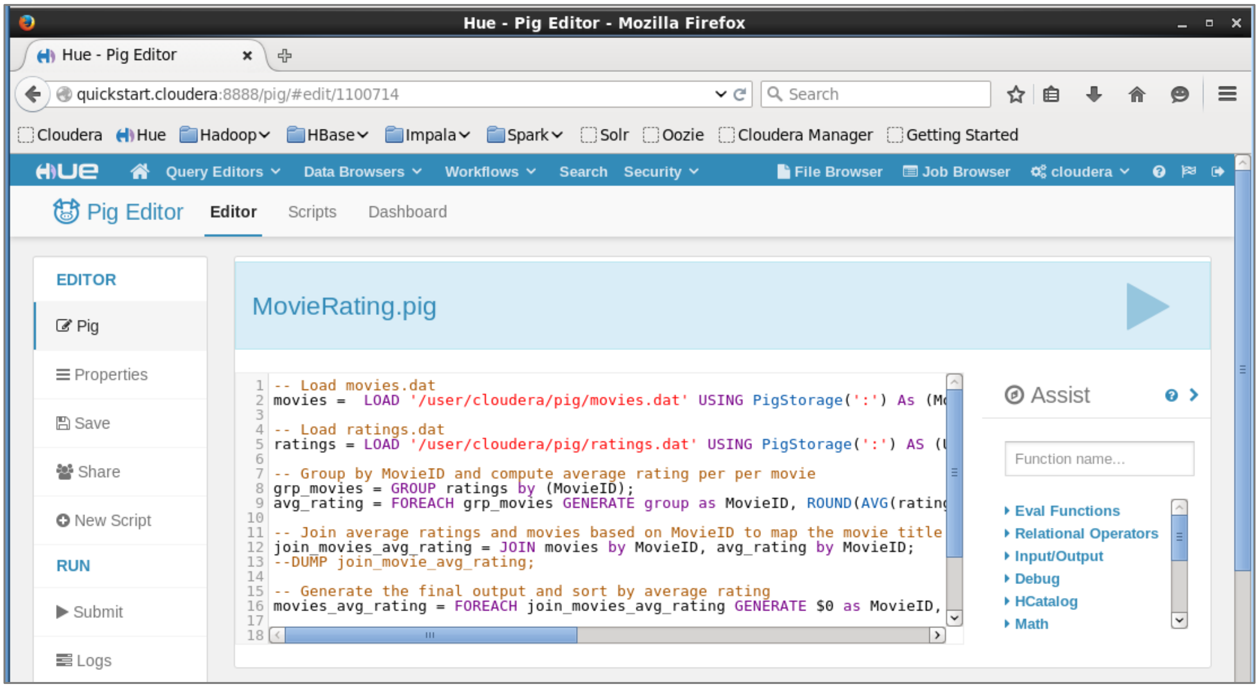


Figure 5.5. Creating a Pig Script in Hue

3. Execute the script by clicking Submit. The progress bar is displayed showing the percentage of progress along with the execution logs.

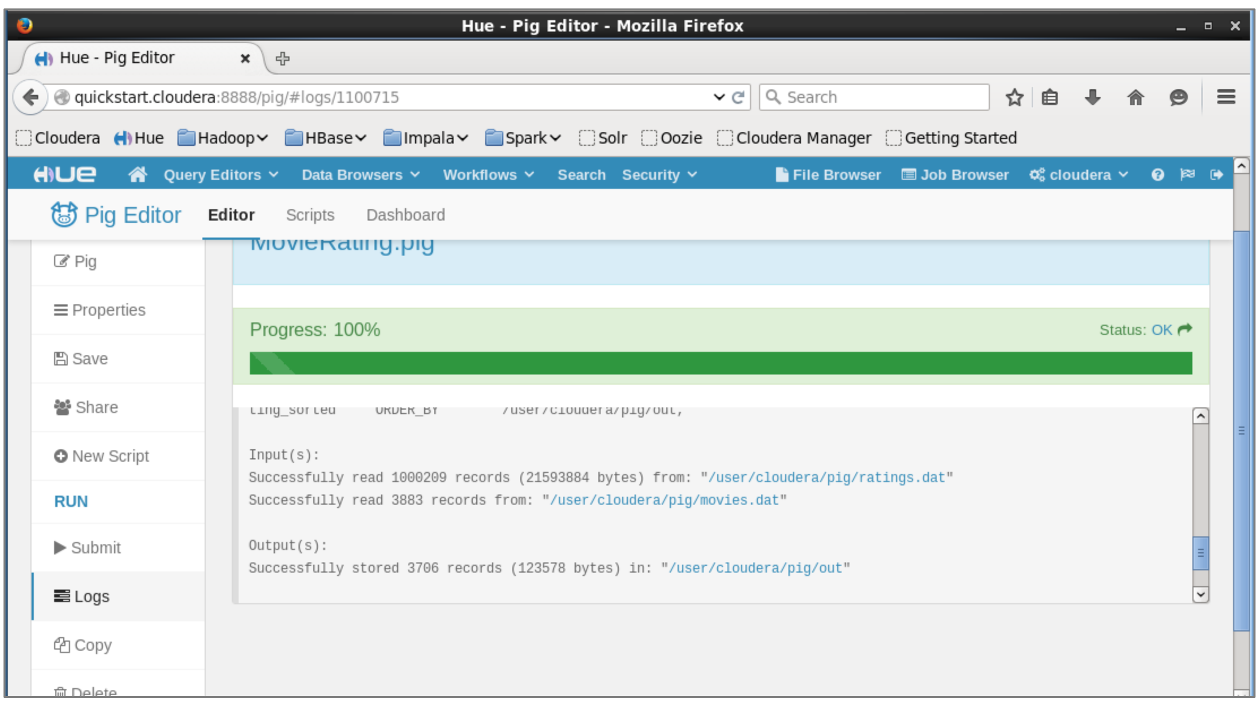


Figure 5.6. Running a Pig Script in Hue

4. To view the output, either click on the output folder link in the log or navigate to the output folder using File Browser application. File Browser lets you manage the

HDFS. By default, the output file is displayed as binary. Click on 'View as text' button under ACTIONS and the output is displayed as shown below.

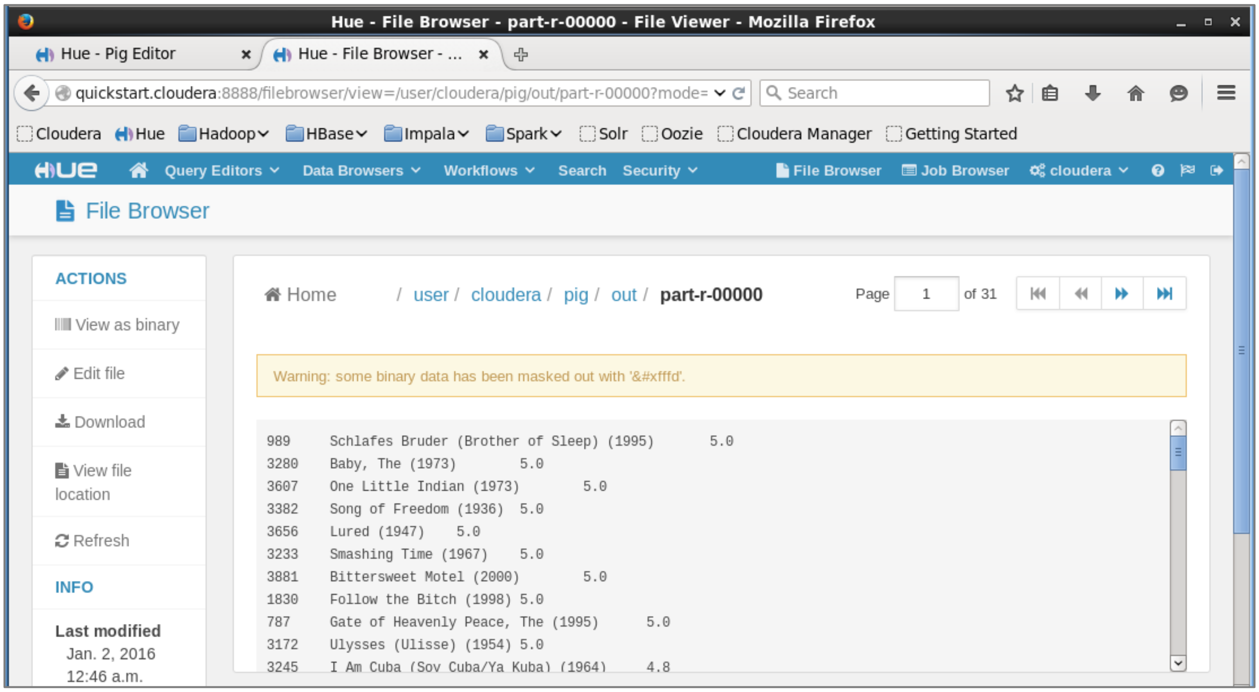


Figure 5.7. Displaying Pig Script Output in Hue

CHAPTER 6

DATA ANALYSIS USING APACHE HIVE

Apache Hive is another popular data processing platform built on top of Hadoop. Hive uses a query language HiveQL, which is very similar to SQL. The queries are converted to a series of MapReduce jobs.

Users interact with Hive through a command-line interface called Hive shell, which can be invoked by ‘hive’ command.

```
% hive
hive>
```

The user can execute the commands in interactive mode by typing in the commands in the Hive shell. Commands must be terminated by a semicolon. To run Hive queries in a batch/non-interactive mode, invoke Hive shell using –e or –f option.

```
$ hive –f <file path>
```

This will execute the queries mentioned in the specified file.

```
$ hive –e ‘<query 1; … query n;>’;
```

-e option is used to specify the queries inline.

6.1 Using Hive For Data Analysis

Let us solve the same problem of finding the average movie rating that was discussed in the earlier chapters.

1. The command below lists all the hive databases. Default database can be referred to by ‘default’.

```
hive> SHOW DATABASES;
```

2. Create a database.

```
hive> CREATE DATABASE movie_analytics;
```

```
hive> use movie_analytics;
```

The specified database will be used for all subsequent commands.

3. Create ‘movies’ table with three columns MovieID (integer), Title (string) and Genres (string). ROW FORMAT here says the files in arrow are delimited by the character ‘:’. The data will be stored as plain text file. TEXTFILE is the default file storage format.

```
hive> CREATE TABLE movies (MovieID INT, Title STRING, Genres STRING)
ROW FORMAT DELIMITED FIELDS TERMINATED BY  ':'
STORED AS TEXTFILE;
```

4. Similarly create a table for ratings.

```
hive>  CREATE  TABLE  ratings  (UserID  INT,  MovieID  STRING,  Rating  FLOAT,  Timestamp
STRING)
ROW FORMAT DELIMITED FIELDS TERMINATED BY  ':'
STORED AS TEXTFILE;
```

5. Verify the table columns using DESCRIBE statement

```
hive> DESCRIBE movies;
hive> DESCRIBE ratings;
```

6. Now load the data stored earlier on HDFS into these tables. (The data files were stored on HDFS in the directory /user/cloudera/data/ during the analysis using pig.)

```
hive> LOAD DATA INPATH '/user/cloudera/data/movies.dat' OVERWRITE INTO TABLE movies;
hive> LOAD DATA INPATH '/user/cloudera/data/ratings.dat' OVERWRITE INTO TABLE ratings;
```

6.1. Files can be loaded from local filesystem using LOCAL keyword as below:

```
hive> LOAD DATA LOCAL INPATH '/home/cloudera/Desktop/movies.dat' OVERWRITE INTO TABLE
movies;
```

6.2. LOAD command puts the specified files in Hive’s warehouse directory which is set by the hive.metastore.warehouse.dir property which defaults to /user/hive/warehouse.

To display the property value:

```
hive > SET hive.metastore.warehouse.dir
```

movies.dat and ratings.dat are copied to /user/hive/warehouse/movies_analytics.db directory.

6.3. Hive follows ‘schema on read.’ During load operation, data is not verified against the table schema. Data files are simply copied to the Hive directory, which makes loading data very fast. The schema is verified only during query operations.

6.4. The actual data is thus stored in HDFS. The table metadata is stored in a relational database. Hive uses an embedded Derby database by default, which runs in the same process as the main Hive service. It can be configured to use a standalone database which is JDBC compliant like MySQL for metadata storage.

