INDEX

1. Multidimensional Data Models

a. Star Schema

Aim:

Understand and write a program to implement Star Schema

Theory:

The star schema (sometimes referenced as star join schema) is the simplest data warehouse schema, consisting of a single "*fact table*" with a compound primary key, with one segment for each "*dimension*" and with additional columns of additive, numeric facts. The star schema makes multi-dimensional database (MDDB) functionality possible using a traditional relational database. Because relational databases are the most common data management system in organizations today, implementing multi-dimensional views of data using a relational database is very appealing. Even if you are using a specific MDDB solution, its sources likely are relational databases. Another reason for using star schema is its ease of understanding. Fact tables in star schema are mostly in third normal form (3NF), but dimensional tables are in de-normalized second normal form (2NF). If we want to normalize dimensional tables, they look like snowflakes (see snowflake schema) and the same problems of relational databases arise - you need complex queries and business users cannot easily understand the meaning of data. Although query performance may be improved by advanced DBMS technology and hardware, highly normalized tables make reporting difficult and applications complex

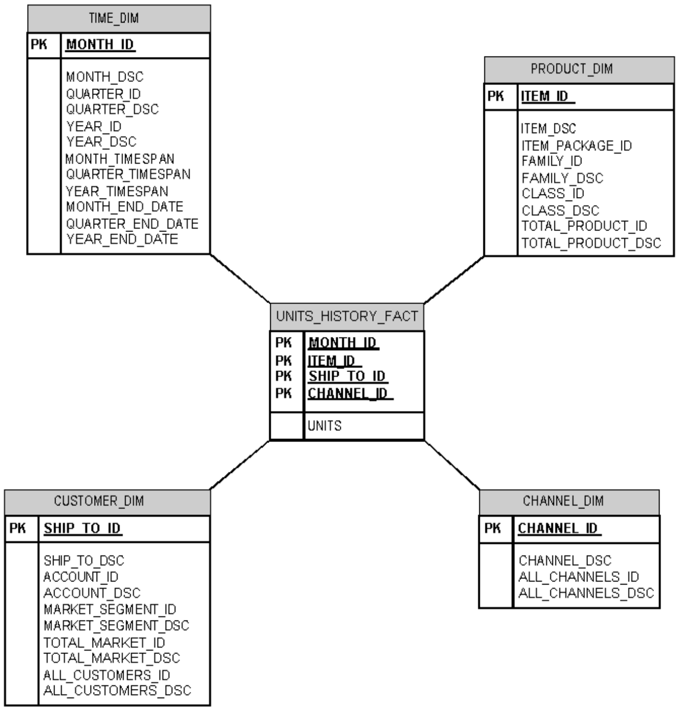


Figure 1: Star Schema

Program:

```
//Star Schema

#include<stdio.h>

#include<conio.h>

struct location

{

        int l_key;

        char street[30];

        char city[30];

        char p_st[100];

        char country[30];
```

```
}l[10];

void main()
{
	int n,flag=0,i,j;
	clrscr();
	printf("*****location table*****");
	printf("\n enter the no of entries\n");
	scanf("%d",&n);
	for(i=0;i<n;i++)
	{
		printf("enter the values for l[%d]\n",i+1);
		printf("enter the location key");
		scanf("%d",&l[i].l_key);
		printf("Enter the street:");
		scanf("%s",l[i].street);
		printf("enter the city");
		scanf("%s",l[i].city);
		fflush(stdin);
		printf("Enter the country");
		scanf("%s",l[i].country);
	}
```

```
        printf("\n Entered Tabels are \n");
        for(i=0;i<n;i++)
        {
printf("%4d%4s%4s%4s %4s\n", l[i].l_key,l[i].street,l[i].city,l[i].p_st,l[i].country);
        }

        for(i=0;i<n;i++)
        {
                for(j=i+1;j<n;j++)
                {
                        if(strcmp(l[i].country,l[j].country)==0)
                        {
                            if(strcmp(l[i].p_st,l[j].p_st)==0)
                                {
                                flag=1;
                                printf("\n Redundancy occurs for entry %d and %d",i,j);
                                }
                        }
                 }
        }

        if(flag==0)
        printf("Redundancy not occurs");
        getch();
}
```

Output:

```
*****location table*****
 enter the no of entries:
2
enter the values for l[1]
enter the location key: 1
Enter the street: Mehdipatnam
enter the city: Hyderabad
Enter the country: India
enter the values for l[2]
enter the location key: 2
Enter the street: Somajiguda
enter the city: Hyderabad
Enter the country: India

 Entered Tables are
   1  Mehdipatnam  Hyderabad       India
   2  Somajiguda  Hyderabad       India
```

Redundancy occurs for entry 1 and 2

b. Snow Flake Schema

Aim:

Understand and write a program to implement Snow Flake

Theory:

A snowflake schema is a logical arrangement of tables in a relational database such that the entity relationship diagram resembles a snowflake in shape. Closely related to the star schema, the snowflake schema is represented by centralized fact tables which are connected to multiple dimensions. In the snowflake schema, however, dimensions are normalized into multiple related tables whereas the star schema's dimensions are de-normalized with each dimension being represented by a single table. When the dimensions of a snowflake schema are elaborate, having multiple levels of relationships, and where child tables have multiple parent tables ("forks in the road"), a complex snowflake shape starts to emerge. The "snowflaking" effect only affects the dimension tables and not the fact tables.

The star and snowflake schema are most commonly found in dimensional data warehouses and data marts where speed of data retrieval is more important than the efficiency of data manipulations. As such, the tables in these schemas are not normalized much, and are frequently designed at a level of normalization short of third normal form.

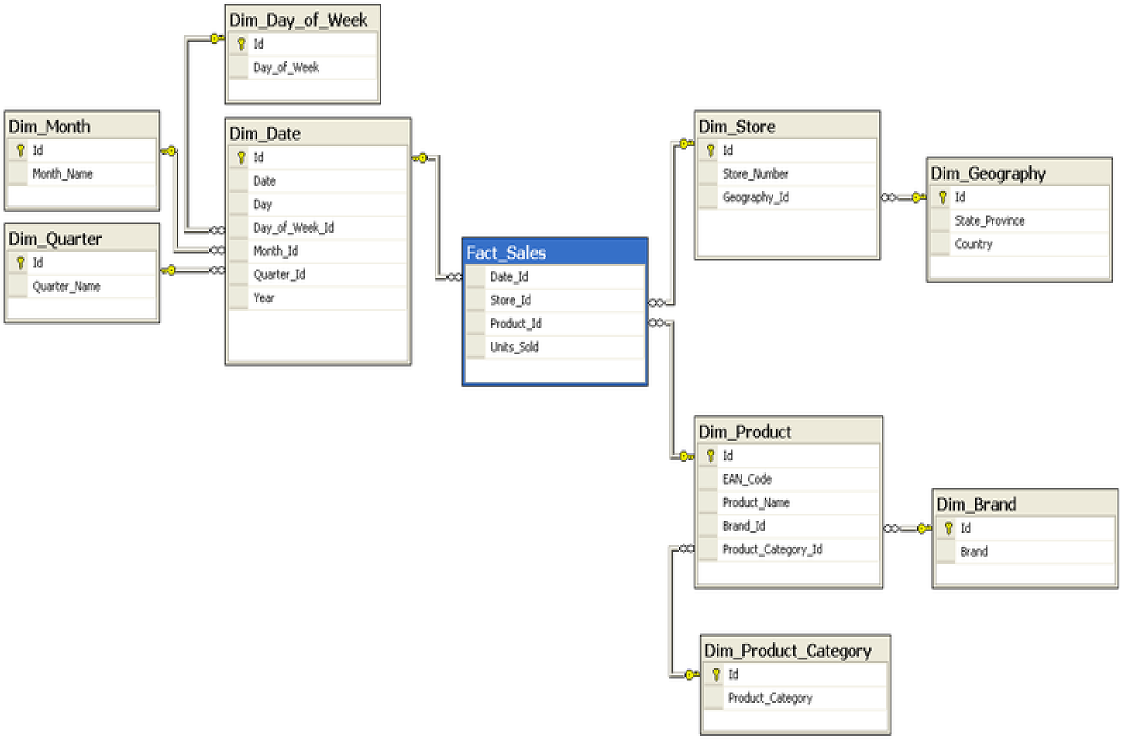


Figure 2: Snow Flake Schema

Program:

```
//Snow Flake schema

#include<stdio.h>

#include<conio.h>

struct location

{

  int l_key;

  char street[10];

  int city_key;

  struct city
  {
      int city_key;
      char city_name[10];
      char p_state[10];
      char country[10];
  }c;
}l[10];

void main()
{
 int n,i,j;
 printf("Enter the number of entries:");
 scanf("%d",&n);
 for(i=0;i<n;i++)
 {
  printf("Enter the values fr location tuple[%d]",i+1);
  printf("\nL_Key:");
  scanf("%d",&l[i].l_key);
  fflush(stdin);
  printf("\nSTREET:");
  gets(l[i].street);
  fflush(stdin);
  printf("\nCITY_KEY:");
  scanf("%d",&l[i].city_key);
  printf("Enter the Values for City Tuples[%d]",i+1);
  printf("\nCITY_KEY:");
  scanf("%d",&l[i].c.city_key);
  fflush(stdin);
  printf("\nCITY:");
  gets(l[i].c.city_name);
  fflush(stdin);
  printf("\n P_STATE:");
  gets(l[i].c.p_state);
  fflush(stdin);
  printf("\n COUNTRY:");
  gets(l[i].c.country);
 }
 printf("Entered location tabel values are:\n");
 printf("L_KEY\tSTREET\tCITY_KEY\n");
 for(i=0;i<n;i++)
 {
   printf("%d\t%s\t%d\n",l[i].l_key,l[i].street,l[i].city_key);
 }

 printf("Entered City tabel Values are:\n");
 printf("C_KEY\tC_NAME\tP_STATE\tCOUNTRY\n");
```

```
 for(i=0;i<n;i++)
 {
  printf("%d\t%s\t%s\t%s\n",l[i].c.city_key,l[i].c.city_name,l[i].c.p_state,l[i].c.country);
 }

 for(i=0;i<n;i++)
 {
  for(j=i+1;j<n;j++)
  {
    if(strcmp(l[i].c.country,l[j].c.country)==0)
       if(strcmp(l[i].c.p_state,l[j].c.p_state)==0)
             printf("\n Redundancy for this data\n");
       else
             printf("\n No redundancy for this data\n");
  }
 }
 getch();
}
```

Output:

```
Enter the number of entries: 2

Enter the values for location tuple[1]

L_KEY: 101
```

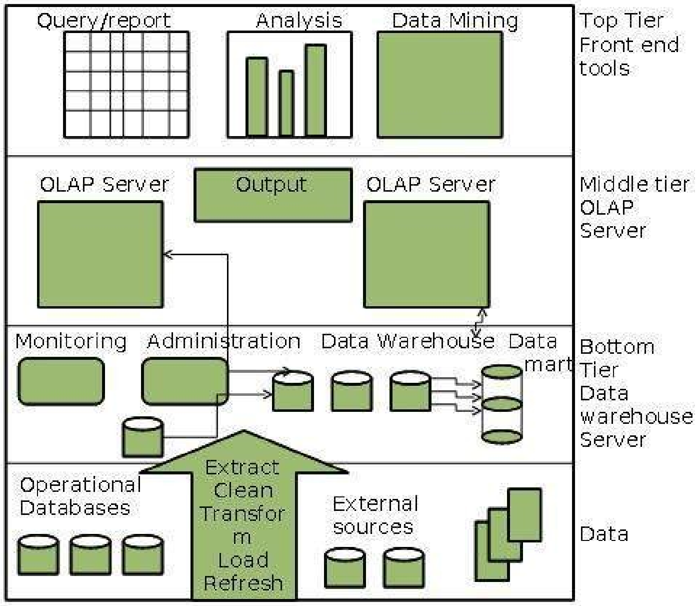
```
STREET: Somajiguda
CITY_KEY: 1001
Enter the values for city tuple[1]
CITY_KEY: 1001
CITY: Hyderabad
P_STATE: AP
COUNTRY: India

Enter the values for location tuple[2]
L_KEY: 102
STREET: Singapore
CITY_KEY: 1002
Enter the values for city tuple[2]
CITY_KEY: 1002
CITY: Singapore
P_STATE: Singapore
COUNTRY: SGP

Entered Location Table values are:
L_KEY          STREET    CITY_KEY
102       Somajiguda  1001
102       Singapore   1002
Entered City Table values are:
```

C_KEY	C_NAME	P_STATE	COUNTRY
1001	Somajiguda	AP	India
1002	Singapore	Singapore	SGP

No Redundancy for this data

2. Data Warehousing

Three-Tier Data Warehouse Architecture



- **Bottom Tier** - The bottom tier of the architecture is the data warehouse database server. It is the relational database system. We use the back-end tools and utilities to feed data into the bottom tier. These back-end tools and utilities perform the Extract, Clean, Load, and refresh functions.

- **Middle Tier** - In the middle tier, we have the OLAP Server that can be implemented in either of the following ways.

o By Relational OLAP (ROLAP), which is an extended relational database management system. The ROLAP maps the operations on multidimensional data to standard relational operations.

o By Multidimensional OLAP (MOLAP) model, which directly implements the multidimensional data and operations.

- **Top-Tier** - This tier is the front-end client layer. This layer holds the query tools and reporting tools, analysis tools and data mining tools.

3. OLAP Cube

An **OLAP cube** is a term that typically refers to multi-dimensional array of data. *OLAP* is an acronym for online analytical processing,[1]which is a computer-based technique of analyzing data to look for insights. The term *cube* here refers to a multi-dimensional dataset, which is also sometimes called a hypercube if the number of dimensions is greater than 3.

Operations:

1. ***Slice*** is the act of picking a rectangular subset of a cube by choosing a single value for one of its dimensions, creating a new cube with one fewer dimension.[4] The picture shows a slicing operation: The sales figures of all sales regions and all product categories of the company in the year 2005 and 2006 are "sliced" out of the data cube.

2. ***Dice*****:** The dice operation produces a subcube by allowing the analyst to pick specific values of multiple dimensions.[5]The picture shows a dicing operation: The new cube shows the sales figures of a limited number of product categories, the time and region dimensions cover the same range as before.

3. ***Drill Down/Up*** allows the user to navigate among levels of data ranging from the most summarized (up) to the most detailed (down).[4] The picture shows a drill-down operation: The analyst moves from the summary category "Outdoor-Schutzausrüstung" to see the sales figures for the individual products.

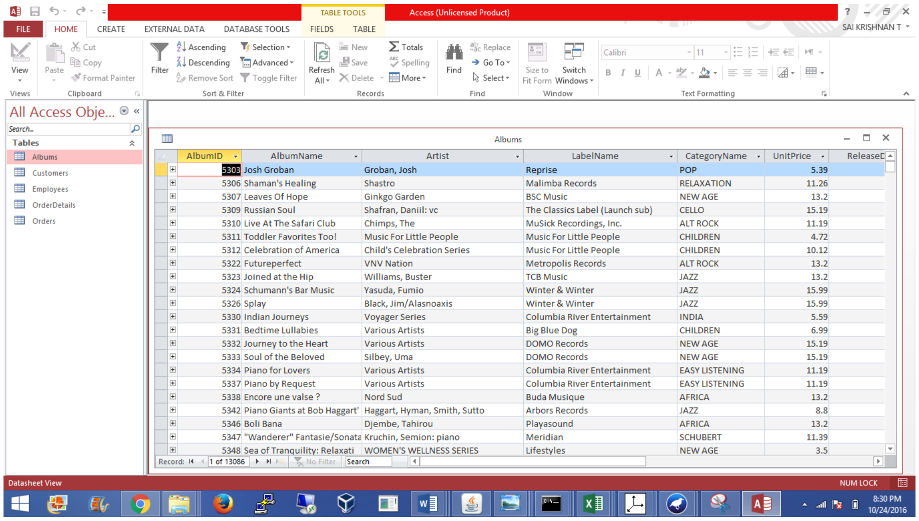
4**.** ***Roll-up*****:** A roll-up involves summarizing the data along a dimension. The summarization rule might be computing totals along a hierarchy or applying a set of formulas such as
profit = sales – expenses.

5**.** ***Pivot:*** allows an analyst to rotate the cube in space to see its various faces. For example, cities could be arranged vertically and products horizontally while viewing data for a particular quarter. Pivoting could replace products with time periods to see data across time for a single product.

OLAP Server Architectures:

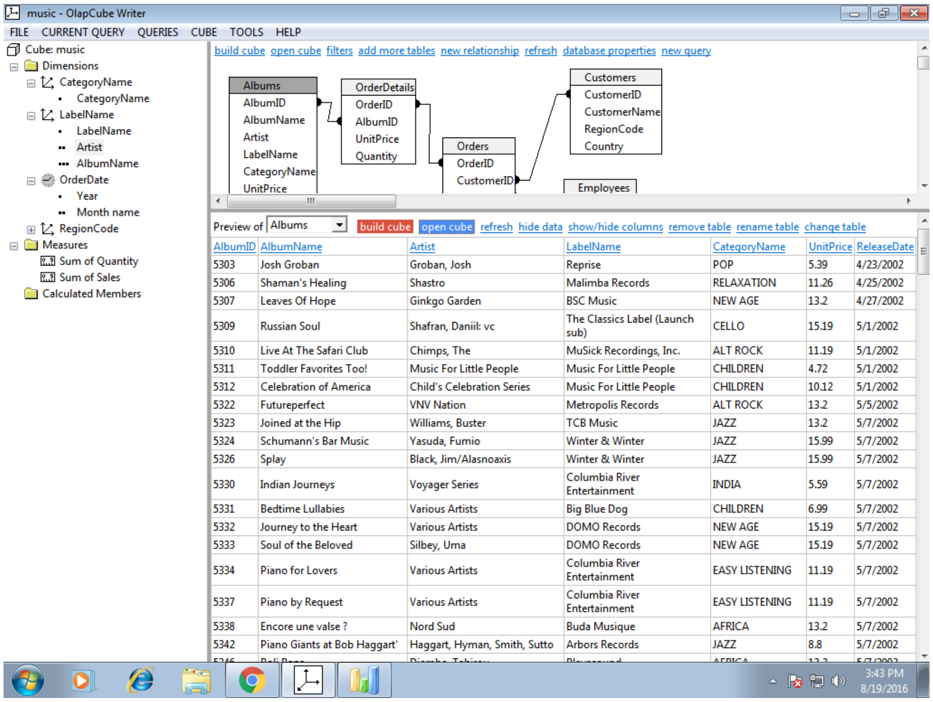
- Relational OLAP (ROLAP) servers: These are the intermediate servers that stand in between a relational back-end server and client front-end tools. They use relational or extended relational DBMS to store and manage warehouse data.
- Multidimensional OLAP (MOLAP) servers: These support multidimensional data views through array based search engines. They map multidimensional views directly to data cube array structures.
- Hybrid OLAP (HOLAP) servers: This approach combines ROLAP and MOLAP technology, benefiting from the greater scalability of ROLAP and faster computation of MOLAP.

