PUNE INSTITUTE OF COMPUTER TECHNOLOGY, PUNE

ACADEMIC YEAR: 2018-19

LAB MANUAL

DEPARTMENT: INFORMATION TECHNOLOGY

CLASS: T.E. **SEMESTER: VI**

Subject Name: Software Laboratory VI

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Subject Co-coordinator **Head of Department**

PartA

Assignments based on the Hadoop

Assignment: 1

AIM: Study of Hadoop Installation.

PROBLEM STATEMENT / DEFINITION:

1. Study of Hadoop Installation on Single Node.
2. Study of Hadoop Installation on Multiple Nodes.

OBJECTIVE:

I. To understand Installation & Configuration of Hadoop on single Node.
II. To understand Installation & Configuration of Hadoop on multiple nodes.

THEORY:

a) THE Single Node:

Introduction

Apache Hadoop is an open-source software framework written in Java for distributed storage and distributed processing of very large data sets on computer clusters built from commodity hardware. All the modules in Hadoop are designed with a fundamental assumption that hardware failures are common and should be automatically handled by the framework. The core of Apache Hadoop consists of a storage part, known as Hadoop Distributed File System (HDFS), and a processing part called MapReduce. Hadoop splits files into large blocks and distributes them across nodes in a cluster. To process data, Hadoop transfers packaged code for nodes to process in parallel based on the data that needs to be processed. This approach takes advantage of data locality— nodes manipulating the data they have access to— to allow the dataset to be processed faster and more efficiently than it would be in a more conventional supercomputer architecture that relies on a parallel file system where computation and data are distributed via high-speed networking. The base Apache Hadoop framework is composed of the following modules:

- Hadoop Common – contains libraries and utilities needed by other Hadoop modules;
- Hadoop Distributed File System (HDFS) – a distributed file-system that stores data on commodity machines, providing very high aggregate bandwidth across the cluster;

 Hadoop YARN – a resource-management platform responsible for managing computing resources in clusters and using them for scheduling of users' applications; and

 Hadoop MapReduce – an implementation of the MapReduce programming model for large scale data processing.

Steps:

sudo apt-get update

sudo apt-get install openjdk-7-jre-headless

sudo apt-get install openjdk-7-jdk

sudo apt-get install ssh

sudo apt-get install rsync

Download hadoop from : http://www.eu.apache.org/dist/hadoop/common/stable/hadoop-2.7.1.tar.gz

copy and extract hadoop-2.7.1.tar.gz in home folder

rename the name of the extracted folder from hadoop-2.7.1 to hadoop

readlink -f /usr/bin/javac

find whether ubuntu is 32 bit (i686) or 64 bit (x86_64)

uname -i

gedit ~/hadoop/etc/hadoop/hadoop-env.sh

add following line in it

for 32 bit ubuntu

export JAVA_HOME=/usr/lib/jvm/java-7-openjdk-**i386**

for 64 bit ubuntu

export JAVA_HOME=/usr/lib/jvm/java-7-openjdk-**amd64**

save and exit the file

to display the usage documentation for the hadoop script try next command

~/hadoop/bin/hadoop

1. For standalone mode

mkdir input

cp ~/hadoop/etc/hadoop/*.xml input

~/hadoop/bin/hadoop jar ~/hadoop/share/hadoop/mapreduce/hadoop-mapreduce-examples-2.7.1.jar grep input output 'us[a-z.]+'

cat output/*

Our task is done, so remove input and output folders

rm -r input output

 # 2. Pseudo-Distributed mode

get your user name

whoami

remember your user name, we'll use it in the next step

gedit ~/hadoop/etc/hadoop/core-site.xml

<configuration>

<property>

<name>fs.defaultFS</name>

<value>hdfs://localhost:1234</value>

</property>

</configuration>

gedit ~/hadoop/etc/hadoop/hdfs-site.xml

<configuration>

<property>

<name>dfs.replication</name>

<value>1</value>

</property>

<property>

<name>dfs.name.dir</name>

<value>file:///home/**your_user_name**/hadoop/name_dir</value>

</property>

<property>

<name>dfs.data.dir</name>

<value>file:///home/**your_user_name**/hadoop/data_dir</value>

</property>

</configuration>

#Setup passphraseless/passwordless ssh

ssh-keygen -t dsa -P '' -f ~/.ssh/id_dsa

cat ~/.ssh/id_dsa.pub >> ~/.ssh/authorized_keys export HADOOP_PREFIX=/home/**your_user_name**/hadoop

ssh localhost

type**exit** in the terminal to close the ssh connection (very important)

exit

 # The following instructions are to run a MapReduce job locally.

#Format the filesystem:(**Do it only once**)

~/hadoop/bin/hdfs namenode -format

#Start NameNode daemon and DataNode daemon:

~/hadoop/sbin/start-dfs.sh

#Browse the web interface for the NameNode; by default it is available at:

http://localhost:50070/

#Make the HDFS directories required to execute MapReduce jobs:

~/hadoop/bin/hdfs dfs -mkdir /user

~/hadoop/bin/hdfs dfs -mkdir /user/**your_user_name**

#Copy the sample files (from ~/hadoop/etc/hadoop) into the distributed filesystem folder(input)

~/hadoop/bin/hdfs dfs -put ~/hadoop/etc/hadoop input

#Run the example map-reduce job

~/hadoop/bin/hadoop jar ~/hadoop/share/hadoop/mapreduce/hadoop-mapreduce-examples-2.7.1.jar grep input output 'us[a-z.]+'

#View the output files on the distributed filesystem

~/hadoop/bin/hdfs dfs -cat output/*

#Copy the output files from the distributed filesystem to the local filesystem and examine them:

~/hadoop/bin/hdfs dfs -get output output

#ignore warnings (if any)

cat output/*

remove local output folder

rm -r output

remove distributed folders (input & output)

~/hadoop/bin/hdfs dfs -rm -r input output

#When you’re done, stop the daemons with

~/hadoop/sbin/stop-dfs.sh

Conclusion: In this way the Hadoop was installed & configured on Ubuntu for BigData.

Reference :: http://hadoop.apache.org/docs/r2.7.1/hadoop-project-dist/hadoop-common/SingleCluster.html

b)Multiple Node

Install a Multi Node Hadoop Cluster on Ubuntu 14.04

This article is about multi-node installation of Hadoop cluster. You would need minimum of 2 ubuntu machines or virtual images to complete a multi-node installation. If you want to just try out a single node cluster, follow this article on Installing Hadoop on Ubuntu 14.04.

I used Hadoop Stable version 2.6.0 for this article. I did this setup on a 3 node cluster. For simplicity, i will designate one node as **master,** and 2 nodes as **slaves (slave-1, and slave-2)**. Make sure all slave nodes are reachable from master node. To avoid any unreachable hosts error, make sure you add the slave hostnames and ip addresses in **/etc/hosts** file. Similarly, slave nodes should be able to resolve **master** hostname.

Installing Java on Master and Slaves

```
$sudo add-apt-repository ppa:webupd8team/java

$sudo apt-get update

$sudo apt-get install oracle-java7-installer

# Updata Java runtime

$sudo update-java-alternatives -s java-7-oracle
```

Disable IPv6

As of now Hadoop does not support IPv6, and is tested to work only on IPv4 networks. If you are using IPv6, you need to switch Hadoop host machines to use IPv4. The Hadoop Wiki link provides a one liner command to disable the IPv6. If you are not using IPv6, skip this step:

```
sudosed -i 's/net.ipv6.bindv6only\ =\ 1/net.ipv6.bindv6only\ =\ 0/'\

/etc/sysctl.d/bindv6only.conf&& sudo invoke-rc.d procps restart
```

Setting up a Hadoop User

Hadoop talks to other nodes in the cluster using no-password ssh. By having Hadoop run under a specific user context, it will be easy to distribute the ssh keys around in the Hadoop cluster. Lets's create a user **hadoopuser** on **master** as well as **slave** nodes.

```
# Create hadoopgroup

$sudo addgroup hadoopgroup

# Create hadoopuser user

$sudo adduser —ingroup hadoopgroup hadoopuser
```

Our next step will be to generate a ssh key for password-less login between master and slave nodes. Run the following commands only on **master** node. Run the last two commands for each slave node. Password less ssh should be working before you can proceed with further steps.

```
# Login as hadoopuser

$su - hadoopuser

#Generate a ssh key for the user

$ ssh-keygen -t rsa -P ""

#Authorize the key to enable password less ssh

$cat/home/hadoopuser/.ssh/id_rsa.pub>>/home/hadoopuser/.ssh/authorized_keys

$chmod600 authorized_keys

#Copy this key to slave-1 to enable password less ssh

$ssh-copy-id -i ~/.ssh/id_rsa.pub slave-1

#Make sure you can do a password less ssh using following command.

$ssh slave-1
```

Download and Install Hadoop binaries on Master and Slave nodes

Pick the best mirror site to download the binaries from Apache Hadoop, and download the stable/hadoop-2.6.0.tar.gz for your installation. **Do this step on master and every slave**

node. You can download the file once and the distribute to each slave node using scp command.

```
$cd/home/hadoopuser

$wget http://www.webhostingjams.com/mirror/apache/hadoop/core/stable/hadoop-2.2.0.tar.gz

$ tar xvf hadoop-2.2.0.tar.gz

$mv hadoop-2.2.0 hadoop
```

Setup Hadoop Environment on Master and Slave Nodes

Copy and paste following lines into your .bashrc file under /home/hadoopuser. **Do this step on master and every slave node.**

```
# Set HADOOP_HOME

exportHADOOP_HOME=/home/hduser/hadoop

# Set JAVA_HOME

exportJAVA_HOME=/usr/lib/jvm/java-7-oracle

# Add Hadoop bin and sbin directory to PATH

exportPATH=$PATH:$HADOOP_HOME/bin;$HADOOP_HOME/sbin
```

Update hadoop-env.sh on Master and Slave Nodes

Update JAVA_HOME in /home/hadoopuser/hadoop/etc/hadoop/hadoop_env.sh to following. **Do this step on master and every slave node.**

```
exportJAVA_HOME=/usr/lib/jvm/java-7-oracle
```

Common Terminologies

Before we start getting into configuration details, lets discuss some of the basic terminologies used in Hadoop.

- **Hadoop Distributed File System**: A distributed file system that provides high-throughput access to application data. A HDFS cluster primarily consists of a NameNode that manages the file system metadata and DataNodes that store the actual data. If you compare HDFS to a traditional storage structures (e.g. FAT, NTFS), then NameNode is analogous to a Directory Node structure, and DataNode is analogous to actual file storage blocks.
- **Hadoop YARN**: A framework for job scheduling and cluster resource management.

- **Hadoop MapReduce**: A YARN-based system for parallel processing of large data sets.

Update Configuration Files

Add/update core-site.xml on **Master and Slave nodes** with following options. Master and slave nodes should all be using the same value for this property **fs.defaultFS,** and should be pointing to master node only.