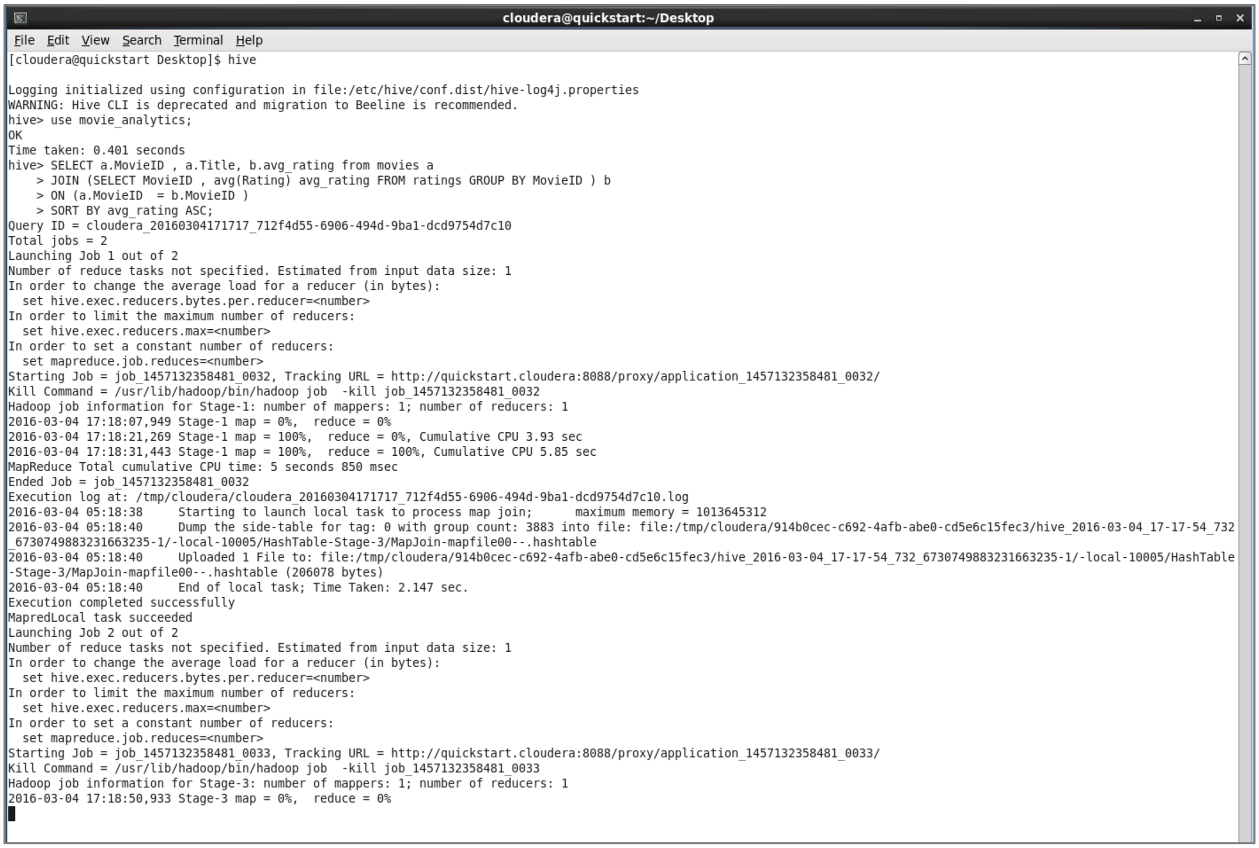
7. Verify the table content using SELECT statement.

```
hive> SELECT * from movies;

hive> SELECT * from ratings;
```

8. Find the average movie ratings from the ratings table and join it with movies table to map the movie details with average rating. The output is displayed in the ascending order of average rating.

```
hive> SELECT a.MovieID , a.Title, b.avg_rating from movies a
JOIN (SELECT MovieID , avg(Rating) avg_rating FROM ratings GROUP BY MovieID ) b
ON (a.MovieID  = b.MovieID )
SORT BY avg_rating ASC;
```



```
cloudera@quickstart:~/Desktop
File Edit View Search Terminal Help
[cloudera@quickstart Desktop]$ hive

Logging initialized using configuration in file:/etc/hive/conf.dist/hive-log4j.properties
WARNING: Hive CLI is deprecated and migration to Beeline is recommended.
hive> use movie_analytics;
OK
Time taken: 0.401 seconds
hive> SELECT a.MovieID , a.Title, b.avg_rating from movies a
    > JOIN (SELECT MovieID , avg(Rating) avg_rating FROM ratings GROUP BY MovieID ) b
    > ON (a.MovieID  = b.MovieID )
    > SORT BY avg_rating ASC;
Query ID = cloudera_20160304171717_712f4d55-6906-494d-9ba1-dcd9754d7c10
Total jobs = 2
Launching Job 1 out of 2
Number of reduce tasks not specified. Estimated from input data size: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1457132358481_0032, Tracking URL = http://quickstart.cloudera:8088/proxy/application_1457132358481_0032/
Kill Command = /usr/lib/hadoop/bin/hadoop job  -kill job_1457132358481_0032
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 1
2016-03-04 17:18:07,949 Stage-1 map = 0%,  reduce = 0%
2016-03-04 17:18:21,269 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 3.93 sec
2016-03-04 17:18:31,443 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 5.85 sec
MapReduce Total cumulative CPU time: 5 seconds 850 msec
Ended Job = job_1457132358481_0032
Execution log at: /tmp/cloudera/cloudera_20160304171717_712f4d55-6906-494d-9ba1-dcd9754d7c10.log
2016-03-04 05:18:38     Starting to launch local task to process map join;      maximum memory = 1013645312
2016-03-04 05:18:40     Dump the side-table for tag: 0 with group count: 3883 into file: file:/tmp/cloudera/914b0cec-c692-4afb-abe0-cd5e6c15fec3/hive_2016-03-04_17-17-54_732
_6730749883231663235-1/-local-10005/HashTable-Stage-3/MapJoin-mapfile00--.hashtable
2016-03-04 05:18:40     Uploaded 1 File to: file:/tmp/cloudera/914b0cec-c692-4afb-abe0-cd5e6c15fec3/hive_2016-03-04_17-17-54_732_6730749883231663235-1/-local-10005/HashTable
-Stage-3/MapJoin-mapfile00--.hashtable (206078 bytes)
2016-03-04 05:18:40     End of local task; Time Taken: 2.147 sec.
Execution completed successfully
MapredLocal task succeeded
Launching Job 2 out of 2
Number of reduce tasks not specified. Estimated from input data size: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1457132358481_0033, Tracking URL = http://quickstart.cloudera:8088/proxy/application_1457132358481_0033/
Kill Command = /usr/lib/hadoop/bin/hadoop job  -kill job_1457132358481_0033
Hadoop job information for Stage-3: number of mappers: 1; number of reducers: 1
2016-03-04 17:18:50,933 Stage-3 map = 0%,  reduce = 0%
```

Figure 6.1. Hive Query Execution

```
cloudera@quickstart:~/Desktop
File Edit View Search Terminal Help
2804    Christmas Story, A (1983)       4.238905325443787
950     Thin Man, The (1934)    4.239726027397261
3468    Hustler, The (1961)     4.24
954     Mr. Smith Goes to Washington (1939)     4.240208877284595
1208    Apocalypse Now (1979)   4.243197278911564
678     Some Folks Call It a Sling Blade (1993) 4.245098039215686
1247    Graduate, The (1967)    4.245836637589215
919     Wizard of Oz, The (1939)        4.247962747380675
1299    Killing Fields, The (1984)      4.248633879781421
951     His Girl Friday (1940)  4.249370277078086
3730    Conversation, The (1974)        4.249448123620309
214     Before the Rain (Pred dozhdot) (1994)   4.25
1002    Ed's Next Move (1996)   4.25
1117    Eighth Day, The (Le Huiti�me jour ) (1996)      4.25
598     Window to Paris (1994)  4.25
1278    Young Frankenstein (1974)       4.250628667225482
969     African Queen, The (1951)       4.251655629139073
1225    Amadeus (1984)  4.251808972503618
1189    Thin Blue Line, The (1988)      4.25278810408922
1276    Cool Hand Luke (1967)   4.253763440860215
3634    Seven Days in May (1964)        4.254545454545455
608     Fargo (1996)    4.254675686430561
926     All About Eve (1950)    4.255583126550868
363     Wonderful, Horrible Life of Leni Riefenstahl, The (Die Macht der Bilder) (1993) 4.258064516129032
1132    Manon of the Spring (Manon des sources) (1986)  4.259090909090909
1272    Patton (1970)   4.266666666666667
1217    Ran (1985)      4.26890756302521
1945    On the Waterfront (1954)        4.269749518304431
2203    Shadow of a Doubt (1943)        4.2703862660944205
903     Vertigo (1958)  4.27292817679558
541     Blade Runner (1982)     4.273333333333333
3679    Decline of Western Civilization, The (1981)     4.274193548387097
1213    GoodFellas (1990)       4.275196137598069
296     Pulp Fiction (1994)     4.278212805158913
3469    Inherit the Wind (1960) 4.279850746268656
905     It Happened One Night (1934)    4.280748663101604
899     Singin' in the Rain (1952)      4.2836218375499335
3091    Kagemusha (1980)        4.283687943262412
2357    Central Station (Central do Brasil) (1998)      4.283720930232558
1224    Henry V (1989)  4.286384976525822
1172    Cinema Paradiso (1988)  4.287804878048781
2937    Palm Beach Story, The (1942)    4.288461538461538
1254    Treasure of the Sierra Madre, The (1948)        4.289183222958058
1196    Star Wars       4.292976588628763
930     Notorious (1946)        4.29438202247191
1203    12 Angry Men (1957)     4.295454545454546
953     It's a Wonderful Life (1946)    4.299039780521262
2931    Time of the Gypsies (Dom za vesanje) (1989)     4.3
2839    West Beirut (West Beyrouth) (1998)      4.3
910     Some Like It Hot (1959) 4.300480769230769
898     Philadelphia Story, The (1940)  4.3006872852233675
1260    M (1931)        4.3019480519480515
1233    Boat, The (Das Boot) (1981)     4.302697302697303
1197    Princess Bride, The (1987)      4.3037100949094045
2186    Strangers on a Train (1951)     4.304979253112033
2360    Celebration, The (Festen) (1998)        4.3076923076923075
1284    Big Sleep, The (1946)   4.312384473197782
2571    Matrix, The (1999)      4.315830115830116
```

Figure 6.2. Hive Query Output

CHAPTER 7

BIG DATA ANALYTICS ON AMAZON CLOUD

7.1 Amazon Web Services

Amazon Web Services (AWS) [20] is a cloud computing platform from Amazon. Amazon Elastic Compute Cloud (EC2) provides the computing resources. EC2 provides different instance types with a range of resource combinations to meet different requirements. You can reserve the resources according to your computing requirements and scale them easily. The resource costs are per the actual usage, i.e. for the duration when the servers are up and running. Amazon Elastic MapReduce (EMR) is basically the Hadoop framework running on cloud. Amazon Simple Storage Service (S3) provides data storage service where bulk input and output data can be stored.

7.2 Create An EMR Cluster

Follow the steps below to create an EMR cluster using AWS console [21].

1. Create an AWS account (http://aws.amazon.com/). Some services are free under the Free Tier registration and additional services can be used at applicable rates [22].

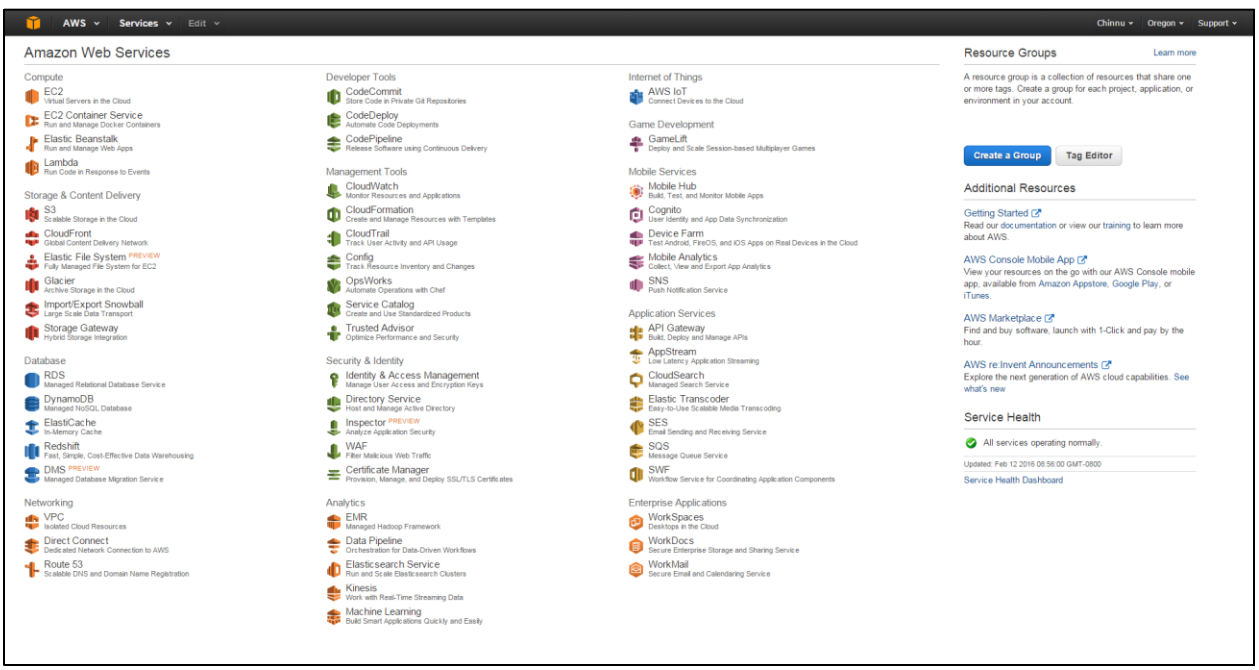


Figure 7.1. AWS Console with Available Services

(EC2 under Compute, S3 under Storage & Content Delivery, EMR under Analytics)

2. Go to S3 (Scalable Storage in the Cloud) console at https://console.aws.amazon.com/s3/ and create an S3 Bucket and folders for data and log files.

3. Create an Amazon EC2 key pair which is required to connect to the nodes in the cluster over Secure Shell (SSH) protocol later.

Go to Amazon EC2 console at https://console.aws.amazon.com/ec2/ and select NETWORK & SECURITY -> Key Pairs. Create a key pair and download the private key file (.pem format).

