COLLEGE OF ENGINEERING & TECHNOLOGY

LABORATORY MANUAL

DATA MINING AND BUSINESS INTELLIGENCE SUBJECT CODE: 2170715 COMPUTER SCIENCE ENGINEERING DEPARTMENT

B.E. 7TH SEMESTER

NAME: _____

ENROLLMENT NO: _____

BATCH NO: _____

YEAR: _____

Amiraj College of Engineering and Technology

Nr.Tata Nano Plant, Khoraj, Sanand, Ahmedabad.

COLLEGE OF ENGINEERING & TECHNOLOGY

Amiraj College of Engineering and Technology

Nr.Tata Nano Plant, Khoraj, Sanand, Ahmedabad.

CERTIFICATE

This is to certify that Mr.	/ Ms		Of
class	Enrolment No		_has
Satisfactorily completed t	he course in		as by
the Gujarat Technologica	l University for	_ Year (B.E.) semester	_of Computer
Science Engineering in t	he Academic year_	·	

Date of Submission:-

Faculty Name and Signature PROF.NENSI KANSAGARA Head of Department (COMPUTER)



COMPUTER ENGINEERING DEPARTMENT B.E. 7[™] SEMESTER SUBJECT: DATA MINING AND BUSINESS INTELLIGENCE SUBJECT CODE: 2170715

List of Experiment

Sr. No.	Title	Date of Performance	Date of submission	Sign	Remark
1	Write a note on KDD process				
1.	XX7 · · ·				
2	algorithm in c language				
3	Demonstration of Association rule process on dataset contactlenses.arff using apriori algorithm				
4	Demonstration of classification rule process on dataset student.arff using j48 algorithm				
5	Demonstration of Association rule process on dataset supermarket.arff using apriori algorithm				
6	Study about different tools: Weka, XLMiner, Hadoop				
7	Introduction to the classification of Mining techniques				
8	Introduction to Decision Tree and Nural Networks				

PRACTICAL 1

AIM:Write a note on KDD process

The term *Knowledge Discovery in Databases*, or KDD for short, refers to the broad process of finding knowledge in data, and emphasizes the "high-level" application of particular data mining methods. It is of interest to researchers in <u>machine learning</u>, pattern recognition, databases, statistics, artificial intelligence, knowledge acquisition for expert systems, and data visualization. The unifying goal of the KDD process is to extract knowledge from data in the context of large databases.

It does this by using <u>data mining methods</u> (algorithms) to extract (identify) what is deemed knowledge, according to the specifications of measures and thresholds, using a database along with any required preprocessing, subsampling, and transformations of that database.

An Outline of the Steps of the KDD Process



- Data Cleaning In this step, the noise and inconsistent data is removed.
- Data Integration In this step, multiple data sources are combined.
- Data Selection In this step, data relevant to the analysis task are retrieved from the database.
- Data Transformation In this step, data is transformed or consolidated into forms appropriate for mining by performing summary or aggregation operations.

- Data Mining In this step, intelligent methods are applied in order to extract data patterns.
- Pattern Evaluation In this step, data patterns are evaluated.
- Knowledge Presentation In this step, knowledge is represented.

The overall process of finding and interpreting patterns from data involves the repeated application of the following steps:

- 1. Developing an understanding of
 - the application domain
 - the relevant prior knowledge
 - \circ the goals of the end-user
- 2. Creating a target data set: selecting a data set, or focusing on a subset of variables, or data samples, on which discovery is to be performed.
- 3. Data cleaning and preprocessing.
 - Removal of noise or outliers.
 - Collecting necessary information to model or account for noise.
 - Strategies for handling missing data fields.
 - Accounting for time sequence information and known changes.
- 4. Data reduction and projection.
 - Finding useful features to represent the data depending on the goal of the task.
 - Using dimensionality reduction or transformation methods to reduce the effective number of variables under consideration or to find invariant representations for the data.
- 5. Choosing the <u>data mining task</u>.
 - Deciding whether the goal of the KDD process is classification, regression, clustering, etc.
- 6. Choosing the <u>data mining algorithm(s)</u>.
 - \circ Selecting method(s) to be used for searching for patterns in the data.
 - Deciding which models and parameters may be appropriate.
 - Matching a particular data mining method with the overall criteria of the KDD process.
- 7. Data mining.
 - Searching for patterns of interest in a particular representational form or a set of such representations as classification rules or trees, regression, clustering, and so forth.
- 8. Interpreting mined patterns.
- 9. Consolidating discovered knowledge.