/home/hadoopuser/hadoop/etc/hadoop/core-site.xml (Other Options)

```
<property>

<name>hadoop.tmp.dir</name>

<value>/home/hadoopuser/tmp</value>

<description>Temporary Directory.</description>

</property>



<property>

<name>fs.defaultFS</name>

<value>hdfs://master:54310</value>

<description>Use HDFS as file storage engine</description>

</property>
```

Add/update mapred-site.xml on **Master node only** with following options.

/home/hadoopuser/hadoop/etc/hadoop/mapred-site.xml (Other Options)

```
<property>

<name>mapreduce.jobtracker.address</name>

<value>master:54311</value>

<description>The host and port that the MapReduce job tracker runs

at. If “local”, then jobs are run in-process as a single map

and reduce task.

</description>
```

```
</property>

<property>

<name>mapreduce.framework.name</name>

<value>yarn</value>

<description>The framework for running mapreduce jobs</description>

</property>
```

Add/update hdfs-site.xml on **Master and Slave Nodes.** We will be adding following three entries to the file.

- **dfs.replication**– Here I am using a replication factor of 2. That means for every file stored in HDFS, there will be one redundant replication of that file on some other node in the cluster.
- **dfs.namenode.name.dir –** This directory is used by Namenode to store its metadata file. Here i manually created this directory /hadoop-data/hadoopuser/hdfs/namenode on master and slave node, and use the directory location for this configuration.
- **dfs.datanode.data.dir –** This directory is used by Datanode to store hdfs data blocks. Here i manually created this directory /hadoop-data/hadoopuser/hdfs/datanode on master and slave node, and use the directory location for this configuration.

/home/hadoopuser/hadoop/etc/hadoop/hdfs-site.xml (Other Options)

```
<property>

<name>dfs.replication</name>

<value>2</value>

<description>Default block replication.

  The actual number of replications can be specified when the file is created.

  The default is used if replication is not specified in create time.

</description>

</property>

<property>

<name>dfs.namenode.name.dir</name>

<value>/hadoop-data/hadoopuser/hdfs/namenode</value>
```

```
<description>Determines where on the local filesystem the DFS name node should store the name table(fsimage). If this is a comma-delimited list of directories then the name table is replicated in all of the directories, for redundancy.

</description>

</property>

<property>

<name>dfs.datanode.data.dir</name>

<value>/hadoop-data/hadoopuser/hdfs/datanode</value>

<description>Determines where on the local filesystem an DFS data node should store its blocks. If this is a comma-delimited list of directories, then data will be stored in all named directories, typically on different devices. Directories that do not exist are ignored.

</description>

</property>
```

Add yarn-site.xml on **Master and Slave Nodes**. This file is required for a Node to work as a Yarn Node. Master and slave nodes should all be using the same value for the following properties, and should be pointing to master node only.

/home/hadoopuser/hadoop/etc/hadoop/yarn-site.xml

```
<property>

<name>yarn.nodemanager.aux-services</name>

<value>mapreduce_shuffle</value>

</property>

<property>

<name>yarn.resourcemanager.scheduler.address</name>

<value>master:8030</value>

</property>

<property>

<name>yarn.resourcemanager.address</name>
```

```
<value>master:8032</value>
</property>
<property>
<name>yarn.resourcemanager.webapp.address</name>
<value>master:8088</value>
</property>
<property>
<name>yarn.resourcemanager.resource-tracker.address</name>
<value>master:8031</value>
</property>
<property>
<name>yarn.resourcemanager.admin.address</name>
<value>master:8033</value>
</property>
```

Add/update **slaves** file on Master node only. Add just name, or ip addresses of master and all slave node. If file has an entry for localhost, you can remove that. This file is just helper file that are used by hadoop scripts to start appropriate services on master and slave nodes.

/home/hadoopuser/hadoop/etc/hadoop/slave

```
master
slave-1
slave-2
```

Format the Namenode

Before starting the cluster, we need to format the Namenode. Use the following command only on **master node**:

```
$ hdfs namenode -format
```

Start the Distributed Format System

Run the following on **master node** command to start the DFS.

```
$./home/hadoopuser/hadoop/sbin/start-dfs.sh
```

You should observe the output to ascertain that it tries to start datanode on slave nodes one by one. To validate the success, run following command on master nodes, and slave node.

```
$ su - hadoopuser

$ jps
```

The output of this command should list ***NameNode, SecondaryNameNode, DataNode*** on **master** node, and ***DataNode*** on all slave nodes. If you don't see the expected output, review the log files listed in Troubleshooting section.

Start the Yarn MapReduce Job tracker

Run the following command to start the Yarn mapreduce framework.

```
$./home/hadoopuser/hadoop/sbin/start-yarn.sh
```

To validate the success, run **jps** command again on master nodes, and slave node.The output of this command should list ***NodeManager, ResourceManager*** on **master** node, and ***NodeManager,*** on all **slave** nodes. If you don't see the expected output, review the log files listed in Troubleshooting section.

Review Yarn Web console

If all the services started successfully on all nodes, then you should see all of your nodes listed under Yarn nodes. You can hit the following url on your browser and verify that:

```
http://master:8088/cluster/nodes
```

Lets's execute a MapReduce example now

You should be all set to run a MapReduce example now. Run the following command

```
$hadoop jar share/hadoop/mapreduce/hadoop-mapreduce-examples-2.2.0.jar pi 30100
```

Once the job is submitted you can validate that its running on the cluster by accessing following url.

```
http://master:8088/cluster/apps
```

Troubleshooting

Hadoop uses $HADOOP_HOME/logs directory. In case you get into any issues with your installation, that should be the first point to look at. In case, you need help with anything else, do leave me a comment.

REFERENCE BOOK:

http://hadoop.apache.org/docs/current/hadoop-project-dist/hadoop-common/ClusterSetup.html

CONCLUSION:

Thus we have successfully installed and tested single and multimode cluster.

Assignment: 2

AIM: Design a distributed application using MapReduce.

PROBLEM STATEMENT /DEFINITION

Design a distributed application using MapReduce which processes a log file of a system. List out the users who have logged for maximum period on the system. Use simple log file from the Internet and process it using a pseudo distribution mode on Hadoop platform.

OBJECTIVE:

- To understand the concept of Map Reduce.
- To understand the details of Hadoop File system
- To understand the technique for log file processing
- Analyze the performance of hadoop file system

- To understand use of distributed processing

THEORY:

What is MapReduce?

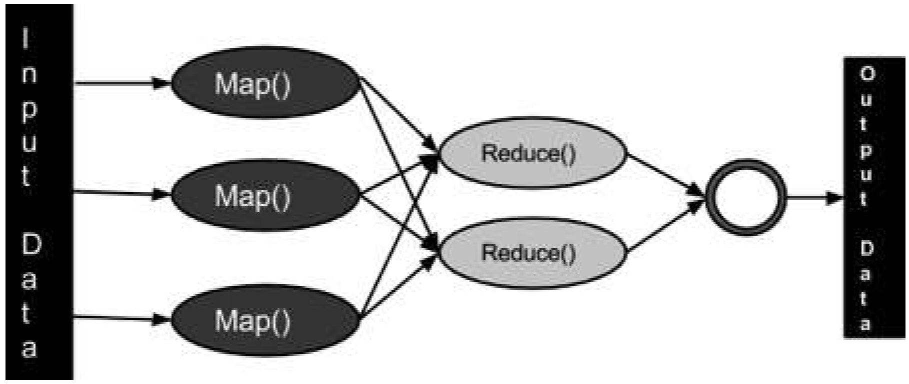
MapReduce is a processing technique and a program model for distributed computing based on java. The MapReduce algorithm contains two important tasks, namely Map and Reduce. Map takes a set of data and converts it into another set of data, where individual elements are broken down into tuples (key/value pairs). Secondly, reduce task, which takes the output from a map as an input and combines those data tuples into a smaller set of tuples. As the sequence of the name MapReduce implies, the reduce task is always performed after the map job.

The major advantage of MapReduce is that it is easy to scale data processing over multiple computing nodes. Under the MapReduce model, the data processing primitives are called mappers and reducers. Decomposing a data processing application into mappers and reducers is sometimes nontrivial. But, once we write an application in the MapReduce form, scaling the application to run over hundreds, thousands, or even tens of thousands of machines in a cluster is merely a configuration change. This simple scalability is what has attracted many programmers to use the MapReduce model.

The Algorithm

- Generally MapReduce paradigm is based on sending the computer to where the data resides!
- MapReduce program executes in three stages, namely map stage, shuffle stage, and reduce stage.
    - **Map stage** : The map or mapper's job is to process the input data. Generally the input data is in the form of file or directory and is stored in the Hadoop file system (HDFS). The input file is passed to the mapper function line by line. The mapper processes the data and creates several small chunks of data.
    - **Reduce stage** : This stage is the combination of the **Shuffle**stage and the **Reduce** stage. The Reducer's job is to process the data that comes from the mapper. After processing, it produces a new set of output, which will be stored in the HDFS.
- During a MapReduce job, Hadoop sends the Map and Reduce tasks to the appropriate servers in the cluster.
- The framework manages all the details of data-passing such as issuing tasks, verifying task completion, and copying data around the cluster between the nodes.
- Most of the computing takes place on nodes with data on local disks that reduces the network traffic.

- After completion of the given tasks, the cluster collects and reduces the data to form an appropriate result, and sends it back to the Hadoop server.



Inputs and Outputs (Java Perspective)

The MapReduce framework operates on <key, value> pairs, that is, the framework views the input to the job as a set of <key, value> pairs and produces a set of <key, value> pairs as the output of the job, conceivably of different types.

The key and the value classes should be in serialized manner by the framework and hence, need to implement the Writable interface. Additionally, the key classes have to implement the Writable-Comparable interface to facilitate sorting by the framework. Input and Output types of a MapReduce job: (Input) <k1, v1> -> map -><k2, v2>-> reduce -><k3, v3>(Output).

	Input	**Output**
Map	<k1, v1>	list (<k2, v2>)
Reduce	<k2, list(v2)>	list (<k3, v3>)

Terminology

- **PayLoad -** Applications implement the Map and the Reduce functions, and form the core of the job.
- **Mapper -** Mapper maps the input key/value pairs to a set of intermediate key/value pair.
- **NamedNode -** Node that manages the Hadoop Distributed File System (HDFS).
- **DataNode -** Node where data is presented in advance before any processing takes place.
- **MasterNode -** Node where JobTracker runs and which accepts job requests from clients.
- **SlaveNode** - Node where Map and Reduce program runs.

- **JobTracker -** Schedules jobs and tracks the assign jobs to Task tracker.
- **Task Tracker -** Tracks the task and reports status to JobTracker.
- **Job -** A program is an execution of a Mapper and Reducer across a dataset.
- **Task -** An execution of a Mapper or a Reducer on a slice of data.
- **Task Attempt -** A particular instance of an attempt to execute a task on a SlaveNode.