The database that needs to analyzed using OLAP cube writer is displayed in Figure 1



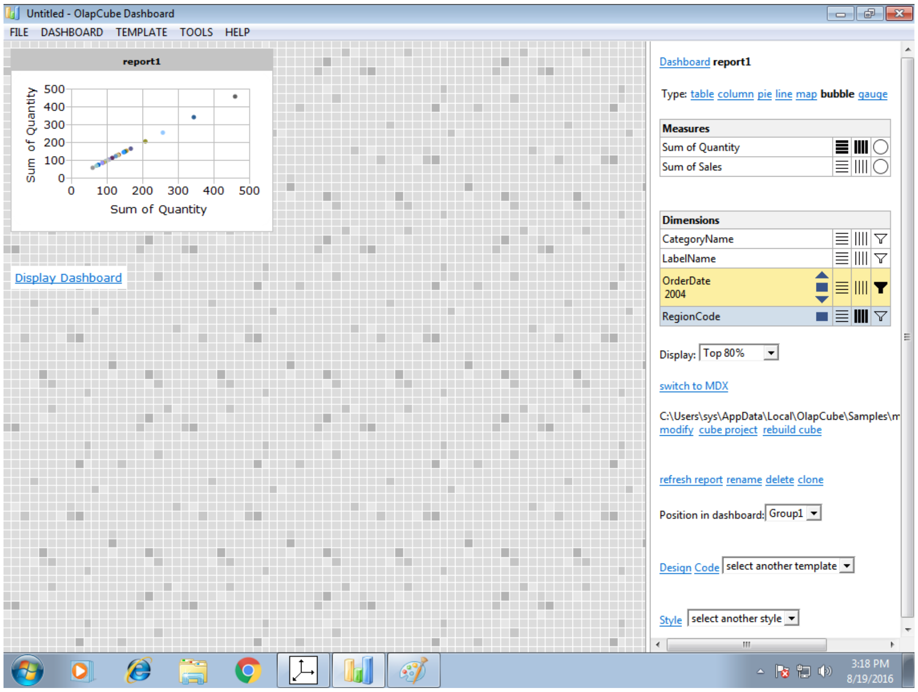
AlbumID	AlbumName	Artist	LabelName	CategoryName	UnitPrice	ReleaseD
5303	Josh Groban	Groban, Josh	Reprise	POP	5.39	
5306	Shaman's Healing	Shastro	Malimba Records	RELAXATION	11.26	
5307	Leaves Of Hope	Ginkgo Garden	BSC Music	NEW AGE	13.2	
5309	Russian Soul	Shafran, Daniil: vc	The Classics Label (Launch sub)	CELLO	15.19	
5310	Live At The Safari Club	Chimps, The	MuSick Recordings, Inc.	ALT ROCK	11.19	
5311	Toddler Favorites Too!	Music For Little People	Music For Little People	CHILDREN	4.72	
5312	Celebration of America	Child's Celebration Series	Music For Little People	CHILDREN	10.12	
5322	Futureperfect	VNV Nation	Metropolis Records	ALT ROCK	13.2	
5323	Joined at the Hip	Williams, Buster	TCB Music	JAZZ	13.2	
5324	Schumann's Bar Music	Yasuda, Fumio	Winter & Winter	JAZZ	15.99	
5326	Splay	Black, Jim/Alasnoaxis	Winter & Winter	JAZZ	15.99	
5330	Indian Journeys	Voyager Series	Columbia River Entertainment	INDIA	5.59	
5331	Bedtime Lullabies	Various Artists	Big Blue Dog	CHILDREN	6.99	
5332	Journey to the Heart	Various Artists	DOMO Records	NEW AGE	15.19	
5333	Soul of the Beloved	Silbey, Uma	DOMO Records	NEW AGE	15.19	
5334	Piano for Lovers	Various Artists	Columbia River Entertainment	EASY LISTENING	11.19	
5337	Piano by Request	Various Artists	Columbia River Entertainment	EASY LISTENING	11.19	
5338	Encore une valse ?	Nord Sud	Buda Musique	AFRICA	13.2	
5342	Piano Giants at Bob Haggart'	Haggart, Hyman, Smith, Sutto	Arbors Records	JAZZ	8.8	
5346	Boli Bana	Djembe, Tahirou	Playasound	AFRICA	13.2	
5347	"Wanderer" Fantasie/Sonata	Kruchin, Semion: piano	Meridian	SCHUBERT	11.39	
5348	Sea of Tranquility: Relaxati	WOMEN'S WELLNESS SERIES	Lifestyles	NEW AGE	3.5	

Figure 1 : Music Database



AlbumID	AlbumName	Artist	LabelName	CategoryName	UnitPrice	ReleaseDate
5303	Josh Groban	Groban, Josh	Reprise	POP	5.39	4/23/2002
5306	Shaman's Healing	Shastro	Malimba Records	RELAXATION	11.26	4/25/2002
5307	Leaves Of Hope	Ginkgo Garden	BSC Music	NEW AGE	13.2	4/27/2002
5309	Russian Soul	Shafran, Daniil: vc	The Classics Label (Launch sub)	CELLO	15.19	5/1/2002
5310	Live At The Safari Club	Chimps, The	MuSick Recordings, Inc.	ALT ROCK	11.19	5/1/2002
5311	Toddler Favorites Too!	Music For Little People	Music For Little People	CHILDREN	4.72	5/1/2002
5312	Celebration of America	Child's Celebration Series	Music For Little People	CHILDREN	10.12	5/1/2002
5322	Futureperfect	VNV Nation	Metropolis Records	ALT ROCK	13.2	5/5/2002
5323	Joined at the Hip	Williams, Buster	TCB Music	JAZZ	13.2	5/7/2002
5324	Schumann's Bar Music	Yasuda, Fumio	Winter & Winter	JAZZ	15.99	5/7/2002
5326	Splay	Black, Jim/Alasnoaxis	Winter & Winter	JAZZ	15.99	5/7/2002
5330	Indian Journeys	Voyager Series	Columbia River Entertainment	INDIA	5.59	5/7/2002
5331	Bedtime Lullabies	Various Artists	Big Blue Dog	CHILDREN	6.99	5/7/2002
5332	Journey to the Heart	Various Artists	DOMO Records	NEW AGE	15.19	5/7/2002
5333	Soul of the Beloved	Silbey, Uma	DOMO Records	NEW AGE	15.19	5/7/2002
5334	Piano for Lovers	Various Artists	Columbia River Entertainment	EASY LISTENING	11.19	5/7/2002
5337	Piano by Request	Various Artists	Columbia River Entertainment	EASY LISTENING	11.19	5/7/2002
5338	Encore une valse ?	Nord Sud	Buda Musique	AFRICA	13.2	5/7/2002
5342	Piano Giants at Bob Haggart'	Haggart, Hyman, Smith, Sutto	Arbors Records	JAZZ	8.8	5/7/2002

Figure 2 Database in OLAP cube writer



Dashboard **report1**

Type: table column pie line map **bubble** gauge

Measures
Sum of Quantity
Sum of Sales

Dimensions
CategoryName
LabelName
OrderDate 2004
RegionCode

Display: Top 80%

switch to MDX

C:\Users\sys\AppData\Local\OlapCube\Samples\m
modify cube project rebuild cube

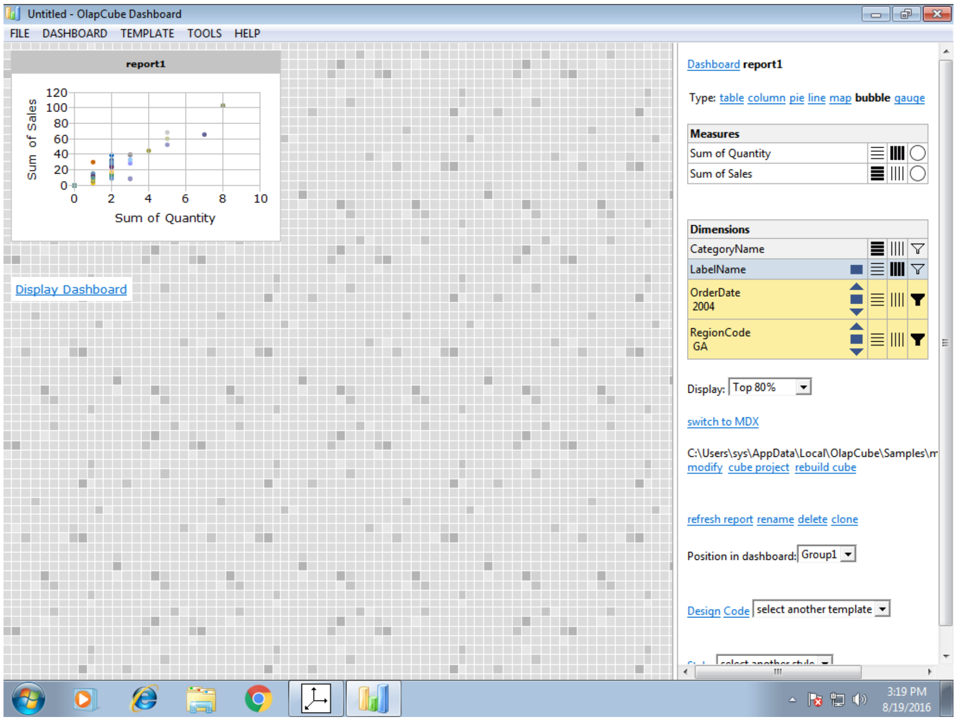
refresh report rename delete clone

Position in dashboard: Group1

Design Code select another template

Style select another style

Figure 3: Graph between sum of quantities



Dashboard **report1**

Type: table column pie line map **bubble** gauge

Measures
Sum of Quantity
Sum of Sales

Dimensions
CategoryName
LabelName
OrderDate 2004
RegionCode GA

Display: Top 80%

switch to MDX

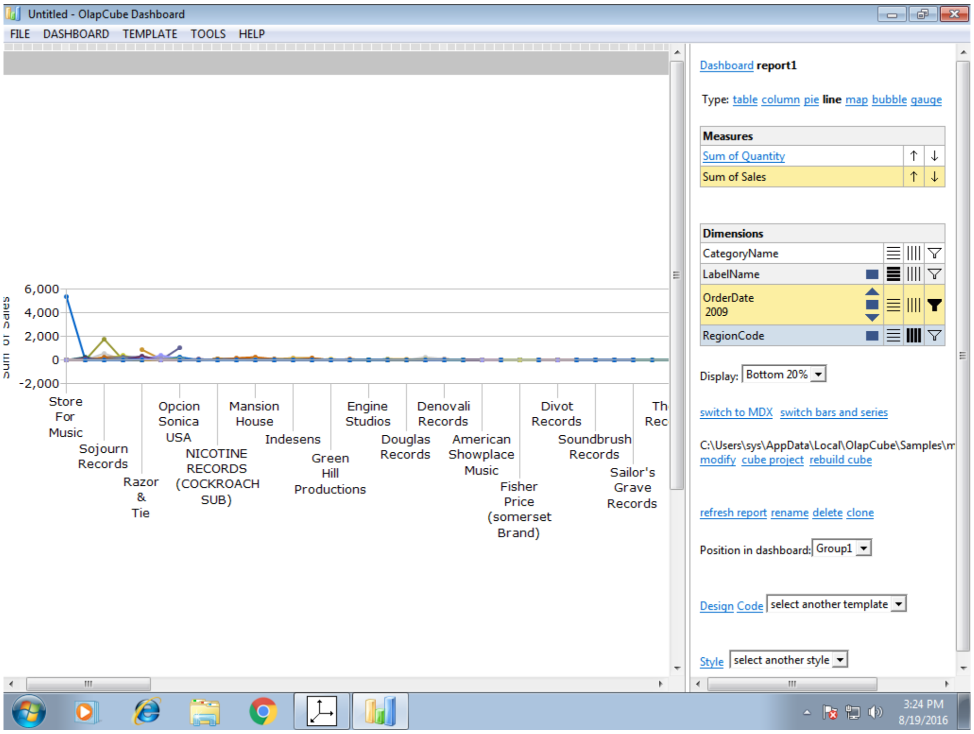
C:\Users\sys\AppData\Local\OlapCube\Samples\m
modify cube project rebuild cube

refresh report rename delete clone

Position in dashboard: Group1

Design Code select another template

Figure 4: Graph between Sum of sales and quantities



Dashboard **report1**

Type: table column pie **line** map bubble gauge

Measures
Sum of Quantity
Sum of Sales

Dimensions
CategoryName
LabelName
OrderDate 2009
RegionCode

Display: Bottom 20%

switch to MDX switch bars and series

C:\Users\sys\AppData\Local\OlapCube\Samples\m

modify cube project rebuild cube

refresh report rename delete clone

Position in dashboard: Group1

Design Code select another template

Style select another style

Figure 5: Sales from different stores

4. Basics of WEKA tool

Aim: A. Investigation the Application interfaces of the Weka tool.

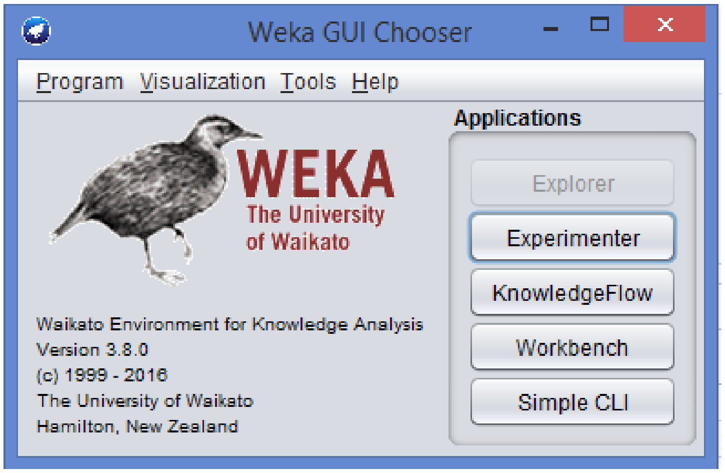
Introduction: Weka (pronounced to rhyme with Mecca) is a workbench that contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to these functions. The original non-Java version of Weka was a Tcl/Tk front-end to (mostly third-party) modeling algorithms implemented in other programming languages, plus data preprocessing utilities in C, and Make file-based system for running machine learning experiments. This original version was primarily designed as a tool for analyzing data from agricultural domains, but the more recent fully Java-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 GNU General Public License.
- Portability, since it is fully implemented in the Java programming language 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.

Description:

Open the program. Once the program has been loaded on the user's machine it is opened by navigating to the programs start option and that will depend on the user's operating system. Figure 1.1 is an example of the initial opening screen on a computer.

There are four options available on this initial screen:

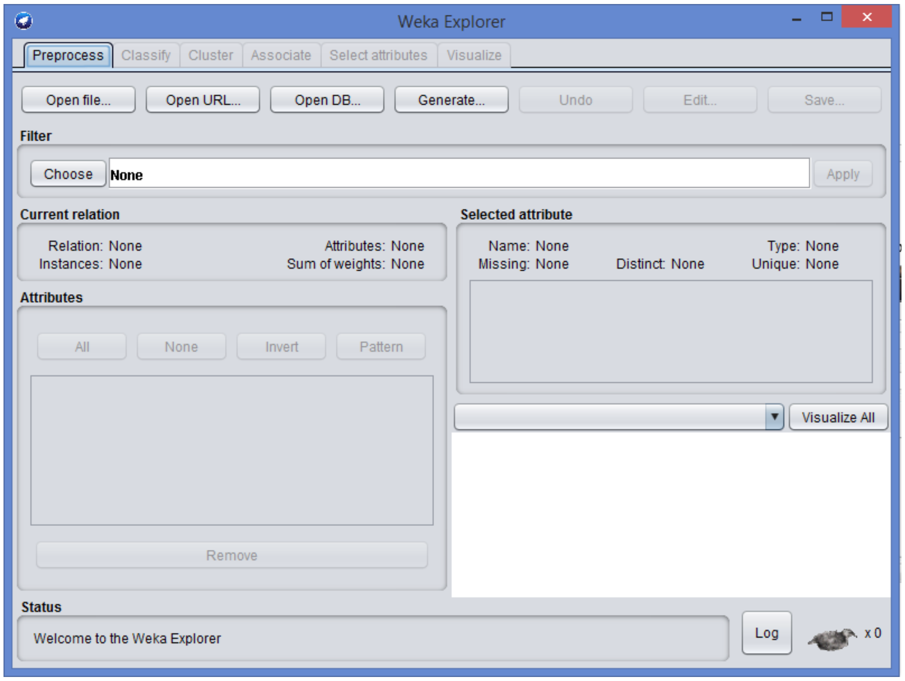


Waikato Environment for Knowledge Analysis
Version 3.8.0
(c) 1999 - 2016
The University of Waikato
Hamilton, New Zealand

Fig: 4.1 Weka GUI

1. **Explorer** - the graphical interface used to conduct experimentation on raw data

   After clicking the Explorer button the weka explorer interface appears.



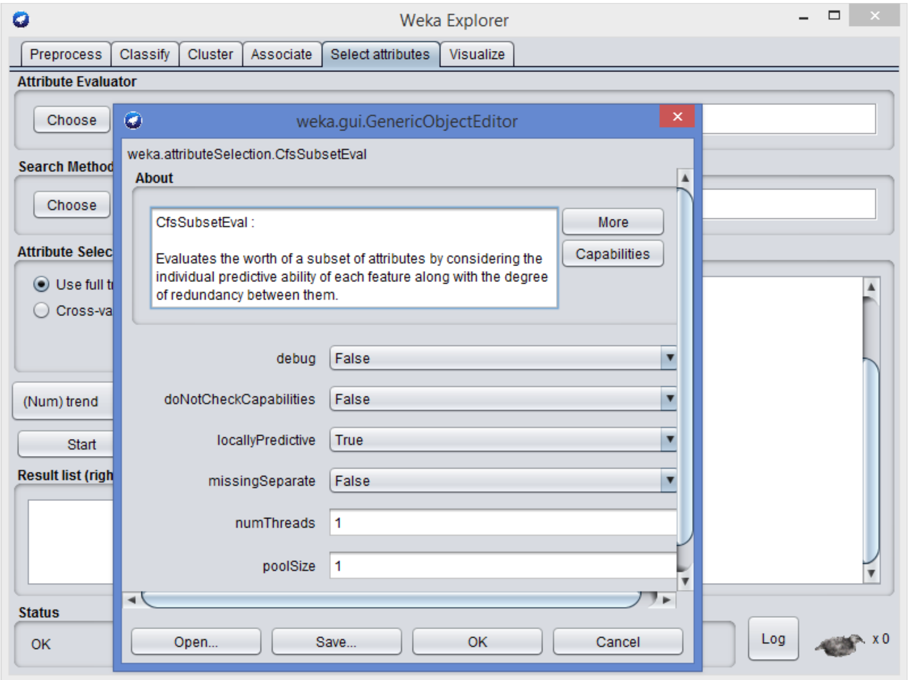
Filter: None

Relation: None
Instances: None
Attributes: None
Sum of weights: None

Name: None
Missing: None
Distinct: None
Type: None
Unique: None

Welcome to the Weka Explorer

Fig: 4.2 Pre-processor



weka.attributeSelection.CfsSubsetEval

CfsSubsetEval :

Evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them.

debug: False
doNotCheckCapabilities: False
locallyPredictive: True
missingSeparate: False
numThreads: 1
poolSize: 1

Fig: 4.3 Parameters

Inside the weka explorer window there are six tabs:

1. **Preprocess-** used to choose the data file to be used by the application.

   ♦**Open File**- allows for the user to select files residing on the local machine or recorded medium

   ♦**Open URL**- provides a mechanism to locate a file or data source from a different location specified by the user

   ♦**Open Database**- allows the user to retrieve files or data from a database source provided by user

2. **Classify-** used to test and train different learning schemes on the preprocessed data file under experimentation

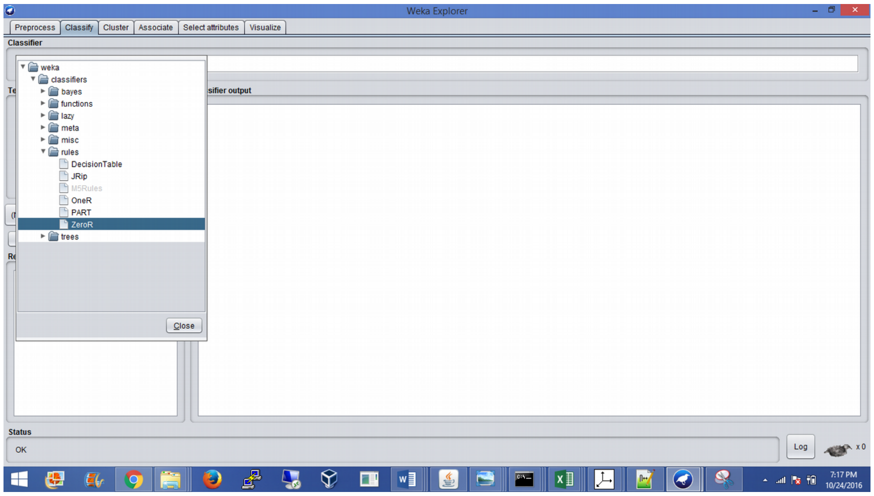


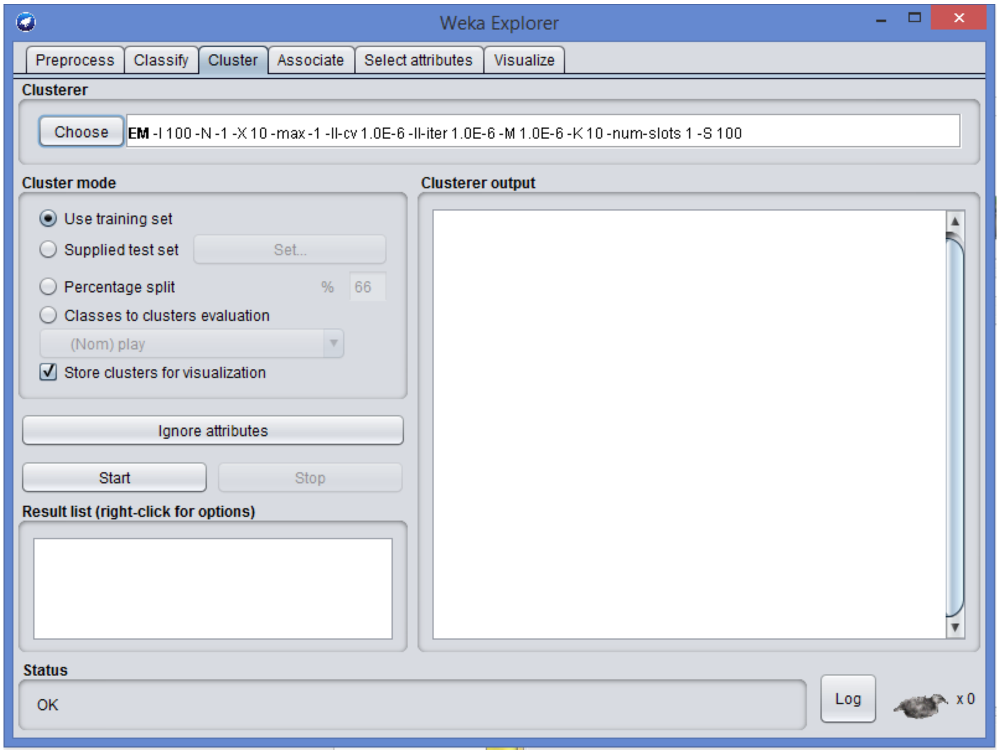
Fig: 4.4 Choosing Zero set from classify

Again there are several options to be selected inside of the classify tab. Test option gives the user the choice of using four different test mode scenarios on the data set.