PRACTICAL 2

AIM:Write a program to implement apriori algorithm in c language

```
#include<stdio.h&gt;
#include<stdlib.h&gt;
int main(int argc, char *argv[])
{
FILE *fin;
int i,cols,rows,*count;
char val;
if(argc!=2)
ł
 return 1;
fin = fopen(argv[1],"r");
//finding the number of cols
cols=0;
fscanf(fin,"%c",&val);
while(1)
{
 if(val == '\n')
 break;
 if(val!=' ')
 cols++;
 fscanf(fin,"%c",&val);
}
printf("\nNumber of columns = %d\n",cols);
fclose(fin);
fin = fopen(argv[1],"r");
//Generation of 1 item frequent items
count = (int*)malloc(sizeof(int)*cols);
for(i=0;i<cols;i++)
{
 count[i] =0;
}
while(!feof(fin))
```

```
{
for(i=0;i<cols;i++)
 {
 fscanf(fin,"%c",&val);
 if(val == '1')
 count[i]++;
 fscanf(fin,"%c",&val);
 }
}
//Generation of 1-item frequent sets completed!!
printf("\n1-item frequent item sets..\n");
for(i=0;i<cols;i++)
{
printf("\n%d -> %d",i+1,count[i]);
}
fclose(fin);
return 0;
}
```

PRACTICAL 3

AIM:Demonstration of Association rule process on dataset contactlenses.arff using apriori algorithm

This experiment illustrates some of the basic elements of association rule mining using WEKA. The sample dataset used for this example is contactlenses.arff

Step1: Open the data file in Weka Explorer. It is presumed that the required data fields have been discretized. In this example it is age attribute. Step2: Clicking on the associate tab will bring up the interface for association rule algorithm.

Step3: We will use apriori algorithm. This is the default algorithm.

Step4: Inorder to change the parameters for the run (example support, confidence etc) we click on the text box immediately to the right of the choose button.

Dataset contactlenses.arff

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The following screenshot shows the association rules that were generated when apriori algorithm is applied on the given dataset.

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PRACTICAL 4

AIM:Demonstration of classification rule process on dataset student.arff using j48 algorithm

This experiment illustrates the use of j-48 classifier in weka. The sample data set used in this experiment is "student" data available at arff format. This document assumes that appropriate data pre processing has been performed. Steps involved in this experiment:

Step-1: We begin the experiment by loading the data (student.arff)into weka.

Step2: Next we select the "classify" tab and click "choose" button t o select the "j48" classifier. Step3: Now we specify the various parameters. These can be specified by clicking in the text box to the right of the chose button. In this example, we accept the default values. The default version does perform some pruning but does not perform error pruning.

Step4: Under the "text" options in the main panel. We select the 10-fold cross validation as our evaluation approach. Since we don't have separate evaluation data set, this is necessary to get a reasonable idea of accuracy of generated model. Step-5: We now click "start" to generate the model .the Ascii version of the tree as well as evaluation statistic will appear in the right panel when the model construction is complete.

Step-6: Note that the classification accuracy of model is about 69%.this indicates that we may find more work. (Either in preprocessing or in selecting current parameters for the classification) Step-7: Now weka also lets us a view a graphical version of the classification tree. This can be done by right clicking the last result set and selecting "visualize tree" from the pop-up menu. Step-8: We will use our model to classify the new instances.

Step-9: In the main panel under "text" options click the "supplied test set" radio button and then click the "set" button. This wills pop-up a window which will allow you to open the file containing test instances.

Dataset student .arff @relation student @attribute age {<30,30-40,>40} @attribute income {low, medium, high} @attribute student {yes, no} @attribute credit-rating {fair, excellent} @attribute buyspc {yes, no} @data % <30, high, no, fair, no <30, high, no, excellent, no 30-40, high, no, fair, yes >40, medium, no, fair, yes >40, low, yes, fair, yes >40, low, yes, excellent, no 30-40, low, yes, excellent, yes <30, medium, no, fair, no <30, low, yes, fair, no >40, medium, yes, fair, yes <30, medium, yes, excellent, yes 30-40, medium, no, excellent, yes 30-40, high, yes, fair, yes >40, medium, no, excellent, no %

The following screenshot shows the classification rules that were generated when j48 algorithm is applied on the given dataset.



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PRACTICAL 5

AIM: Demonstration of Association rule process on dataset supermarket.arff using apriori algorithm

Execution steps

Step1: Open the data file in Weka Explorer. It is presumed that the required data fields have been discretized. In this example it is age attribute.

Step2: Clicking on the associate tab will bring up the interface for association rule

algorithm.

Step3: We will use apriori algorithm. This is the default algorithm.

Step4: Inorder to change the parameters for the run (example support, confidence etc) we click on the text box immediately to the right of the choose button.

Dataset contactlenses.arff

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Dataset test.arff

@relation test

@attribute admissionyear {2005,2006,2007,2008,2009,2010}

@attribute course {cse,mech,it,ece}

@data

% 2005, cse 2005, it 2005, cse 2006, mech 2006, it 2006, ece 2007, it 2007, cse 2008, it 2008, cse 2009, it 2009, ece

%

The following screenshot shows the association rules that were generated when Apriori algorithm is applied on the given dataset.