Example Scenario

Given below is the data regarding the electrical consumption of an organization. It contains the monthly electrical consumption and the annual average for various years.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg
1979	23	23	2	43	24	25	26	26	26	26	25	26	25
1980	26	27	28	28	28	30	31	31	31	30	30	30	29
1981	31	32	32	32	33	34	35	36	36	34	34	34	34
1984	39	38	39	39	39	41	42	43	40	39	38	38	40
1985	38	39	39	39	39	41	41	41	00	40	39	39	45

If the above data is given as input, we have to write applications to process it and produce results such as finding the year of maximum usage, year of minimum usage, and so on. This is a walkover for the programmers with finite number of records. They will simply write the logic to produce the required output, and pass the data to the application written.

But, think of the data representing the electrical consumption of all the largescale industries of a particular state, since its formation.

When we write applications to process such bulk data,

- They will take a lot of time to execute.
- There will be a heavy network traffic when we move data from source to network server and so on.

To solve these problems, we have the MapReduce framework.

Input Data

The above data is saved as **sample.txt**and given as input. The input file looks as shown below.

```
197923232432425262626252625

198026272828283031313130303029

198131323232333435363634343434

198439383939394142434039383840

198538393939394141410040393945
```

Example Program

Given below is the program to the sample data using MapReduce framework.

```
package hadoop;


import java.util.*;


import java.io.IOException;

import java.io.IOException;


import org.apache.hadoop.fs.Path;

import org.apache.hadoop.conf.*;

import org.apache.hadoop.io.*;

import org.apache.hadoop.mapred.*;

import org.apache.hadoop.util.*;


publicclassProcessUnits

{

//Mapper class

publicstaticclass E_EMapper extendsMapReduceBaseimplements

Mapper<LongWritable,/*Input key Type */

Text,/*Input value Type*/
```

```
Text,/*Output key Type*/

IntWritable>/*Output value Type*/

{


//Map function

publicvoid map(LongWritable key,Text value,

OutputCollector<Text,IntWritable> output,

Reporter reporter)throwsIOException

{

String line =value.toString();

String lasttoken =null;

StringTokenizer s =newStringTokenizer(line,"\t");

String year =s.nextToken();


while(s.hasMoreTokens())

{

lasttoken=s.nextToken();

}


int avgprice =Integer.parseInt(lasttoken);

output.collect(newText(year),newIntWritable(avgprice));

}

}




//Reducer class

publicstaticclass E_EReduce extendsMapReduceBaseimplements

Reducer<Text,IntWritable,Text,IntWritable>
```

```
{

//Reduce function
publicvoid reduce(Text key,Iterator<IntWritable> values,
OutputCollector<Text,IntWritable> output,Reporter reporter)throwsIOException
{
int maxavg=30;
int val=Integer.MIN_VALUE;

while(values.hasNext())
{
if((val=values.next().get())>maxavg)
{
output.collect(key,newIntWritable(val));
}
}

}
}


//Main function
publicstaticvoid main(String args[])throwsException
{
JobConf conf =newJobConf(ProcessUnits.class);

conf.setJobName("max_eletricityunits");
conf.setOutputKeyClass(Text.class);
```

```
conf.setOutputValueClass(IntWritable.class);

conf.setMapperClass(E_EMapper.class);

conf.setCombinerClass(E_EReduce.class);

conf.setReducerClass(E_EReduce.class);

conf.setInputFormat(TextInputFormat.class);

conf.setOutputFormat(TextOutputFormat.class);


FileInputFormat.setInputPaths(conf,newPath(args[0]));

FileOutputFormat.setOutputPath(conf,newPath(args[1]));


JobClient.runJob(conf);

}

}
```

Save the above program as **ProcessUnits.java.** The compilation and execution of the program is explained below.

Compilation and Execution of Process Units Program

Let us assume we are in the home directory of a Hadoop user (e.g. /home/hadoop).

Follow the steps given below to compile and execute the above program.

Step 1

The following command is to create a directory to store the compiled java classes.

```
$ mkdir units
```

Step 2

Download **Hadoop-core-1.2.1.jar,** which is used to compile and execute the MapReduce program. Visit the following link http://mvnrepository.com/artifact/org.apache.hadoop/hadoop-core/1.2.1to download the jar. Let us assume the downloaded folder is **/home/hadoop/.**

Step 3

The following commands are used for compiling the **ProcessUnits.java**program and creating a jar for the program.

```
$ javac-classpath hadoop-core-1.2.1.jar-d units ProcessUnits.java

$ jar -cvf units.jar -C units/.
```

Step 4

The following command is used to create an input directory in HDFS.

```
$HADOOP_HOME/bin/hadoop fs -mkdir input_dir
```

Step 5

The following command is used to copy the input file named **sample.txt**in the input directory of HDFS.

```
$HADOOP_HOME/bin/hadoop fs -put /home/hadoop/sample.txt input_dir
```

Step 6

The following command is used to verify the files in the input directory.

```
$HADOOP_HOME/bin/hadoop fs -ls input_dir/
```

Step 7

The following command is used to run the Eleunit_max application by taking the input files from the input directory.

```
$HADOOP_HOME/bin/hadoop jar units.jar hadoop.ProcessUnits input_dir output_dir
```

Wait for a while until the file is executed. After execution, as shown below, the output will contain the number of input splits, the number of Map tasks, the number of reducer tasks, etc.

```
INFO mapreduce.Job:Job job_1414748220717_0002

completed successfully

14/10/3106:02:52

INFO mapreduce.Job:Counters:49

FileSystemCounters


FILE:Number of bytes read=61

FILE:Number of bytes written=279400

FILE:Number of read operations=0
```

```
FILE:Number of large read operations=0

FILE:Number of write operations=0

HDFS:Number of bytes read=546

HDFS:Number of bytes written=40

HDFS:Number of read operations=9

HDFS:Number of large read operations=0

HDFS:Number of write operations=2JobCounters



Launched map tasks=2

Launched reduce tasks=1

Data-local map tasks=2

Total time spent by all maps in occupied slots (ms)=146137

Total time spent by all reduces in occupied slots (ms)=441

Total time spent by all map tasks (ms)=14613

Total time spent by all reduce tasks (ms)=44120

Total vcore-seconds taken by all map tasks=146137


Total vcore-seconds taken by all reduce tasks=44120

Total megabyte-seconds taken by all map tasks=149644288

Total megabyte-seconds taken by all reduce tasks=45178880

Map-ReduceFramework

Map input records=5

Map output records=5

Map output bytes=45

Map output materialized bytes=67

Input split bytes=208

Combine input records=5
```

```
Combine output records=5
Reduce input groups=5
Reduce shuffle bytes=6
Reduce input records=5
Reduce output records=5
SpilledRecords=10
ShuffledMaps=2
FailedShuffles=0
MergedMap outputs=2
  GC time elapsed (ms)=948
  CPU time spent (ms)=5160
Physical memory (bytes) snapshot=47749120
Virtual memory (bytes) snapshot=2899349504
Total committed heap usage (bytes)=277684224

FileOutputFormatCounters
BytesWritten=40
```

Step 8

The following command is used to verify the resultant files in the output folder.

```
$HADOOP_HOME/bin/hadoop fs -ls output_dir/
```

Step 9

The following command is used to see the output in **Part-00000** file. This file is generated by HDFS.

```
$HADOOP_HOME/bin/hadoop fs -cat output_dir/part-00000
```

Below is the output generated by the MapReduce program.

```
198134
198440
```

```
198545
```

Step 10

The following command is used to copy the output folder from HDFS to the local file system for analyzing.

```
$HADOOP_HOME/bin/hadoop fs -cat output_dir/part-00000/bin/hadoop dfs get output_dir /home/hadoop
```

Important Commands

All Hadoop commands are invoked by the **$HADOOP_HOME/bin/hadoop**command. Running the Hadoop script without any arguments prints the description for all commands.

Usage : hadoop [--config confdir] COMMAND

The following table lists the options available and their description.

Options	Description
namenode -format	Formats the DFS filesystem.
secondarynamenode	Runs the DFS secondary namenode.
namenode	Runs the DFS namenode.
datanode	Runs a DFS datanode.
dfsadmin	Runs a DFS admin client.
mradmin	Runs a Map-Reduce admin client.
fsck	Runs a DFS filesystem checking utility.
fs	Runs a generic filesystem user client.
balancer	Runs a cluster balancing utility.

oiv	Applies the offline fsimage viewer to an fsimage.
fetchdt	Fetches a delegation token from the NameNode.
jobtracker	Runs the MapReduce job Tracker node.
pipes	Runs a Pipes job.
tasktracker	Runs a MapReduce task Tracker node.
historyserver	Runs job history servers as a standalone daemon.
job	Manipulates the MapReduce jobs.
queue	Gets information regarding JobQueues.
version	Prints the version.
jar <jar>	Runs a jar file.
distcp <srcurl><desturl>	Copies file or directories recursively.
distcp2 <srcurl><desturl>	DistCp version 2.
archive -archiveName NAME -p	Creates a hadoop archive.
<parent path><src>* <dest>	
classpath	Prints the class path needed to get the Hadoop jar and the required libraries.
daemonlog	Get/Set the log level for each daemon

How to Interact with MapReduce Jobs

Usage: hadoop job [GENERIC_OPTIONS]

The following are the Generic Options available in a Hadoop job.

GENERIC_OPTIONS	**Description**
-submit <job-file>	Submits the job.
-status <job-id>	Prints the map and reduce completion percentage and all job counters.
-counter <job-id><group-name><countername>	Prints the counter value.
-kill <job-id>	Kills the job.
-events <job-id><fromevent-#><#-of-events>	Prints the events' details received by jobtracker for the given range.
-history [all] <jobOutputDir> -history < jobOutputDir>	Prints job details, failed and killed tip details. More details about the job such as successful tasks and task attempts made for each task can be viewed by specifying the [all] option.
-list[all]	Displays all jobs. -list displays only jobs which are yet to complete.
-kill-task <task-id>	Kills the task. Killed tasks are NOT counted against failed attempts.
-fail-task <task-id>	Fails the task. Failed tasks are counted against failed attempts.
-set-priority <job-id><priority>	Changes the priority of the job. Allowed priority values are VERY_HIGH, HIGH, NORMAL, LOW, VERY_LOW

To see the status of job

```
$ $HADOOP_HOME/bin/hadoop job -status <JOB-ID>
```

```
e.g.

$ $HADOOP_HOME/bin/hadoop job -status job_201310191043_0004
```

To see the history of job output-dir

```
$ $HADOOP_HOME/bin/hadoop job -history <DIR-NAME>

e.g.

$ $HADOOP_HOME/bin/hadoop job -history /user/expert/output
```

To kill the job

```
$ $HADOOP_HOME/bin/hadoop job -kill <JOB-ID>

e.g.

$ $HADOOP_HOME/bin/hadoop job -kill job_201310191043_0004
```

2. MapReduce (Log File)

Use Hadoop to Analyze Java Logs (Tomcat catalina.out)

One of the Java applications I develop deploys in Tomcat and is load-balanced across a couple dozen servers. Each server can produce gigabytes of log output daily due to the high volume. This post demonstrates simple use of hadoop to quickly extract useful and relevant information from catalina.out files using Map Reduce. I followed Hadoop: The Definitive Guide for setup and example code.