1. Use training set
2. Supplied training set
3. Cross validation
4. Split percentage

3. Cluster- used to apply different tools that identify clusters within the data file.

The Cluster tab opens the process that is used to identify commonalties or clusters of occurrences within the data set and produce information for the user to analyze.



```
EM -I 100 -N -1 -X 10 -max -1 -ll-cv 1.0E-6 -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100
```

● Use training set

○ Supplied test set

○ Percentage split % 66

○ Classes to clusters evaluation

(Nom) play

☑ Store clusters for visualization

Status: OK

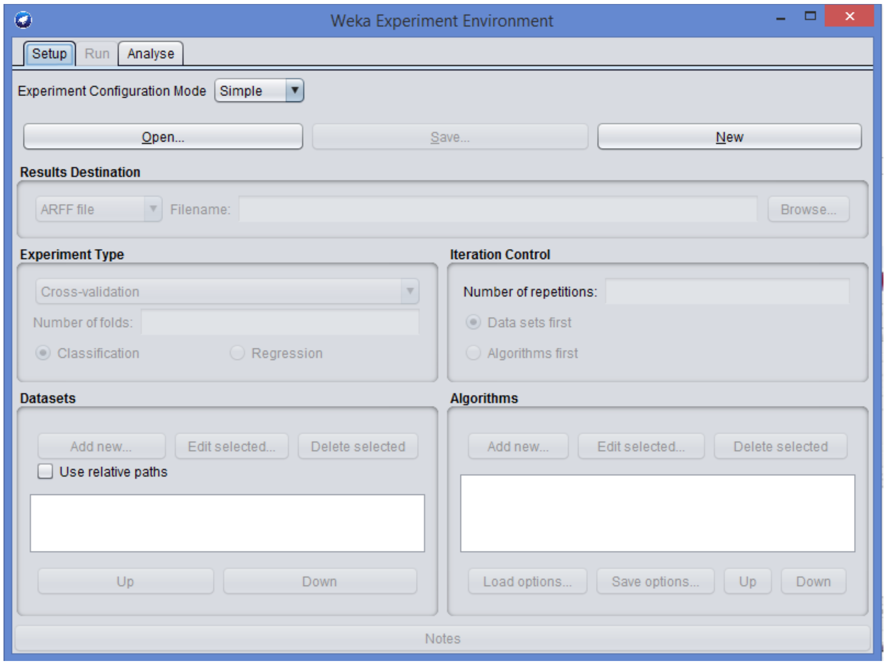
Fig: 4.5 Using training data set

4. Association- used to apply different rules to the data file that identify association within the data. The associate tab opens a window to select the options for associations within the data set.

5. Select attributes-used to apply different rules to reveal changes based on selected attributes inclusion or exclusion from the experiment

6. Visualize- used to see what the various manipulation produced on the data set in a 2D format, in scatter plot and bar graph output.

2. Experimenter - this option allows users to conduct different experimental variations on data sets and perform statistical manipulation. The Weka Experiment Environment enables the user to create, run, modify, and analyze experiments in a more convenient manner than is possible when processing the schemes individually. For example, the user can create an experiment that runs several schemes against a series of datasets and then analyze the results to determine if one of the schemes is (statistically) better than the other schemes.



Experiment Configuration Mode: Simple

Results Destination

ARFF file — Filename:

Experiment Type

Cross-validation

Number of folds:

● Classification ○ Regression

Iteration Control

Number of repetitions:

● Data sets first

○ Algorithms first

Datasets

□ Use relative paths

Algorithms

Fig: 4.6 Weka experiment

Results destination: ARFF file, CSV file, JDBC database.

Experiment type: Cross-validation (default), Train/Test Percentage Split (data randomized).

Iteration control: Number of repetitions, Data sets first/Algorithms first.

Algorithms: filters

3. Knowledge Flow -basically the same functionality as Explorer with drag and drop functionality. The advantage of this option is that it supports incremental learning from previous results

4. Simple CLI - provides users without a graphic interface option the ability to execute commands from a terminal window.

b. Explore the default datasets in weka tool.

Click the "***Open file…***" button to open a data set and double click on the "***data***" directory. Weka provides a number of small common machine learning datasets that you can use to practice on. Select the "***iris.arff***" file to load the Iris dataset

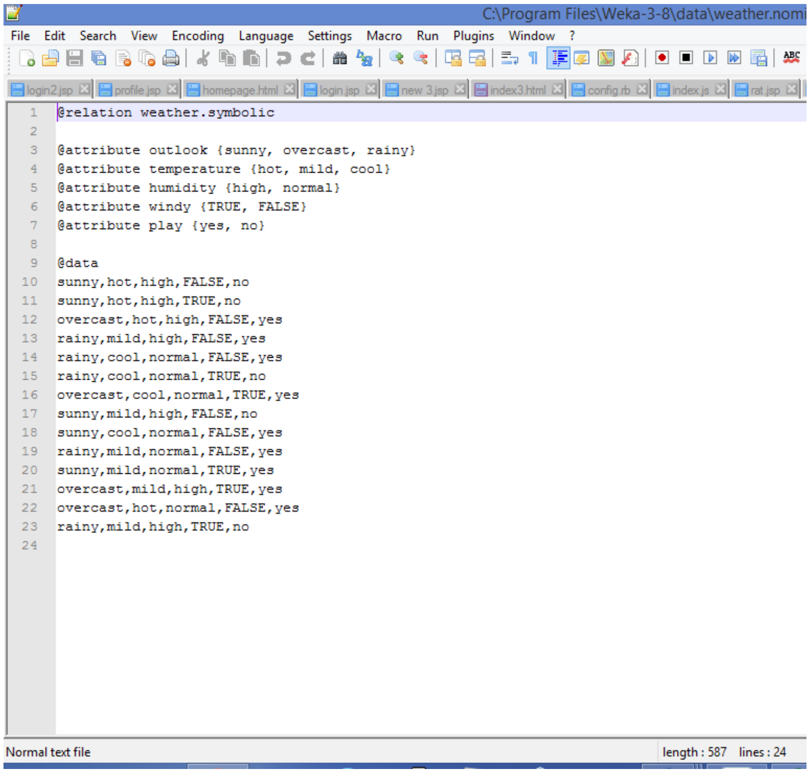
5. Creating new ARFF file

<u>Aim</u>: Creating a new ARFF file

An ARFF (Attribute-Relation File Format) file is an ASCII text file that describes a list of instances sharing a set of attributes. ARFF files were developed by the Machine Learning Project at the Department of Computer Science of The University of Waikato for use with the Weka machine learning software in WEKA, each data entry is an instance of the java class weka.core. Instance, and each instance consists of a For loading datasets in WEKA, WEKA can load ARFF files. Attribute Relation File Format has two sections:

1) The Header section defines relation (dataset) name, attribute name, and type.

2) The Data section lists the data instances.



```
@relation weather.symbolic

@attribute outlook {sunny, overcast, rainy}
@attribute temperature {hot, mild, cool}
@attribute humidity {high, normal}
@attribute windy {TRUE, FALSE}
@attribute play {yes, no}

@data
sunny,hot,high,FALSE,no
sunny,hot,high,TRUE,no
overcast,hot,high,FALSE,yes
rainy,mild,high,FALSE,yes
rainy,cool,normal,FALSE,yes
rainy,cool,normal,TRUE,no
overcast,cool,normal,TRUE,yes
sunny,mild,high,FALSE,no
sunny,cool,normal,FALSE,yes
rainy,mild,normal,FALSE,yes
sunny,mild,normal,TRUE,yes
overcast,mild,high,TRUE,yes
overcast,hot,normal,FALSE,yes
rainy,mild,high,TRUE,no

```

Fig: 5.1 ARFF file

The figure above is from the textbook that shows an ARFF file for the weather data. Lines beginning with a % sign are comments. And there are three basic keywords:

 "@relation" in Header section, followed with relation name.

 "@attribute" in Header section, followed with attributes name and its type (or range).

 "@data" in Data section, followed with the list of data instances.

The external representation of an Instances class Consists of:

− **A header:** Describes the attribute types

− **Data section:** Comma separated list of data

Procedure:

- Create a csv file in any of the editors. (notepad, excel etc)
- Save it as <filename>.csv and open Weks.
- Open the file in Weka and save it in the .ARFF format.
- Open the ARFF file in Wordpad to view the relations between attributes. (see above figure for example)

6. Data pre-processesing Techniques

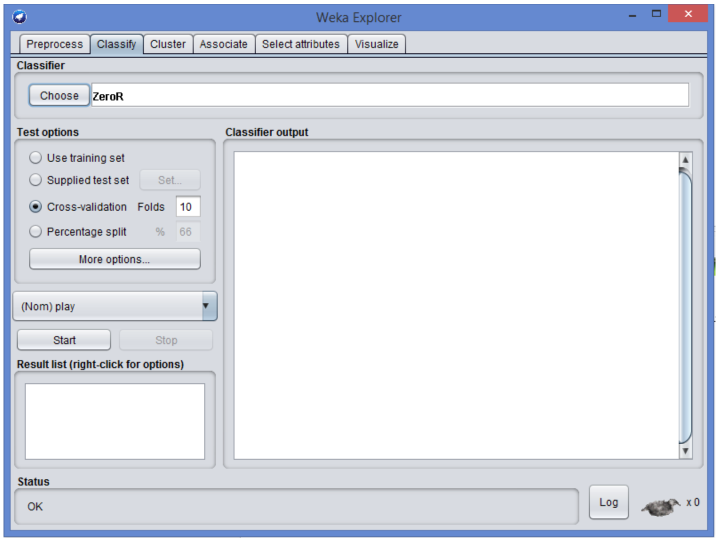
Aim: 6a) Pre-process a given dataset based on Attribute selection

To search through all possible combinations of attributes in the data and find which subset of attributes works best for prediction, make sure that you set up attribute evaluator to ‘Cfs SubsetEval’ and a search method to ‘Best First’. The evaluator will determine what method to use to assign a worth to each subset of attributes. The search method will determine what style of search to perform. The options that you can set for selection in the ‘Attribute Selection Mode’ fig no: 3.2

1. Use full training set. The worth of the attribute subset is determined using the full set of training data.

2. Cross-validation. The worth of the attribute subset is determined by a process of cross-validation. The ‘Fold’ and ‘Seed’ fields set the number of folds to use and the random seed used when shuffling the data.

Specify which attribute to treat as the class in the drop-down box below the test options. Once all the test options are set, you can start the attribute selection process by clicking on ‘Start’ button.



Classifier: ZeroR

Test options: ● Cross-validation Folds 10

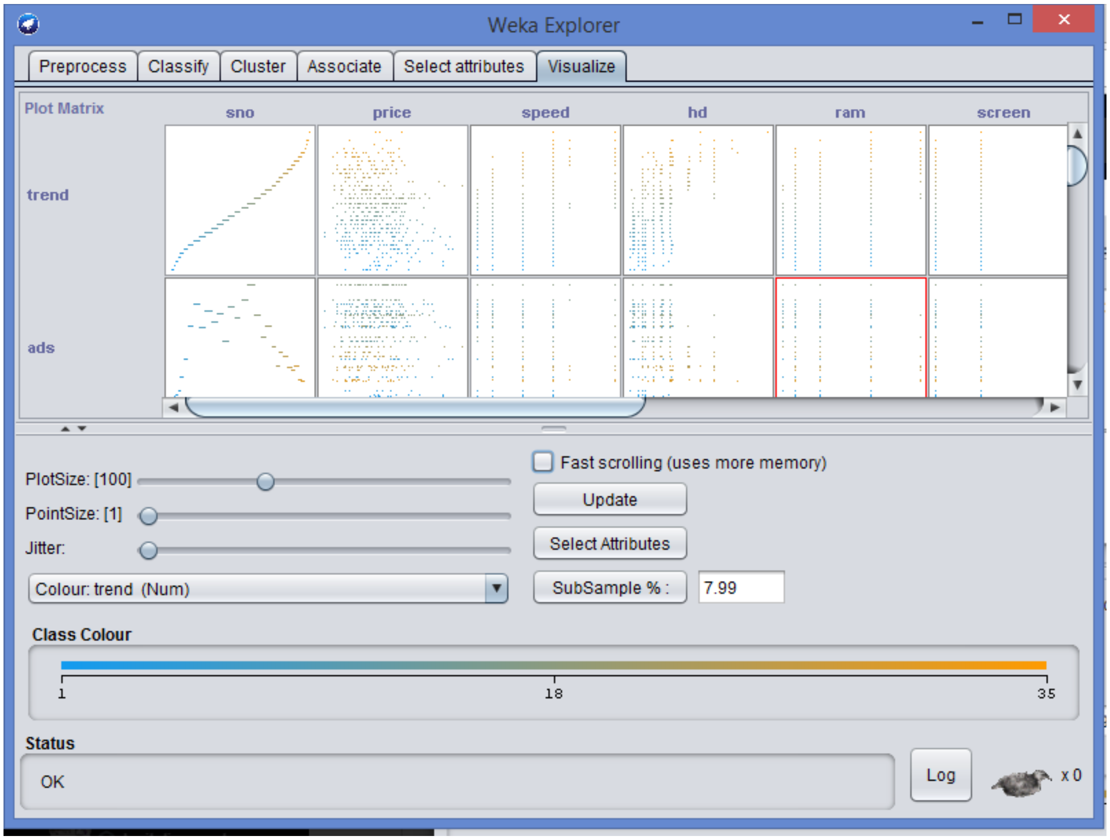
(Nom) play

Status: OK

Fig: 6.1 Choosing Cross validation

When it is finished, the results of selection are shown on the right part of the window and entry is added to the ‘Result list’.

2. Visualizing Results



PlotSize: [100]

PointSize: [1]

Jitter:

Colour: trend (Num)

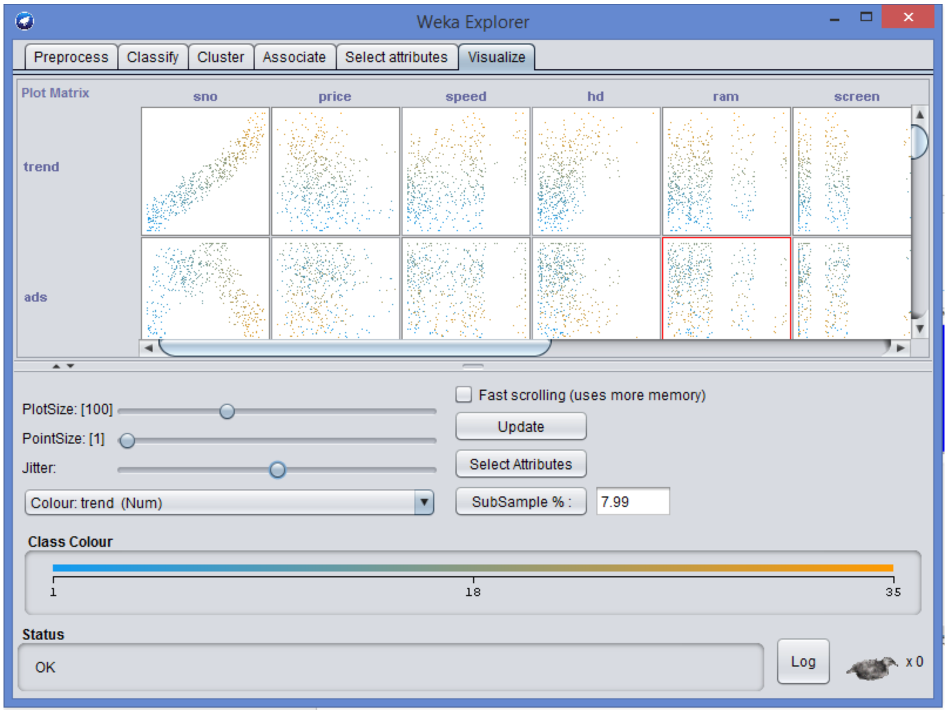
SubSample % : 7.99

Status

OK

Fig: 6.2 Data Visualization

WEKA's visualization allows you to visualize a 2-D plot of the current working relation. Visualization is very useful in practice; it helps to determine difficulty of the learning problem. WEKA can visualize single attributes (1-d) and pairs of attributes (2-d), rotate 3-d visualizations (Xgobi-style). WEKA has "Jitter" option to deal with nominal attributes and to detect "hidden" data points.