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Conclusion:

The experiment displays Set of large itemsets, best rule found for the given support and the confidence values. We get the results faster using the toolkits.

PRACTICAL 6 AIM: Study about different tools: Weka, XLMiner, Hadoop

<u>WEKA</u>

Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes.

Waikato Environment for Knowledge Analysis (Weka) is a suite of <u>machine learning</u> software written in <u>Java</u>, developed at the <u>University of Waikato</u>, <u>New Zealand</u>. It is <u>free software</u> licensed under the <u>GNU General Public License</u>.

Weka contains a collection of visualization tools and algorithms for <u>data analysis</u> and <u>predictive</u> <u>modeling</u>, together with graphical user interfaces for easy access to these functions.^[11] The original non-Java version of Weka was a <u>Tcl</u>/Tk front-end to (mostly third-party) modeling algorithms implemented in other programming languages, plus <u>data preprocessing</u> utilities in <u>C</u>, and a <u>Makefile</u>-based system for running machine learning experiments. This original version was primarily designed as a tool for analyzing data from agricultural domains,^{[2][3]} but the more recent fully <u>Java</u>-based version (Weka 3), for which development started in 1997, is now used in many different application areas, in particular for educational purposes and research. Advantages of Weka include:

- Free availability under the <u>GNU General Public License</u>.
- Portability, since it is fully implemented in the <u>Java programming language</u> and thus runs on almost any modern computing platform.
- A comprehensive collection of data preprocessing and modeling techniques.
- Ease of use due to its graphical user interfaces.

Weka supports several standard <u>data mining</u> tasks, more specifically, data preprocessing, <u>clustering</u>, <u>classification</u>, <u>regression</u>, visualization, and <u>feature selection</u>. All of Weka's techniques are predicated on the assumption that the data is available as one flat file or relation, where each data point is described by a fixed number of attributes (normally, numeric or nominal attributes, but some other attribute types are also supported). Weka provides access to <u>SQL</u> <u>databases</u> using <u>Java Database Connectivity</u> and can process the result returned by a database query. Weka provides access to <u>deep learning</u>with <u>Deeplearning4j</u>.^[4] It is not capable of multi-relational data mining, but there is separate software for converting a collection of linked database tables into a single table that is suitable for processing using Weka.^[5] Another important area that is currently not covered by the algorithms included in the Weka distribution is sequence modeling.



Weka GUI Chooser	
Program Visualization Tools Help	
<u>A</u>	Applications
WEKA	Explorer
of Waikato	Experimenter
Waikato Environment for Knowledge Analysis Version 3.6.0	KnowledgeFlow
(c) 1999 - 2008 The University of Weikato Hamilton, New Zealand	Simple CLI

CLI Vs GUI

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	Geber das Nort

- Recommended for in-depth usage
- Offers some functionality not available via the GUI
- Explorer
- Experimenter
- Knowledge Flow

WEKA only deals with "flat" files

@relation heart-disease-simplified

```
@attribute age numeric
@attribute sex { female, male}
@attribute chest_pain_type { typ_angina, asympt, non_anginal, atyp_angina}
@attribute cholesterol numeric
@attribute exercise_induced_angina { no, yes}
@attribute class { present, not_present}
@data
63,male,typ_angina,233,no,not_present
67,male,asympt,286,yes,present
67,male,asympt,229,yes,present
38,female,non_anginal,?,no,not_present
```

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XLMINER:

XLMinerTM is a comprehensive data mining add-in for Excel. Data mining is a discovery-driven data analysis technology used for identifying patterns and relationships in data sets. With overwhelming amounts of data now available from transaction systems and external data sources, organizations are presented with increasing opportunities to understand their data and gain insights into it. Data mining is still an emerging field, and is a convergence of fields like statistics, machine learning, and artificial intelligence.

XLMiner is a tool belt offering a variety of methods to analyze data. It has extensive coverage of statistical and machine-learning techniques for classification, prediction, affinity analysis, data exploration, and reduction.

On the XLMiner ribbon, click XLMiner Platform to view the XLMiner ribbon tabs.

The XLMiner ribbon is divided into five tabs: Data, Data Analysis, Time Series, Data Mining, and Applying Your Model.

Data - This tab includes the Get Data icon. Click Get Data to retrieve a sample from a worksheet or database. Select File Folder to import a collection of text documents located within a file folder. Select Big Data to use Apache Spark to bring big data into Excel.