Installing Hadoop

Hadoop in standalone mode was the most convenient for initial development of the Map Reduce classes. The following commands were executed on a virtual server running RedHat Enterprise Linux 6.3. First verify Java 6 is installed:

```
[watrous@myhost ~]$ java-version
java version "1.6.0_24"
OpenJDK Runtime Environment (IcedTea6 1.11.5)(rhel-1.50.1.11.5.el6_3-x86_64)
OpenJDK 64-Bit Server VM (build 20.0-b12, mixed mode)
```

Next, download and extract Hadoop. Hadoop can be downloaded using a mirror. Hadoop can be setup and run locally and does not require any special privileges. Always verify that you have a good download.

```
[watrous@myhost ~]$ wget http://download.nextag.com/apache/hadoop/common/stable/hadoop-2.2.0.tar.gz
[watrous@myhost ~]$ md5sum hadoop-2.2.0.tar.gz
25f27eb0b5617e47c032319c0bfd9962  hadoop-2.2.0.tar.gz
[watrous@myhost ~]$ tar xzf hadoop-2.2.0.tar.gz
[watrous@myhost ~]$ hdfs namenode -format
```

That last command creates an HDFS file system in the **tmp** folder. In my case it was created here: **/tmp/hadoop-watrous/dfs/**.

Environment variables were added to **.bash_profile** for JAVA_HOME and HADOOP_INSTALL, as shown. These can also be run locally each time you login.

```
exportJAVA_HOME=/usr/lib/jvm/jre
exportHADOOP_INSTALL=/home/watrous/hadoop-2.2.0
exportPATH=$PATH:$HADOOP_INSTALL/bin
```

I can now verify that Hadoop is installed and ready to run.

```
[watrous@myhost ~]$ hadoop version
Hadoop 2.2.0
Subversion https://svn.apache.org/repos/asf/hadoop/common -r1529768
Compiled by hortonmu on 2013-10-07T06:28Z
Compiled with protoc 2.5.0
From source with checksum 79e53ce7994d1628b240f09af91e1af4
This command was run using /home/watrous/hadoop-2.2.0/share/hadoop/common/hadoop-common-2.2.0.jar
```

Get some seed data

Now that Hadoop is all setup, I need some seed data to operate on. For this I just reached out and grabbed a log file from one of my production servers.

```
[watrous@myhost ~]$ mkdir input
[watrous@myhost ~]$ scp watrous@mywebhost.com:/var/lib/tomcat/logs/catalina.out ./input/
```

Creating Map Reduce Classes

The most simple operation in Hadoop requires a Mapper class, a Reducer class and a third class that identifies the Mapper and Reducer including the datatypes that connect them. The examples below required two jars from the release downloaded above:

- hadoop-2.2.0.tar.gz\hadoop-2.2.0.tar\hadoop-2.2.0\share\hadoop\common\hadoop-common-2.2.0.jar
- hadoop-2.2.0.tar.gz\hadoop-2.2.0.tar\hadoop-2.2.0\share\hadoop\mapreduce\hadoop-mapreduce-client-core-2.2.0.jar

I also use regular expressions in Java to analyze each line in the log. Regular expressions can be more resilient to variations and allow for grouping, which gives easy access to specific data elements. As always, I used Kodos to develop the regular expression.

In the example below, I don’t actually use the log value, but instead I just count up how many occurrences there are by key.

Mapper class

```
importjava.io.IOException;
importjava.util.regex.Matcher;
importjava.util.regex.Pattern;
importorg.apache.hadoop.io.IntWritable;
importorg.apache.hadoop.io.LongWritable;
importorg.apache.hadoop.io.Text;
importorg.apache.hadoop.mapreduce.Mapper;

publicclass TomcatLogErrorMapper extends Mapper<LongWritable, Text, Text, Text>{

String pattern ="([0-9]{4}-[0-9]{2}-[0-9]{2}\\s[0-9]{2}:[0-9]{2}:[0-9]{2}.[0-9]{3})\\s*([a-zA-Z]+)\\s*([a-zA-Z.]+)\\s*-\\s*(.+)$";
// Create a Pattern object
    Pattern r = Pattern.compile(pattern);

    @Override
publicvoid map(LongWritable key, Text value, Context context)
throwsIOException, InterruptedException{
String line = value.toString();

        Matcher m = r.matcher(line);
if(m.find()){
// only consider ERRORs for this example
if(m.group(2).contains("ERROR")){
// example log line
// 2013-11-08 04:06:56,586 DEBUG component.helpers.GenericSOAPConnector  - Attempting to connect to: https://remotehost.com/app/rfc/entry/msg_status
//              System.out.println("Found value: " + m.group(0)); //complete line
//              System.out.println("Found value: " + m.group(1)); // date
//              System.out.println("Found value: " + m.group(2)); // log level
//              System.out.println("Found value: " + m.group(3)); // class
//              System.out.println("Found value: " + m.group(4)); // message
          context.write(new Text(m.group(1)), new Text(m.group(2)+ m.group(3)+ m.group(4)));
}
}
}
}
```

Reducer class

```
importjava.io.IOException;
importorg.apache.hadoop.io.IntWritable;
importorg.apache.hadoop.io.Text;
importorg.apache.hadoop.mapreduce.Reducer;

publicclass TomcatLogErrorReducer extends Reducer<Text, Text, Text, IntWritable>{

    @Override
publicvoid reduce(Text key, Iterable<Text> values, Context context)
throwsIOException, InterruptedException{
int countValue =0;
for(Text value : values){
          countValue++;
```

```
}
        context.write(key, new IntWritable(countValue));
}
}
```

Job class with main

```
importorg.apache.hadoop.fs.Path;
importorg.apache.hadoop.io.IntWritable;
importorg.apache.hadoop.io.Text;
importorg.apache.hadoop.mapreduce.Job;
importorg.apache.hadoop.mapreduce.lib.input.FileInputFormat;
importorg.apache.hadoop.mapreduce.lib.output.FileOutputFormat;

publicclass TomcatLogError {
publicstaticvoid main(String[] args)throwsException{
if(args.length!=2){
System.err.println("Usage: TomcatLogError <input path><output path>");
System.exit(-1);
}
        Job job =new Job();
        job.setJarByClass(TomcatLogError.class);
        job.setJobName("Tomcat Log Error");
        FileInputFormat.addInputPath(job, new Path(args[0]));
        FileOutputFormat.setOutputPath(job, new Path(args[1]));
        job.setMapperClass(TomcatLogErrorMapper.class);
        job.setReducerClass(TomcatLogErrorReducer.class);
        job.setOutputKeyClass(Text.class);
        job.setOutputValueClass(Text.class);
System.exit(job.waitForCompletion(true)?0:1);
}
}
```

Running Hadoop

In netbeans I made sure that the Main Class was TomcatLogError in the compiled jar. I then ran Clean and Build to get a jar which I transferred up to the server where I installed Hadoop.

```
[watrous@myhost ~]$ hadoop jar HadoopExample.jar input/catalina.out ~/output
13/11/1119:20:52 WARN util.NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
13/11/1119:20:52 INFO Configuration.deprecation: session.id is deprecated. Instead, use dfs.metrics.session-id
...
13/11/1118:36:57 INFO mapreduce.Job: Job job_local1725513594_0001 completed successfully
13/11/1118:36:57 INFO mapreduce.Job: Counters: 27
        File System Counters
                FILE: Number of bytes read=430339145
                FILE: Number of bytes written=1057396
                FILE: Number of readoperations=0
                FILE: Number of large readoperations=0
                FILE: Number of writeoperations=0
        Map-Reduce Framework
                Map input records=1101516
                Map output records=105
                Map output bytes=20648
```

```
            Map output materialized bytes=20968
            Input splitbytes=396
            Combine input records=0
            Combine output records=0
            Reduce input groups=23
            Reduce shuffle bytes=0
            Reduce input records=105
            Reduce output records=23
            Spilled Records=210
            Shuffled Maps =0
            Failed Shuffles=0
            Merged Map outputs=0
            GC time elapsed (ms)=234
            CPU time spent (ms)=0
            Physical memory (bytes)snapshot=0
            Virtual memory (bytes)snapshot=0
            Total committed heap usage (bytes)=1827143680
      File Input Format Counters
            Bytes Read=114455257
      File Output Format Counters
            Bytes Written=844
```

The output folder now contains a file named **part-r-00000** with the results of the processing.

```
[watrous@c0003913 ~]$ more output/part-r-00000
2013-11-08 04:04:51,8942
2013-11-08 05:04:52,7112
2013-11-08 05:33:23,073 3
2013-11-08 06:04:53,6892
2013-11-08 07:04:54,3663
2013-11-08 08:04:55,096 2
2013-11-08 13:34:28,9362
2013-11-08 17:32:31,6293
2013-11-08 18:51:17,3571
2013-11-08 18:51:17,4231
2013-11-08 18:51:17,4911
2013-11-08 18:51:17,4991
2013-11-08 18:51:17,5001
2013-11-08 18:51:17,5021
2013-11-08 18:51:17,5031
2013-11-08 18:51:17,5041
2013-11-08 18:51:17,5061
2013-11-08 18:51:17,6516
2013-11-08 18:51:17,65223
2013-11-08 18:51:17,65325
2013-11-08 18:51:17,65419
2013-11-08 19:01:13,7712
2013-11-08 21:32:34,5222
```

Based on this analysis, there were a number of errors produced around the hour **18:51:17**. It is then easy to change the Mapper class to emit based on a different key, such as Class or Message to identify more precisely what the error is, now that I know when the errors happened.

References:

https://hadoop.apache.org/docs/current/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html

CONCLUSION:

Understand the uses of distributed data processing using Map reduce.

Assignment: 3

AIM: Design and develop a distributed application using MapReduce.

PROBLEM STATEMENT /DEFINITION

Design and develop a distributed application to find the coolest/hottest year from the available weather data. Use weather data from the Internet and process it using MapReduce.

OBJECTIVE:

- To understand use of various aggregate operation in Map Reduce.
- To understand use of various Key Value passing techniques in Map Reduce.
- To understand preprocessing on input data file.