PlotSize: [100]

PointSize: [1]

Jitter:

Colour: trend (Num)

SubSample % : 7.99

Status

OK

Fig 6.3: Preprocessing with jitter

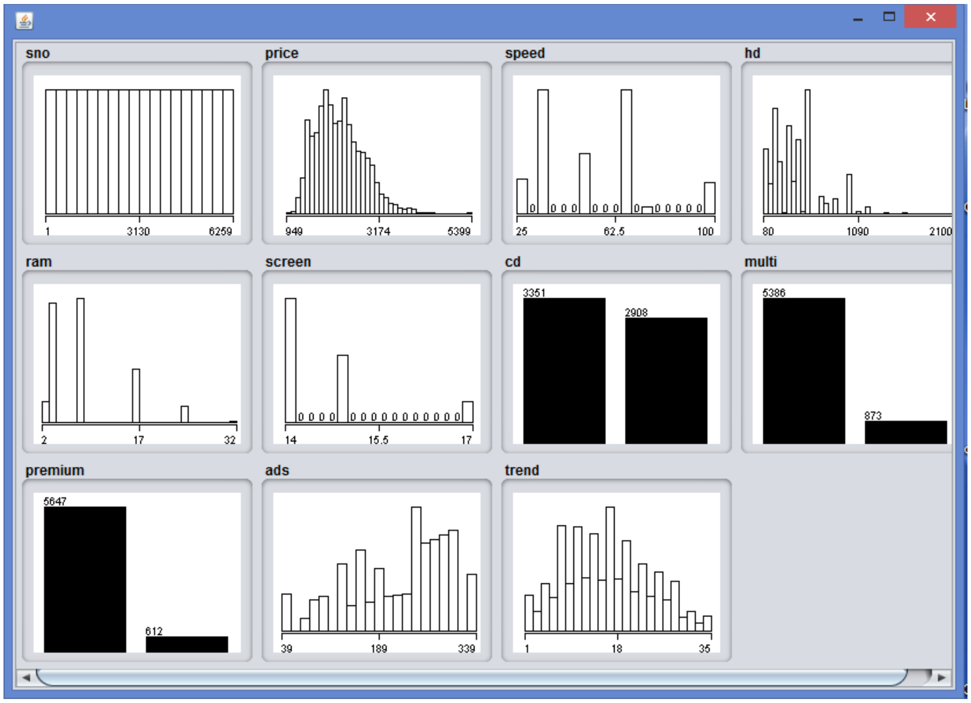
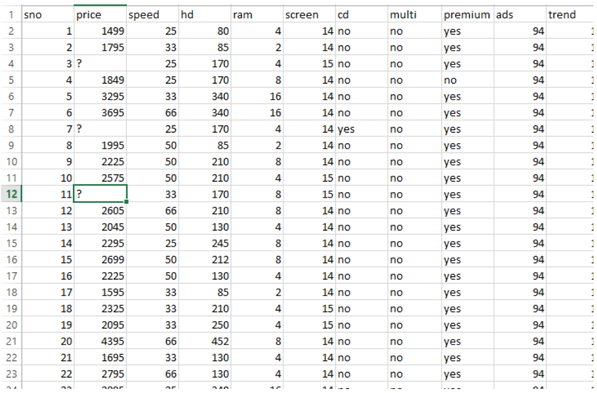


Fig: 6.4 Data visualization

Aim: 6b). Pre-process a given dataset based on Handling Missing Values

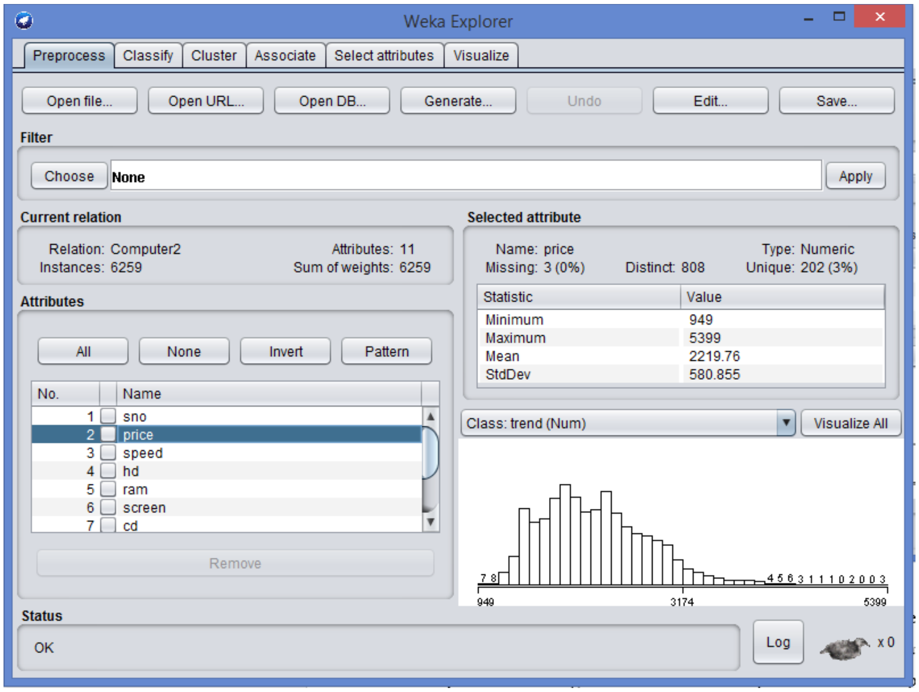
Process: Replacing Missing Attribute Values by the Attribute Mean.

This method is used for data sets with numerical attributes. An example of such a data set is presented in fig no: 3.4



1	sno	price	speed	hd	ram	screen	cd	multi	premium	ads	trend
2	1	1499	25	80	4	14	no	no	yes	94	1
3	2	1795	33	85	2	14	no	no	yes	94	1
4	3	?	25	170	4	15	no	no	yes	94	1
5	4	1849	25	170	8	14	no	no	no	94	1
6	5	3295	33	340	16	14	no	no	yes	94	1
7	6	3695	66	340	16	14	no	no	yes	94	1
8	7	?	25	170	4	14	yes	no	yes	94	1
9	8	1995	50	85	2	14	no	no	yes	94	1
10	9	2225	50	210	8	14	no	no	yes	94	1
11	10	2575	50	210	4	15	no	no	yes	94	1
12	11	?	33	170	8	15	no	no	yes	94	1
13	12	2605	66	210	8	14	no	no	yes	94	1
14	13	2045	50	130	4	14	no	no	yes	94	1
15	14	2295	25	245	8	14	no	no	yes	94	1
16	15	2699	50	212	8	14	no	no	yes	94	1
17	16	2225	50	130	4	14	no	no	yes	94	1
18	17	1595	33	85	2	14	no	no	yes	94	1
19	18	2325	33	210	4	15	no	no	yes	94	1
20	19	2095	33	250	4	15	no	no	yes	94	1
21	20	4395	66	452	8	14	no	no	yes	94	1
22	21	1695	33	130	4	14	no	no	yes	94	1
23	22	2795	66	130	4	14	no	no	yes	94	1

Fig: 6.5 Missing values



Filter: None

Current relation

Relation: Computer2 Attributes: 11
Instances: 6259 Sum of weights: 6259

Selected attribute

Name: price Type: Numeric
Missing: 3 (0%) Distinct: 808 Unique: 202 (3%)

Statistic	Value
Minimum	949
Maximum	5399
Mean	2219.76
StdDev	580.855

Attributes

No.	Name
1	sno
2	price
3	speed
4	hd
5	ram
6	screen
7	cd

Class: trend (Num)

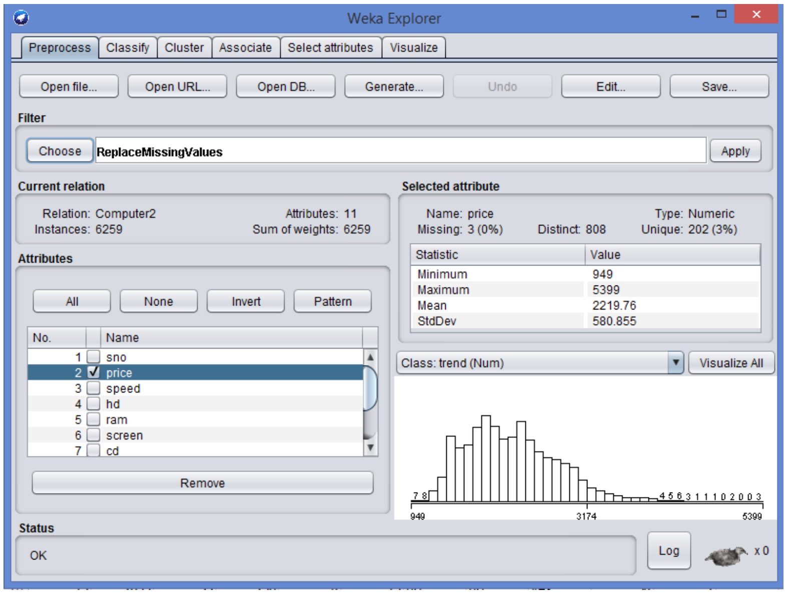
Status

OK

Fig: 6.6 Choosing a dataset

In this method, every missing attribute value for a numerical attribute is replaced by the arithmetic mean of known attribute values. In Fig, the mean of known attribute values for

Temperature is 99.2, hence all missing attribute values for Temperature should be replaced by 99.2. The table with missing attribute values replaced by the mean is presented in fig. For symbolic attributes Headache and Nausea, missing attribute values were replaced using the most common value of the Replace Missing Values.



Filter: ReplaceMissingValues

Current relation
Relation: Computer2 Attributes: 11
Instances: 6259 Sum of weights: 6259

Attributes

No.		Name
1	□	sno
2	☑	price
3	□	speed
4	□	hd
5	□	ram
6	□	screen
7	□	cd

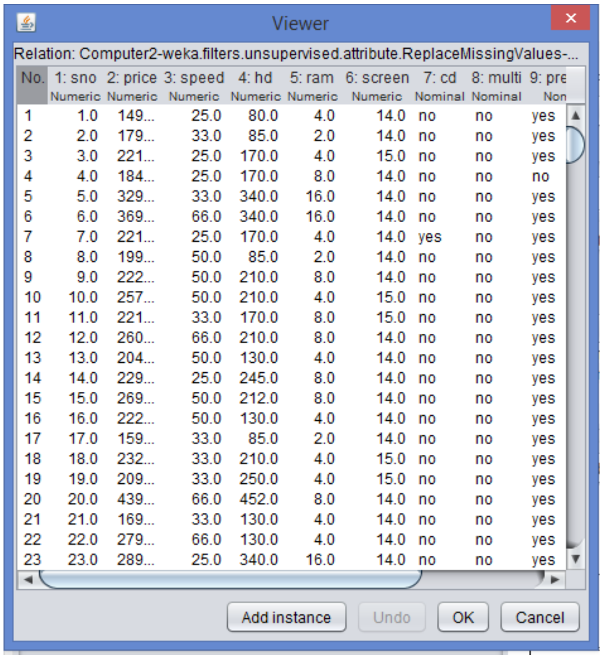
Selected attribute
Name: price Type: Numeric
Missing: 3 (0%) Distinct: 808 Unique: 202 (3%)

Statistic	Value
Minimum	949
Maximum	5399
Mean	2219.76
StdDev	580.855

Class: trend (Num)

Status
OK

Fig: 6.6 Replace missing values



Relation: Computer2-weka.filters.unsupervised.attribute.ReplaceMissingValues-...

No.	1: sno Numeric	2: price Numeric	3: speed Numeric	4: hd Numeric	5: ram Numeric	6: screen Numeric	7: cd Nominal	8: multi Nominal	9: pre Non
1	1.0	149...	25.0	80.0	4.0	14.0	no	no	yes
2	2.0	179...	33.0	85.0	2.0	14.0	no	no	yes
3	3.0	221...	25.0	170.0	4.0	15.0	no	no	yes
4	4.0	184...	25.0	170.0	8.0	14.0	no	no	no
5	5.0	329...	33.0	340.0	16.0	14.0	no	no	yes
6	6.0	369...	66.0	340.0	16.0	14.0	no	no	yes
7	7.0	221...	25.0	170.0	4.0	14.0	yes	no	yes
8	8.0	199...	50.0	85.0	2.0	14.0	no	no	yes
9	9.0	222...	50.0	210.0	8.0	14.0	no	no	yes
10	10.0	257...	50.0	210.0	4.0	15.0	no	no	yes
11	11.0	221...	33.0	170.0	8.0	15.0	no	no	yes
12	12.0	260...	66.0	210.0	8.0	14.0	no	no	yes
13	13.0	204...	50.0	130.0	4.0	14.0	no	no	yes
14	14.0	229...	25.0	245.0	8.0	14.0	no	no	yes
15	15.0	269...	50.0	212.0	8.0	14.0	no	no	yes
16	16.0	222...	50.0	130.0	4.0	14.0	no	no	yes
17	17.0	159...	33.0	85.0	2.0	14.0	no	no	yes
18	18.0	232...	33.0	210.0	4.0	15.0	no	no	yes
19	19.0	209...	33.0	250.0	4.0	15.0	no	no	yes
20	20.0	439...	66.0	452.0	8.0	14.0	no	no	yes
21	21.0	169...	33.0	130.0	4.0	14.0	no	no	yes
22	22.0	279...	66.0	130.0	4.0	14.0	no	no	yes
23	23.0	289...	25.0	340.0	16.0	14.0	no	no	yes

Fig: 6.7 After replacing

Aim: 6c). Discretization of data

Description:

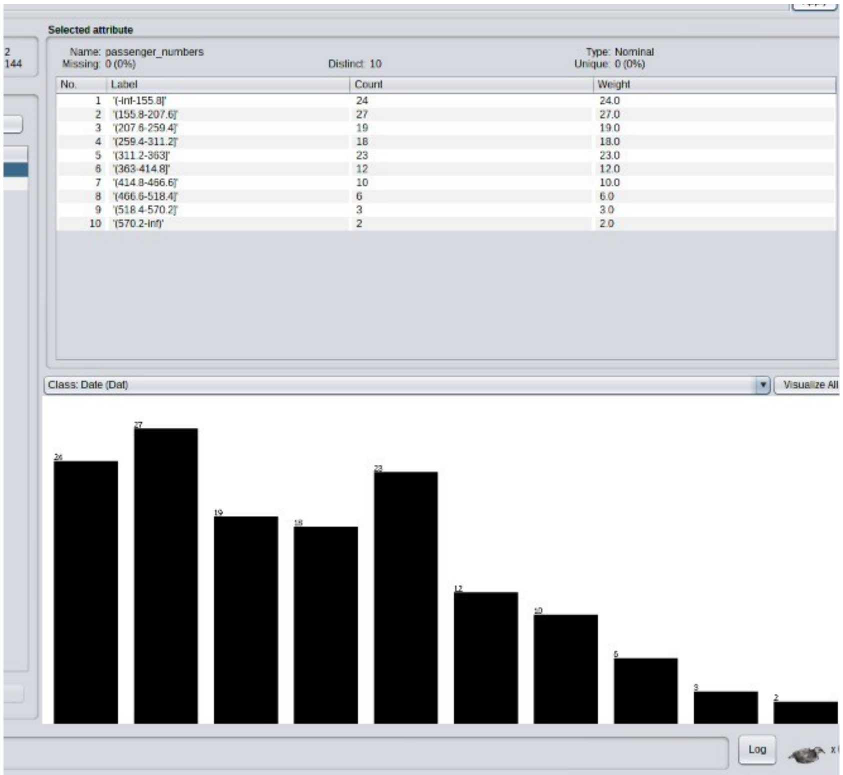
Discretization is the process of converting continuous attribute to discrete attribute. It is a process of data reduction.

Data discretization transforms numeric data by mapping values to interval or concept labels. Such methods can be used to automatically generate concept hierarchies for the data, which allows for mining at multiple levels of granularity. Discretization techniques include binning, histogram analysis, cluster analysis, decision tree analysis, and correlation analysis. For nominal data, concept hierarchies may be generated based on schema definitions as well as the number of distinct values per attribute.

Steps:

- Open CSV file in weka.
- Under filter, choose discretize and click apply.
- We can find that attributes are converted to discrete attributes.

Initial Data



Selected attribute

Name: passenger_numbers
Missing: 0 (0%)
Distinct: 10
Type: Nominal
Unique: 0 (0%)

No.	Label	Count	Weight
1	'(-inf-155.8]'	24	24.0
2	'(155.8-207.6]'	27	27.0
3	'(207.6-259.4]'	19	19.0
4	'(259.4-311.2]'	18	18.0
5	'(311.2-363]'	23	23.0
6	'(363-414.8]'	12	12.0
7	'(414.8-466.6]'	10	10.0
8	'(466.6-518.4]'	6	6.0
9	'(518.4-570.2]'	3	3.0
10	'(570.2-inf)'	2	2.0

Class: Date (Dat)

Fig: 6.6 After Discretization

Aim: 6d). Normalization of data

Description:

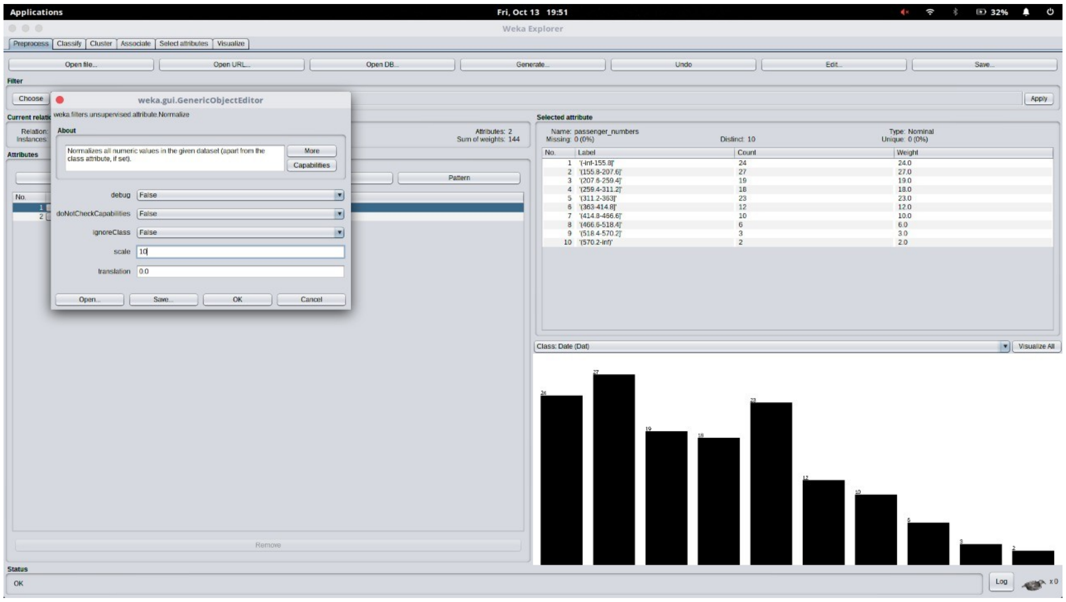
Normalization is the process of converting the scale of an attribute from one form to other form. Normalization is of 3 types:

- Min-max Normalization: Min max normalization performs a linear transformation on the original data.
- Z score normalization (zero-mean normalization): The values for an attribute, A,are normalized based on the mean(i.e., average) and standard deviation of A.
- Decimal scaling : Normalization by decimal scaling normalizes by moving the decimal point of values of attribute A.

Procedure:

- Select the csv file to be normalized.
- Select normalization from the filters.
- Set scale value to 10.
- Values are displayed in range of 0 to 10.

-



Attributes: 2
Sum of weights: 144

weka.gui.GenericObjectEditor

weka.filters.unsupervised.attribute.Normalize

About

Normalizes all numeric values in the given dataset (apart from the class attribute, if set).

debug: False

doNotCheckCapabilities: False

ignoreClass: False

scale: 10

translation: 0.0

Selected attribute

Name: passenger_numbers
Missing: 0 (0%)
Distinct: 10
Type: Nominal
Unique: 0 (0%)

No.	Label	Count	Weight
1	'(-inf-155.8]'	24	24.0
2	'(155.8-207.6]'	27	27.0
3	'(207.6-259.4]'	19	19.0
4	'(259.4-311.2]'	18	18.0
5	'(311.2-363]'	23	23.0
6	'(363-414.8]'	12	12.0
7	'(414.8-466.6]'	10	10.0
8	'(466.6-518.4]'	6	6.0
9	'(518.4-570.2]'	3	3.0
10	'(570.2-inf)'	2	2.0

Class: Date (Dat)

Status

OK

7. Generate Association Rules using the Apriori Algorithm

Description:

The Apriori algorithm is an influential algorithm for mining frequent item sets for Boolean association rules. It uses a “bottom-up” approach, where frequent subsets are extended one at a time (a step known as candidate generation, and groups of candidates are tested against the data).

- **Problem:**

TID	ITEMS
100	1,3,4
200	2,3,5
300	1,2,3,5
400	2,5

To find frequent item sets for above transaction with a minimum support of 2 having confidence measure of 70% (i.e, 0.7).

Procedure:

Step 1:

Count the number of transactions in which each item occurs

ITEM	NO. OF TRANSACTIONS
1	2
2	3
3	3
4	1
5	3

Step 2:

Eliminate all those occurrences that have transaction numbers less than the minimum support (2 in this case).

ITEM	NO. OF TRANSACTIONS

1	2
2	3
3	3
5	3

This is the single items that are bought frequently. Now let’s say we want to find a pair of items that are bought frequently. We continue from the above table (Table in step 2).

Step 3:

We start making pairs from the first item like 1,2;1,3;1,5 and then from second item like 2,3;2,5. We do not perform 2,1 because we already did 1,2 when we were making pairs with 1 and buying 1 and 2 together is same as buying 2 and 1 together. After making all the pairs we get,

ITEM PAIRS
1,2
1,3
1,5
2,3
2,5
3,5

Step 4:

Now, we count how many times each pair is bought together.

ITEM PAIRS	NO.OF TRANSACTIONS
1,2	1
1,3	2
1,5	1
2,3	2
2,5	3
3,5	2

Step 5:

Again remove all item pairs having number of transactions less than 2.

ITEM PAIRS	NO.OF TRANSACTIONS
1,3	2
2,3	2
2,5	3
3,5	2

These pair of items is bought frequently together. Now, let’s say we want to find a set of three items that are bought together. We use above table (of step 5) and make a set of three items.

Step 6:

To make the set of three items we need one more rule (It’s termed as self-join), it simply means, from item pairs in above table, we find two pairs with the same first numeric, so, we get (2,3) and (2,5), which gives (2,3,5). Then we find how many times (2, 3, 5) are bought together in the original table and we get the following

ITEM SET	**NO. OF TRANSACTIONS**
(2,3,5)	2

Thus, the set of three items that are bought together from this data are (2, 3, 5).