Data Analysis - This tab includes four icons: Explore, Transform, Cluster, and Text. Click Explore to use the Chart Wizard, Feature Selection, or view existing charts. Click Transform to transform data sets with missing data, perform binning, or to transform categorical data. Click Cluster to perform cluster analysis using k-Means or Hierarchical methods. Click Text to perform an analysis on a collection of text documents using the new Text Miner feature.

Time Series - This tab includes three icons: Partition, ARIMA, and Smoothing. These functions are used when analyzing a time series.

Data Mining - This tab includes four icons: Partition, Classify, Predict, and Associate. These functions are used to perform data mining activities.

Applying Your Model - This tab includes two icons: Score and Help. Click Score to score data in a database or worksheet using the classification or prediction algorithms. Click Help to change the product, check your license status, view data set examples, view the Help File, download the User Guide, check for updates, and view copyright information related to XLMiner.

1. Open your Computations file in Excel. Go to XL Miner tab. Then click Explore -> Chart Wizard

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2. You will be prompted to choose your chart type. Choose Line Chart for this Dashboard. Click Next

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3. Now you need to select your variables. For this dashboard, choose the following variables and click Next.

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4. You will be prompted to choose X- axis. Choose Observations # and click Finish.

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5. You will see the goal dashboard displayed

6. When you are done with this chart, you can close it by clicking X in the top right corner. You will be given an option to either save or discard the chart



HADOOP:

Hadoop is an open-source framework that allows to store and process big data in a distributed environment across clusters of computers using simple programming models. It is designed to

scale up from single servers to thousands of machines, each offering local computation and storage.

Hadoop Architecture

Hadoop framework includes following four modules:

- Hadoop Common: These are Java libraries and utilities required by other Hadoop modules.
 These libraries provides filesystem and OS level abstractions and contains the necessary
 Java files and scripts required to start Hadoop.
- Hadoop YARN: This is a framework for job scheduling and cluster resource management.
- Hadoop Distributed File System (HDFS[™]): A distributed file system that provides highthroughput access to application data.
- Hadoop MapReduce: This is YARN-based system for parallel processing of large data sets.

We can use following diagram to depict these four components available in Hadoop framework.



MapReduce

Hadoop MapReduce is a software framework for easily writing applications which process big amounts of data in-parallel on large clusters (thousands of nodes) of commodity hardware in a reliable, fault-tolerant manner.

The term MapReduce actually refers to the following two different tasks that Hadoop programs perform:

• The Map Task: This is the first task, which takes input data and converts it into a set of

data, where individual elements are broken down into tuples (key/value pairs).

• The Reduce Task: This task takes the output from a map task as input and combines those

data tuples into a smaller set of tuples. The reduce task is always performed after the map

task.

Typically both the input and the output are stored in a file-system. The framework takes care of scheduling tasks, monitoring them and re-executes the failed tasks.

The MapReduce framework consists of a single master JobTracker and one slave TaskTracker per cluster-node. The master is responsible for resource management, tracking resource consumption/availability and scheduling the jobs component tasks on the slaves, monitoring them and re-executing the failed tasks. The slaves TaskTracker execute the tasks as directed by the master and provide task-status information to the master periodically.

The JobTracker is a single point of failure for the Hadoop MapReduce service which means if JobTracker goes down, all running jobs are halted.

Hadoop Distributed File System

Hadoop can work directly with any mountable distributed file system such as Local FS, HFTP FS, S3 FS, and others, but the most common file system used by Hadoop is the Hadoop Distributed File System (HDFS).

The Hadoop Distributed File System (HDFS) is based on the Google File System (GFS) and provides a distributed file system that is designed to run on large clusters (thousands of computers) of small computer machines in a reliable, fault-tolerant manner.

HDFS uses a master/slave architecture where master consists of a single NameNode that manages the file system metadata and one or more slave DataNodes that store the actual data.

A file in an HDFS namespace is split into several blocks and those blocks are stored in a set of DataNodes. The NameNode determines the mapping of blocks to the DataNodes. The DataNodes takes care of read and write operation with the file system. They also take care of block creation, deletion and replication based on instruction given by NameNode.

HDFS provides a shell like any other file system and a list of commands are available to interact with the file system. These shell commands will be covered in a separate chapter along with appropriate examples.

How Does Hadoop Work?

Stage 1A user/application can submit a job to the Hadoop (a hadoop job client) for required process by specifying the following items:

- 1. The location of the input and output files in the distributed file system.
- 2. The java classes in the form of jar file containing the implementation of map and reduce

functions.

3. The job configuration by setting different parameters specific to the job.

Stage 2

The Hadoop job client then submits the job (jar/executable etc) and configuration to the JobTracker which then assumes the responsibility of distributing the software/configuration to the slaves, scheduling tasks and monitoring them, providing status and diagnostic information to the job-client.

Stage 3

The TaskTrackers on different nodes execute the task as per MapReduce implementation and output of the reduce function is stored into the output files on the file system.