THEORY:

```
# Download dataset.zipfile (Weather data)
# It contains NCDC weather data from year 1901 to year 1920.
# Copy and extract dataset.zip in yourhome folder
# Open terminal
whoami
# It will display your user name, we will use it later.
# Open eclipse->new java project->project name
exp7
->new class->
MaxTemperatureMapper
# Add following code in that class
Packageexp7;
Importjava.io.IOException;
Importorg.apache.hadoop.io.IntWritable;
Importorg.apache.hadoop.io.LongWritable;
Importorg.apache.hadoop.io.Text;
Importorg.apache.hadoop.mapreduce.Mapper;
Publicclass MaxTemperatureMapper
extendsMapper<LongWritable,Text,Text,IntWritable>
{
PrivatestaticfinalintMISSING= 9999;
@Overridepublicvoid map(LongWritablekey,Text value,Contextcontext)
throws IOException,InterruptedException
{
String line = value.toString();
```

```
String year = line.substring(15, 19);
intairTemperature;
if (line.charAt(87)=='+')
{
airTemperature= Integer.parseInt(line.substring(88, 92));
}
else
{
airTemperature= Integer.parseInt(line.substring(87, 92));
}
Stringquality= line.substring(92, 93);
if (airTemperature != MISSING&& quality.matches("[01459]"))
{
context.write(new Text(year), new IntWritable(airTemperature));
}
}
}
```

Save the file
It will display some errors, so we are going to import two jar files in our project.
Copy hadoop-mapreduce-client-core-2.7.1.jar from ~/hadoop/share/hadoop/mapreduce directory
In eclipse-> right click on exp7 project- >paste
Right click on pasted hadoop-mapreduce-client-core-2.7.1.jar-> Buid path-> add to buid path
#Copy hadoop-common-2.7.1.jar from ~/hadoop/share/hadoop/common directory
In eclipse-> right click on exp7 project- >paste
Right click on pasted hadoop-common-2.7.1.jar-> Buid path-> add to buid path
Right click on project exp7->new class-> MaxTemperatureReducer
Add following code in that class

```
Packageexp7;
Importjava.io.IOException;
Importorg.apache.hadoop.io.IntWritable;
Importorg.apache.hadoop.io.Text;
Importorg.apache.hadoop.mapreduce.Reducer;
PublicclassMaxTemperatureReducerextendsReducer<Text,IntWritable,Text,IntWritable>
{
@Overridepublicvoidreduce(Text key, Iterable<IntWritable> values, Context context)
ThrowsIOException,InterruptedException
```

```
{
IntmaxValue= Integer.MIN_VALUE;
For(IntWritable value: values)
{
maxValue= Math.Max(maxValue,value.get());
}
Context.write(key,newIntWritable(maxValue));
}
}
```

Save the file
Right click on project exp7->new class->
MaxTemperature
Add following code in that class (
replace
your_user_name
by your own username
)
hdfs port number here is 1234, replace it with your port no (if different).

```
Packageexp7;
Importjava.io.BufferedReader;
Importjava.io.File;
Importjava.io.FileReader;
Importjava.util.ArrayList;
Importjava.util.List;
Importjava.util.Scanner;
Importorg.apache.hadoop.conf.Configuration;
Importorg.apache.hadoop.fs.FileStatus;
Importorg.apache.hadoop.fs.FileSystem;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
public classMaxTemperature
{
Publicstaticvoidmain(String[] args)
ThrowsException
{
If(args.length != 2)
{
System.err.println("Usage:MaxTemperature<input path><output path>");
System.exit(-1);
}
@SuppressWarnings
(
```

```
"deprecation"
)
Job job= newJob();
Job.setJarByClass(MaxTemperature.class);
Job.setJobName("Max temperature");
FileInputFormat.addInputPath(job,newPath(args[0]));
FileOutputFormat.setOutputPath(job,newPath(args[1]));
job.setMapperClass(MaxTemperatureMapper.class);
job.setReducerClass(MaxTemperatureReducer.class);
job.setOutputKeyClass(Text.class);
job.setOutputValueClass(IntWritable.class);
job.waitForCompletion(true);
Configuration conf= newConfiguration();
conf.set("fs.defaultFS", "hdfs://localhost:1234/user/your_user_name/");
FileSystem fs= FileSystem.get(conf);
FileStatus[] status= fs.listStatus(newPath(args[1]));
//copy hdfsoutput file to local folder
for(inti=0;i<status.length;i++)
{
System.out.println(status[i].getPath());
fs.copyToLocalFile(false, status[i].getPath(), newPath("/home/your_user_name/"+args[1]));
}
System.out.println("\nYear\tTemperature\n");
//display contents of local file
BufferedReader br= newBufferedReader(newFileReader("/home/your_user_name/"+args[1]));
String line= null;
while((line= br.readLine()) != null)
{
System.out.println(line);
}
br.close();
Scanner s= newScanner(newFile("/home/your_user_name/"+args[1]));
List<Integer> temps= newArrayList<Integer>();
List<String> years= newArrayList<String>();
while(s.hasNext())
{
years.add(s.next());
temps.add(Integer.parseInt(s.next()));
}
Intmax_temp=0,min_temp=999,i=0,j=0;
String hottest_year="", coolest_year="";
for(inttemp: temps)
{
if(temp>max_temp)
{
max_temp=temp;
hottest_year=years.get(i);
}
```

```
i++;
}
Floatmax_temp1=max_temp;
System.out.println("Hottest Year:"+hottest_year);
System.out.println("\tTemperature:"+max_temp1/10+" Degree Celcius");
for(inttemp: temps)
{
if(temp<min_temp)
{
min_temp=temp;
coolest_year=years.get(j);
}
j++;
}
Floatmin_temp1=min_temp;
System.out.println("Coolest Year:"+coolest_year);
System.out.println("\tTemperature:"+min_temp1/10+" Degree Celcius");
s.close();
}
}
```

Save the file

In eclipse->Right click on project exp7-> export->java->jar file->next-> select the export destination -> /home/ your_user_name /exp7.jar ->next -> next -> select main class ->browse -> MaxTemperature -> finish

exp7.jar file will be created in your home folder

Open terminal

Now Start NameNode daemon and DataNode daemon:

~/hadoop/sbin/start-dfs.sh

Make the HDFS directories required to execute MapReduce jobs (if not already done)

~/hadoop/bin/hdfs dfs -mkdir /user

~/hadoop/bin/hdfs dfs -mkdir /user/

```
your_user_name
# Put NCDC weather dataset in hdfs
~/hadoop/bin/hdfs dfs -put ~/dataset input_dataset
# Perform MapReduce job
~/hadoop/bin/hadoop jar ~/exp7.jar input_dataset output_dataset
# Output
# Stop haddop
~/hadoop/sbin/stop-dfs.sh
jps
```

REFERENCES:

https://hadoop.apache.org/docs/current/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html

CONCLUSION:

Understand to use various aggregate functions using map reduce.

Assignment: 4

AIM: Write an application using HBase and HiveQL for flight information system

PROBLEM STATEMENT /DEFINITION

Write an application using HBase and HiveQL for flight information system which will include

a. Creating, Dropping, and altering Database tables
b. Creating an external Hive table to connect to the HBase for Customer Information Table
c. Load table with data, insert new values and field in the table, Join tables with Hive

Create index on Flight information Table 5) Find the average departure delay per day in 2008.

OBJECTIVE

- To understand various NOSQL database
- To understand the integration of NOSQL database with Hadoop.
- To analyze the performance of distributed processing with NOSQL.

THEORY:

HBase via Hive

This is the second of two posts examining the use of Hive for interaction with HBase tables. This is a hands-on exploration so the first post isn't required reading for consuming this one. Still, it might be good context.

"Nick!" you exclaim, "that first post had too many words and I don't care about JIRA tickets. Show me how I use this thing!"

This is post is exactly that: a concrete, end-to-end example of consuming HBase over Hive. The whole mess was tested to work on a tiny little 5-node cluster running HDP-1.3.2, which means Hive 0.11.0 and HBase 0.94.6.1.

Grab some data and register it in Hive

We'll need some data to work with. For this purpose, grab some traffic stats from wikipedia. Once we have some data, copy it up to HDFS.

```
$ mkdir pagecounts ; cd pagecounts
$ for x in {0..9} ; do wget "http://dumps.wikimedia.org/other/pagecounts-raw/2008/2008-10/pagecounts-20081001-0${x}
0000.gz" ; done
$ hadoop fs -copyFromLocal $(pwd) ./
```

For reference, this is what the data looks like.

```
$ zcat pagecounts-20081001-000000.gz | head -n5
aa.b Special:Statistics 1 837
aa Main_Page 4 41431
```

```
aa Special:ListUsers 1 5555
aa Special:Listusers 1 1052
aa Special:PrefixIndex/Comparison_of_Guaze%27s_Law_and_Coulomb%27s_Law 1 4332
```

As I understand it, each record is a count of page views of a specific page on Wikipedia. The first column is the language code, second is the page name, third is the number of page views, and fourth is the size of the page in bytes. Each file contains an hour's worth of aggregated data. None of the above pages were particularly popular that hour.

Now that we have data and understand its raw schema, create a Hive table over it. To do that, we'll use a DDL script that looks like this.

```
$ cat 00_pagecounts.ddl
-- define an external table over raw pagecounts data
CREATE TABLE IF NOT EXISTS pagecounts (projectcode STRING, pagename STRING, pageviews STRING, bytes STRING)
ROW FORMAT
  DELIMITED FIELDS TERMINATED BY ' '
  LINES TERMINATED BY '\n'
STORED AS TEXTFILE
LOCATION '/user/ndimiduk/pagecounts';
```

Run the script to register our dataset with Hive.

```
$ hive -f 00_pagecounts.ddl
OK
Time taken: 2.268 seconds
```

Verify that the schema mapping works by calculating a simple statistic over the dataset.

```
$ hive -e "SELECT count(*) FROM pagecounts;"
Total MapReduce jobs = 1
Launching Job 1 out of 1
...
OK
36668549
Time taken: 25.31 seconds, Fetched: 1 row(s)
```

Hive says the 10 files we downloaded contain just over 36.5mm records. Let's just confirm things are working as expected by getting a second opinion. This isn't that much data, so confirm on the command line.

```
$ zcat * | wc -l
36668549
```

The record counts match up – excellent.

Transform the schema for HBase

The next step is to transform the raw data into a schema that makes sense for HBase. In our case, we'll create a schema that allows us to calculate aggregate summaries of pages according to their titles. To do this, we want all the data for a single page grouped together. We'll manage that by creating a Hive view that represents our target HBase schema. Here's the DDL.

```
$ cat 01_pgc.ddl
-- create a view, building a custom hbase rowkey
CREATE VIEW IF NOT EXISTS pgc (rowkey, pageviews, bytes) AS
SELECT concat_ws('/',
         projectcode,
         concat_ws('/',
           pagename,
           regexp_extract(INPUT__FILE__NAME, 'pagecounts-(\\d{8}-\\d{6})\\..*$', 1))),
       pageviews, bytes
FROM pagecounts;
```

The `SELECT` statement uses hive to build a compound rowkey for HBase. It concatenates the project code, page name, and date, joined by the `'/'` character. A handy trick: it uses a simple regex to extract the date from the source file names. Run it now.

```
$ hive -f 01_pgc.ddl
OK
Time taken: 2.712 seconds
```

This is just a view, so the `SELECT` statement won't be evaluated until we query it for data. Registering it with hive doesn't actually process any data. Again, make sure it works by querying Hive for a subset of the data.

```
$ hive -e "SELECT * FROM pgc WHERE rowkey LIKE 'en/q%' LIMIT 10;"
Total MapReduce jobs = 1
Launching Job 1 out of 1
...
OK
en/q:Special:Search/Blues/20081001-090000	1	1168
en/q:Special:Search/rock/20081001-090000	1	985
en/qadam_rasul/20081001-090000	1	1108
en/qarqay/20081001-090000	1	933
en/qemu/20081001-090000	1	1144
en/qian_lin/20081001-090000	1	918
en/qiang_(spear)/20081001-090000	1	973
en/qin_dynasty/20081001-090000	1	1120
```

```
en/qinghe_special_steel_corporation_disaster/20081001-090000    1       963
en/qmail/20081001-090000        1       1146
Time taken: 40.382 seconds, Fetched: 10 row(s)
```