Confidence:

We can take our frequent item set knowledge even further, by finding association rules using the frequent item set. In simple words, we know (2, 3, 5) are bought together frequently, but what is the association between them. To do this, we create a list of all subsets of frequently bought items (2, 3, 5) in our case we get following subsets:

- {2}
- {3}
- {5}
- {2,3}
- {3,5}
- {2,5}

Now, we find association among all the subsets.

{2} => {3,5}: (If ‘2’ is bought , what’s the probability that ‘3’ and ‘5’ would be bought in same transaction)

Confidence = P (3ᴗ5ᴗ2)/ P(2) =2/3 =67%

{3}=>{2,5}= P (3ᴗ5ᴗ2)/ P(3)=2/3=67%

{5}=>{2,3}= P (3ᴗ5ᴗ2)/ P(5)=2/3=67%

{2,3}=>{5}= P (3ᴗ5ᴗ2)/ P(2ᴗ3)=2/2=100%

{3,5}=>{2}= P (3ᴗ5ᴗ2)/ P(3ᴗ5)=2/2=100%

{2,5}=>{3}= P (3ᴗ5ᴗ2)/ P(2ᴗ5)=2/3=67%

Also, considering the remaining 2-items sets, we would get the following associations-

{1}=>{3}=P(1ᴗ3)/P(1)=2/2=100%

{3}=>{1}=P(1ᴗ3)/P(3)=2/3=67%

{2}=>{3}=P(3ᴗ2)/P(2)=2/3=67%

{3}=>{2}=P(3ᴗ2)/P(3)=2/3=67%

{2}=>{5}=P(2ᴗ5)/P(2)=3/3=100%

{5}=>{2}=P(2ᴗ5)/P(5)=3/3=100%

{3}=>{5}=P(3ᴗ5)/P(3)=2/3=67%

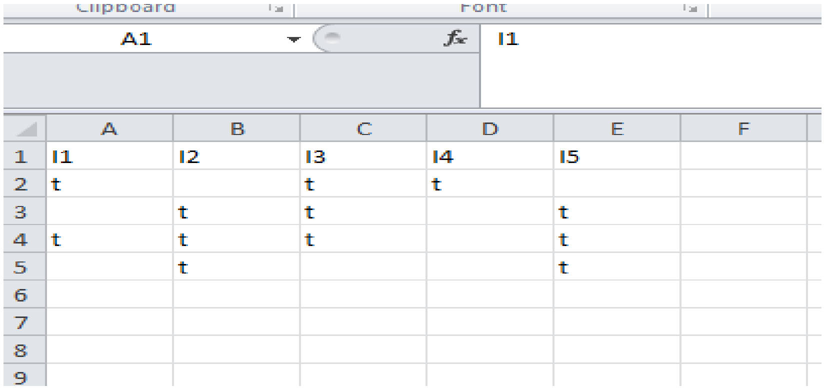
{5}=>{3}=P(3ᴗ5)/P(5)=2?3=67%

Eliminate all those having confidence less than 70%.

Hence, the rules would be –

{2,3}=>{5}, {3,5}=>{2}, {1}=>{3},{2}=>{5}, {5}=>{2}.

Now these manual results should be checked with the rules generated in WEKA. So first create a csv file for the above problem, the csv file for the above problem will look like the rows and columns in the above figure. This file is written in excel sheet.



	A	B	C	D	E	F
1	I1	I2	I3	I4	I5	
2	t		t	t		
3		t	t		t	
4	t	t	t		t	
5		t			t	
6						
7						
8						
9						

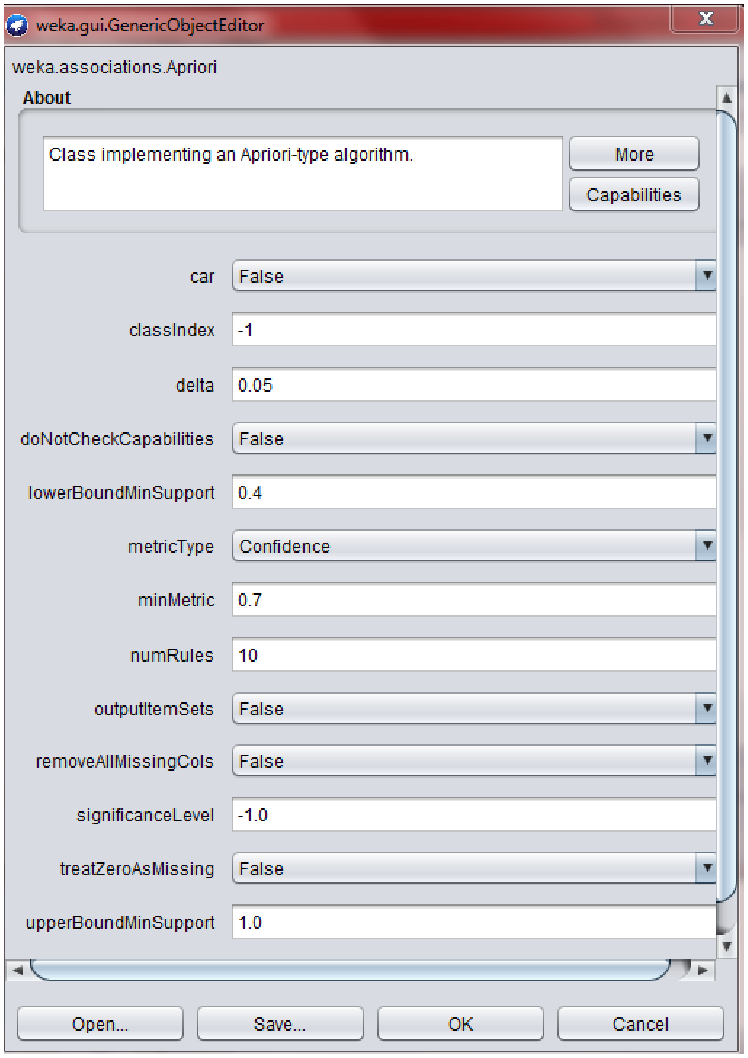
Fig: 7.1 Data for Apriori

<u>Procedure for running the rules in weka:</u>

<u>Step 1:</u>

Open weka explorer and open the file and then select all the item sets. The figure gives a better understanding of how to do that.

<u>Step 2:</u>Now select the association tab and then choose apriori algorithm by setting the minimum support and confidence as shown in the figure.



weka.gui.GenericObjectEditor

weka.associations.Apriori

About

Class implementing an Apriori-type algorithm.

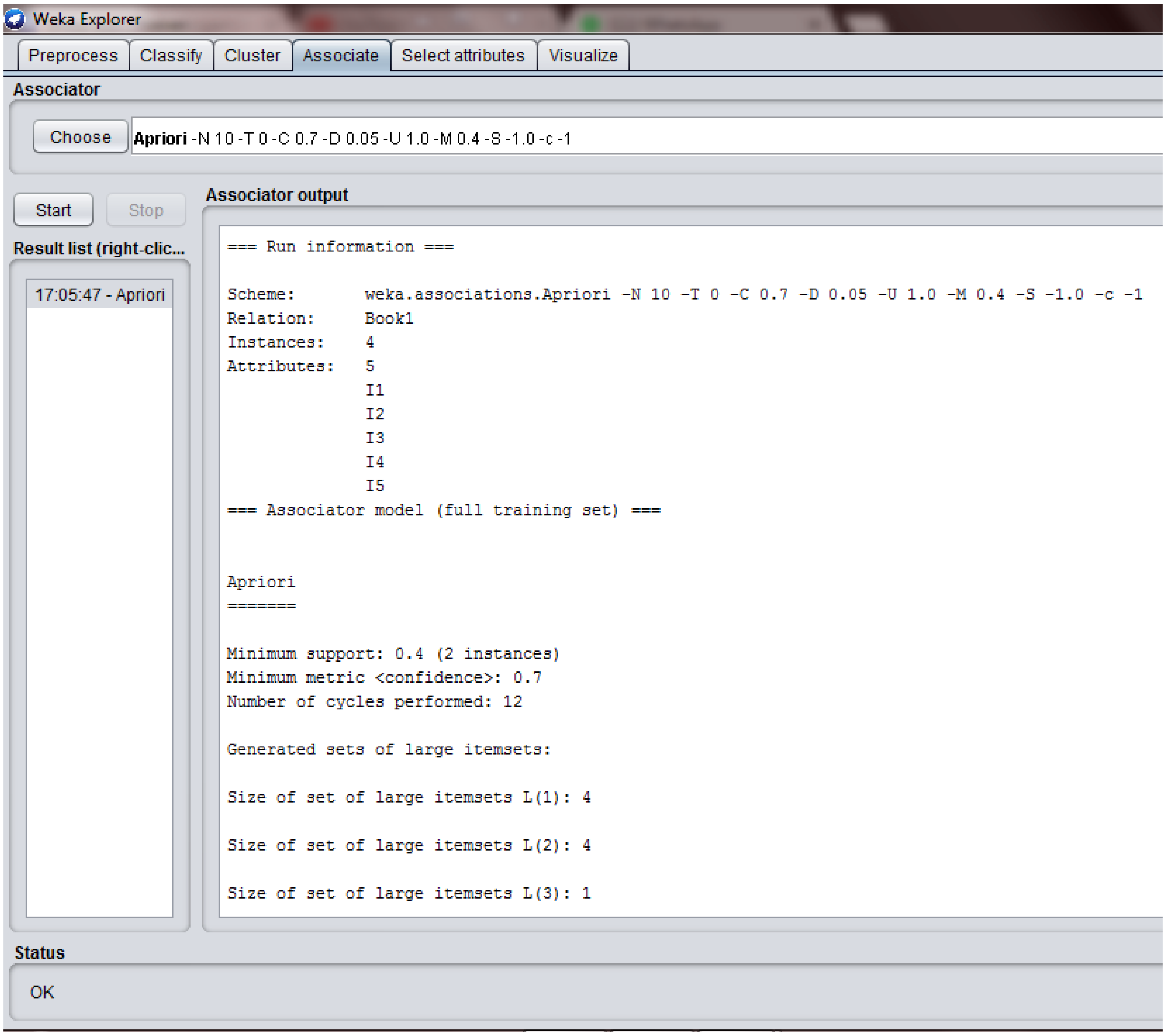
car	False
classIndex	-1
delta	0.05
doNotCheckCapabilities	False
lowerBoundMinSupport	0.4
metricType	Confidence
minMetric	0.7
numRules	10
outputItemSets	False
removeAllMissingCols	False
significanceLevel	-1.0
treatZeroAsMissing	False
upperBoundMinSupport	1.0

Fig: 7.2 Apriori Parameters

Step 3:

Now run the apriori algorithm with the set values of minimum support and the confidence. After running the weka generates the association rules and the respective confidence with minimum support as shown in the figure.

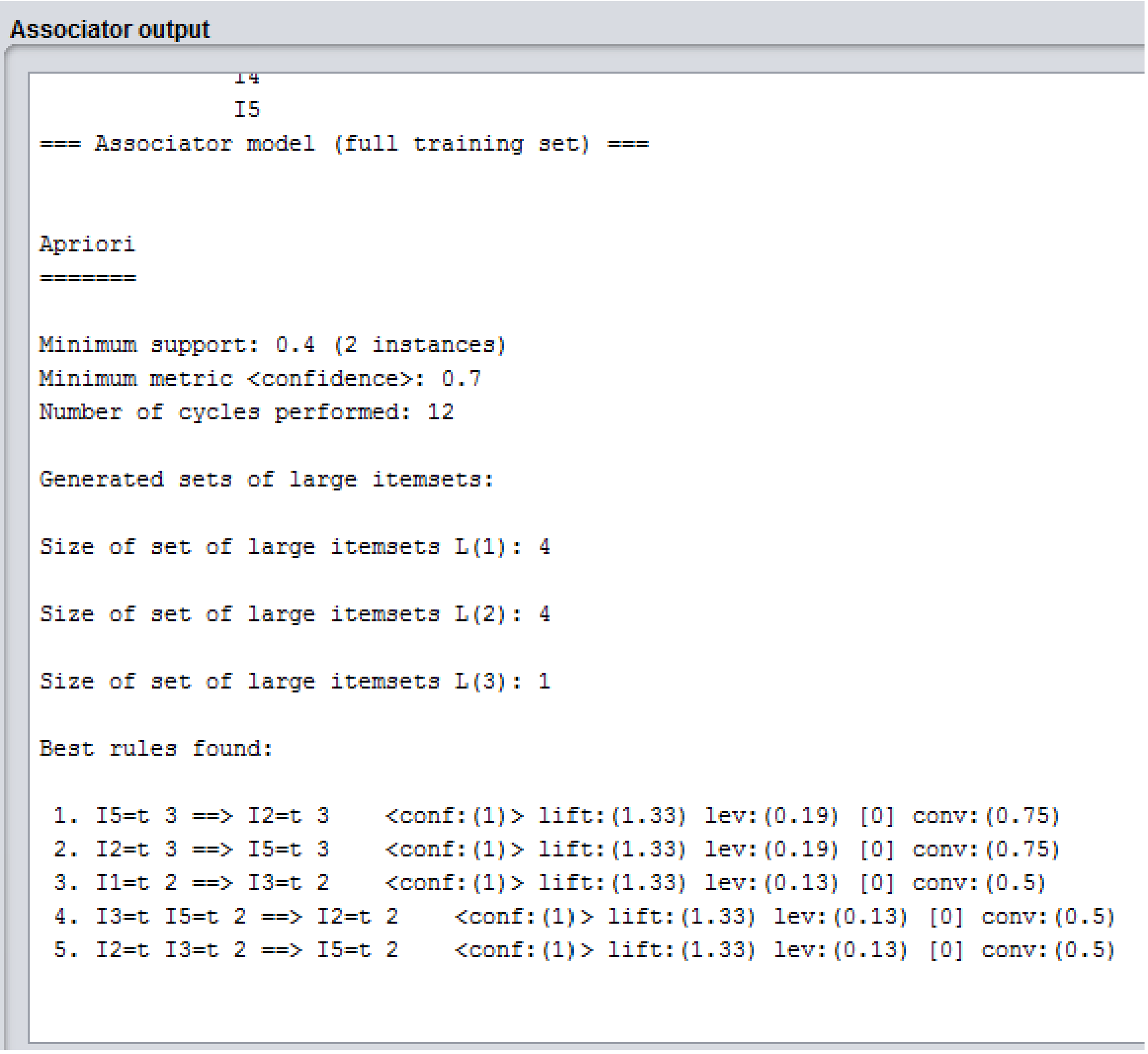
The above csv file has generated 5 rules as shown in the figure:



Apriori -N 10 -T 0 -C 0.7 -D 0.05 -U 1.0 -M 0.4 -S -1.0 -c -1

```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.7 -D 0.05 -U 1.0 -M 0.4 -S -1.0 -c -1
Relation:     Book1
Instances:    4
Attributes:   5
              I1
              I2
              I3
              I4
              I5
=== Associator model (full training set) ===


Apriori
=======

Minimum support: 0.4 (2 instances)
Minimum metric <confidence>: 0.7
Number of cycles performed: 12

Generated sets of large itemsets:

Size of set of large itemsets L(1): 4

Size of set of large itemsets L(2): 4

Size of set of large itemsets L(3): 1
```

Fig: 7.3 Frequent Item Sets



```
               I4
               I5
=== Associator model (full training set) ===


Apriori
=======

Minimum support: 0.4 (2 instances)
Minimum metric <confidence>: 0.7
Number of cycles performed: 12

Generated sets of large itemsets:

Size of set of large itemsets L(1): 4

Size of set of large itemsets L(2): 4

Size of set of large itemsets L(3): 1

Best rules found:

 1. I5=t 3 ==> I2=t 3    <conf:(1)> lift:(1.33) lev:(0.19) [0] conv:(0.75)
 2. I2=t 3 ==> I5=t 3    <conf:(1)> lift:(1.33) lev:(0.19) [0] conv:(0.75)
 3. I1=t 2 ==> I3=t 2    <conf:(1)> lift:(1.33) lev:(0.13) [0] conv:(0.5)
 4. I3=t I5=t 2 ==> I2=t 2    <conf:(1)> lift:(1.33) lev:(0.13) [0] conv:(0.5)
 5. I2=t I3=t 2 ==> I5=t 2    <conf:(1)> lift:(1.33) lev:(0.13) [0] conv:(0.5)
```

Fig: 7.4 Frequent Item Sets (cont.…)

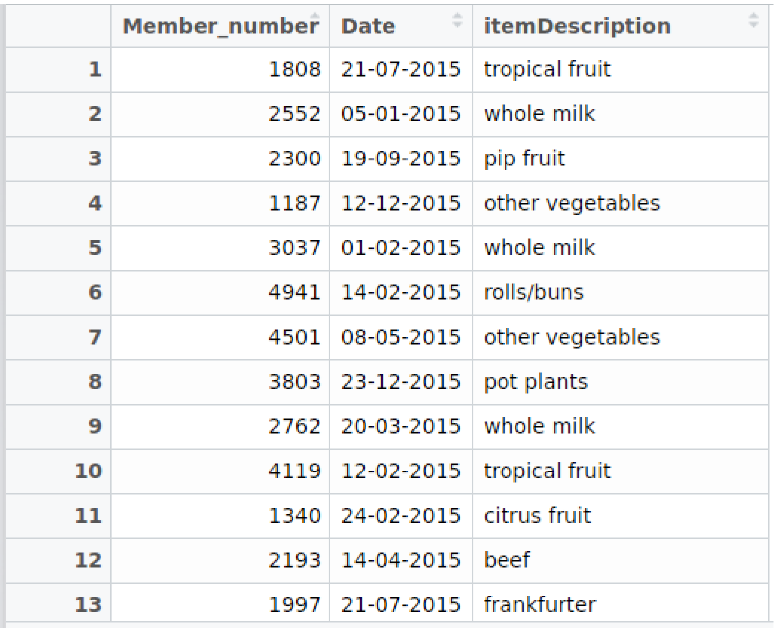
Conclusion:

As we have seen the total rules generated by us manually and by the weka are matching, hence the rules generated are 5.