Advantages of Hadoop

• Hadoop framework allows the user to quickly write and test distributed systems. It is

efficient, and it automatic distributes the data and work across the machines and in turn,

utilizes the underlying parallelism of the CPU cores.

• Hadoop does not rely on hardware to provide fault-tolerance and high availability (FTHA),

rather Hadoop library itself has been designed to detect and handle failures at the application layer.

- Servers can be added or removed from the cluster dynamically and Hadoop continues to operate without interruption.
- Another big advantage of Hadoop is that apart from being open source, it is compatible on all the platforms since it is Java based.

Hadoop Installation Step:

Step 1: <u>Click here</u> to download the Java 8 Package. Save this file in your home directory.

Step 2: Extract the Java Tar File.

Command: tar -xvf jdk-8u101-linux-i586.tar.gz



Fig: Hadoop Installation – Extracting Java Files

Step 3: Download the Hadoop 2.7.3 Package.

Command: wget https://archive.apache.org/dist/hadoop/core/hadoop-2.7.3/hadoop-2.7.3.tar.gz



Fig: Hadoop Installation – Downloading Hadoop

Step 4: Extract the Hadoop tar File.

Command: tar -xvf hadoop-2.7.3.tar.gz



Fig: Hadoop Installation – Extracting Hadoop Files

Step 5: Add the Hadoop and Java paths in the bash file (.bashrc).

Open. bashrc file. Now, add Hadoop and Java Path as shown below.

Command: vi .bashrc

E	edureka@localhost:~ _ = =
File Edit View Search Terminal Help	
<pre>[edureka@localhost ~]\$ vi .bashro</pre>	

# User	
export	HADOOP HOME=\$HOME/hadoop-2.7.3
export	HADOOP CONF DIR=\$HOME/hadoop-2.7.3/etc/hadoop
export	HADOOP MAPRED HOME=\$HOME/hadoop-2.7.3
export	HADOOP COMMON HOME=\$HOME/hadoop-2.7.3
export	HADOOP HDFS HOME=\$HOME/hadoop-2.7.3
export	YARN HOME=\$HOME/hadoop-2.7.3
export	PATH=\$PATH:\$HOME/hadoop-2.7.3/bin
# Set J	AVA_HOME
export	JAVA_HOME=/home/edureka/jdk1.8.0_101
export	PATH=/home/edureka/jdk1.8.0_101/bin:\$PATH

Fig: Hadoop Installation – Setting Environment Variable

Then, save the bash file and close it.

For applying all these changes to the current Terminal, execute the source command.

Command: source .bashrc



Fig: Hadoop Installation – Refreshing environment variables

To make sure that Java and Hadoop have been properly installed on your system and can be accessed through the Terminal, execute the java -version and hadoop version commands.

Command: java -version



Fig: Hadoop Installation – Checking Java Version

Command: hadoop version



Fig: Hadoop Installation – Checking Hadoop Version

Step 6: Edit the <u>Hadoop Configuration files</u>.

Command: cd hadoop-2.7.3/etc/hadoop/

Command: 1s

All the Hadoop configuration files are located in hadoop-2.7.3/etc/hadoop directory as you can

see in the snapshot below:

ाड ed	lureka@localhost:~/hadoop-2.7.3/etc/ha	adoop _ = :
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[edureka@localhost ~]\$ cd h	adoop-2.7.3/etc/hadoop/	
[edureka@localhost hadoop]\$	ls	
capacity-scheduler.xml	httpfs-env.sh	mapred-env.sh
configuration.xsl	httpfs-log4j.properties	mapred-queues.xml.template
container-executor.cfg	httpfs-signature.secret	mapred-site.xml.template
core-site.xml	httpfs-site.xml	slaves
hadoop-env.cmd	kms-acls.xml	ssl-client.xml.example
hadoop-env.sh	kms-env.sh	ssl-server.xml.example
hadoop-metrics2.properties	kms-log4j.properties	yarn-env.cmd
hadoop-metrics.properties	kms-site.xml	yarn-env.sh
hadoop-policy.xml	log4j.properties	yarn-site.xml
hdfs-site.xml	mapred-env.cmd	
[edureka@localhost hadoop]\$		

Fig: Hadoop Installation – Hadoop Configuration Files

Step 7: Open *core-site.xml* and edit the property mentioned below inside configuration tag:

core-site.xml informs Hadoop daemon where NameNode runs in the cluster. It contains configuration settings of Hadoop core such as I/O settings that are common to HDFS & MapReduce.