4. Go to Amazon EMR console at https://console.aws.amazon.com/elasticmapreduce/ and create a cluster.

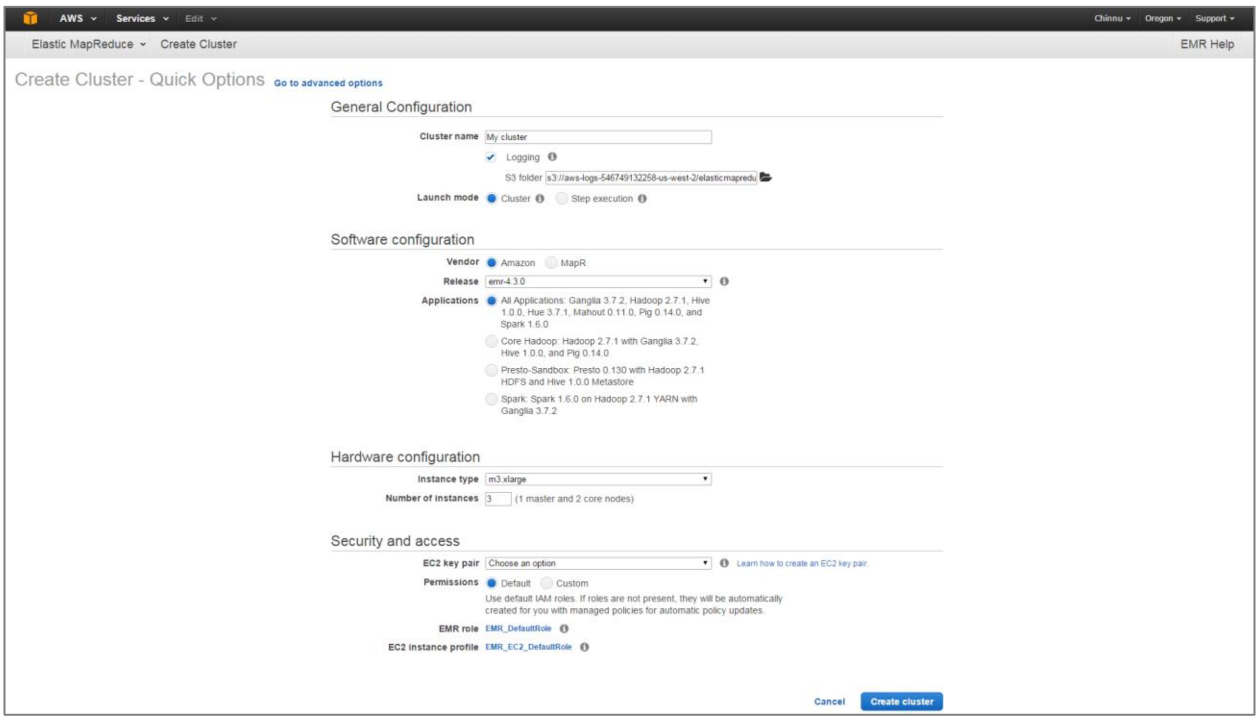


Figure 7.2. Create Cluster - Quick Options

5. Click on Go to advanced options for a detailed view.

6. Go with the default Software Configuration. By default, Hadoop, Pig, Hive and Hue are selected.

   6.1. Steps like Hive program, Pig program, Custom JAR (MapReduce program) etc. can be specified so that these will be executed once the cluster is up.

   6.2. Marking the check box 'Auto-terminate cluster after the last step is completed' will create a transient cluster. A transient cluster automatically terminates when all the steps are executed (even if Termination Protection is turned on in the next screen). If auto-termination is disabled, it will create a long-running cluster which persists even after all the steps are executed.

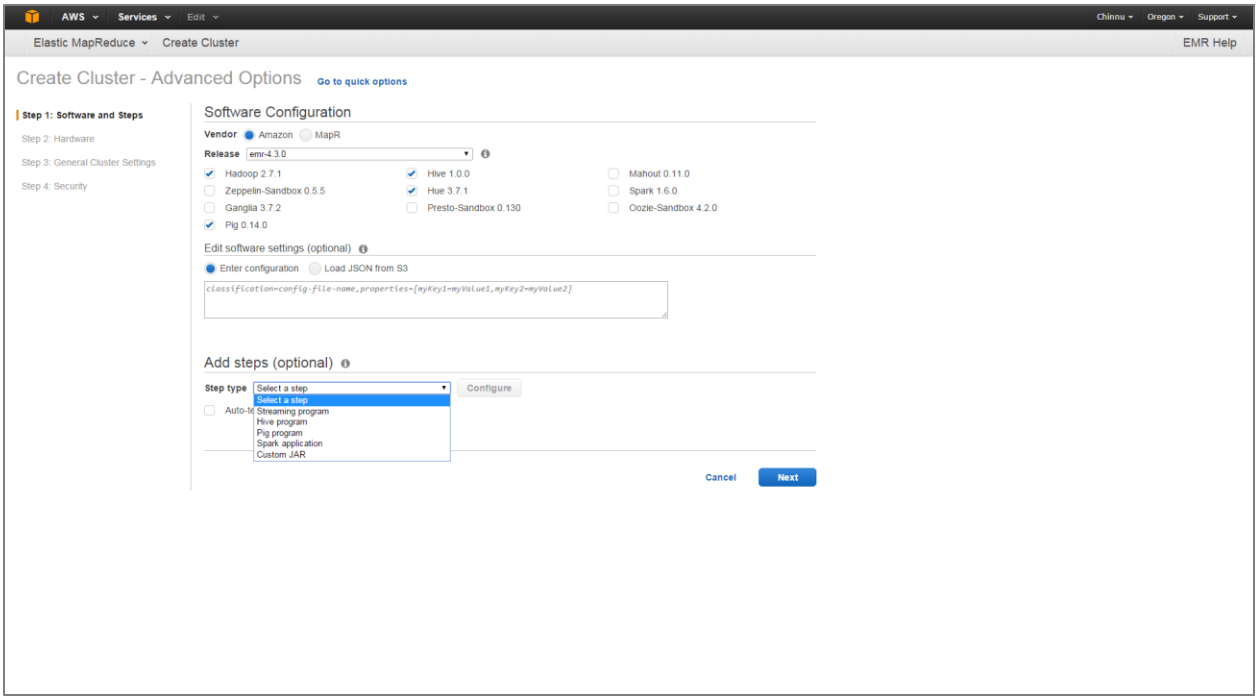


Figure 7.3. Create Cluster - Software Configuration

7. By default, a cluster with one master and two slaves with m3.xlarge (vCPU: 4, Mem (GiB):15) instance type [23] is configured under Hardware Configuration.

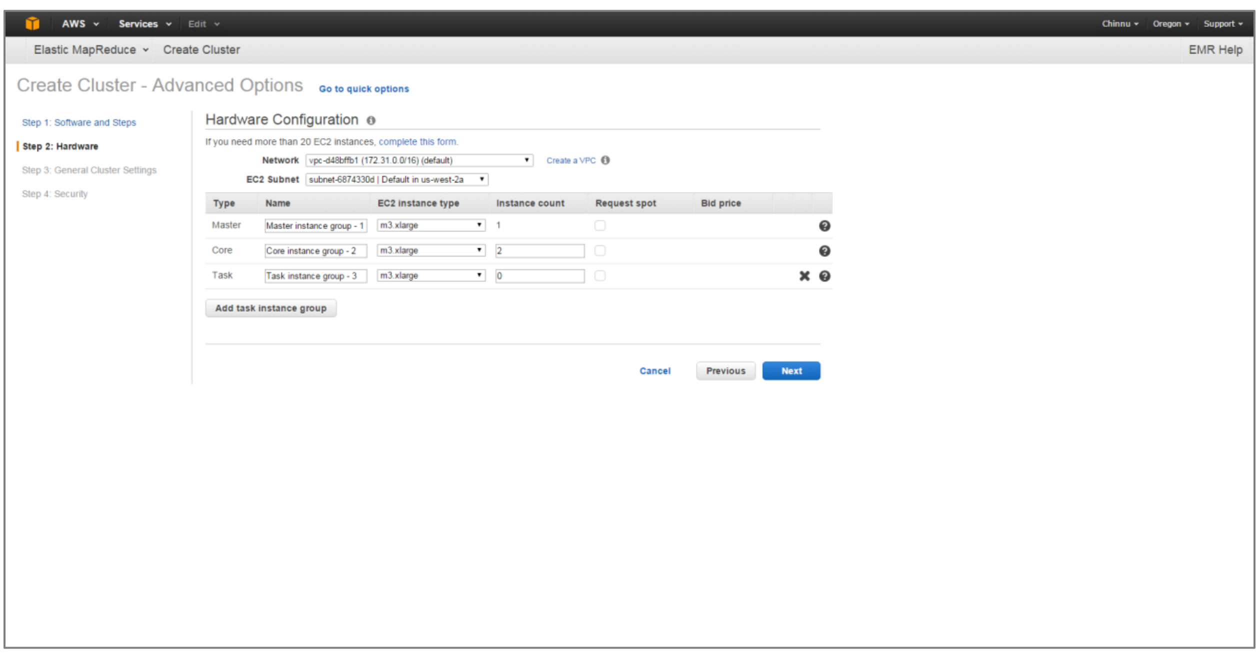


Figure 7.4. Create Cluster - Hardware Configuration

8. In General Option screen, select the S3 folder created in step 2 for logging. Bootstrap Actions can be specified which are setup scripts to be executed before Hadoop starts on each cluster node.

8.1. By default Termination protection is turned on to protect the cluster from termination by accident. This must be disabled before a cluster has to be terminated. When a user terminates a running cluster for which the termination protection was turned on, user will be prompted to turn off the termination protection before the cluster can be terminated.