Rscript for Association Analysis:

```
#includes the libraries
library(arules)

#finding association rules
txn ←  read.transactions(file="ItemList.csv", rm.duplicates= TRUE,
format="basket",sep=",",cols=1)
txn@itemInfo$labels <- gsub("\"","",txn@itemInfo$labels)
basket_rules <- apriori(txn,parameter = list(sup = 0.01, conf = 0.5,target="rules"));
inspect(basket_rules)

#Plot the baskets
itemFrequencyPlot(txn, topN = 5)
```

Input DataSet (groceries dataset):

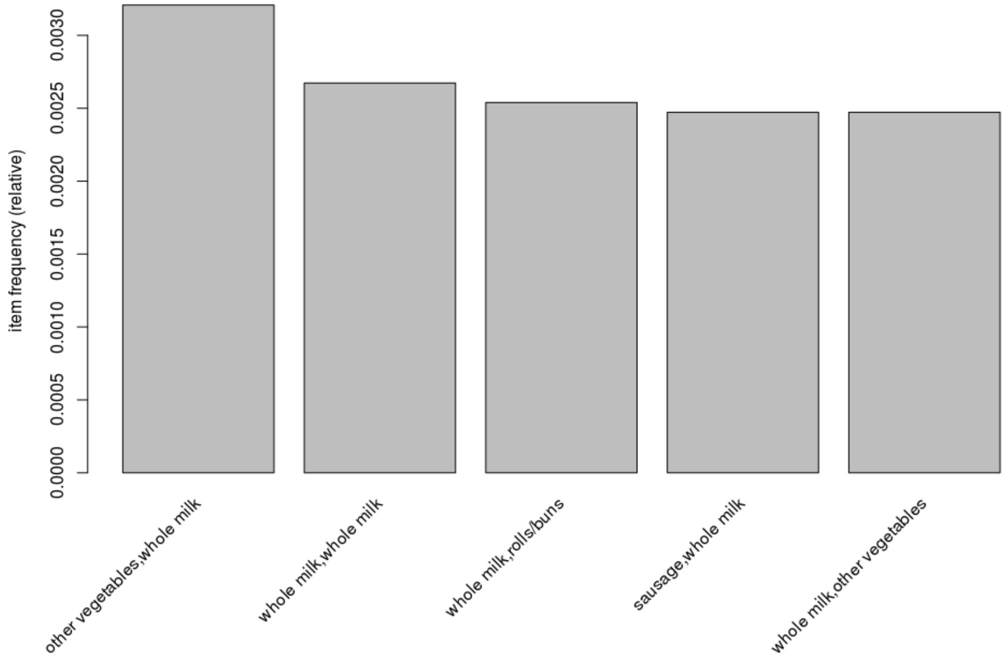


	Member_number	Date	itemDescription
1	1808	21-07-2015	tropical fruit
2	2552	05-01-2015	whole milk
3	2300	19-09-2015	pip fruit
4	1187	12-12-2015	other vegetables
5	3037	01-02-2015	whole milk
6	4941	14-02-2015	rolls/buns
7	4501	08-05-2015	other vegetables
8	3803	23-12-2015	pot plants
9	2762	20-03-2015	whole milk
10	4119	12-02-2015	tropical fruit
11	1340	24-02-2015	citrus fruit
12	2193	14-04-2015	beef
13	1997	21-07-2015	frankfurter

Output:

```
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen maxlen target   ext
        0.5    0.1    1 none FALSE            TRUE       5    0.01      1     10  rules FALSE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 149

 items      support count
[1] {i1}       0.50    2
[2] {i2}       0.75    3
[3] {i5}       0.75    3
[4] {i3}       0.75    3
[5] {i1,i3}    0.50    2
[6] {i2,i5}    0.75    3
[7] {i2,i3}    0.50    2
[8] {i3,i5}    0.50    2
[9] {i2,i3,i5} 0.50    2
  lhs        rhs  support confidence lift     count
[1]  {i1}    => {i3} 0.50    1.0000000  1.333333 2
[2]  {i3}    => {i1} 0.50    0.6666667  1.333333 2
[3]  {i2}    => {i5} 0.75    1.0000000  1.333333 3
[4]  {i5}    => {i2} 0.75    1.0000000  1.333333 3
[5]  {i2,i3} => {i5} 0.50    1.0000000  1.333333 2
[6]  {i3,i5} => {i2} 0.50    1.0000000  1.333333 2
[7]  {}      => {i1} 0.50    0.5000000  1.000000 2
[8]  {}      => {i2} 0.75    0.7500000  1.000000 3
[9]  {}      => {i5} 0.75    0.7500000  1.000000 3
[10] {}      => {i3} 0.75    0.7500000  1.000000 3
```

Graph:


item frequency (relative)
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
other vegetables,whole milk
whole milk,whole milk
whole milk,rolls/buns
sausage,whole milk
whole milk,other vegetables

8. Generating Association Rules Using FP Growth Algorithm

(8a) Aim: To generate association rules using FP Growth Algorithm

PROBLEM:

To find all frequent item sets in following dataset using FP-growth algorithm. Minimum support=2 and confidence =70%

TID	ITEMS
100	1,3,4
200	2,3,5
300	1,2,3,5
400	2,5

Solution:

Similar to Apriori Algorithm, find the frequency of occurrences of all each item in dataset and then prioritize the items according to its descending order of its frequency of occurrence. Eliminating those occurrences with the value less than minimum support and assigning the priorities, we obtain the following table.

ITEM	NO. OF TRANSACTIONS	PRIORITY
1	2	4
2	3	1
3	3	2
5	3	3

Re-arranging the original table, we obtain-

TID	ITEMS
100	1,3
200	2,3,5
300	2,3,5,1
400	2,5

Construction of tree:

Note that all FP trees have 'null' node as the root node. So, draw the root node first and attach the items of the row 1 one by one respectively and write their occurrences in front of it. The tree is further expanded by adding nodes according to the prefixes (count) formed and by further incrementing the occurrences every time they occur and hence the tree is built.

Prefixes:

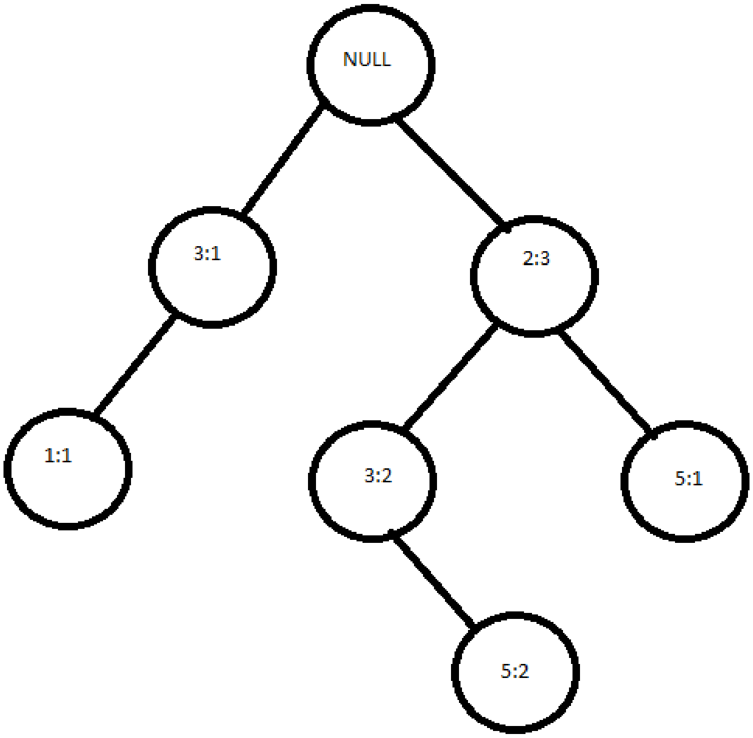
- 1->3:1 2,3,5:1
- 5->2,3:2 2:1
- 3->2:2

Frequent item sets:

- 1-> 3:2 /*2 and 5 are eliminated because they're less than minimum support, and the occurrence of 3 is obtained by adding the occurrences in both the instances*/
- Similarly, 5->2,3:2 ; 2:3;3:2
- 3->2 :2

Therefore, the frequent item sets are {3,1}, {2,3,5}, {2,5}, {2,3},{3,5}

The tree is constructed as below:



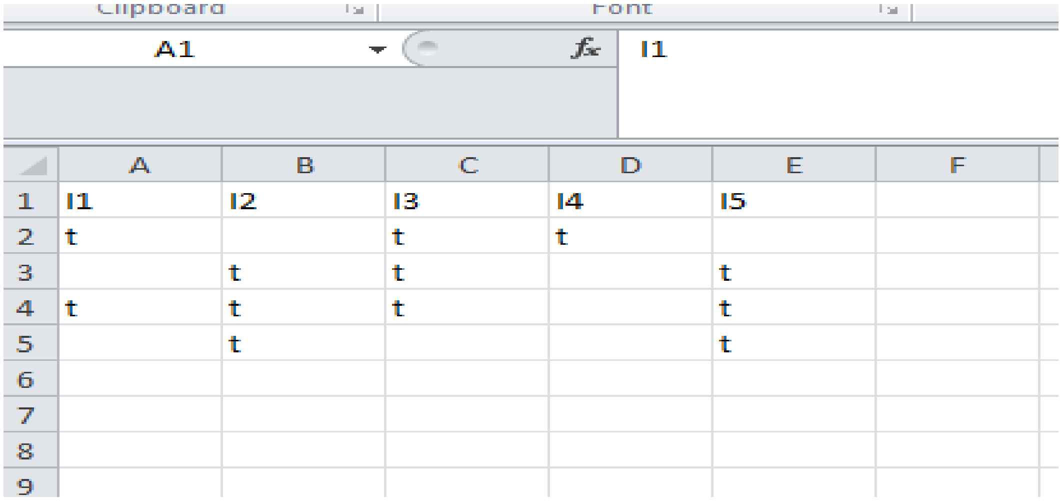
Generating the association rules for the following tree and calculating the confidence measures we get-

- {3}=>{1}=2/3=67%
- {1}=>{3}=2/2=100%
- {2}=>{3,5}=2/3=67%
- {2,5}=>{3}=2/3=67%
- {3,5}=>{2}=2/2=100%
- {2,3}=>{5}=2/2=100%
- {3}=>{2,5}=2/3=67%
- {5}=>{2,3}=2/3=67%
- {2}=>{5}=3/3=100%
- {5}=>{2}=3/3=100%
- {2}=>{3}=2/3=67%
- {3}=>{2}=2/3=67%

Thus, eliminating all the sets having confidence less than 70%, we obtain the following conclusions:
{1} => {3} , {3,5}=>{2} , {2,3}=>{5} , {2}=>{5}, {5}=>{2}.

As we see there are 5 rules that are being generated manually and these are to be checked against the results in WEKA. Inorder to check the results in the tool we need to follow the similar procedure like Apriori.

So first create a csv file for the above problem, the csv file for the above problem will look like the rows and columns in the above figure. This file is written in excel sheet.



	A	B	C	D	E	F
1	I1	I2	I3	I4	I5	
2	t		t	t		
3		t	t		t	
4	t	t	t		t	
5		t			t	
6						
7						
8						
9						

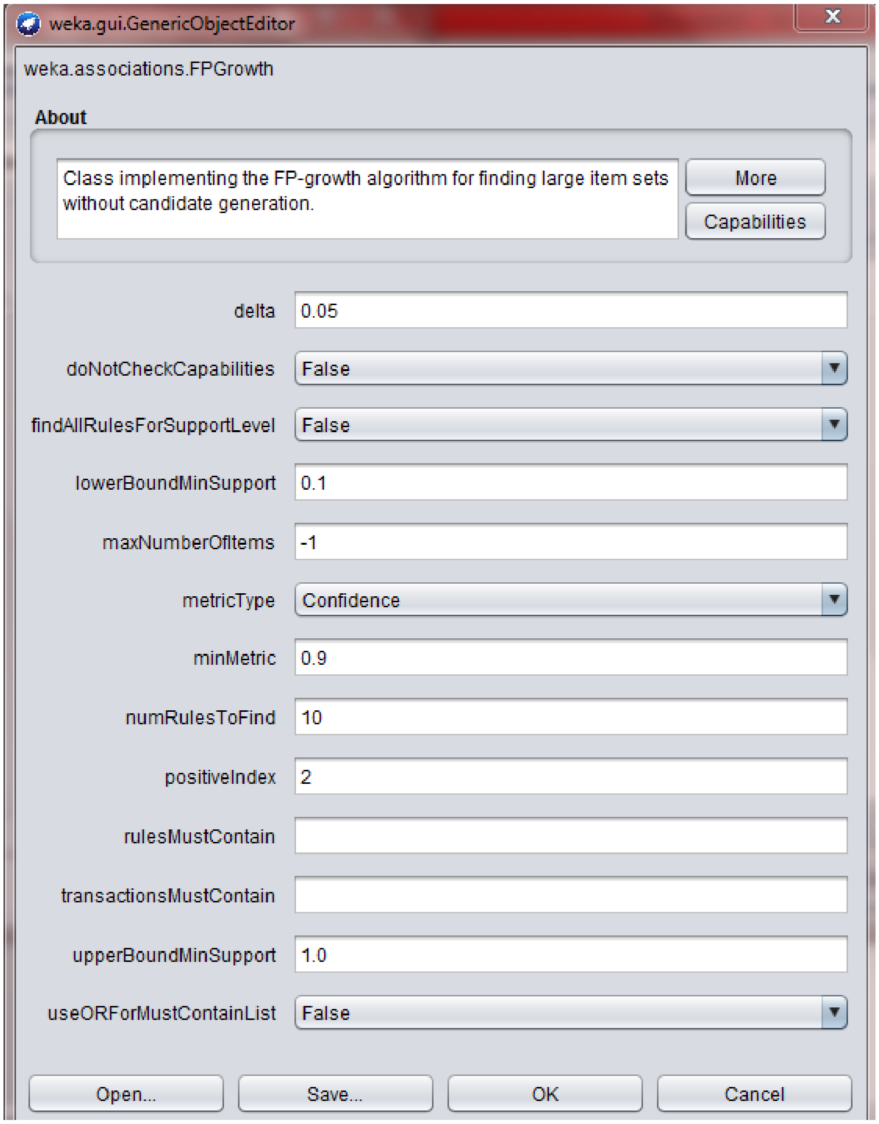
Fig: 8.1 Data for FP Growth

Procedure for running the rules in weka:

Step 1:

Open weka explorer and open the file and then select all the item sets. The figure gives a better understanding of how to do that.

Step 2: Now select the association tab and then choose FPgrowth algorithm by setting the minimum support and confidence as shown in the figure.



weka.associations.FPGrowth

Class implementing the FP-growth algorithm for finding large item sets without candidate generation.

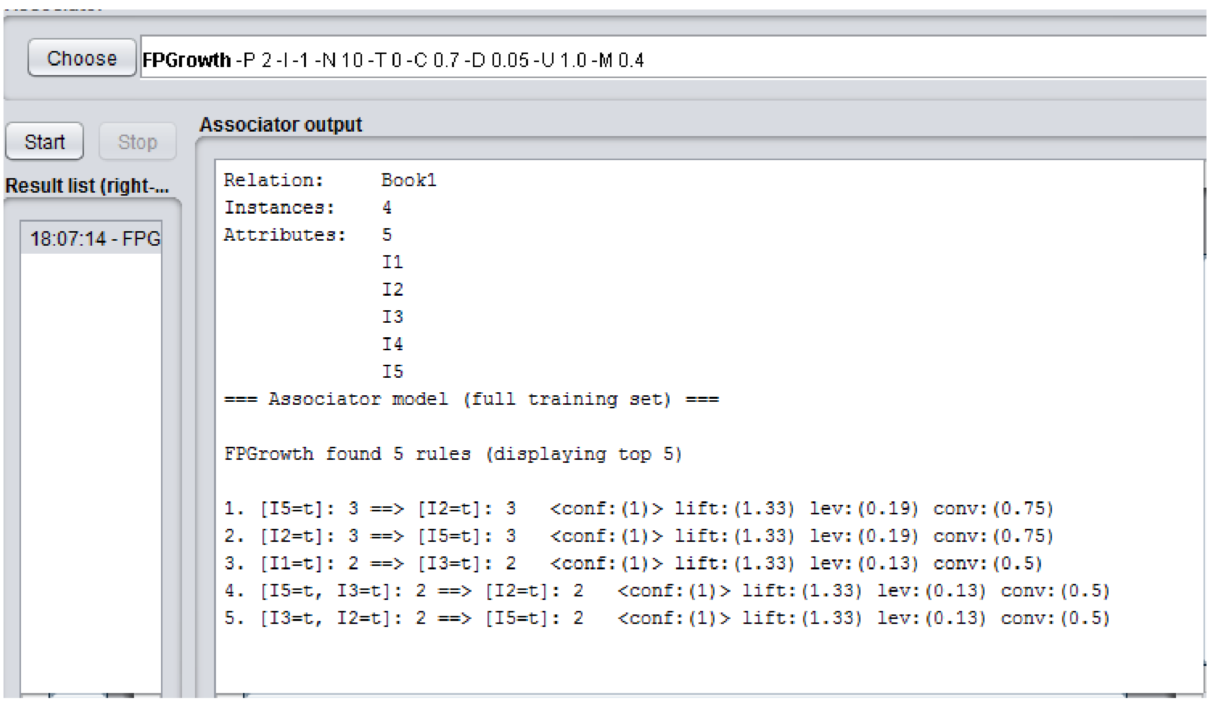
delta	0.05
doNotCheckCapabilities	False
findAllRulesForSupportLevel	False
lowerBoundMinSupport	0.1
maxNumberOfItems	-1
metricType	Confidence
minMetric	0.9
numRulesToFind	10
positiveIndex	2
rulesMustContain	
transactionsMustContain	
upperBoundMinSupport	1.0
useORForMustContainList	False

Fig: 8.2 FP growth algorithm

<u>Step 3:</u>

Now run the FP Growth algorithm with the set values of minimum support and the confidence. After running the weka generates the association rules and the respective confidence with minimum support as shown in the figure.

The above csv file has generated 5 rules as shown in the figure:



FPGrowth -P 2 -I -1 -N 10 -T 0 -C 0.7 -D 0.05 -U 1.0 -M 0.4

```
Relation:     Book1
Instances:    4
Attributes:   5
              I1
              I2
              I3
              I4
              I5
=== Associator model (full training set) ===

FPGrowth found 5 rules (displaying top 5)

1. [I5=t]: 3 ==> [I2=t]: 3   <conf:(1)> lift:(1.33) lev:(0.19) conv:(0.75)
2. [I2=t]: 3 ==> [I5=t]: 3   <conf:(1)> lift:(1.33) lev:(0.19) conv:(0.75)
3. [I1=t]: 2 ==> [I3=t]: 2   <conf:(1)> lift:(1.33) lev:(0.13) conv:(0.5)
4. [I5=t, I3=t]: 2 ==> [I2=t]: 2   <conf:(1)> lift:(1.33) lev:(0.13) conv:(0.5)
5. [I3=t, I2=t]: 2 ==> [I5=t]: 2   <conf:(1)> lift:(1.33) lev:(0.13) conv:(0.5)
```

Fig: 8.3 Output for FP Growth

Conclusion:

As we have seen the total rules generated by us manually and by the weka are matching, hence the rules generated are 5.

9. Build a Decision Tree by using J48 algorithm

(9a) Aim: Generate a Decision Tree by using J48 algorithm.

DESCRIPTION:

Decision tree learning is one of the most widely used and practical methods for inductive inference over supervised data. It represents a procedure for classifying categorical databased on their attributes. This representation of acquired knowledge in tree form is intuitive and easy to assimilate by humans.

ILLUSTRATION:

Build a decision tree for the following data

AGE	INCOME	STUDENT	CREDIT_RATING	BUYS_COMPUTER
Youth	High	No	Fair	No
Youth	High	No	Excellent	No
Middle aged	High	No	Fair	Yes
Senior	Medium	No	Fair	Yes
Senior	Low	Yes	Fair	Yes
Senior	Low	Yes	Excellent	No
Middle aged	Medium	Yes	Excellent	Yes
Youth	Low	No	Fair	No
Youth	Medium	Yes	Fair	Yes
Senior	Medium	Yes	Fair	Yes
Youth	Medium	Yes	Excellent	Yes
Middle aged	Medium	No	Excellent	Yes
Middle aged	High	Yes	Fair	Yes
Senior	Medium	No	Excellent	No

The entropy is a measure of the uncertainty associated with a random variable. As uncertainty increases, so does entropy, values range from [0-1] to present the entropy of information

$$\text{Entropy (D)} = \sum_{j=1}^{c} -p \log_2 p$$

Information gain is used as an attribute selection measure; pick the attribute having the highest information gain, the gain is calculated by:

$$\left|Dj\right|/\square \vee D \vee Entropy\left(D\right)$$

Gain (D, A) = Entropy (D) - $\sum_{j=1}^{c}\square$

Where, D: A given data partition

A: Attribute

V: Suppose we were partition the tuples in D on some attribute A having v distinct values D is split into v partition or subsets, (D1, D2….. Dj) , where Dj contains those tuples in D that have outcome Aj of A.

- Class P: buys_computer=”yes”
- Class N: buys_computer=”no”

Entropy (D) = -9/14log (9/14)-5/15log (5/14) =0.940

- Compute the expected information requirement for each attribute start with the attribute age

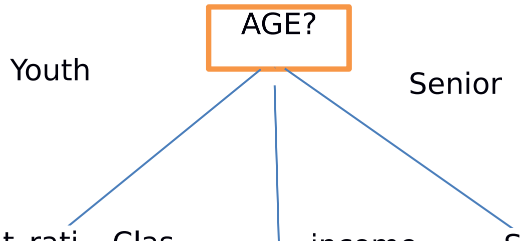
Gain (age, D) = Entropy (D) - $\sum_{youth, middle-aged, senior}^{n}\left(\frac{Sv}{S}\right)Entropy\left(Sv\right)$

= Entropy (D) – 5/14Entropy(Syouth) - 4/14Entropy(Smiddle-aged) - 5/14Entropy(Ssenior)

= 0.940-0.694

=0.246

Similarly, for other attributes,
Gain (Income, D) =0.029
Gain (Student, D) = 0.151
Gain (credit_rating, D) = 0.04



Income	Student	Credit_rating	Class
High	No	Fair	No
High	No	Excellent	No
Medium	No	Fair	No
Low	Yes	Fair	Yes
medium	Yes	excellent	yes

income	Student	Credit_rating	class
Medium	No	Fair	No
Low	Yes	Fair	Yes
Low	Yes	Excellent	No
Medium	Yes	Fair	Yes
medium	No	Excellent	No

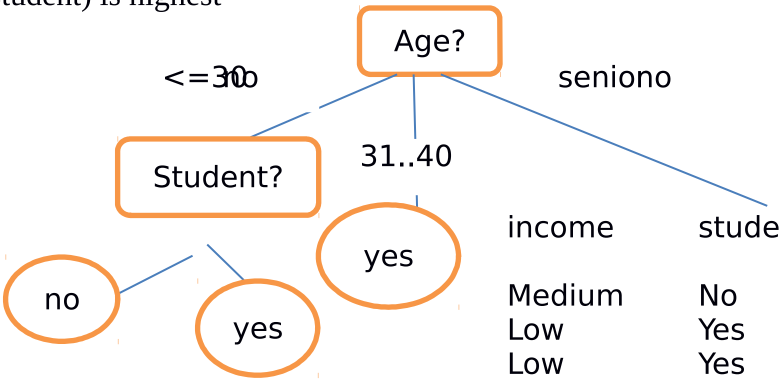
Income	student	Credit_rating	class
High	No	Fair	***Yes***
Low	Yes	Excellent	***Yes***
Medium	No	Excellent	***Yes***
High	yes	Fair	***yes***

The attribute age has the highest information gain and therefore becomes the splitting attribute at the root node of the decision tree. Branches are grown for each outcome of age. These tuples are shown partitioned accordingly.