Command: vi core-site.xml



Fig: Hadoop Installation – Configuring core-site.xml

<?xml versi <?xml-stylesheet tyj <configuration> <property> <name>fs.default.name</name> <value>hdfs://localhost:9000</value> </property> </configuration>

version="1.0" type="text/xsl" encoding="UTF-8"?> href="configuration.xsl"?>

Step 8: Edit *hdfs-site.xml* and edit the property mentioned below inside configuration tag: *hdfs-site.xml* contains configuration settings of HDFS daemons (i.e. NameNode, DataNode,

Secondary NameNode). It also includes the replication factor and block size of HDFS.

Command: vi hdfs-site.xml



Fig: Hadoop Installation – Configuring hdfs-site.xml

<?xml <?xml-stylesheet <configuration> version="1.0" type="text/xsl" encoding="UTF-8"?> href="configuration.xsl"?> <property> <name>dfs.replication</name> <value>1</value> </property> <property> <name>dfs.permission</name> <value>false</value> </property> </configuration>

Step 9: Edit the *mapred-site.xml* file and edit the property mentioned below inside configuration tag:

mapred-site.xml contains configuration settings of MapReduce application like number of JVM

that can run in parallel, the size of the mapper and the reducer process, CPU cores available for a

process, etc.

In some cases, mapred-site.xml file is not available. So, we have to create the mapred-site.xml file

using mapred-site.xml template.

Command: cp mapred-site.xml.template mapred-site.xml

Command: vi mapred-site.xml.



E	edureka@localhost:~/hadoop-2.7.3/etc/hadoop	
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<configuration></configuration>		
<pre>coropertv></pre>		
<name>mapreduce.framework</name>	.name	
<value>varn</value>		

Fig: Hadoop Installation – Configuring mapred-site.xml

<?xml version="1.0" <?xml-stylesheet type="text/xsl" <configuration> <property> <name>mapreduce.framework.name</name> <value>yarn</value> </property> </configuration> encoding="UTF-8"?> href="configuration.xsl"?>

Step 10: Edit *yarn-site.xml* and edit the property mentioned below inside configuration tag: *yarn-site.xml* contains configuration settings of ResourceManager and NodeManager like application memory management size, the operation needed on program & algorithm, etc.

Command: vi yarn-site.xml

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Fig: Hadoop Installation – Configuring yarn-site.xml

<?xml version="1.0"> <configuration> <property> <name>yarn.nodemanager.aux-services</name> <value>mapreduce_shuffle</value> </property> <property> <name>yarn.nodemanager.auxservices.mapreduce.shuffle.class</name> <value>org.apache.hadoop.mapred.ShuffleHandler</value> </property> </configuration>

Step 11: Edit *hadoop-env.sh* and add the Java Path as mentioned below:

hadoop-env.sh contains the environment variables that are used in the script to run Hadoop like

Java home path, etc.

Command: vi hadoop-env.sh



Fig: Hadoop Installation – Configuring hadoop-env.sh

Step 12: Go to Hadoop home directory and format the NameNode.

Command: cd

Command: cd hadoop-2.7.3

Command: bin/hadoop namenode -format



Fig: Hadoop Installation – Formatting NameNode

This formats the HDFS via NameNode. This command is only executed for the first time. Formatting the file system means initializing the directory specified by the dfs.name.dir variable.

Never format, up and running Hadoop filesystem. You will lose all your data stored in the HDFS.

Step 13: Once the NameNode is formatted, go to hadoop-2.7.3/sbin directory and start all the daemons.

Command: cd hadoop-2.7.3/sbin

Either you can start all daemons with a single command or do it individually.

Command: ./start-all.sh

The above command is a combination of *start-dfs.sh*, *start-yarn.sh* & *mr-jobhistory-daemon.sh*

Or you can run all the services individually as below:

Start NameNode:

The NameNode is the centerpiece of an HDFS file system. It keeps the directory tree of all files

stored in the HDFS and tracks all the file stored across the cluster.

Command: ./hadoop-daemon.sh start namenode



Fig: Hadoop Installation – Starting NameNode

Start DataNode:

On startup, a DataNode connects to the Namenode and it responds to the requests from the Namenode for different operations.

Command: ./hadoop-daemon.sh start datanode



Fig: Hadoop Installation – Starting DataNode

Start ResourceManager:

ResourceManager is the master that arbitrates all the available cluster resources and thus helps in

managing the distributed applications running on the YARN system. Its work is to manage each

NodeManagers and the each application's ApplicationMaster.

Command: ./yarn-daemon.sh start resourcemanager



Fig: Hadoop Installation – Starting ResourceManager

Start NodeManager:

The NodeManager in each machine framework is the agent which is responsible for managing containers, monitoring their resource usage and reporting the same to the ResourceManager.

Command: ./yarn-daemon.sh start nodemanager



Fig: Hadoop Installation – Starting NodeManager

Start JobHistoryServer:

JobHistoryServer is responsible for servicing all job history related requests from client.