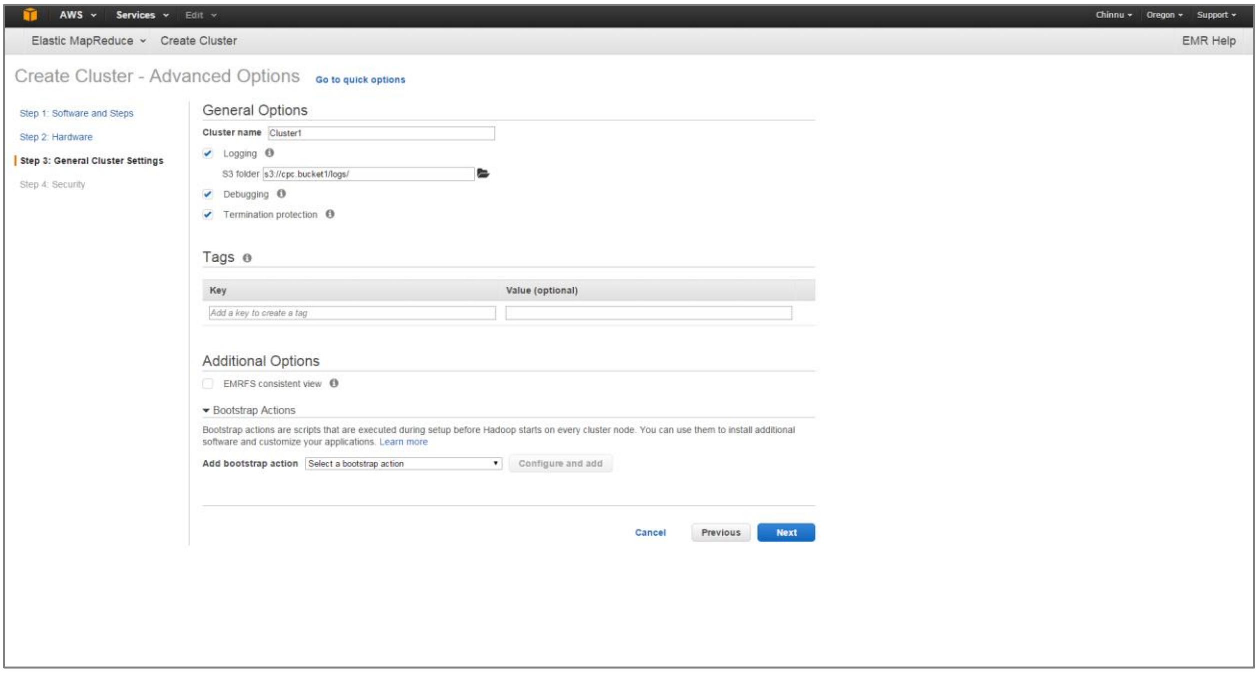


Figure 7.5. Create Cluster - General Options

9. In Security Options screen, choose the EC2 key pair created in step 3.

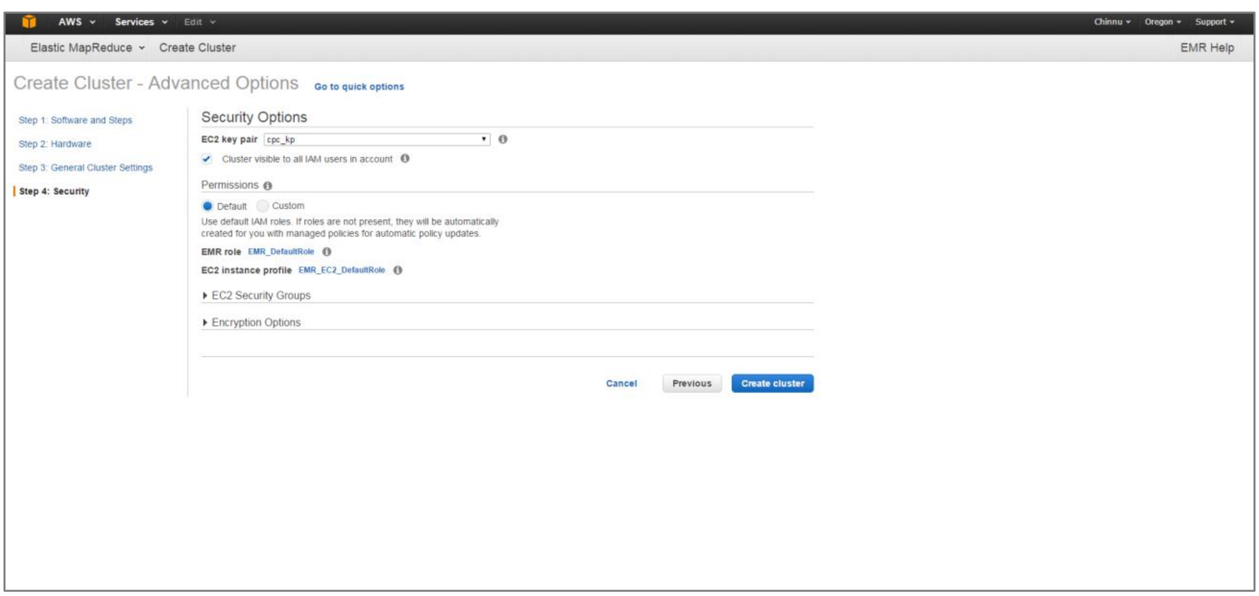


Figure 7.6. Create Cluster - Security Options

10. Click on Create Cluster. Cluster will be in Starting state while the EC2 instances are being provisioned.

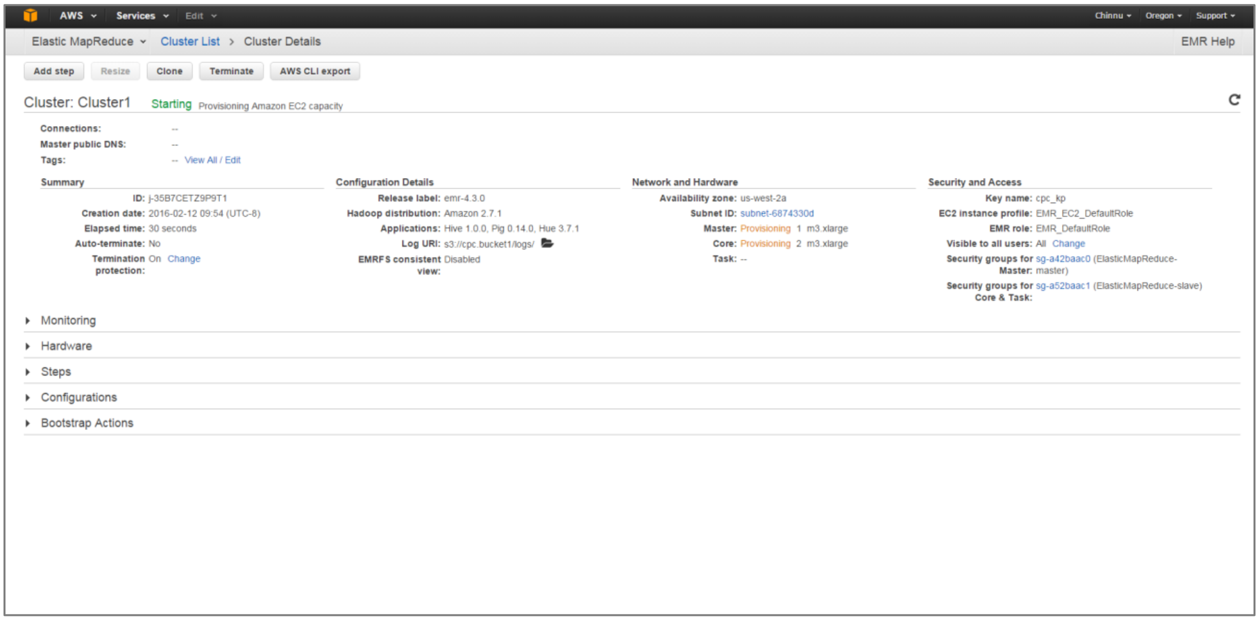


Figure 7.7. Cluster in Starting State

11. If Steps were specified, those will be executed in order. Cluster goes into Running state while processing the steps. If auto-termination was on, the cluster will be terminated after the steps are completed, or the cluster will go into Waiting state.

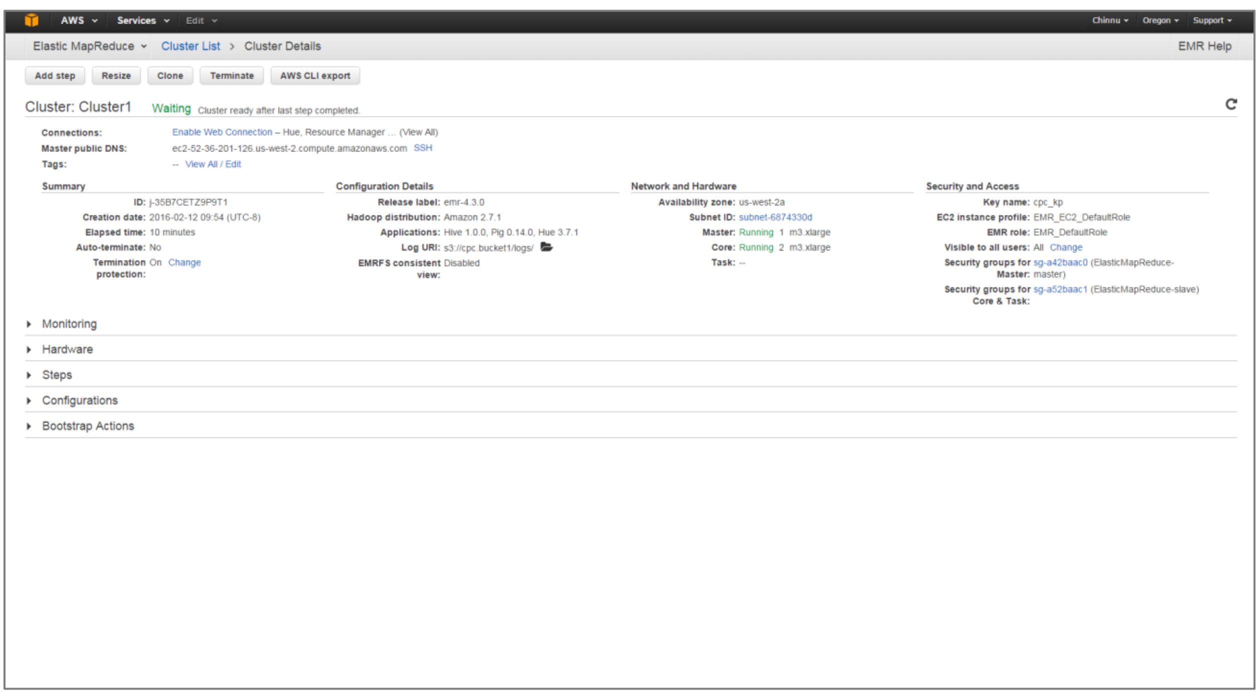


Figure 7.8. Cluster in Waiting State

7.3 Connect To The Master Node

To connect to the master node of the cluster using PuTTY, an SSH client, on Windows:

1. PuTTY needs private key in .ppk format.

   1.1. Use PuTTYgen to convert the private key .pem file stored earlier to .ppk format.

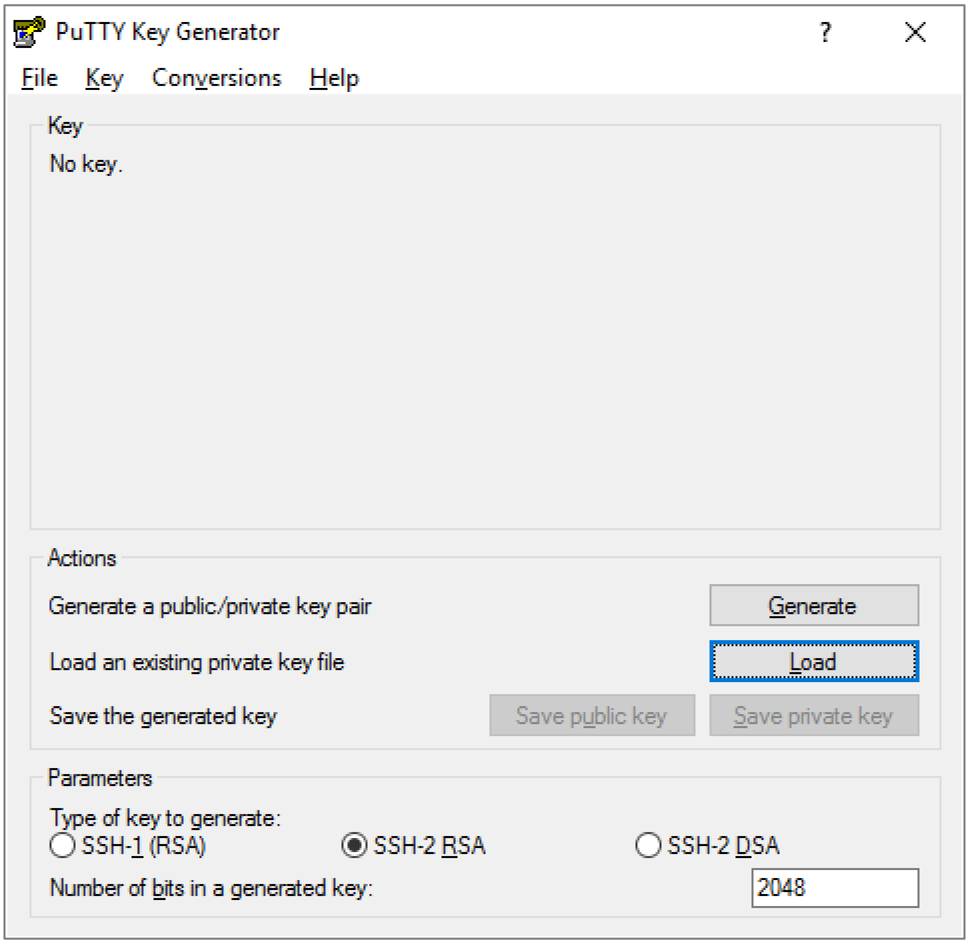


Figure 7.9. PuTTYgen

1.2. Select SSH-2 RSA for the type of key to generate. Click on Load and select All Files (*.*) and select the .pem file. Click OK in the pop up.

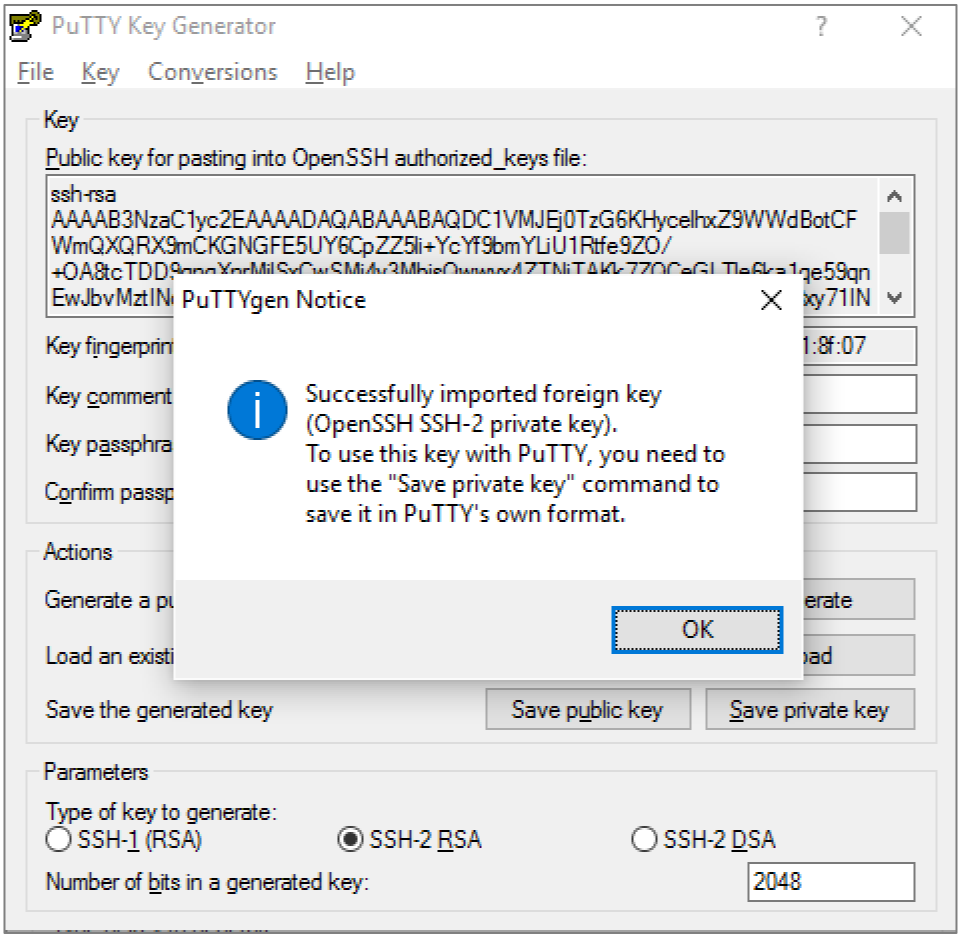


Figure 7.10. Converting Private Key to .ppk Format

1.3. Save the private key in .ppk format by clicking ‘Save private key’.

2. Open PuTTY. For Host Name, enter hadoop@<Public DNS name of Master node>. Public DNS name of Master node can be obtained by going to the cluster in Amazon EMR console.

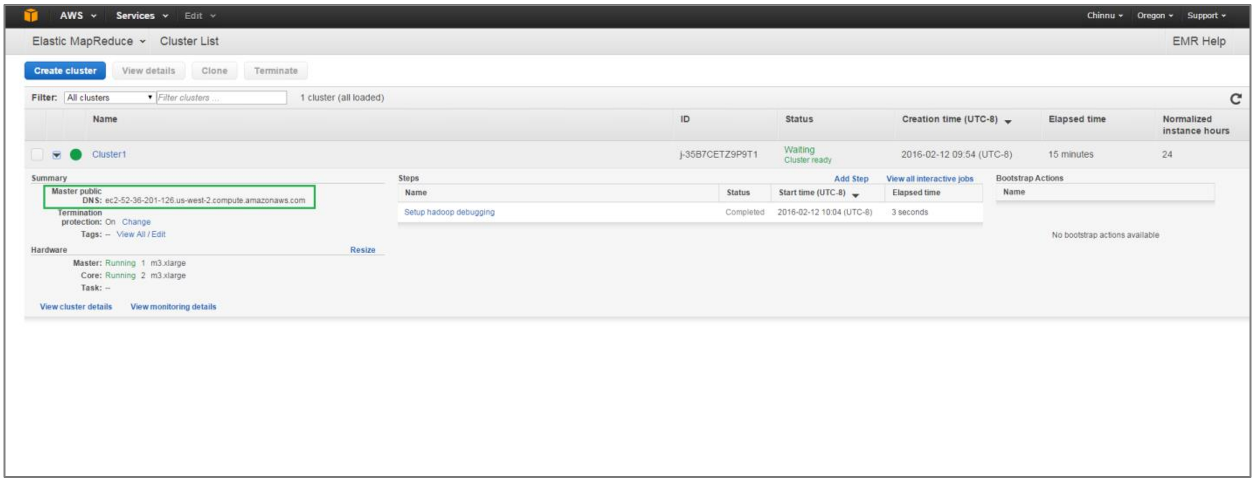


Figure 7.11. Public DNS Name of Cluster Master Node Displayed in EMR Console

3. Select Category -> Connection -> SSH -> Auth and select the .ppk file from step 1 for 'Private key file for authentication'.
4. To view the web interfaces Hosted on the Master Node (as explained in detail in the following section), an SSH Tunnel needs to be set up to the Master Node Using Dynamic Port Forwarding.