Now, calculating information gain for subtable (age<=30)
I (2,3) = -(2/5)log(2/5)-(3/5)log(3/5)=0.971
INCOME
Income=”high” S11=0, S12=2
I=0
Income=”medium” S21=1 S22=1
I (S21, S23) = 1
Income=”low” S31=1 S32=0
I=0
Entropy for income
E(income) = (2/5)(0) + (2/5)(1) + (1/5)(0) = 0.4
Gain(income) = 0.971 - 0.4 = 0.571

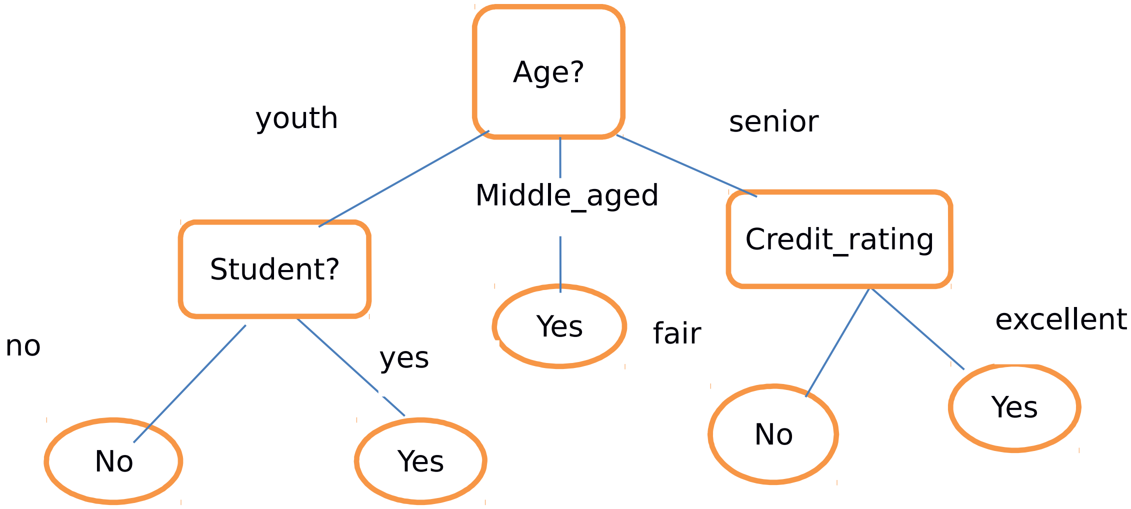
Similarly,
  Gain(student)=0.971
  Gain(credit)=0.0208

Gain(student) is highest



income	student	Credit_rating	class
Medium	No	Fair	No
Low	Yes	Fair	Yes
Low	Yes	Excellent	No
Medium	Yes	Fair	Yes
medium	No	Excellent	No

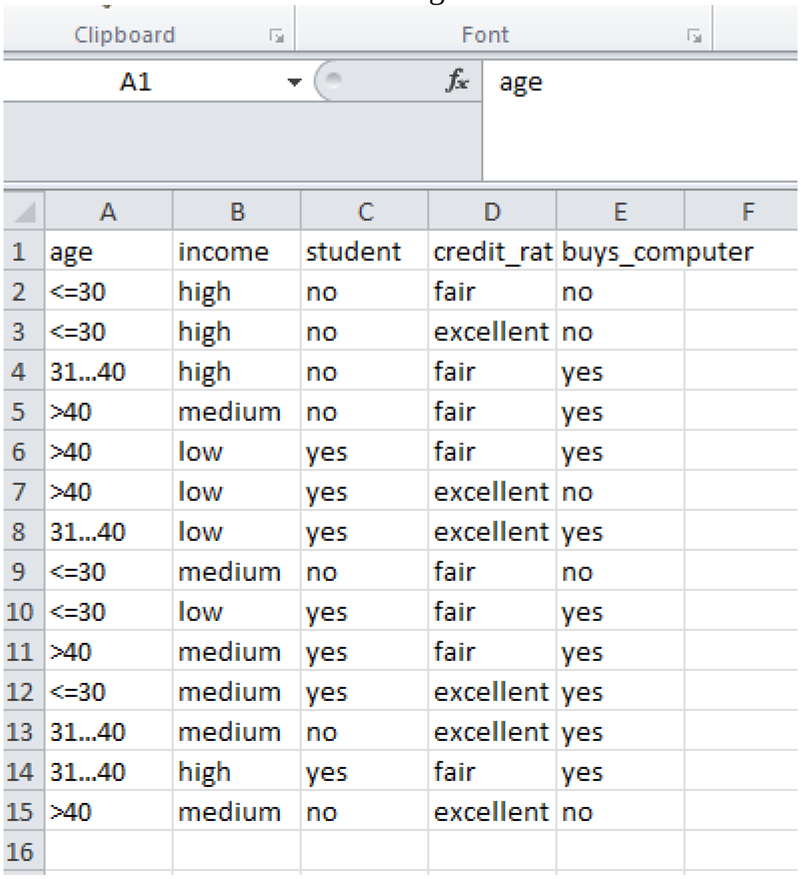
For age > 40, information gain= -(3/5)log(3/5)-(2/5)log(2/5)=0.971
income income=”low” I=1, income=”medium” I=0.917 , E(income)=(2/5)(1)+(3/5)(0.917)=0.9502
Gain(income)=0.0208.Similarly, gain(student)=0.0208, gain(credit)=0.971 and this would result in final decision tree



A decision tree for the concept buys_computer, indicating whether a customer at AllElectronics is likely to purchase a computer. Each internal (non-leaf) node represents a test on an attribute. Each leaf node represents a class (either buys_computer=”yes” or buys_computer=”no”.

<u>CHECKING THE RESULT IN WEKA</u>**:**

First create a csv file for the above problem,the csv file for the above problem will look like the rows and columns in the above figure. This file is written in excel sheet.



	A	B	C	D	E	F
1	age	income	student	credit_rat	buys_computer	
2	<=30	high	no	fair	no	
3	<=30	high	no	excellent	no	
4	31...40	high	no	fair	yes	
5	>40	medium	no	fair	yes	
6	>40	low	yes	fair	yes	
7	>40	low	yes	excellent	no	
8	31...40	low	yes	excellent	yes	
9	<=30	medium	no	fair	no	
10	<=30	low	yes	fair	yes	
11	>40	medium	yes	fair	yes	
12	<=30	medium	yes	excellent	yes	
13	31...40	medium	no	excellent	yes	
14	31...40	high	yes	fair	yes	
15	>40	medium	no	excellent	no	
16						

Fig: 9.1 Input Data for Decision tree algorithm

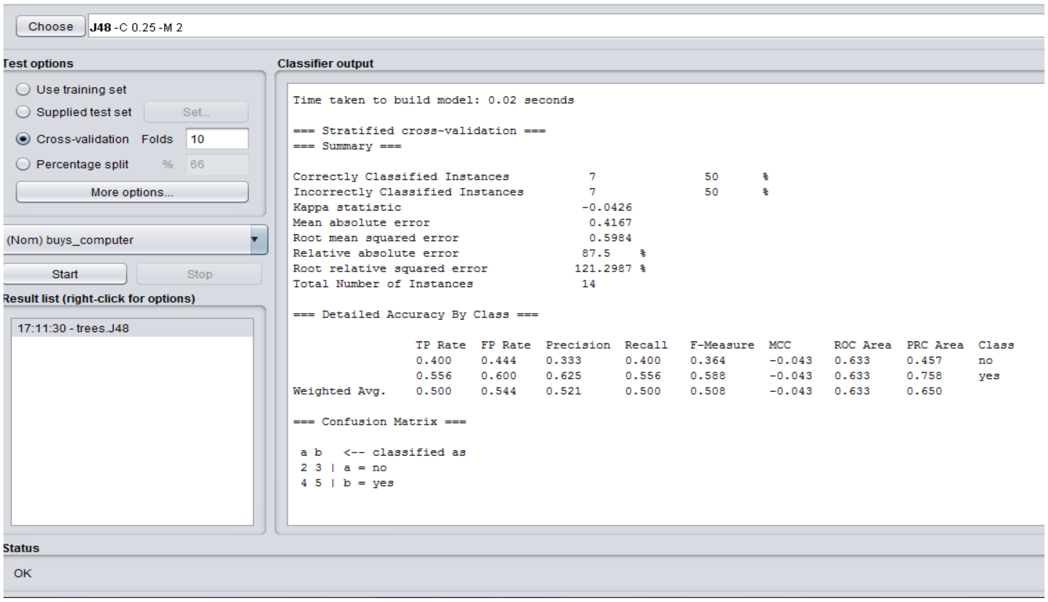
<u>Procedure for running the rules in weka:</u>

<u>Step 1:</u>

Open weka explorer and open the file and then select all the item sets.The figure gives a better understanding of how to do that.

Step2:

Now select the classify tab in the tool and click on start button and then we can see the result of the problem as below



J48 -C 0.25 -M 2

○ Use training set
○ Supplied test set
● Cross-validation Folds 10
○ Percentage split % 66

(Nom) buys_computer

```
Time taken to build model: 0.02 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances           7               50      %
Incorrectly Classified Instances         7               50      %
Kappa statistic                         -0.0426
Mean absolute error                      0.4167
Root mean squared error                  0.5984
Relative absolute error                 87.5    %
Root relative squared error            121.2987 %
Total Number of Instances               14

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.400    0.444    0.333      0.400    0.364      -0.043   0.633     0.457     no
                 0.556    0.600    0.625      0.556    0.588      -0.043   0.633     0.758     yes
Weighted Avg.    0.500    0.544    0.521      0.500    0.508      -0.043   0.633     0.650

=== Confusion Matrix ===

 a b   <-- classified as
 2 3 | a = no
 4 5 | b = yes
```

Fig: 9.2 Decision tree output summary

Step3:

Check the main result which we got manually and the result in weka by right clicking on the result and visualizing the tree.

The visualized tree in weka is as shown below:

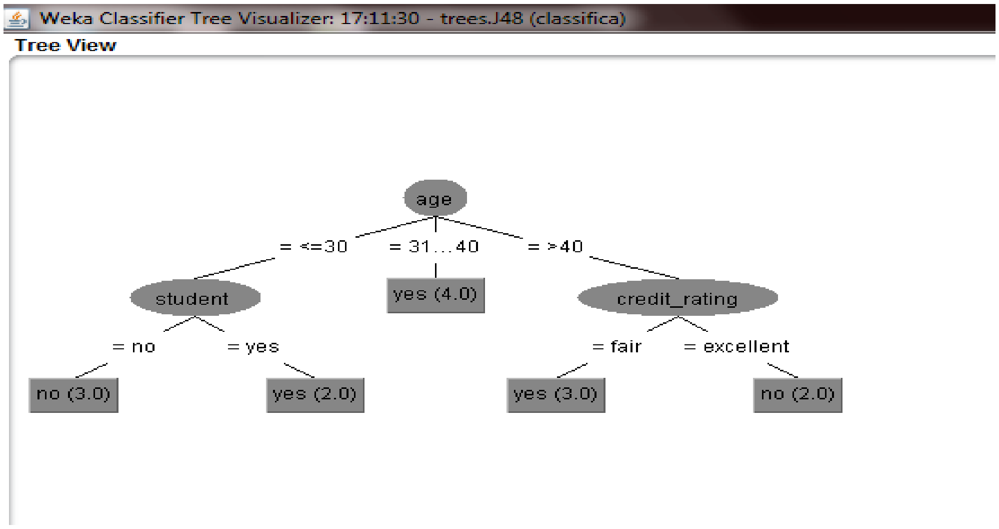


Fig: 9.3 Decision tree

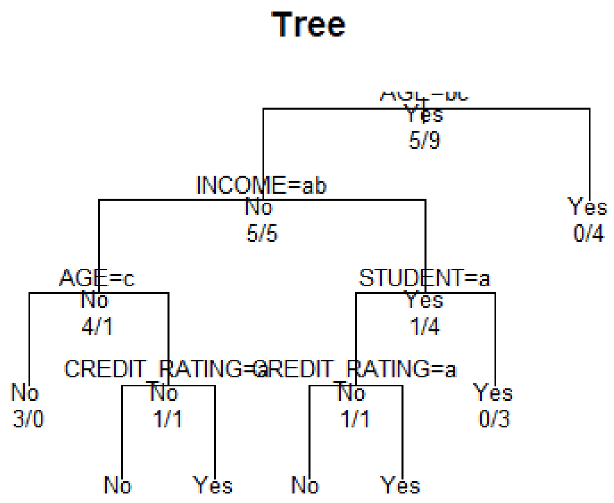
Conclusion:

The solution what we got manually and the weka both are same.

Rscript for Decision Tree

```
#load libraries

library('rpart')

library('rpart.plot')

# Classification Tree with rpart

library(rpart)

input.dat = read.csv("data.csv",header=TRUE,sep = "\t")

input.dat

# grow tree

fit <- rpart(BUYS_COMPUTER ~ AGE + INCOME + STUDENT + CREDIT_RATING,
method = 'class',data = input.dat,control =rpart.control(minsplit = 1,minbucket=1, cp=0))
```

```
# plot tree

plot(fit, uniform=TRUE, main="Tree")

text(fit, use.n=TRUE, all=TRUE, cex=.8)
```



10. Naïve Bayes classification on a given data set

AIM:

To apply naïve bayes classifier on a given data set.

Description:

In machine learning, Naïve Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' Theorem with strong (naïve) independence assumptions between the features.

Example:

AGE	INCOME	STUDENT	CREDIT_RATING	BUYS_COMPUTER
<=30	High	No	Fair	No
<=30	High	No	Excellent	No
31..40	High	No	Fair	Yes
>40	Medium	No	Fair	Yes
>40	Low	Yes	Fair	Yes
>40	Low	Yes	Excellent	No
31..40	Medium	Yes	Excellent	Yes
<=30	Low	No	Fair	No
<=30	Medium	Yes	Fair	Yes
>40	Medium	Yes	Fair	Yes
<=30	Medium	Yes	Excellent	Yes
31..40	Medium	No	Excellent	Yes
31..40	High	Yes	Fair	Yes
>40	Medium	No	Excellent	No

CLASS:

C1:buys_computer = ‘yes’

C2:buys_computer=’no’

DATA TO BE CLASSIFIED:

X= (age<=30, income=Medium, Student=Yes, credit_rating=Fair)

- P(C1):   P(buys_computer=”yes”)= 9/14 = 0.643

  P (buys_computer=”no”) =5/14=0.357

- Compute P(X/C1) and p(x/c2) we get:
  1. P(age=”<=30” |buys_computer=”yes”)=2/9
  2. P(age=”<=30”|buys_computer=”no”)=3/5
  3. P(income=”medium ”|buys_computer=”yes”)=4/9
  4. P(income=”medium ”|buys_computer=”no”)=2/5
  5. P(student=”yes ”|buys_computer=”yes”)=6/9
  6. P(student=”yes” |buys_computer=”no”)=1/5=0.2
  7. P(credit_rating=”fair ”|buys_computer=”yes”)=6/9
  8. P(credit_rating=”fair” | buys_computer=”no”)=2/5

- X=(age<=30, income=medium, student=yes, credit_rating=fair)
  P(X/C1): P (X/buys_computer=”yes”)=2/9*4/9*6/9*6/9=32/1134
  P(X/C2): P(X/buys_computer=”no”)=3/5*2/5*1/5*2/5=12/125

  P(C1/X) = P(X/C1)P(C1) * P(X/buys_computer=”yes”) * P(buys_computer=”yes”)
  =(32/1134)*(9/14)
  =0.019

  P(C2/X) = p(x/c2)*p(c2)
  P (X/buys_computer=”no”)*P(buys_computer=”no”)
  = (12/125)*(5/14)
  = 0.007

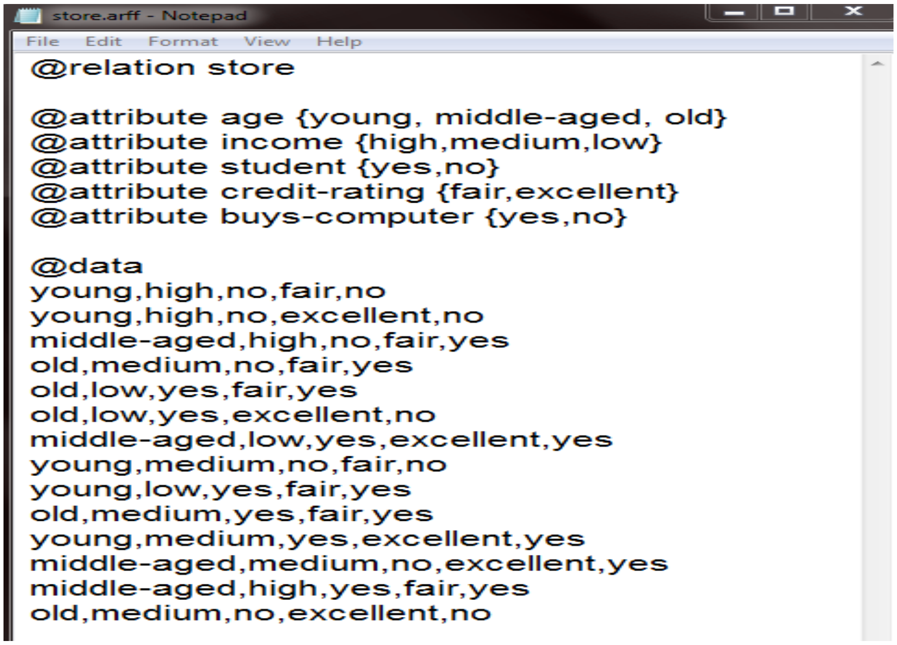
  Therefore, conclusion is that the given data belongs to C1 since P(C1/X)>P(C2/X)

Checking the result in the WEKA tool:

In order to check the result in the tool we need to follow a procedure.

Step 1:

Create a csv file with the above table considered in the example.the arff file will look as shown below:



```
@relation store

@attribute age {young, middle-aged, old}
@attribute income {high,medium,low}
@attribute student {yes,no}
@attribute credit-rating {fair,excellent}
@attribute buys-computer {yes,no}

@data
young,high,no,fair,no
young,high,no,excellent,no
middle-aged,high,no,fair,yes
old,medium,no,fair,yes
old,low,yes,fair,yes
old,low,yes,excellent,no
middle-aged,low,yes,excellent,yes
young,medium,no,fair,no
young,low,yes,fair,yes
old,medium,yes,fair,yes
young,medium,yes,excellent,yes
middle-aged,medium,no,excellent,yes
middle-aged,high,yes,fair,yes
old,medium,no,excellent,no
```

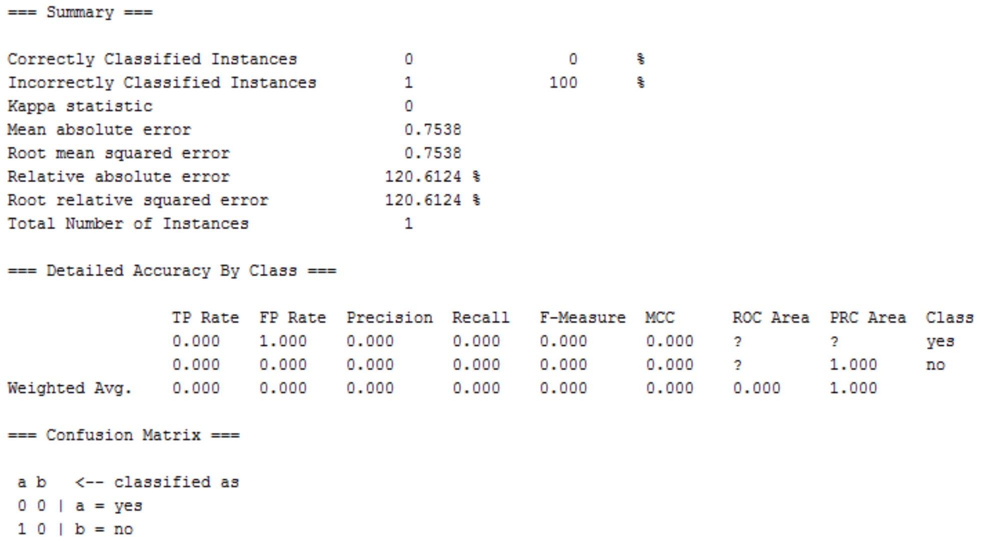
Fig: 10.1 Input data

Step 2:

Now open weka explorer and then select all the attributes in the table.