Register the HBase table

Now that we have a dataset in Hive, it's time to introduce HBase. The first step is to register our HBase table in Hive so that we can interact with it using Hive queries. That means another DDL statement. Here's what it looks like.

```
$ cat 02_pagecounts_hbase.ddl
-- create a table in hbase to host the view
CREATE TABLE IF NOT EXISTS pagecounts_hbase (rowkey STRING, pageviews STRING, bytes STRING)
STORED BY 'org.apache.hadoop.hive.hbase.HBaseStorageHandler'
WITH SERDEPROPERTIES ('hbase.columns.mapping' = ':key,f:c1,f:c2')
TBLPROPERTIES ('hbase.table.name' = 'pagecounts');
```

This statement will tell Hive to go create an HBase table named `pagecounts` with the single column family `f`. It registers that HBase table in the Hive metastore by the name `pagecounts_hbase` with 3 columns: `rowkey`, `pageviews`, and `bytes`. The SerDe property `hbase.columns.mapping` makes the association from Hive column to HBase column. It says the Hive column `rowkey` is mapped to the HBase table's rowkey, the Hive column `pageviews` to the HBase column `f:c1`, and `bytes` to the HBase column `f:c2`. To keep the example simple, we have Hive treat all these columns as the `STRING` type.
In order to use the HBase library, we need to make the HBase jars and configuration available to the local Hive process (at least until HIVE-5518 is resolved). Do that by specifying a value for the `HADOOP_CLASSPATH` environment variable before executing the statement.

```
$ export HADOOP_CLASSPATH=/etc/hbase/conf:/usr/lib/hbase/hbase-0.94.6.1.3.2.0-111-security.jar:/usr/lib/
zookeeper/zookeeper.jar
$ hive -f 02_pagecounts_hbase.ddl
OK
Time taken: 4.399 seconds
```

Populate the HBase table

Now it's time to write data to HBase. This is done using a regular Hive `INSERT` statement, sourcing data from the view with `SELECT`. There's one more bit of administration we need to take care of though. This `INSERT` statement will run a mapreduce job that writes data to HBase. That means we need to tell Hive to ship the HBase jars and dependencies with the job.
Note that this is a separate step from the classpath modification we did previously. Normally you can do this with an `export` statement from the shell, the same way we specified the `HADOOP_CLASSPATH`. However there's a bug in HDP-1.3 that requires me to use Hive's `SET` statement in the script instead.

```
$ cat 03_populate_hbase.hql
-- ensure hbase dependency jars are shipped with the MR job
-- Should export HIVE_AUX_JARS_PATH but this is broken in HDP-1.3.x
SET hive.aux.jars.path = file:///etc/hbase/conf/hbase-site.xml,file:///usr/lib/hive/lib/hive-hbase-handler-0.11.0.1.3.2.0-111.jar,file:///usr/lib/hbase/hbase-0.94.6.1.3.2.0-111-security.jar,file:///usr/lib/zookeeper/zookeeper-3.4.5.1.3.2.0-111.jar;

-- populate our hbase table
FROM pgc INSERT INTO TABLE pagecounts_hbase SELECT pgc.* WHERE rowkey LIKE 'en/q%' LIMIT 10;
```

Note there's a big ugly bug in Hive 0.12.0 which means this doesn't work with that version. Never fear though, we have a patch in progress. Follow along at HIVE-5515.

If you choose to use a different method for setting Hive's auxpath, be advised that it's a tricky process – depending on how you specify it (`HIVE_AUX_JARS_PATH`, `--auxpath`), Hive will interpret the argument differently. HIVE-2349seeks to remedy this unfortunate state of affairs.

```
$ hive -f 03_populate_hbase.hql
Total MapReduce jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 1
...
OK
Time taken: 40.296 seconds
```

Be advised also that this step is currently broken on secured HBase deployments. Follow along HIVE-5523 if that's of interest to you.

Query data from HBase-land

40 seconds later, you now have data in HBase. Let's have a look using the HBase shell.

```
$ echo "scan 'pagecounts'" | hbase shell
HBase Shell; enter 'help<RETURN>' for list of supported commands.
Type "exit<RETURN>" to leave the HBase Shell
Version 0.94.6.1.3.2.0-111, r410a7a1c151ca953553eae68aa84e2a9f0d6e4ca, Mon Aug 19 19:00:12 PDT 2013

scan 'pagecounts'
ROW                                          COLUMN+CELL
 en/q:Pan%27s_Labyrinth/20081001-080000          column=f:c1, timestamp=1381534232485, value=1
 en/q:Pan%27s_Labyrinth/20081001-080000          column=f:c2, timestamp=1381534232485, value=1153
 en/q:Special:Search/Jazz/20081001-080000        column=f:c1, timestamp=1381534232485, value=1
 en/q:Special:Search/Jazz/20081001-080000        column=f:c2, timestamp=1381534232485, value=980
 en/q:Special:Search/peinture/20081001-080000      column=f:c1, timestamp=1381534232485, value=1
```

```
en/q:Special:Search/peinture/20081001-080000      column=f:c2, timestamp=1381534232485, value=989
en/q:Special:Search/rock/20081001-080000          column=f:c1, timestamp=1381534232485, value=1
en/q:Special:Search/rock/20081001-080000          column=f:c2, timestamp=1381534232485, value=980
en/qadi/20081001-080000                           column=f:c1, timestamp=1381534232485, value=1
en/qadi/20081001-080000                           column=f:c2, timestamp=1381534232485, value=1112
en/qalawun%20complex/20081001-080000              column=f:c1, timestamp=1381534232485, value=1
en/qalawun%20complex/20081001-080000              column=f:c2, timestamp=1381534232485, value=942
en/qalawun/20081001-080000                        column=f:c1, timestamp=1381534232485, value=1
en/qalawun/20081001-080000                        column=f:c2, timestamp=1381534232485, value=929
en/qari'/20081001-080000                          column=f:c1, timestamp=1381534232485, value=1
en/qari'/20081001-080000                          column=f:c2, timestamp=1381534232485, value=929
en/qasvin/20081001-080000                         column=f:c1, timestamp=1381534232485, value=1
en/qasvin/20081001-080000                         column=f:c2, timestamp=1381534232485, value=921
en/qemu/20081001-080000                           column=f:c1, timestamp=1381534232485, value=1
en/qemu/20081001-080000                           column=f:c2, timestamp=1381534232485, value=1157
10 row(s) in 0.4960 seconds
```

Here we have 10 rows with two columns each containing the data loaded using Hive. It's now accessible in your online world using HBase. For example, perhaps you receive an updated data file and have a corrected value for one of the stats. You can update the record in HBase with a regular `PUT` command.

Verify data from from Hive

The HBase table remains available to you Hive world; Hive's `HBaseStorageHandler` works both ways, after all.

Note that this command expects that the `HADOOP_CLASSPATH` is still set and `HIVE_AUX_JARS_PATH` as well if your query is complex.

```
$ hive -e "SELECT * from pagecounts_hbase;"
OK
en/q:Pan%27s_Labyrinth/20081001-080000  1       1153
en/q:Special:Search/Jazz/20081001-080000        1       980
en/q:Special:Search/peinture/20081001-080000    1       989
en/q:Special:Search/rock/20081001-080000        1       980
en/qadi/20081001-080000 1       1112
en/qalawun%20complex/20081001-080000    1       942
en/qalawun/20081001-080000      1       929
en/qari'/20081001-080000        1       929
en/qasvin/20081001-080000       1       921
en/qemu/20081001-080000 1       1157
Time taken: 2.554 seconds, Fetched: 10 row(s)
```

Continue using Hive for analysis

Since the HBase table is accessible from Hive, you can continue to use Hive for your ETL processing with mapreduce. Keep in mind that the auxpath considerations apply here too, so I've scripted out the query instead of just running it directly at the command line.

```
$ cat 04_query_hbase.hql
-- ensure hbase dependency jars are shipped with the MR job
-- Should export HIVE_AUX_JARS_PATH but this is broken in HDP-1.3.x
SET hive.aux.jars.path = file:///etc/hbase/conf/hbase-site.xml,file:///usr/lib/hive/lib/hive-hbase-handler-0.11.0.1.3.2.0-111.jar,file:///usr/

-- query hive data
SELECT count(*) from pagecounts_hbase;
```

Run it the same way we did the others.

```
$ hive -f 04_query_hbase.hql
Total MapReduce jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 1
...
OK
10
Time taken: 19.473 seconds, Fetched: 1 row(s)
```

REFERENCES:

https://hadoop.apache.org/docs/current/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html

CONCLUSION:

Understand to use various aggregate functions using map reduce.

PartB

Assignments based on R and Python

Assignment: 5

AIM: Perform different operations using R/Python

PROBLEM STATEMENT /DEFINITION

Perform the following operations using R/Python on the Amazon book review and facebook metrics data sets

a. Create data subsets
b. Merge Data
c. Sort Data
d. Transposing Data
e. Melting Data to long format

Casting data to wide format

OBJECTIVE:

To learnR/Python programming
To learndifferent data preprocessing techniques.

THEORY:

Subsetting Data

R has powerful indexing features for accessing object elements. These features can be used to select and exclude variables and observations. The following code snippets demonstrate ways to keep or delete variables and observations and to take random samples from a dataset.

Selecting (Keeping) Variables

```
# select variables v1, v2, v3
myvars <- c("v1", "v2", "v3")
newdata <- mydata[myvars]
```

```
# another method
myvars <- paste("v", 1:3, sep="")
newdata <- mydata[myvars]
```

```
# select 1st and 5th thru 10th variables
newdata <- mydata[c(1,5:10)]
```

To practice this interactively, try [the selection of data frame elements exercises]() in the Data frames chapter of this [introduction to R course.]()

Excluding (DROPPING) Variables

```
# exclude variables v1, v2, v3
myvars <- names(mydata) %in% c("v1", "v2", "v3")
newdata <- mydata[!myvars]
```

```
# exclude 3rd and 5th variable
newdata <- mydata[c(-3,-5)]

# delete variables v3 and v5
mydata$v3 <- mydata$v5 <- NULL
```

Selecting Observations

```
# first 5 observations
newdata <- mydata[1:5,]

# based on variable values
newdata <- mydata[ which(mydata$gender=='F'
& mydata$age > 65), ]

# or
attach(mydata)
newdata <- mydata[ which(gender=='F' & age > 65),]
detach(mydata)
```

Selection using the Subset Function

The **subset( )** function is the easiest way to select variables and observations. In the following example, we select all rows that have a value of age greater than or equal to 20 or age less then 10. We keep the ID and Weight columns.

```
# using subset function
```

```
newdata <- subset(mydata, age >= 20 | age < 10,
```

```
select=c(ID, Weight))
```

In the next example, we select all men over the age of 25 and we keep variables weight *through* income (weight, income and all columns between them).

```
# using subset function (part 2)
```

```
newdata <- subset(mydata, sex=="m" & age > 25,
```

```
select=weight:income)
```

To practice the **subset()** function, try this [this interactive exercise.]() on subsetting data.tables.