   4.1. Select Category -> Connection -> SSH ->Tunnels. Enter 8157 (an unused local port) for 'Source port'.

   4.2. Leave the Destination field blank. Select Dynamic and Auto options. Choose Add.

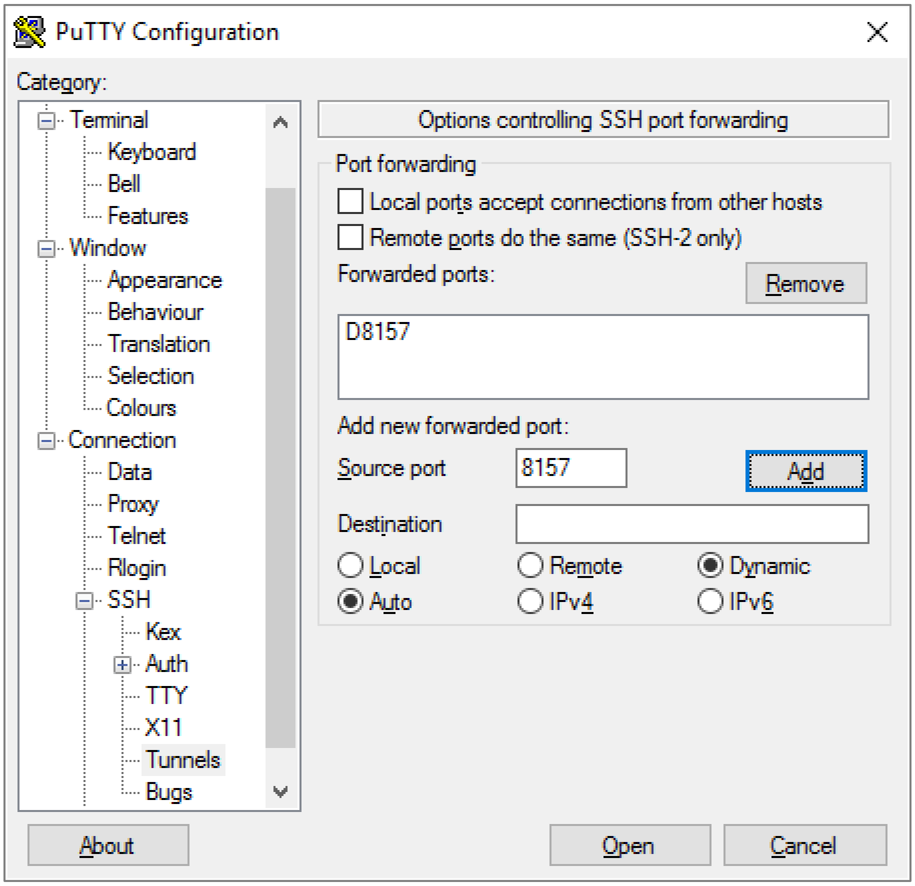


Figure 7.12. Setting up an SSH Tunnel to the Master Node Using Dynamic Port Forwarding

5. Click on 'Open' to connect.

7.4 View Web Interfaces Hosted on the Master Node

Web connection needs to be enabled in order to view the web interfaces for Hue, Resource Manager, etc. hosted on the master node. Enable Web Connection link is displayed on the cluster creation page with instructions on how to set up the web connection.

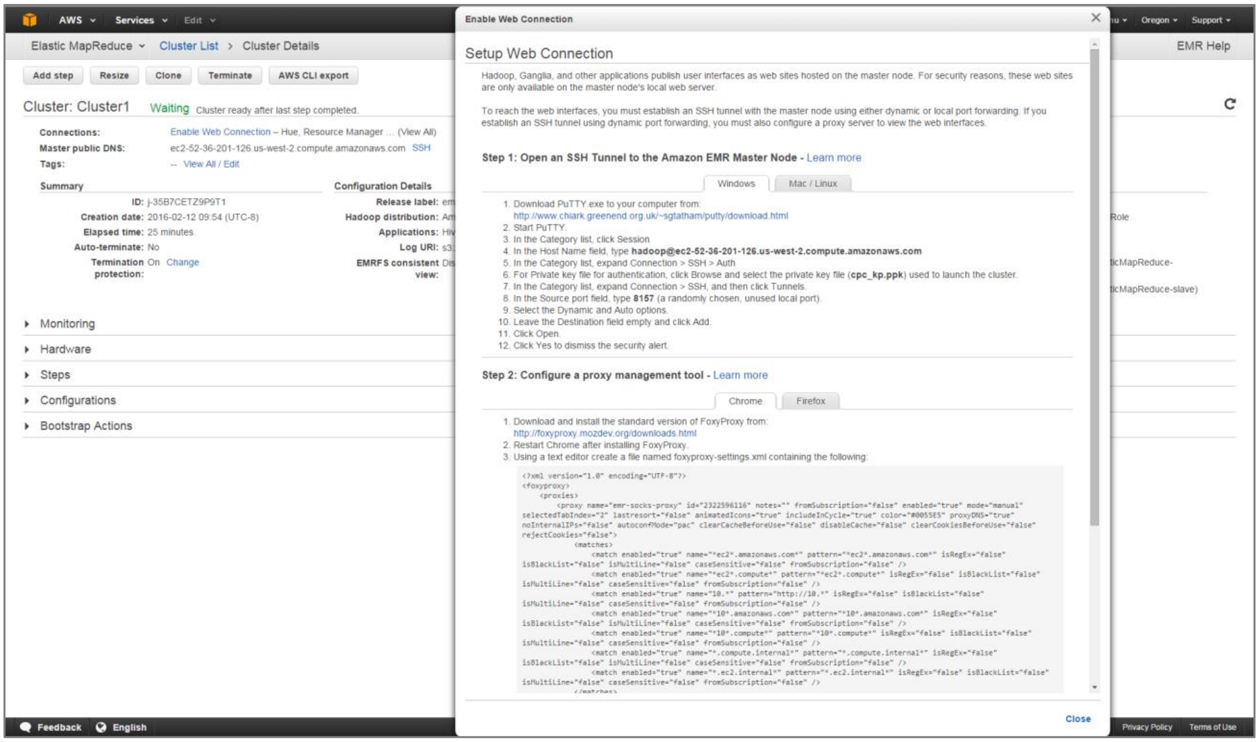


Figure 7.13. Instructions to Setup Web Connection

1. Set up an SSH Tunnel to the Master Node Using Dynamic Port Forwarding by performing step 1 - 4 above for connecting to the Master using PuTTY.
2. Configure Proxy Settings in the browser.
   To configure FoxyProxy for Chrome:
   - Download and install FoxyProxy Standard from http://getfoxyproxy.org/downloads.html Chrome
   - Restart Chrome
   - Create foxyproxy-settings.xml file containing the following:

```
<?xml version="1.0" encoding="UTF-8"?>
<foxyproxy>
   <proxies>
      <proxy name="emr-socks-proxy" id="2322596116" notes=""
fromSubscription="false" enabled="true" mode="manual" selectedTabIndex="2"
lastresort="false" animatedIcons="true" includeInCycle="true"
color="#0055E5" proxyDNS="true" noInternalIPs="false" autoconfMode="pac"
clearCacheBeforeUse="false" disableCache="false"
clearCookiesBeforeUse="false" rejectCookies="false">
         <matches>
            <match enabled="true" name="*ec2*.amazonaws.com*"
pattern="*ec2*.amazonaws.com*" isRegEx="false" isBlackList="false"
isMultiLine="false" caseSensitive="false" fromSubscription="false" />
            <match enabled="true" name="*ec2*.compute*"
pattern="*ec2*.compute*" isRegEx="false" isBlackList="false"
isMultiLine="false" caseSensitive="false" fromSubscription="false" />
            <match enabled="true" name="10.*" pattern="http://10.*"
isRegEx="false" isBlackList="false" isMultiLine="false"
caseSensitive="false" fromSubscription="false" />
            <match enabled="true" name="*10*.amazonaws.com*"
pattern="*10*.amazonaws.com*" isRegEx="false" isBlackList="false"
isMultiLine="false" caseSensitive="false" fromSubscription="false" />
            <match enabled="true" name="*10*.compute*"
pattern="*10*.compute*" isRegEx="false" isBlackList="false"
isMultiLine="false" caseSensitive="false" fromSubscription="false"/>
            <match enabled="true" name="*.compute.internal*"
pattern="*.compute.internal*" isRegEx="false" isBlackList="false"
isMultiLine="false" caseSensitive="false" fromSubscription="false"/>
            <match enabled="true" name="*.ec2.internal* "
pattern="*.ec2.internal*" isRegEx="false" isBlackList="false"
isMultiLine="false" caseSensitive="false" fromSubscription="false"/>
        </matches>
         <manualconf host="localhost" port="8157" socksversion="5"
isSocks="true" username="" password="" domain="" />
      </proxy>
   </proxies>
</foxyproxy>
```


- Open Chrome and click on Firefox icon on the toolbar and choose Options.
- Select Import/Export. Click Choose File, select foxyproxy-settings.xml, and click Open. In the Import FoxyProxy Settings dialog, click Add.
- For Proxy mode, choose Use proxies based on their pre-defined patterns and priorities.
- Now that the web connection set up is done, on the Cluster Details screen, active links for the web interfaces hosted on the cluster will be displayed (Click on the cluster name in the cluster list in EMR to go to the Cluster Details screen.)

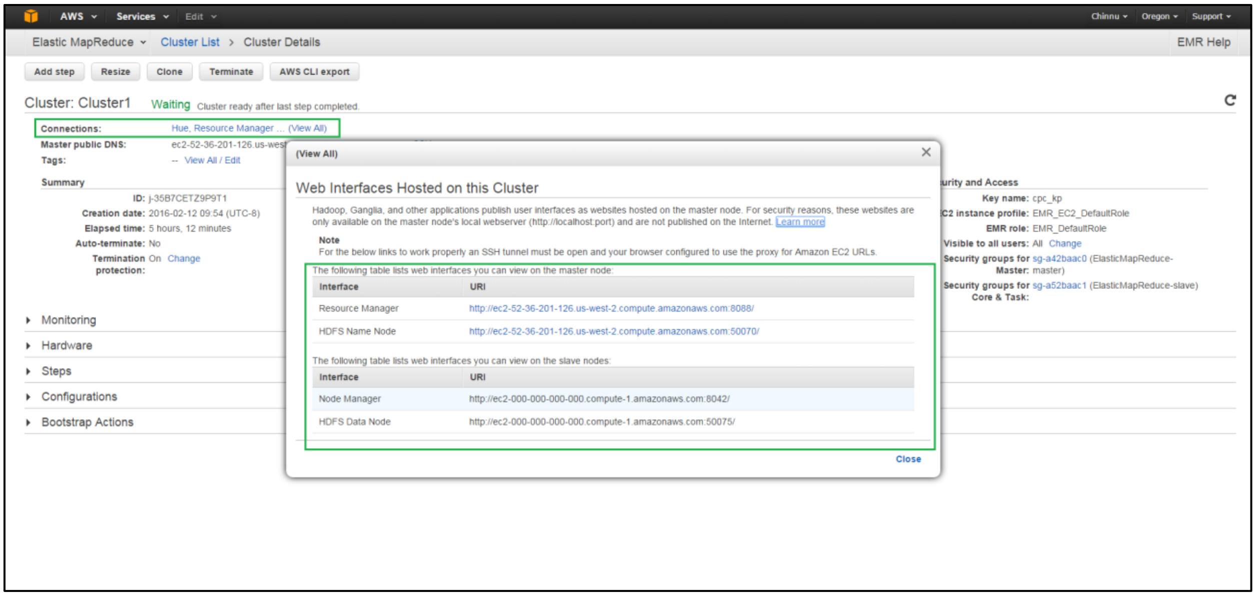


Figure 7.14. Web Links for the Web Interfaces Hosted on the Cluster

7.5 Submit A Job To The Cluster

To submit a job to a running cluster:

1. Upload the jar file and input file to S3.

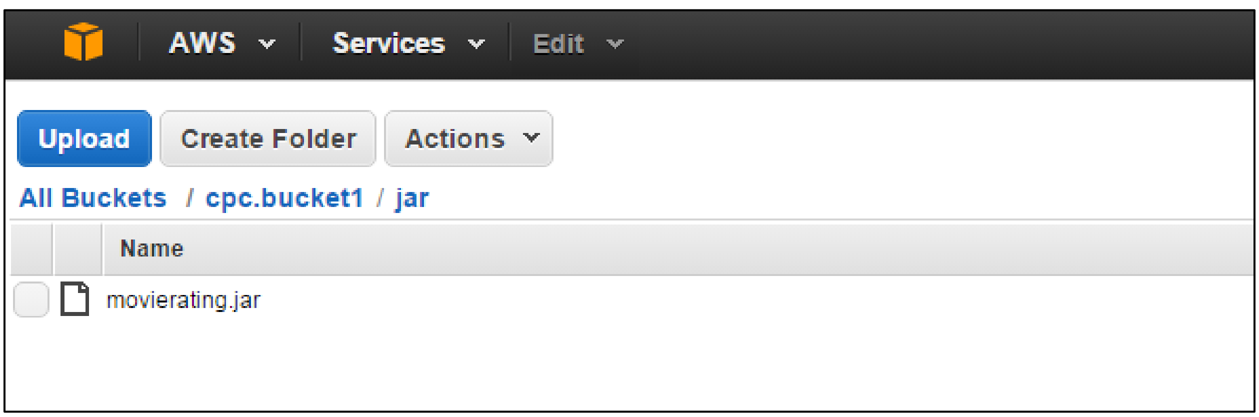


Figure 7.15. Upload MapReduce Program Jar File to S3

Figure 7.16. Upload Input File to S3

2. Go to the cluster in the Cluster List in Elastic MapReduce console and click on Add Step.

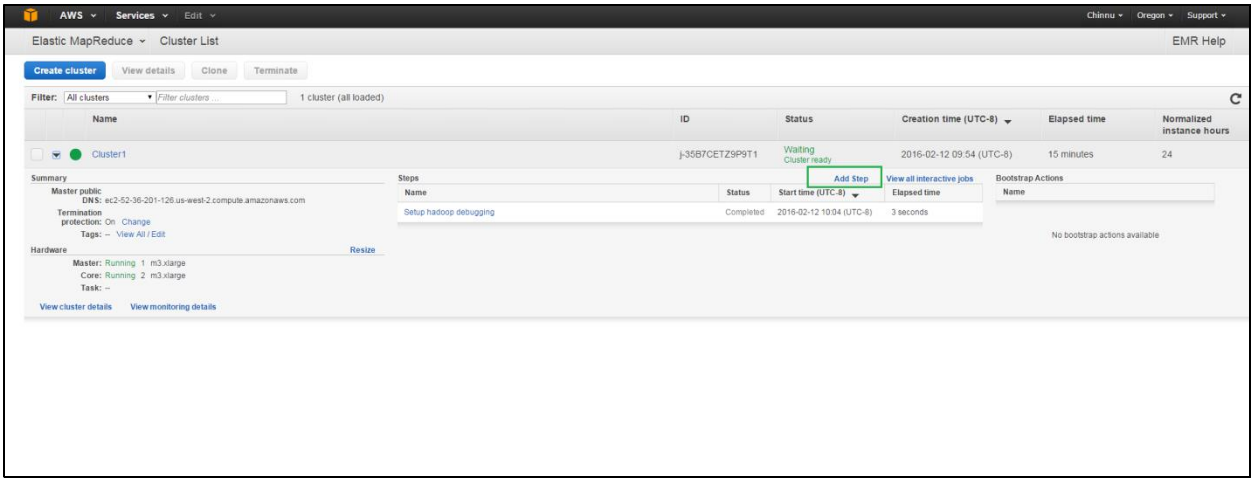


Figure 7.17. Add Step to a Running Cluster

3. Provide the jar location in S3 and input and output path as arguments. Make sure output path given does not exist already. If the class of the application entry point was not specified while exporting the jar (This can be verified by checking if Main-Class was specified in the jar's manifest file), specify the main class as the first argument.

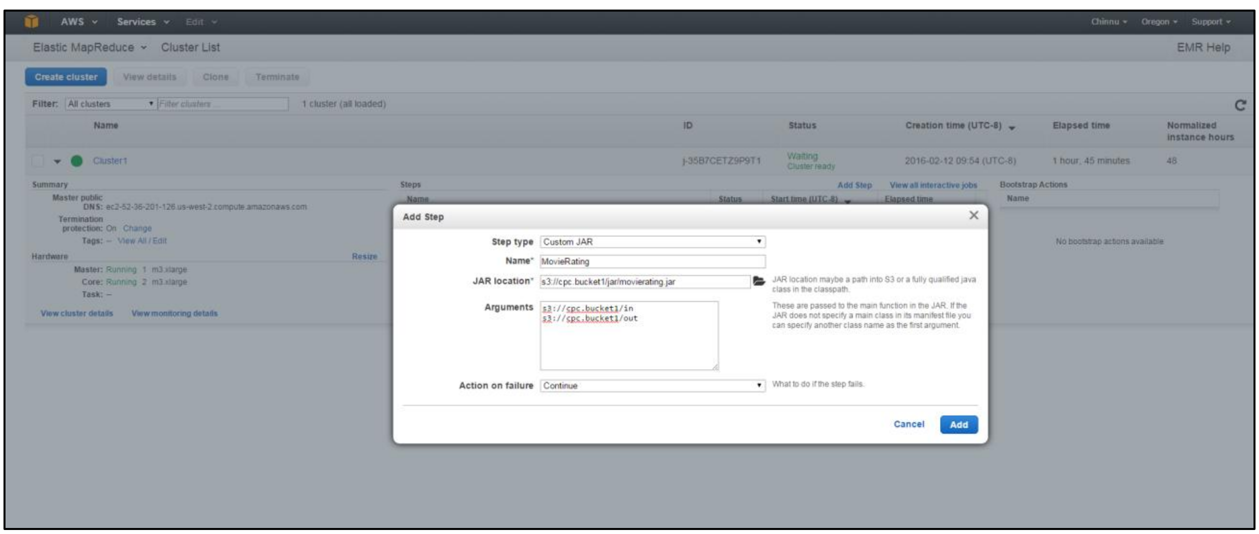


Figure 7.18. Add Step to Execute a Custom Jar File

4. The step will be in Pending state initially. It will then move to Running state and finally to Completed state when the execution is complete. If the step execution fails, it will move to Failed state. Output folder is created and the output can be verified from the S3 console. Logs are generated in the configured S3 logs location and it can be used for debugging failed steps.

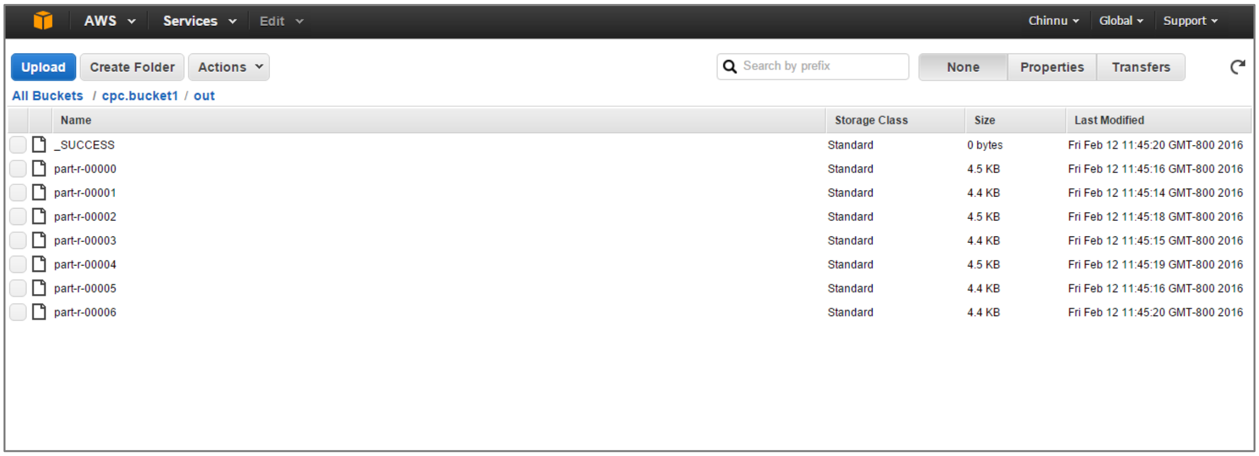


Figure 7.19. Output Folder in S3

7.6 Using Hue On Amazon EMR

Go to Hue at http://<public DNS Name of Master>:8888 or by clicking the link for Hue on the Cluster Details screen (Figure 7.14). Give username as hadoop and create a password. Note: Username other than hadoop can also be used. Since the SSH connections uses hadoop user, it is safe to use the same user in hue to avoid file ownership issues.

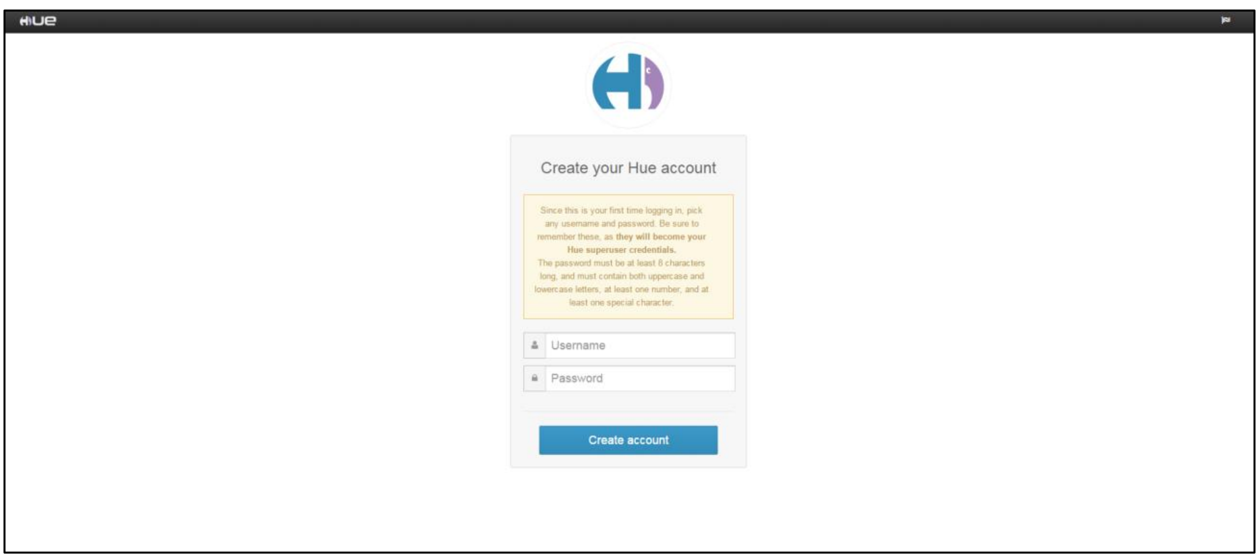


Figure 7.20. Hue Login Screen

Using Pig Editor in Hue was already explained in chapter 6. In this section, using Hive Editor in Hue to run the Hive queries and using Hue's Metastore Manager to manage Hive metastore are discussed.

7.6.1 Using Hive Editor in Hue

1. Copy input files to the master node using WinSCP

   1.1 Give public DNS name of the master node in Host name and Hadoop as user name. Click on Advanced and under SSH -> Authentication.