Step 3:

Select the classifier tab in the tool and choose baye’s folder and then naïve baye’s classifier to see the result as shown below.



```
=== Summary ===

Correctly Classified Instances           0                0      %
Incorrectly Classified Instances         1              100      %
Kappa statistic                          0
Mean absolute error                      0.7538
Root mean squared error                  0.7538
Relative absolute error                120.6124 %
Root relative squared error            120.6124 %
Total Number of Instances                1

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.000    1.000    0.000      0.000    0.000      0.000    ?         ?         yes
                 0.000    0.000    0.000      0.000    0.000      0.000    ?         1.000     no
Weighted Avg.    0.000    0.000    0.000      0.000    0.000      0.000    0.000     1.000

=== Confusion Matrix ===

 a b   <-- classified as
 0 0 | a = yes
 1 0 | b = no
```

R program for Naïve Bayes Classifier

```
library(e1071)
library(rjson)
#Load Data

input.dat <- fromJSON(file = "credit-g.json")

#Train the Model
model <- naiveBayes(BUYS_COMPUTER ~ AGE + INCOME + STUDENT +
CREDIT_RATING, data = input.dat)
#Predict using that model
input.dat[1,]
predict(model, input.dat[1,-5])
```

Output:

```
         AGE INCOME STUDENT CREDIT_RATING BUYS_COMPUTER
1       Youth   High      No          Fair           No
2       Youth   High      No     Excellent           No
3      Middle aged   High      No          Fair          Yes
4      Senior Medium      No          Fair          Yes
5      Senior    Low     Yes          Fair          Yes
6      Senior    Low     Yes     Excellent           No
7  Middle aged Medium     Yes     Excellent          Yes
```

```
8       Youth    Low      No         Fair           No
9       Youth Medium     Yes         Fair          Yes
10      Senior Medium     Yes         Fair          Yes
11       Youth Medium     Yes     Excellent          Yes
12 Middle aged Medium      No     Excellent          Yes
13 Middle aged   High     Yes         Fair          Yes
14      Senior Medium      No     Excellent           No

> #Train the Model
> model <- naiveBayes(BUYS_COMPUTER ~ AGE + INCOME + STUDENT +
CREDIT_RATING, data = input.dat)

> #Predict using that model
> input.dat[1,]
   AGE INCOME STUDENT CREDIT_RATING BUYS_COMPUTER
1 Youth   High      No         Fair           No
> predict(model, input.dat[1,-5])
[1] No
Levels: No Yes
```

11. K-means clustering

DESCRIPTION:

K-means algorithm aims to partition n observations into “k clusters” in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in partitioning of the data into Voronoi cells.

ILLUSTRATION:

As a simple illustration of a k-means algorithm, consider the following data set consisting of the scores of two variables on each of the five variables.

I	X1	X2
A	1	1
B	1	0
C	0	2
D	2	4
E	3	5

This data set is to be grouped into two clusters: As a first step in finding a sensible partition, let the A & C values of the two individuals furthest apart (using the Euclidean distance measure), define the initial cluster means, giving:

Cluster	Individual	Mean Vector(Centroid)
Cluster1	A	(1,1)
Cluster2	C	(0,2)

The remaining individuals are now examined in sequence and allocated to the cluster to which they are closest, in terms of Euclidean distance to the cluster mean. The mean vector is recalculated each time a new member is added. This leads to the following series of steps:

	A	C
A	0	1.4
B	1	2.5
C	1.4	0
D	3.2	2.82
E	4.5	4.2

Initial partitions have changed, and the two clusters at this stage having the following characteristics.

	Individual	Mean vector(Centroid)
Cluster 1	A,B	(1,0.5)
Cluster 2	C,D,E	(1.7,3.7)

But we cannot yet be sure that each individual has been assigned to the right cluster. So, we compare each individual’s distance to its own cluster mean and to that of the opposite cluster. And, we find:

I	A	C
A	0.5	2.7
B	0.5	3.7
C	1.8	2.4
D	3.6	0.5
E	4.9	1.9

The individuals C is now relocated to Cluster 1 due to its less mean distance with the centroid points. Thus, its relocated to cluster 1 resulting in the new partition

	Individual	Mean vector(Centroid)
Cluster 1	A,B,C	(0.7,1)
Cluster 2	D,E	(2.5,4.5)

The iterative relocation would now continue from this new partition until no more relocation occurs. However, in this example each individual is now nearer its own cluster mean than that of the other cluster and the iteration stops, choosing the latest partitioning as the final cluster solution.

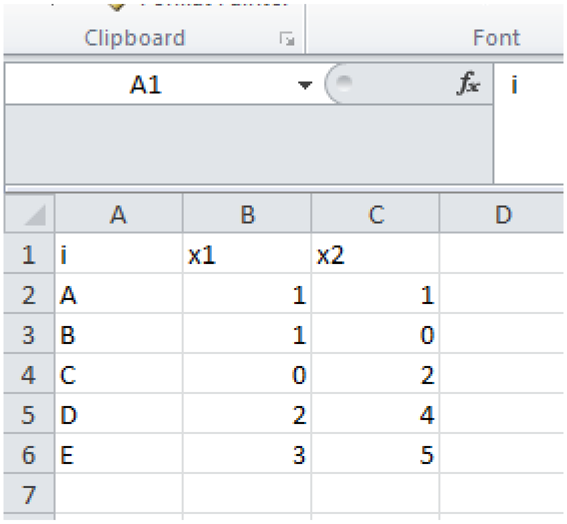
Also, it is possible that the k-means algorithm won't find a final solution. In this case, it would be a better idea to consider stopping the algorithm after a pre-chosen maximum number of iterations.

Checking the solution in weka:

In order to check the result in the tool we need to follow a procedure.

Step 1:

Create a csv file with the above table considered in the example.the csv file will look as shown below:



i	x1	x2
A	1	1
B	1	0
C	0	2
D	2	4
E	3	5

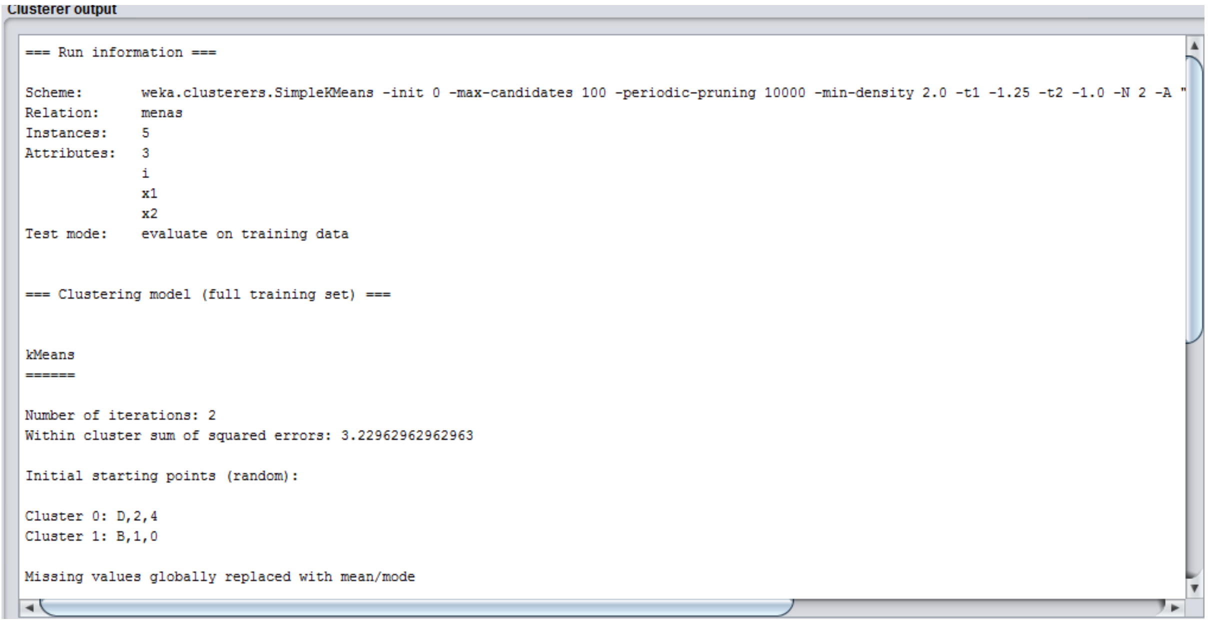
Fig: 11.1 Input data

Step 2:

Now open weka explorer and then select all the attributes in the table.

Step 3:

Select the cluster tab in the tool and choose normal k-means technique to see the result as shown below.



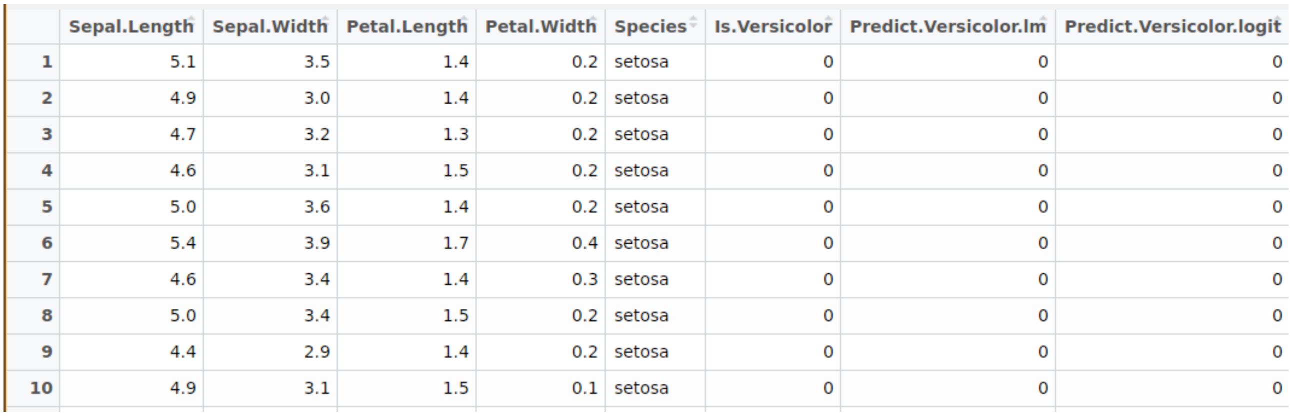
```
=== Run information ===

Scheme:       weka.clusterers.SimpleKMeans -init 0 -max-candidates 100 -periodic-pruning 10000 -min-density 2.0 -t1 -1.25 -t2 -1.0 -N 2 -A "
Relation:     menas
Instances:    5
Attributes:   3
              i
              x1
              x2
Test mode:    evaluate on training data


=== Clustering model (full training set) ===


kMeans
======

Number of iterations: 2
Within cluster sum of squared errors: 3.22962962962963

Initial starting points (random):

Cluster 0: D,2,4
Cluster 1: B,1,0

Missing values globally replaced with mean/mode
```

```
Final cluster centroids:
                         Cluster#
Attribute     Full Data         0         1
                  (5.0)     (2.0)     (3.0)
============================================
i                     A         D         A
x1                  1.4       2.5    0.6667
x2                  2.4       4.5         1




Time taken to build model (full training data) : 0 seconds

=== Model and evaluation on training set ===

Clustered Instances

0       2 ( 40%)
1       3 ( 60%)
```

Rscript for K-means:

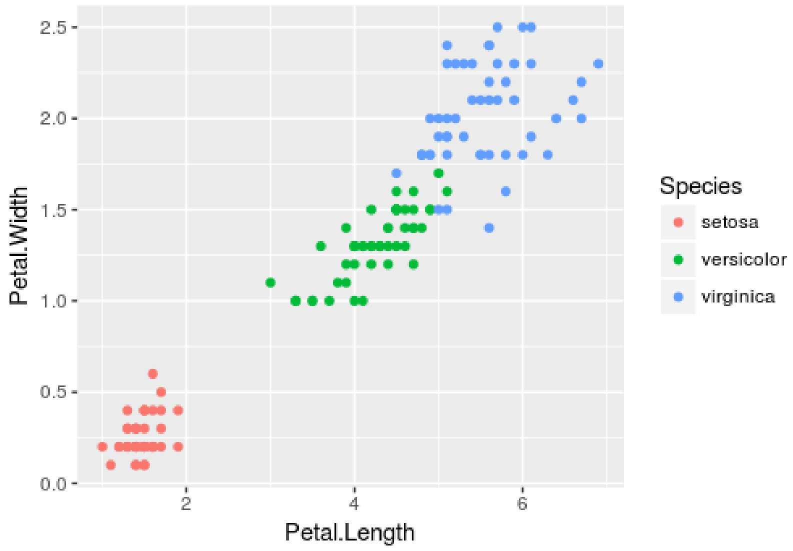
```
#load the required packages

#ggplot is used to create plots

library(ggplot2)

#plot the iris data set

ggplot(iris, aes(Petal.Length, Petal.Width, color = Species)) + geom_point()

#clustering

set.seed(20)

#forming a kmeans cluster

irisCluster <- kmeans(iris[,3:4], 3, nstart=20)

irisCluster

#plot to see the clusters

irisCluster$cluster <- as.factor(irisCluster$cluster)

ggplot(iris, aes(Petal.Length, Petal.Width, color = irisCluster$cluster)) + geom_point()
```

Iris data set



	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species	Is.Versicolor	Predict.Versicolor.lm	Predict.Versicolor.logit
1	5.1	3.5	1.4	0.2	setosa	0	0	0
2	4.9	3.0	1.4	0.2	setosa	0	0	0
3	4.7	3.2	1.3	0.2	setosa	0	0	0
4	4.6	3.1	1.5	0.2	setosa	0	0	0
5	5.0	3.6	1.4	0.2	setosa	0	0	0
6	5.4	3.9	1.7	0.4	setosa	0	0	0
7	4.6	3.4	1.4	0.3	setosa	0	0	0
8	5.0	3.4	1.5	0.2	setosa	0	0	0
9	4.4	2.9	1.4	0.2	setosa	0	0	0
10	4.9	3.1	1.5	0.1	setosa	0	0	0

Plotting iris data set

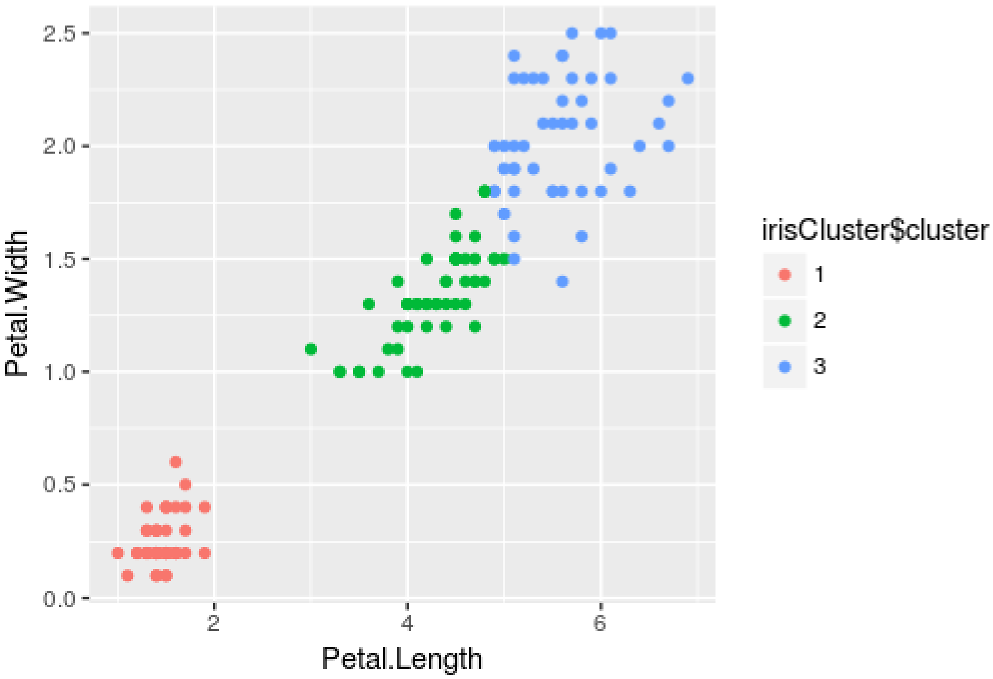


Output:

```
K-means clustering with 3 clusters of sizes 50, 52, 48

Cluster means:
  Petal.Length Petal.Width
1     1.462000    0.246000
2     4.269231    1.342308
3     5.595833    2.037500
Clustering vector:
  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
```

```
 [67] 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3
3 3 3 3 2 3 3 3 3 3 3 2 3 3 3 3 3
[133] 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3

Within cluster sum of squares by cluster:
[1]  2.02200 13.05769 16.29167
 (between_SS / total_SS =  94.3 %)
```

Clusters Formed:



12. Regression analysis

Aim: To generate a linear regression using R

Description:
Regression analysis is a very widely used statistical tool to establish a relationship model between two variables. One of these variable is called predictor variable whose value is gathered through experiments. The other variable is called response variable whose value is derived from the predictor variable.
The general mathematical equation for a linear regression is −

y = ax + b

Following is the description of the parameters used −

- **y** is the response variable.
- **x** is the predictor variable.
- **a** and **b** are constants which are called the coefficients.

Steps to Establish a Regression

A simple example of regression is predicting weight of a person when his height is known. To do this we need to have the relationship between height and weight of a person.

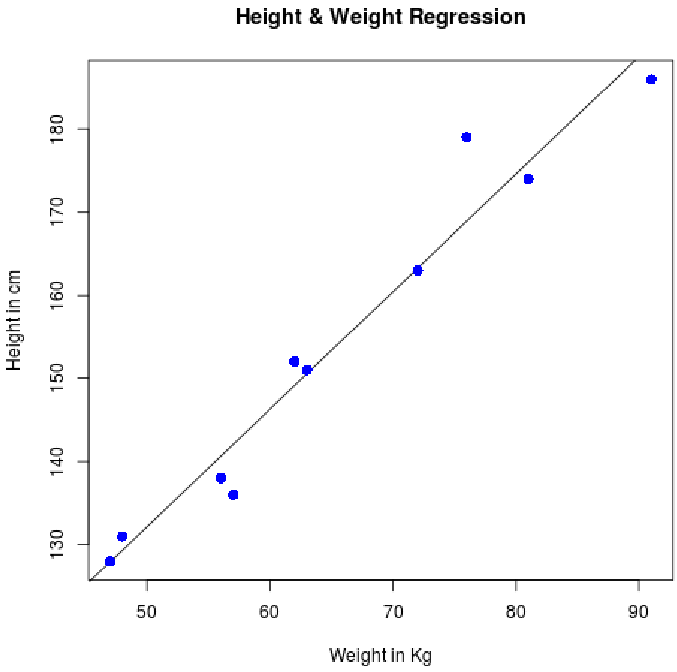
The steps to create the relationship is −

- Carry out the experiment of gathering a sample of observed values of height and corresponding weight.
- Create a relationship model using the **lm()** functions in R.
- Find the coefficients from the model created and create the mathematical equation using these
- Get a summary of the relationship model to know the average error in prediction. Also called **residuals**.
- To predict the weight of new persons, use the **predict()** function in R.

Rscript:

```
# Create the predictor and response variable.
x <- c(151, 174, 138, 186, 128, 136, 179, 163, 152, 131)

y <- c(63, 81, 56, 91, 47, 57, 76, 72, 62, 48)

relation <- lm(y~x)

# Give the chart file a name.

png(file = "linearregression.png")

plot(y,x,col = "blue",main = "Height & Weight Regression",

abline(lm(x~y)),cex = 1.3,pch = 16,xlab = "Weight in Kg",ylab = "Height in cm")

# Save the file.

dev.off()
```

Output:


Height & Weight Regression
Height in cm
Weight in Kg