Random Samples

Use the **sample( )** function to take a **random sample of size n** from a dataset.

```
# take a random sample of size 50 from a dataset mydata
```

```
# sample without replacement
```

```
mysample <- mydata[sample(1:nrow(mydata), 50,
```

```
   replace=FALSE),]
```

Merging Data

Adding Columns

To merge two data frames (datasets) horizontally, use the **merge** function. In most cases, you join two data frames by one or more common key variables (i.e., an inner join).

```
#        merge        two        data        frames        by        ID
```

```
total <- merge(data frameA,data frameB,by="ID")
```

```
# merge two data frames by ID and Country
```

```
total <- merge(data frameA,data frameB,by=c("ID","Country"))
```

Adding Rows

To join two data frames (datasets) vertically, use the **rbind** function. The two data frames **must** have the same variables, but they do not have to be in the same order.

```
total<- rbind(data frameA, data frameB)
```

If data frameA has variables that data frameB does not, then either:

1. Delete the extra variables in data frameA or
2. Create the additional variables in data frameB and set them to NA (missing)

before joining them with **rbind( )**.

Going Further

To practice manipulating data frames with the dplyr package, try this interactive course on data frame manipulation in R.

Sorting Data

To sort a data frame in R, use the **order( )** function. By default, sorting is ASCENDING. Prepend the sorting variable by a minus sign to indicate DESCENDING order. Here are some examples.

```
# sorting examples using the mtcars dataset
```

```
attach(mtcars)
```

```
# sort by mpg
```

```
newdata <- mtcars[order(mpg),]
```

```
# sort by mpg and cyl
```

```
newdata <- mtcars[order(mpg, cyl),]
```

```
#sort by mpg (ascending) and cyl (descending)
newdata <- mtcars[order(mpg, -cyl),]
```

```
detach(mtcars)
```

Transpose

Use the t() function to transpose a matrix or a data frame. In the later case, rownames become variable (column) names.

```
# example using built-in dataset
mtcars
t(mtcars)
```

The Reshape Package

Hadley Wickham has created a comprehensive package called reshape to massage data. Both an introduction and article are available. There is even a video!

Basically, you "melt" data so that each row is a unique id-variable combination. Then you "cast" the melted data into any shape you would like. Here is a very simple example.

mydata

id	time	x1	x2
1	1	5	6
1	2	3	5
2	1	6	1

2	2	2	4

```
# example of melt function
library(reshape)
mdata <- melt(mydata, id=c("id","time"))
```

newdata

id	time	variable	value
1	1	x1	5
1	2	x1	3
2	1	x1	6
2	2	x1	2
1	1	x2	6
1	2	x2	5
2	1	x2	1
2	2	x2	4

```
# cast the melted data
# cast(data, formula, function)
subjmeans <- cast(mdata, id~variable, mean)
timemeans <- cast(mdata, time~variable, mean)
```

subjmeans

id	x1	x2
1	4	5.5

2	4	2.5

timemeans

time	x1	x2
1	5.5	3.5
2	2.5	4.5

Melting

There are many situations where data is presented in a format that is not ready to dive straight to exploratory data analysis or to use a desired statistical method. The **reshape2** package for **R** provides useful functionality to avoid having to hack data around in a spreadsheet prior to import into **R**.

The **melt** function takes data in wide format and stacks a set of columns into a single column of data. To make use of the function we need to specify a data frame, the id variables (which will be left at their settings) and the measured variables (columns of data) to be stacked. The default assumption on measured variables is that it is all columns that are not specified as id variables.

Consider the following set of data:

```
> dat
  FactorA FactorB    Group1     Group2     Group3      Group4
1     Low     Low -1.1616334 -0.5228371 -0.6587093  0.45064563
2  Medium     Low -0.5991478 -1.0461138 -0.1942979  2.47985577
3    High     Low  0.8420797 -1.5413266  0.6318852 -0.98948125
4     Low  Medium  1.6225569 -1.2706469 -0.8026467 -0.32332181
5  Medium  Medium -0.3450745 -1.3377985  1.4988363  0.36541918
6    High  Medium  1.6025044  0.7631882 -0.5375833  0.85028148
7     Low    High -1.2991011 -0.2223622 -0.6321478 -1.57284216
8  Medium    High -0.4906400 -1.1802192  0.1235253  0.09891793
9    High    High  0.3897769 -0.3832142  0.6671101  0.23407257
```

There four groups are to used as part of a statistical analysis so we want to stack them into a single column and create an factor variable to indicate which group the measurement corresponds to and the **melt** function does the trick:

```
> melt(dat)
Using FactorA, FactorB as id variables
   FactorA FactorB variable       value
1      Low     Low   Group1 -1.16163338
2   Medium     Low   Group1 -0.59914783
3     High     Low   Group1  0.84207974
4      Low  Medium   Group1  1.62255690
5   Medium  Medium   Group1 -0.34507455
6     High  Medium   Group1  1.60250438
```

```
...
36    High    High   Group4  0.23407257
```

Consider a second set of data where there are two groups but we only want to retain the FactorB variable in the molten data set:

```
   FactorA   FactorB   Group1   Group2
1      Low  Very Low 6.851828 3.061329
2   Medium  Very Low 7.352169 1.303077
3     High  Very Low 6.918091 2.477875
4      Low       Low 7.402351 2.450527
5   Medium       Low 6.928385 4.334323
6     High       Low 7.400626 3.074158
7      Low    Medium 8.312145 5.725185
8   Medium    Medium 8.251806 4.384492
9     High    Medium 8.339398 3.443789
10     Low      High 5.127386 2.868952
11  Medium      High 8.561181 3.616898
12    High      High 6.993838 3.450634
13     Low Very High 7.880877 2.950622
14  Medium Very High 9.439892 3.220295
15    High Very High 8.799447 3.106060
```

We now need to specify both the **id.vars** and **measure.vars** arguments in the **melt** function to get the desired output:

```
> melt(dat, id.vars = "FactorB", measure.vars = c("Group1", "Group2"))
     FactorB variable    value
1   Very Low   Group1 6.851828
2   Very Low   Group1 7.352169
3   Very Low   Group1 6.918091
4        Low   Group1 7.402351
5        Low   Group1 6.928385
6        Low   Group1 7.400626
...
30 Very High   Group2 3.106060
```

REFERENCES:

https://www.statmethods.net/

CONCLUSION:

Understand different data preprocessing techniques

Assignment: 6

AIM: Perform different data cleaning operations using R/Python

PROBLEM STATEMENT /DEFINITION

Perform the following operations using R/Python on the Air quality and Heart Diseases data sets

a. Data cleaning
b. Data integration
c. Data transformation
d. Error correcting
e. Data model building

OBJECTIVE:

To learndata processing methods
To learnbuilding data model

THEORY:

Statistical analysis in five steps In this tutorial a statistical analysis is viewed as the result of a number of data processing steps where each step increases the ``value" of the data* . Raw data . Technically correct data Consistent data Statistical results Formatted output type checking, normalizing fix and impute estimate, analyze, derive, etc. tabulate, plot data cleaning

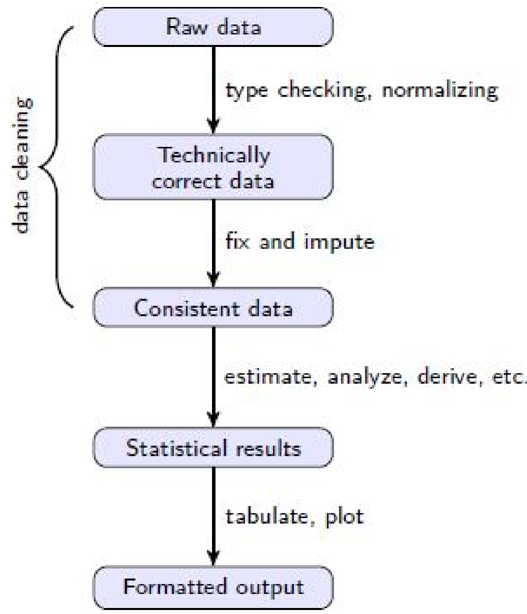


Fig. 1 Statistical analysis value chain

Figure 1 shows an overview of a typical data analysis project. Each rectangle represents data in a certain state while each arrow represents the activities needed to get from one state to the other. The first state (Raw data) is the data as it comes in. Raw data files may lack headers, contain wrong data types (e.g. numbers stored as strings), wrong category labels, unknown or unexpected character encoding and so on. In short, reading such files into an R data.frame directly is either difficult or impossible without some sort of preprocessing. Once this preprocessing has taken place, data can be deemed technically correct. That is, in this state data can be read into an R data.frame, with correct names, types and labels, without further trouble. However, that does not mean that the values are error-free or complete. For example, an age variable may be reported negative, an under-aged person may be registered to possess a driver's license, or data may simply be missing. Such inconsistencies obviously depend on the subject matter * In fact, such a value chain is an integral part of Statistics Netherlands business architecture. An introduction to data cleaning with R 7 that the data pertains to, and they should be ironed out before valid statistical inference from such data can be produced. Consistent data is the stage where data is ready for statistical inference. It is the data that most statistical theories use as a starting point. Ideally, such theories can still be applied without taking previous data cleaning steps into account. In practice however, data cleaning methods like imputation of missing values will influence statistical results and so must be accounted for in the following analyses or interpretation thereof.

1.2.1 Variable types and indexing techniques

If you had to choose to be proficient in just one R-skill, it should be indexing. By indexing we mean all the methods and tricks in R that allow you to select and manipulate data using logical, integer or named indices. Since indexing skills are important for data cleaning, we quickly review vectors, data.frames and indexing techniques. The most basic variable in R is a vector. An R vector is a sequence of values of the same type. All basic operations in R act on vectors (think of the element-wise arithmetic, for example). The basic types in R are as follows. numeric Numeric data (approximations of the real numbers, ℝ) integer Integer data (whole numbers, ℤ) factor Categorical data (simple classifications, like gender) ordered Ordinal data (ordered classifications, like educational level) character Character data (strings) raw Binary data All basic operations in R work element-wise on vectors where the shortest argument is recycled if necessary. This goes for arithmetic operations (addition, subtraction,…), comparison operators (==, <=,…), logical operators (&, |, !,…) and basic math functions like sin, cos, exp and so on. If you want to brush up your basic knowledge of vector and recycling properties, you can execute the following code and think about why it works the way it does.

```
# vectors have variables of _one_ type
c(1, 2, "three")
# shorter arguments are recycled
(1:3) * 2
(1:4) * c(1, 2)
# warning! (why?)

(1:4) * (1:3)
```

Each element of a vector can be given a name. This can be done by passing named arguments to the c() function or later with the names function. Such names can be helpful giving meaning to your variables. For example compare the vector

x <- c("red", "green", "blue")

with the one below.

capColor = c(huey = "red", duey = "blue", louie = "green")