Command: ./mr-jobhistory-daemon.sh start historyserver

Step 14: To check that all the Hadoop services are up and running, run the below command. *Command:* jps



Fig: Hadoop Installation – Checking Daemons

Step 15: Now open the Mozilla browser and go to **localhost:50070/dfshealth.html** to check the NameNode interface.

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| Overview 'localit | nost:9000' (active) | |
| Started: | Wed Nov 02 08:32:45 CET 2016 | |
| Version: | 2.7.3, rbaa91f7c6bc9cb92be5982de4719c1c8af91ccff | |
| Compiled: | 2016-08-18T01:41Z by root from branch-2.7.3 | |
| Cluster ID: | CID-617e6b4f-a7e8-45ee-abae-e59744b38d66 | |
| Block Pool ID: | BP-1874109370-127.0.0.1-1477077288629 | |
| | | |

Fig: Hadoop Installation – Starting WebUI

PRACTICAL 7

AIM: Introduction to the classification of Mining techniques

Data mining techniques can be classified broadly as

- 1. Predictive:
- a. Classification
- b. Regression
- c. Time series Analysis
- d. Prediction
- 2. Descriptive:
- a. clustering
- b. Summarization
- c. Association Rules
- d. Sequence Discovery
- You can refer the below chat about that.



- •
- Data Mining Techniques Graph
- Now I am going to give brief intro about each types.
- <u>Classification:</u>
- It is often refered as "supervised learning". It has a predefined set of groups or models based on that we predict values.
- (e.g) Airport security maintains a set of metrics and try to predict the terrorist
- <u>Regression:</u>
- The regression using known data formats like linear or logistic and assume the future data format will fall in to the data structure. It then try to predict the value by applying some mathematical algorithms on the data set.
- (e.g) Investing on Pension fund. Calculating your annual income and try to predict what you need after you retire. Then based on the present income and needed income makes investment decision. The Prediction done by simple regression formula to revise every year.
- <u>Time series Analysis:</u>
- With time series analysis, every attribute value determine by the different time interval.

- (e.g) Buying a company stock. Take X,Y,Z companies month by month performance and try to predict their next one year growth and based on the growth you buy stocks.
- **Prediction:**
- Prediction is relates with time series but not time bound. It is used to predict value based on past data and current data.
- (e.g) Water flow of a river will be calculated by various monitors at different levels and different time intervals. It then using those information to predict the water flow of future.

• <u>Clustering:</u>

- It is widely called as unsupervised learning. It is similar to classification except it won't have any predefined groups. instead the data itself define the group.
- (e.g) Consider a super market has buying details like age, job and purchase amount we can group by age against percentage as well job against percentage to make meaningful business decision to target the specific user group.

• <u>Summarization:</u>

• Summarization is associating the sample subset with small description or snippet.

<u>Association Rules:</u>

- It is also called as linked analysis. It is all about under covering relationship among data.
- (e.g) Amazon "People bought this also bought this" model
- Sequence Discovery:
- Sequence discovery is about finding sequence of an activity.
- (e.g) In a shop people may often buy tothpaste after toothbrush. It is all about what sequence user buying the product and based on theo shop owner can arrange the items near by each others.

PRACTICAL 8

AIM:Introduction to Decision Tree and Nural Networks

Decision Tree

A decision tree is a structure that includes a root node, branches, and leaf nodes. Each internal node denotes a test on an attribute, each branch denotes the outcome of a test, and each leaf node holds a class label. The topmost node in the tree is the root node.

The following decision tree is for the concept buy_computer that indicates whether a customer at a company is likely to buy a computer or not. Each internal node represents a test on an attribute. Each leaf node represents a class.



The benefits of having a decision tree are as follows -

- It does not require any domain knowledge.
- It is easy to comprehend.
- The learning and classification steps of a decision tree are simple and fast.

Decision Tree Induction Algorithm

A machine researcher named J. Ross Quinlan in 1980 developed a decision tree algorithm known as ID3 (Iterative Dichotomiser). Later, he presented C4.5, which was the successor of ID3. ID3 and C4.5 adopt a greedy approach. In this algorithm, there is no backtracking; the trees are constructed in a top-down recursive divide-and-conquer manner.

Generating a decision tree form training tuples of data partition D Algorithm : Generate_decision_tree

Input:

Data partition, D, which is a set of training tuples and their associated class labels. attribute_list, the set of candidate attributes. Attribute selection method, a procedure to determine the splitting criterion that best partitions that the data tuples into individual classes. This criterion includes a splitting_attribute and either a splitting point or splitting subset.