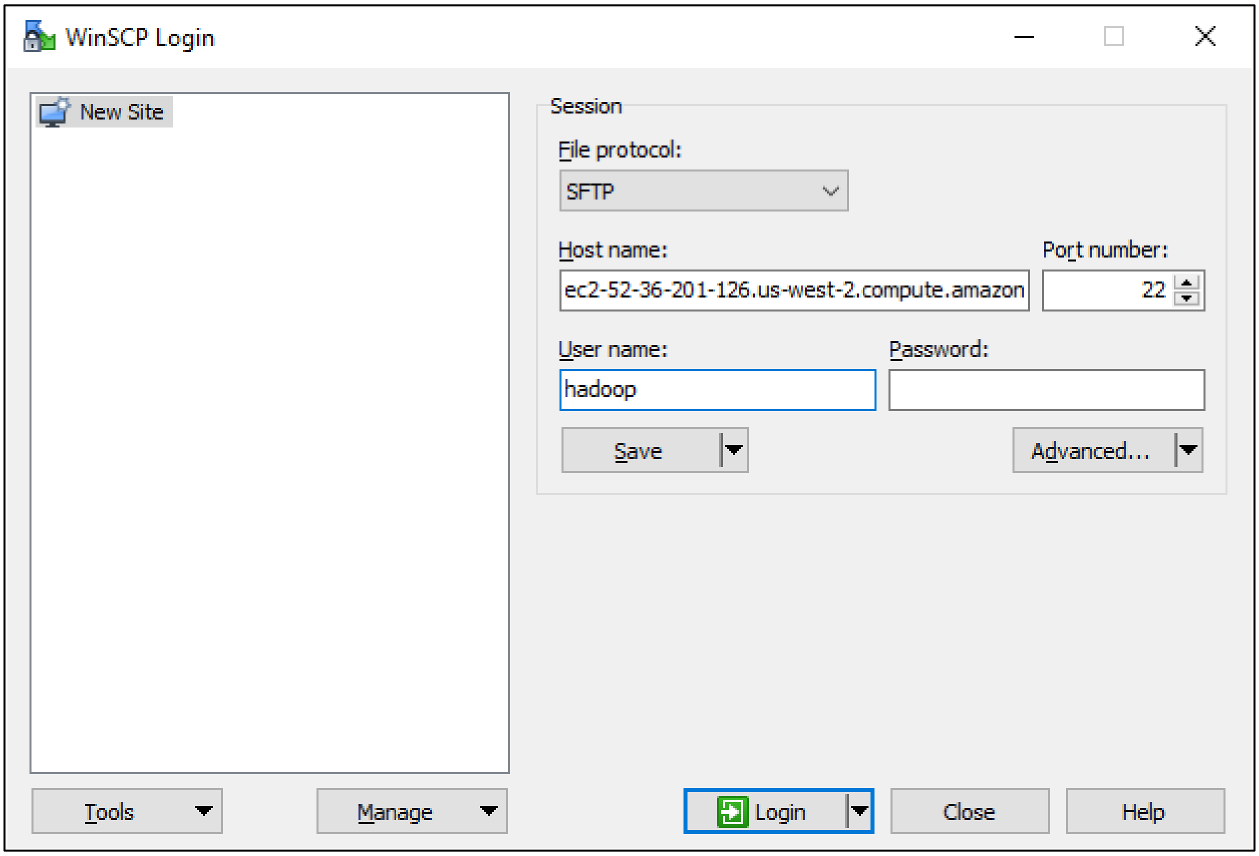


Figure 7.21. Using WinSCP to Copy Files to Master Node

   1.2 Select .ppk generated earlier in the private key file and click Ok. Click on Login.

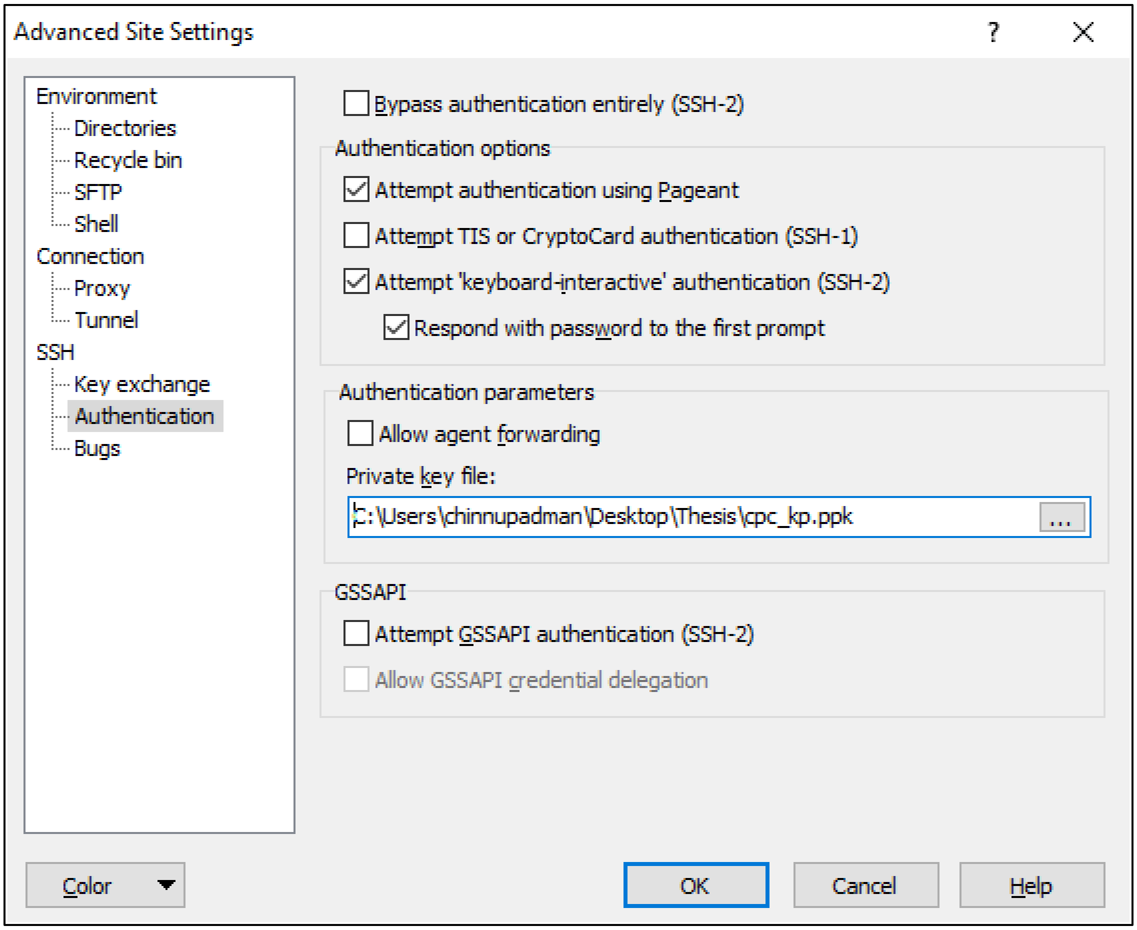


Figure 7.22. Provide Private Key File for Authentication

1.3 Copy movies.dat and ratings.dat to /home/Hadoop directory.

2. Connect to the master node via PuTTy (section 7.3) and copy these files to HDFS.

```
[hadoop@ip-172-31-17-242 ~]$ pwd
/home/hadoop
[hadoop@ip-172-31-17-242 ~]$ ll
total 21248
-rw-rw-r-- 1 hadoop hadoop   163542 Feb 13 07:43 movies.dat
-rw-rw-r-- 1 hadoop hadoop 21593504 Feb 13 07:43 ratings.dat
[hadoop@ip-172-31-17-242 ~]$ hdfs dfs -mkdir /user/hadoop/data
[hadoop@ip-172-31-17-242 ~]$ hdfs dfs -copyFromLocal movies.dat
/user/hadoop/data
[hadoop@ip-172-31-17-242 ~]$ hdfs dfs -copyFromLocal ratings.dat
/user/hadoop/data
[hadoop@ip-172-31-17-242 ~]$ hdfs dfs -ls ratings.dat /user/hadoop/data
ls: `ratings.dat': No such file or directory
Found 2 items
-rw-r--r--   1 hadoop hadoop     163542 2016-02-13 07:50
/user/hadoop/data/movies.dat
-rw-r--r--   1 hadoop hadoop   21593504 2016-02-13 07:50
/user/hadoop/data/ratings.dat
```

3. Hive metastore can be managed by MetaStore Manager in Hue. Go to MetaStore Manager. Click on Databases link and select Create a new database named movie_analytics. Give a database name and by default it gets stored in /user/hive/warehouse/database_name or another location in HDFS can be specified.

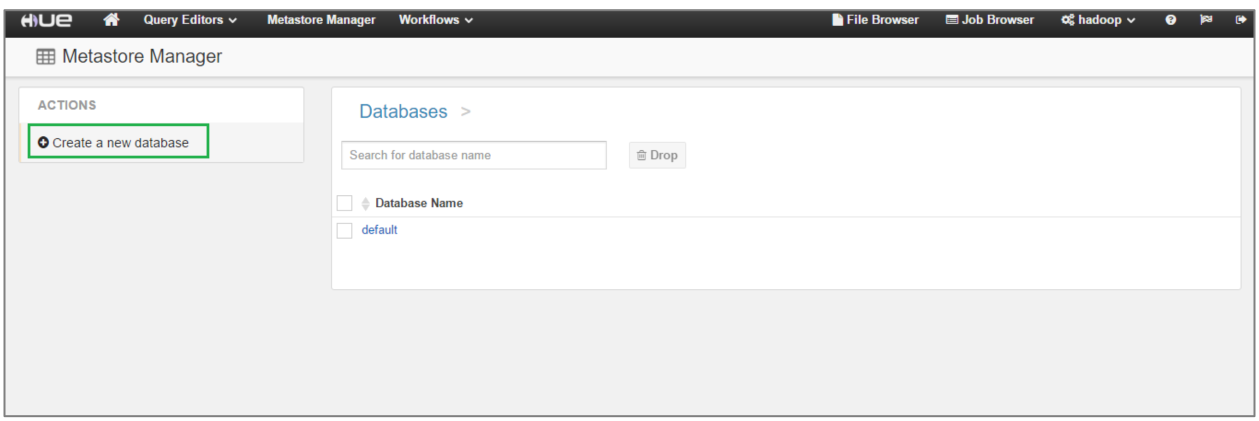


Figure 7.23. Create Database Using Metastore Manager

4. Select the created database and create tables. A table can be created either from a file or manually. Select the option to create a new table from a file.

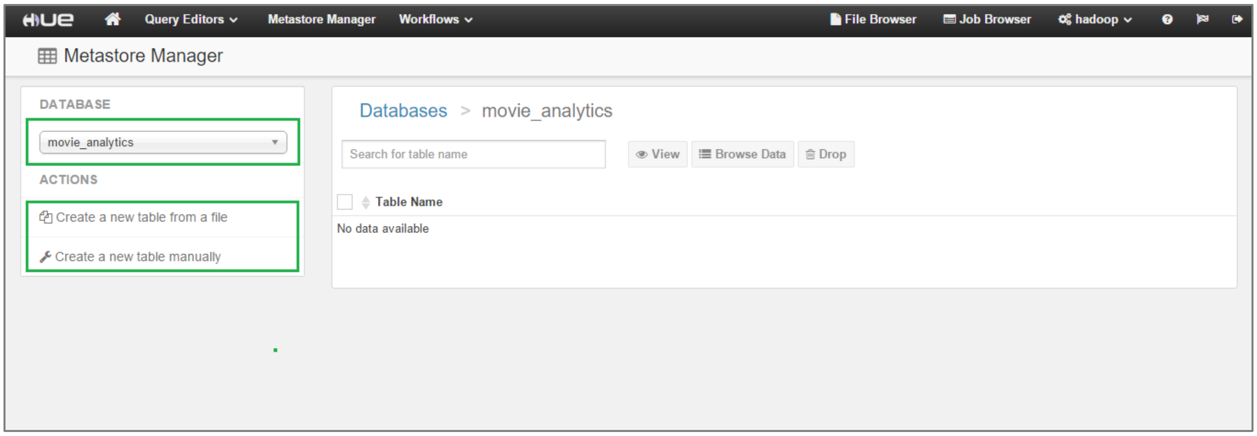


Figure 7.24. Create Tables Using Metastore Manager

4.1. Give table name 'movies' and input file path on HDFS(/user/hadoop/data/movies.dat) from where the table definition is to be used and data is to be imported. Keep the checkbox for 'Import data from file' checked. Note the warning that the selected file is going to be moved during the import.

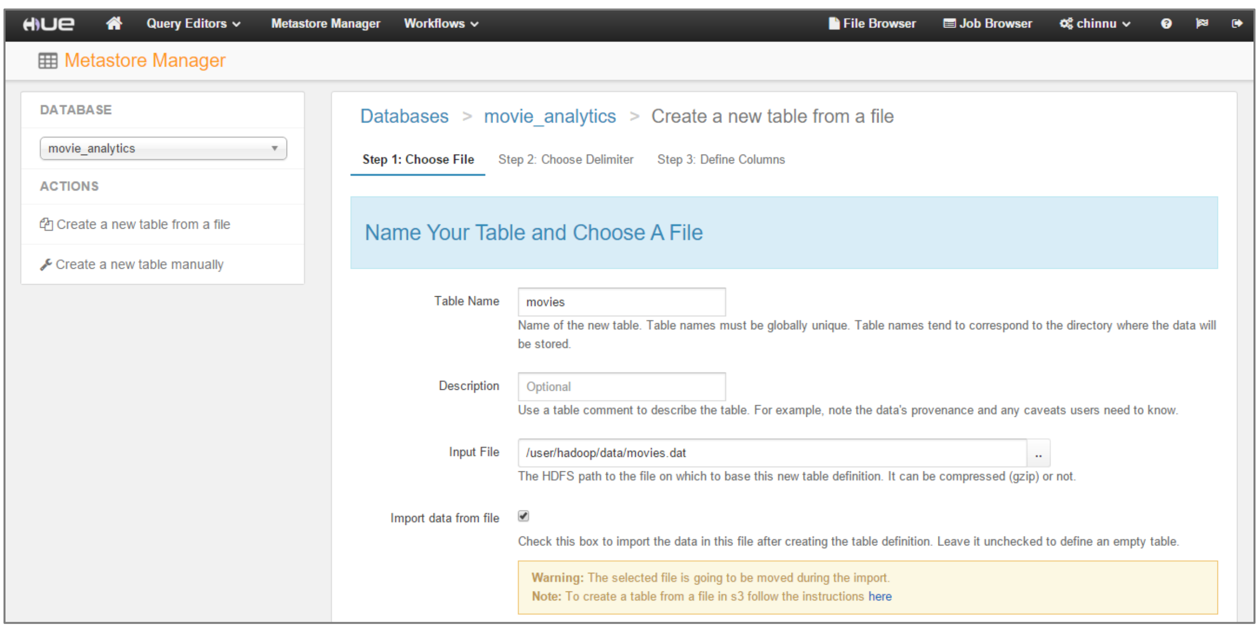


Figure 7.25. Create a New Table From a File - Choose File

4.2. Tables can be imported from HDFS to a database stored in HDFS. For example, the database movie_analytics megastore exists in HDFS (in /user/hive/warehouse/ movie_analytics.db). The procedure is different to import a table from Amazon S3 [24].