Obviously the second version is much more suggestive of its meaning. The names of a vector need not be unique, but in most applications you'll want unique names (if any). Elements of a vector can be selected or replaced using the square bracket operator [ ]. The square brackets accept either a vector of names, index numbers, or a logical. In the case of a logical, the index is recycled if it is shorter than the indexed vector. In the case of numerical indices, negative indices omit, in stead of select elements. Negative and positive indices are not allowed in the same index vector. You can repeat a name or an index number, which results in multiple instances of the same value. You may check the above by predicting and then verifying the result of the following statements.

```
capColor["louie"]

names(capColor)[capColor == "blue"]

x <- c(4, 7, 6, 5, 2, 8)

I <- x < 6

J <- x > 7

x[I | J]

x[c(TRUE, FALSE)]

x[c(-1, -2)]
```

Replacing values in vectors can be done in the same way. For example, you may check that in the following assignment

```
x <- 1:10

x[c(TRUE, FALSE)] <- 1
```

every other value of x is replaced with 1. A list is a generalization of a vector in that it can contain objects of different types, including other lists. There are two ways to index a list. The single bracket operator always returns a sub-list of the indexed list. That is, the resulting type is again a list. The double bracket operator ([[ ]]) may only result in a single item, and it returns the object in the list itself. Besides indexing, the dollar operator $ can be used to retrieve a single element. To understand the above, check the results of the following statements.

```
L <- list(x = c(1:5), y = c("a", "b", "c"), z = capColor)

L[[2]]

L$y

L[c(1, 3)]

L[c("x", "y")]

L[["z"]]
```

Especially, use the class function to determine the type of the result of each statement. A data.frame is not much more than a list of vectors, possibly of different types, but with every vector (now columns) of the same length. Since data.frames are a type of list, indexing them with a single index returns a sub-data.frame; that is, a data.frame with less columns. Likewise, the dollar operator returns a vector, not a sub-data.frame. Rows can be indexed using two indices in the bracket operator, separated by a comma. The first index indicates rows, the second indicates columns. If one of the indices is left out, no selection is made (so everything is returned). It is important to realize that the result of a two-index selection is simplified by R as much as possible. Hence, selecting a single column using a two-index results in a vector. This behaviour may be switched off using drop=FALSE as an extra parameter. Here are some short examples demonstrating the above.

```
d <- data.frame(x = 1:10, y = letters[1:10], z = LETTERS[1:10])

d[1]

d[, 1]

d[, "x", drop = FALSE]

d[c("x", "z")]

d[d$x > 3, "y", drop = FALSE]

d[2, ]
```

1.2.2 Special values Like most programming languages, R has a number of Special values that are exceptions to the normal values of a type. These are NA, NULL, ±Inf and NaN. Below, we quickly illustrate the meaning and differences between them. NA Stands for not available. NA is a placeholder for a missing value. All basic operations in R handle NA without crashing and mostly return NA as an answer whenever one of the input arguments is NA. If you understand NA, you should be able to predict the result of the following R statements.

```
NA + 1

sum(c(NA, 1, 2))

median(c(NA, 1, 2, 3), na.rm = TRUE)

length(c(NA, 2, 3, 4))

3 == NA

NA == NA

TRUE | NA
```

The function is.na can be used to detect NA's. NULL You may think of NULL as the empty set from mathematics. NULL is special since it has no class (its class is NULL) and has length 0 so it does not take up any space in a vector. In particular, if you understand NULL, the result of the following statements should be clear to you without starting R.

```
length(c(1, 2, NULL, 4))

sum(c(1, 2, NULL, 4))

x <- NULL
```

```
c(x, 2)
```

The function is.null can be used to detect NULL variables. Inf Stands for infinity and only applies to vectors of class numeric. A vector of class integer can never be Inf. This is because the Inf in R is directly derived from the international standard for floating point arithmetic 1 . Technically, Inf is a valid numeric that results from calculations like division of a number by zero. Since Inf is a numeric, operations between Inf and a finite numeric are well-defined and comparison operators work as expected. If you understand Inf, the result of the following statements should be clear to you.

```
pi/0

2 * Inf

Inf - 1e+10

Inf + Inf

3 < -Inf

Inf == Inf
```

NaN Stands for not a number. This is generally the result of a calculation of which the result is unknown, but it is surely not a number. In particular operations like 0/0, Inf-Inf and Inf/Inf result in NaN. Technically, NaN is of class numeric, which may seem odd since it is used to indicate that something is not numeric. Computations involving numbers and NaN always result in NaN, so the result of the following computations should be clear.

```
NaN + 1

exp(NaN)
```

The function is.nan can be used to detect NaN's.

c.Data Transformations

A number of reasons can be attributed to when a predictive model crumples such as:

- Inadequate data pre-processing
- Inadequate model validation
- Unjustified extrapolation
- Over-fitting

(Kuhn, 2013)

Before we dive into data preprocessing, let me quickly define a few terms that I will be commonly using.

- *Predictor/Independent/Attributes/Descriptors* – are the different terms that are used as input for the prediction equation.

- *Response/Dependent/Target/Class/Outcome* – are the different terms that are referred to the outcome event that is to be predicted.

In this article, I am going to summarize some common data pre-processing approaches with examples in R

1. Centering and Scaling

Variable centering is perhaps the most intuitive approach used in predictive modeling. To center a predictor variable, the average predictor value is subtracted from all the values. as a result of centering, the predictor has zero mean.
To scale the data, each predictor value is divided by its standard deviation (sd). This helps in coercing the predictor value to have a *sd* of one. Needless to mention, centering and scaling will work for continuous data. The drawback of this activity is loss of interpretability of the individual values.
An R example:

```
# Load the default datasets
> library(datasets)
> data(mtcars)
> dim(mtcars)
32 11
> str(mtcars)
'data.frame':   32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
 $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
 $ qsec: num  16.5 17 18.6 19.4 17 ...
 $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
 $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
 $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
 $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
> cov(mtcars$disp, mtcars$cyl) # check for covariance
[1] 199.6603
> mtcars$disp.scl<-scale(mtcars$disp, center = TRUE, scale = TRUE)  > mtcars$cyl.scl<- s
check for covariance in scaled data
          [,1]
[1,] 0.9020329
```

2. Resolving Skewness

Skewness is a measure of shape. A common appraoch to check for skewness is to plot the predictor variable. As a rule, negative skewness indicates that the mean of the data values is less than the median, and the data distribution is left-skewed. Positive skewness would indicates that the mean of the data values is larger than the median, and the data distribution is right-skewed.

- If the skewness of the predictor variable is 0, the data is perfectly symmetrical,
- If the skewness of the predictor variable is less than -1 or greater than +1, the data is highly skewed,
- If the skewness of the predictor variable is between -1 and -1/2 or between +1 and +1/2 then the data is moderately skewed,

- If the skewness of the predictor variable is -1/2 and +1/2, the data is approximately symmetric.

I will use the function skewness from the e1071 package to compute the skewness coefficient
An R example:

```
> library(e1071)
> engine.displ<-skewness(mtcars$disp) > engine.displ
[1] 0.381657
```

So the variable displ is moderately positively skewed.

3. Resolving Outliers
The outliers package provides a number of useful functions to systematically extract outliers. Some of these are convenient and come handy, especially the outlier() and scores() functions.
Outliers
The function outliers() gets the extreme most observation from the mean.
If you set the argument opposite=TRUE, it fetches from the other side.
An R example:

```
> set.seed(4680) # for code reproducibility
> y<- rnorm(100) # create some dummy data > library(outliers) # load the library
> outlier(y)
[1] 3.581686
> dim(y)<-c(20,5) # convert it to a matrix > head(y,2)# Look at the first 2 rows of t
          [,1]       [,2]      [,3]      [,4]       [,5]
[1,] 0.5850232  1.7782596  2.051887  1.061939 -0.4421871
[2,] 0.5075315 -0.4786253 -1.885140 -0.582283  0.8159582
> outlier(y) # Now, check for outliers in the matrix
[1] -1.902847 -2.373839  3.581686  1.583868  1.877199
> outlier(y, opposite = TRUE)
[1]  1.229140  2.213041 -1.885140 -1.998539 -1.571196
```

There are two aspects the the scores() function.
Compute the normalised scores based on “z”, “t”, “chisq” etc
Find out observations that lie beyond a given percentile based on a given score.

```
> set.seed(4680)
> x = rnorm(10)
> scores(x)  # z-scores => (x-mean)/sd
[1]  0.9510577  0.8691908  0.6148924 -0.4336304 -1.6772781...
> scores(x, type="chisq")  # chi-sq scores => (x - mean(x))^2/var(x)
[1] 0.90451084 0.75549262 0.37809269 0.18803531 2.81326197 . . .
> scores(x, type="t")  # t scores
[1]  0.9454321  0.8562050  0.5923010 -0.4131696 -1.9073009
> scores(x, type="chisq", prob=0.9)  # beyond 90th %ile based on chi-sq
[1] FALSEFALSEFALSEFALSE TRUEFALSEFALSEFALSEFALSEFALSE
> scores(x, type="chisq", prob=0.95)  # beyond 95th %ile
[1] FALSEFALSEFALSEFALSEFALSEFALSEFALSEFALSEFALSEFALSE
> scores(x, type="z", prob=0.95)  # beyond 95th %ile based on z-scores
[1] FALSEFALSEFALSEFALSE TRUEFALSEFALSEFALSEFALSEFALSE
> scores(x, type="t", prob=0.95)  # beyond 95th %ile based on t-scores
[1] FALSEFALSEFALSEFALSE TRUEFALSEFALSEFALSEFALSEFALSE
```

3.1 Outlier Treatment
Once the outliers are identified, you may rectify it by using one of the following approaches.

- A. Imputation

  Imputation with mean / median / mode.

- B. Capping

  For missing values that lie outside the 1.5 * IQR limits, we could cap it by replacing those observations outside the lower limit with the value of 5th %ile and those that lie above the upper limit, with the value of 95th %ile. For example, it can be done like this as shown;

```
> par(mfrow=c(1, 2)) # for side by side plotting
> x <- mtcars$mpg > plot(x)
> qnt <- quantile(x, probs=c(.25, .75), na.rm = T)
> caps <- quantile(x, probs=c(.05, .95), na.rm = T)
> H <- 1.5 * IQR(x, na.rm = T)
> x[x < (qnt[1] - H)] <- caps[1]
> x[x > (qnt[2] + H)] <- caps[2]
> plot(x)
```

4. Missing value treatment

- A. Impute Missing values with median or mode
- B. Impute Missing values based on K-nearest neighbors

Use the library DMwR or mice or rpart. If using DMwR, for every observation to be imputed, it identifies ‘k’ closest observations based on the euclidean distance and computes the weighted average (weighted based on distance) of these ‘k’ obs. The advantage is that you could impute all the missing values in all variables with one call to the function. It takes the whole data frame as the argument and you don’t even have to specify which variabe you want to impute. But be cautious not to include the response variable while imputing.

There are many other types of transformations like treating colinearity, dummy variable encoding, covariance treatment

REFERENCES:

https://cran.r-project.org/doc/contrib/de_Jonge+van_der_Loo-Introduction_to_data_cleaning_with_R.pdf

https://www.r-bloggers.com/data-transformations/

CONCLUSION:

Understand different data preprocessing techniques