Output: A Decision Tree

Method create a node N;

```
if tuples in D are all of the same class, C then
return N as leaf node labeled with class C;
```

if attribute_list is empty then return N as leaf node with labeled with majority class in D;|| majority voting

apply attribute_selection_method(D, attribute_list) to find the best splitting_criterion; label node N with splitting_criterion;

if splitting_attribute is discrete-valued and multiway splits allowed then // no restricted to binary trees

attribute_list = splitting attribute; // remove splitting attribute for each outcome j of splitting criterion

// partition the tuples and grow subtrees for each partition
let Dj be the set of data tuples in D satisfying outcome j; // a partition

if Dj is empty then attach a leaf labeled with the majority class in D to node N; else attach the node returned by Generate decision tree(Dj, attribute list) to node N; end for return N;

Tree Pruning

Tree pruning is performed in order to remove anomalies in the training data due to noise or outliers. The pruned trees are smaller and less complex.

Tree Pruning Approaches

There are two approaches to prune a tree -

- Pre-pruning The tree is pruned by halting its construction early.
- Post-pruning This approach removes a sub-tree from a fully grown tree.

Cost Complexity

The cost complexity is measured by the following two parameters -

- Number of leaves in the tree, and
- Error rate of the tree.

Nural Network

Neural network method is used for classification, clustering, feature mining, prediction and pattern recognition. It imitates the neurons structure of animals, bases on the M-P model and Hebb learning rule, so in essence it is a distributed matrix structure. Through training data mining, the neural network method gradually calculates (including repeated iteration or cumulative calculation) the weights the neural network connected. The neural network model can be broadly divided into the following three types: (a) Feed-forward networks: It regards the perception back-propagation model and the function network as representatives, and mainly used in the areas such as prediction and pattern recognition; (b) Feedback network: It regards Hopfield discrete model and continuous model as representatives, and mainly used for associative memory and optimization calculation; (c) Self-organization networks: it regards adaptive resonance theory (ART) model and Kohonen model as representatives, and mainly used for cluster analysis.

NEURAL NETWORKS IN DATA MINING In more practical terms neural networks are nonlinear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Using neural networks as a tool, data warehousing firms are harvesting information from datasets in the process known as data mining. The difference between these data warehouses and ordinary databases is that there is actual anipulation and cross-fertilization of the data helping users makes more informed decisions. Neural networks essentially comprise three pieces: the architecture or model; the learning algorithm; and the activation functions. Neural networks are programmed or "trained" to ". . . store, recognize, and associatively retrieve patterns or database entries; to solve combinatorial optimization problems; to filter noise from measurement data; to control ill-defined problems; in summary, to estimate sampled functions when we do not know the form of the functions." It is precisely these two abilities (pattern recognition and function estimation) which make artificial neural networks (ANN) so prevalent a utility in data mining. As data sets grow to massive sizes, the need for automated processing becomes clear. With their "model-free" estimators and their dual nature, neural networks serve data mining in a myriad of ways.



Figure 3. Image of data-mining process.



Figure 5. Data mining process based on neural network.

A. Data Preparation Data preparation is to define and process the mining data to make it fit specific data mining method. Data preparation is the first important step in the data mining and plays a decisive role in the entire data mining process. It mainly includes the following four processes: a) Data cleaning: Data cleansing is to fill the vacancy value of the data, eliminate the noise data and correct the inconsistencies data in the data. b) Data option: Data option is to select the data arrange and row used in this mining. c) Data preprocessing: Data preprocessing is to enhanced process the clean data which has been selected. d) Data expression Data expression is to transform the data after preprocessing into the form which can be accepted by the data mining algorithm based on neural network. The data mining based on neural network can only handle numerical data, so it is need to transform the sign data into numerical data. The simplest method is to establish a table with one-to-one correspondence between the sign data and the numerical data. The other more complex approach is to adopt appropriate Hash function to generate a unique numerical data according to given string. Although there are many data types in relational database, but they all basically can be simply come down to sign data, discrete numerical data and serial numerical data three logical data types. Fig. 6 gives the conversion of the three data types. The symbol "Apple" in the figure can be transformed into the corresponding discrete numerical data by using symbol table or Hash function. Then, the discrete numerical data can be quantified into continuous numerical data and can also be encoded into coding data.



Fig. 6 Data expression and conversion in data mining based on neural network

B. Rules Extracting There are many methods to extract rules, in which the most commonly used methods are LRE method, black-box method, the method of extracting fuzzy rules, the method of extracting rules from recursive network, the algorithm of binary input and output rules extracting (BIO-RE), partial rules extracting algorithm (Partial-RE) and full rules extracting algorithm (Full-RE). C. Rules Assessment Although the objective of rules assessment depends on each specific application, but, in general terms, the rules can be assessed in accordance with the following objectives. 1) Find the optimal sequence of extracting rules, making it obtains the best results in the given data set; 2) Test the accuracy of the rules extracted; 3) Detect how much knowledge in the neural network has not been extracted; 4) Detect the inconsistency between the extracted rules and the trained neural network.