4.3. Specify the delimiter as ":" and the table data can be previewed to verify the correctness.

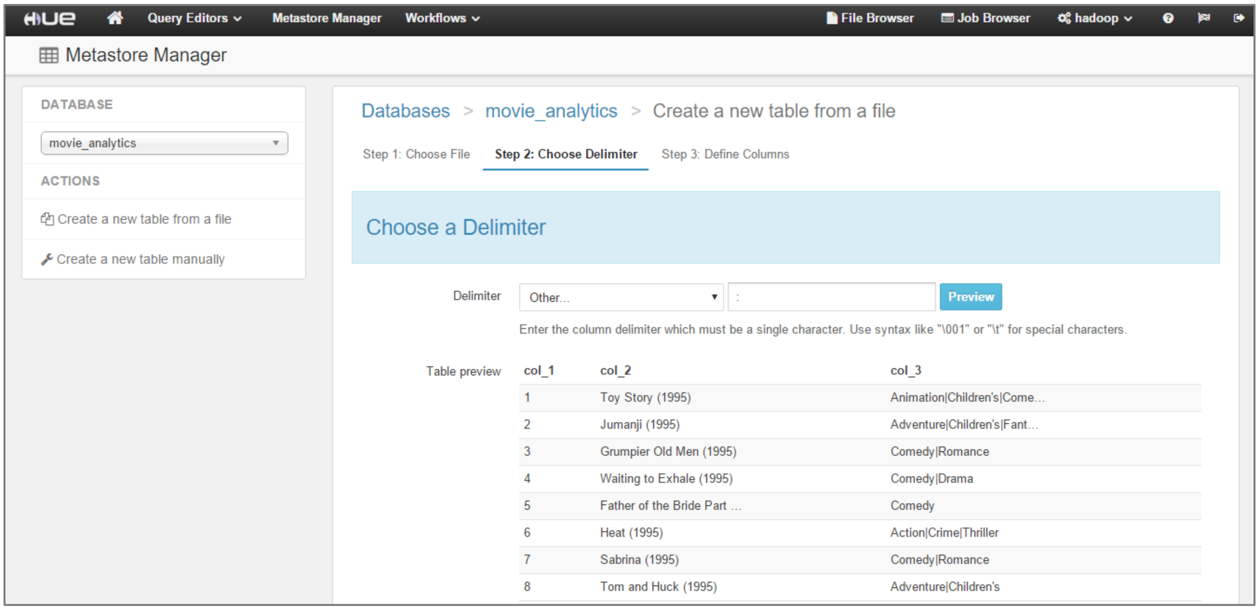


Figure 7.26. Create a New Table From a File - Choose Delimiter

4.4. Specify column names and column type.

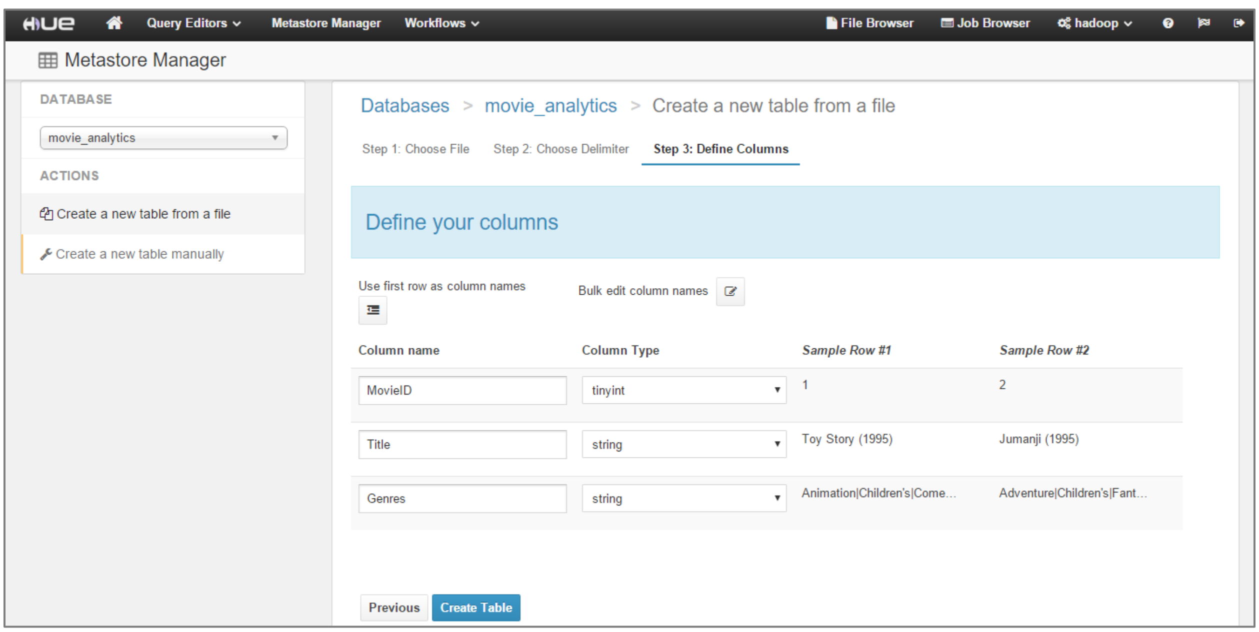


Figure 7.27. Create a New Table From a File - Define Columns

4.5. Click create table. Table gets created and data is imported.

Select the table movies under the database movie_analytics. The schema can be verified under the Columns tab. Verify if the data is imported successfully by checking Sample tab which displays sample rows of the table.

4.6. Similarly, create table ‘ratings’ from the file on HDFS /user/hadoop/data/ratings.dat.

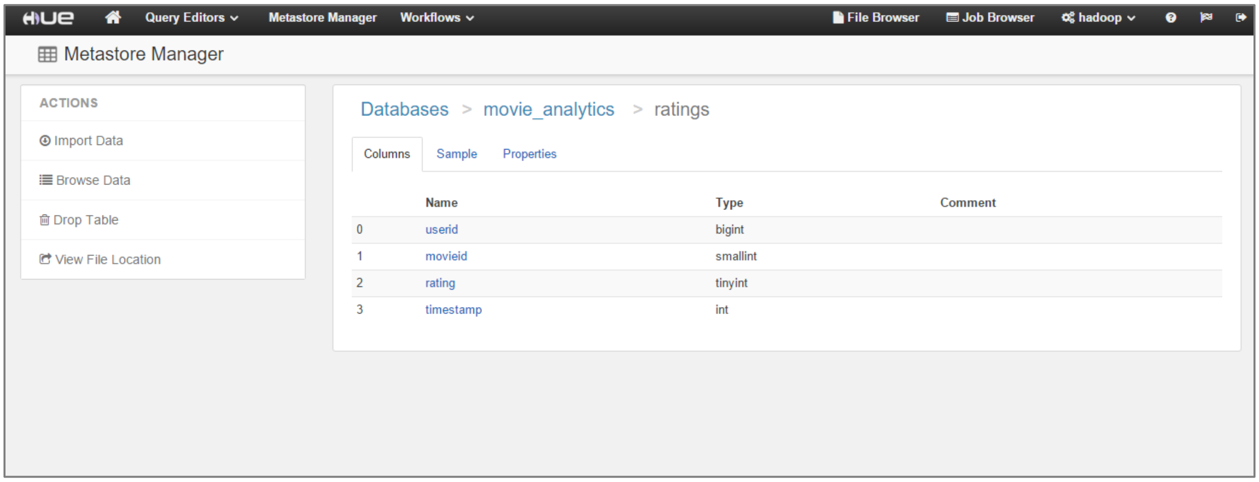


Figure 7.28. 'ratings' Table Created

5. To run the Hive queries, go to Hive Editor by selecting Query Editors -> Hive. ‘Editor’ screen is displayed.
6. Select the database from the DATABSE drop down. (Click the refresh button if the newly created database is not listed.)
7. In the editor, enter single or multiple queries and click Execute.

For example, type in “select * from movies”. The result is displayed under Results tab.

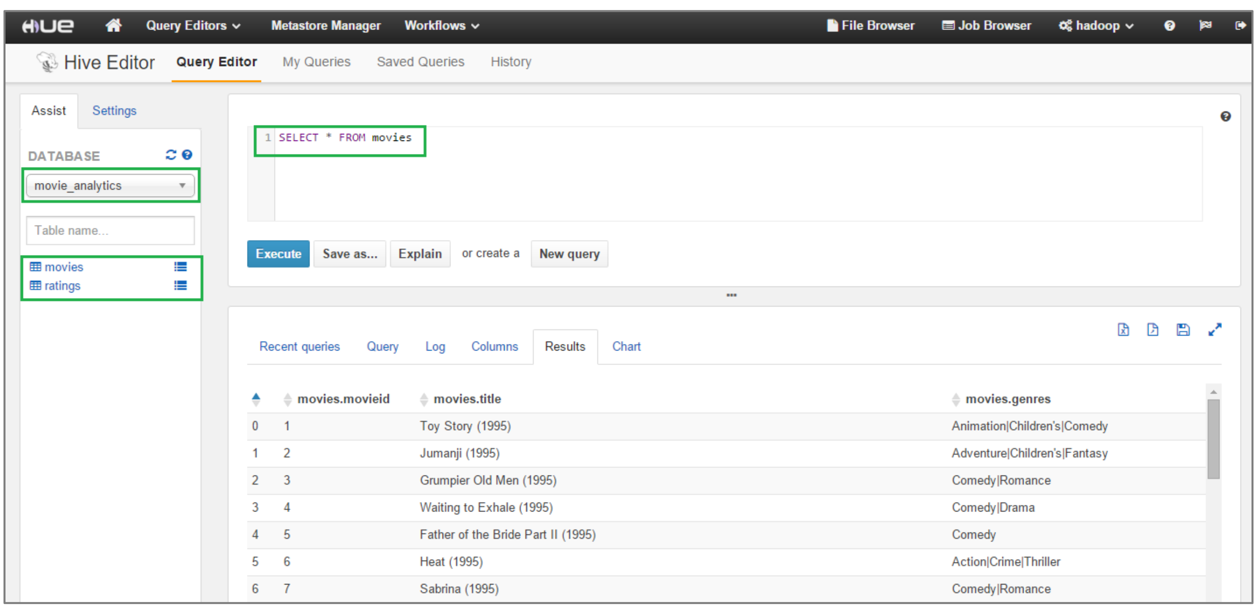


Figure 7.29. Executing a Hive Query

8. Queries can be saved and later accessed from ‘Saved Queries’ tab. ‘My Queries’ tab will show recent saved and run queries.
9. Execute below query to calculate the average movie rating:

```
SELECT a.MovieID , a.Title, b.avg_rating from movies a
JOIN (SELECT MovieID , avg(Rating) avg_rating FROM ratings GROUP BY MovieID )
ON (a.MovieID  = b.MovieID )
```

10. The result can be exported to xls/csv or saved to HDFS or a new hive table. Logs can be viewed from Logs tab. The results can be viewed in different chart formats (Bars, Lines, Pie, and Map) in the Chart tab.

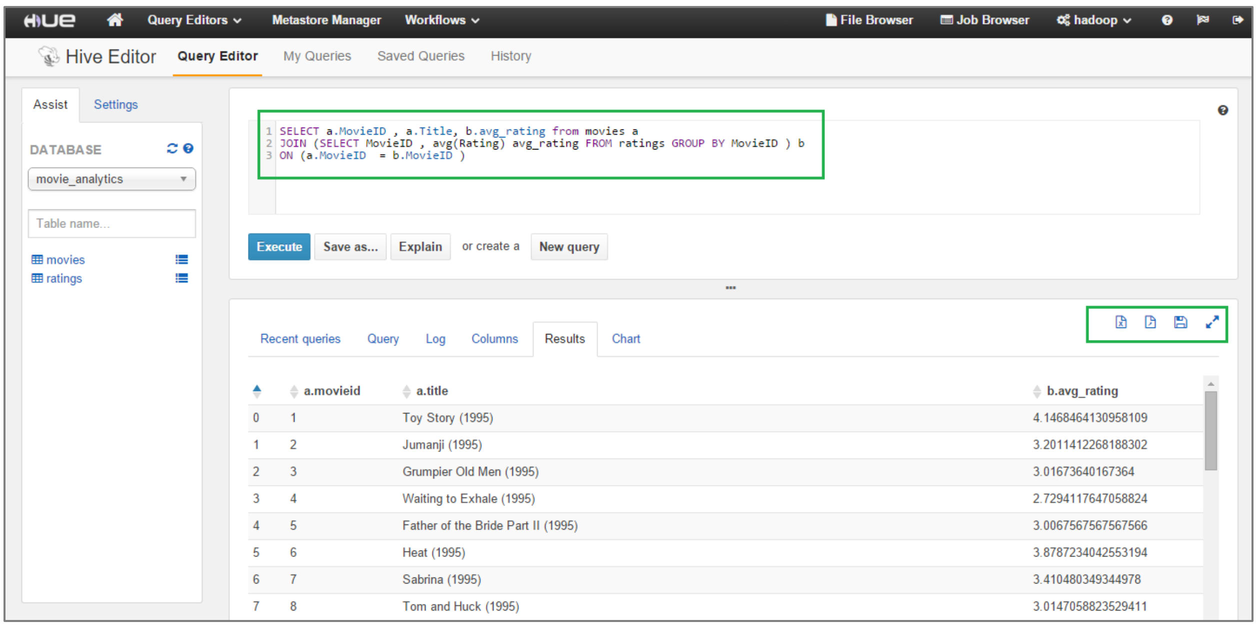


Figure 7.30. Hive Query and Result to Calculate Average Movie Rating

CHAPTER 8

SUMMARY AND FUTURE WORK

We live in a data flooded age. More organizations are becoming aware of the need to analyze their data to get insights, increase efficiency, derive competitive advantage and create new business dimensions. As the need to create value from large volumes of data increases, so do the technologies to store and process such data. There is an increased demand in the market for efficient and cost effective big data technologies as more industries seek these for their data analytical needs.

Apache Hadoop is a popular open source big data framework for distributed data storage and processing. We saw how HDFS and MapReduce, the two core components of Hadoop, enable data storage and data processing of big data. There are a number of supporting tools built around Hadoop's core components, which together form the 'Hadoop Ecosystem' and aid in data analysis, data transfer, scheduling, monitoring, performance and visualization. We saw how Pig and Hive, two data analytical platforms built around Hadoop, enable big data analysis. The main advantage of Pig and Hive is that they abstract data processing from the underlying MapReduce. Writing multi stage map and reduce functions to perform complex data processing tasks in MapReduce can be difficult and time consuming. High-level frameworks like Pig and Hive provide ease of programming with their powerful abstracted built-in capabilities. For example, we saw the ease of using the join operation in Pig and Hive to join data from two data sets. Writing MapReduce code to perform join operations would be more challenging and time consuming. Pig and Hive also provide capabilities to integrate user defined functions for specific processing needs.

Since both Pig and Hive aid in analysis of large volumes of data, these are often compared against each other to see which is best in specific scenarios. Pig is suitable for data preparation needs like ETL (Extract Transform Load) tasks, whereas Hive is widely used for data warehousing/analysis needs [25]. Pig is comparatively more efficient than Hive for complex queries with lots of joins and filters. Another difference is the type of data that these tools can process efficiently. Hive is efficient for structured data, whereas Pig handles both structured and unstructured data efficiently. Hive is easy to use for developers who are already familiar with

SQL queries since HiveQL, Hive’s query language, is very SQL-like. Users who are new to Pig Latin, the data-flow language used by Pig, would need to be familiarized with the language initially.

There are other Hadoop related projects such as Apache Spark, Apache HBase, Apache Sqoop, Apache Flume, Apache Zookeeper and Apache Oozie. Spark is a distributed computing engine for fast large-scale data processing. Instead of the MapReduce execution engine, it uses its own runtime engine. Spark runs programs up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk [26], which makes it suitable for low-latency applications. In MapReduce, data is always loaded from disk, whereas Spark uses in-memory caching to store datasets in memory in between jobs. This makes Spark more efficient for iterative tasks where the operations need to be repeated on a data set. HBase is a distributed, non-relational database built on top of HDFS to provide random, real-time read/write access to big data [27]. It was inspired from Google's BigTable [28]. Sqoop is a tool used for transferring data between Hadoop and relational databases [29]. Flume is used as a log aggregator for collecting large log data from multiple sources and moving to a centralized location [30]. Zookeeper provides centralized coordination services for managing and monitoring large distributed systems [31]. Oozie is a workflow scheduler system to manage Hadoop jobs [32]. It would be interesting to explore the features and use cases of these supporting big data tools to see how these technologies fit together to form the larger ecosystem for efficient storage, processing, and analysis of big data.

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