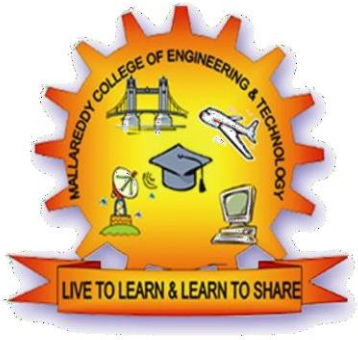
LABORATORY MANUAL
DATA WAREHOUSING AND MINING LAB

B.TECH
(IV YEAR – I SEM)
(2019-20)



DEPARTMENT OF
COMPUTER SCIENCE AND ENGINEERING

MALLA REDDY COLLEGE OF ENGINEERING & TECHNOLOGY

(Autonomous Institution – UGC, Govt. of India)

Recognized under 2(f) and 12 (B) of UGC ACT 1956
Affiliated to JNTUH,Hyderabad, Approved by AICTE - Accredited by NBA & NAAC – 'A' Grade - ISO 9001:2008 Certified)
Maisammaguda, Dhulapally (Post Via. Hakimpet), Secunderabad – 500100, Telangana State, India

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Vision

- To acknowledge quality education and instill high patterns of discipline making the students technologically superior and ethically strong which involves the improvement in the quality of life in human race.

Mission

- To achieve and impart holistic technical education using the best of infrastructure, outstanding technical and teaching expertise to establish the students into competent and confident engineers.
- Evolving the center of excellence through creative and innovative teaching learning practices for promoting academic achievement to produce internationally accepted competitive and world class professionals.

PROGRAMME EDUCATIONAL OBJECTIVES (PEOs)

PEO1 – ANALYTICAL SKILLS

1. To facilitate the graduates with the ability to visualize, gather information, articulate, analyze, solve complex problems, and make decisions. These are essential to address the challenges of complex and computation intensive problems increasing their productivity.

PEO2 – TECHNICAL SKILLS

2. To facilitate the graduates with the technical skills that prepare them for immediate employment and pursue certification providing a deeper understanding of the technology in advanced areas of computer science and related fields, thus encouraging to pursue higher education and research based on their interest.

PEO3 – SOFT SKILLS

3. To facilitate the graduates with the soft skills that include fulfilling the mission, setting goals, showing self-confidence by communicating effectively, having a positive attitude, get involved in team-work, being a leader, managing their career and their life.

PEO4 – PROFESSIONAL ETHICS

To facilitate the graduates with the knowledge of professional and ethical responsibilities by paying attention to grooming, being conservative with style, following dress codes, safety codes, and adapting themselves to technological advancements.

PROGRAM SPECIFIC OUTCOMES (PSOs)

After the completion of the course, B. Tech Computer Science and Engineering, the graduates will have the following Program Specific Outcomes:

1. **Fundamentals and critical knowledge of the Computer System:-** Able to Understand the working principles of the computer System and its components , Apply the knowledge to build, asses, and analyze the software and hardware aspects of it .

2. **The comprehensive and Applicative knowledge of Software Development:** Comprehensive skills of Programming Languages, Software process models, methodologies, and able to plan, develop, test, analyze, and manage the software and hardware intensive systems in heterogeneous platforms individually or working in teams.

3. **Applications of Computing Domain & Research:** Able to use the professional, managerial, interdisciplinary skill set, and domain specific tools in development processes, identify the research gaps, and provide innovative solutions to them.

PROGRAM OUTCOMES (POs)

Engineering Graduates will be able to:

1. **Engineering knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. **Problem analysis**: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
3. **Design / development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
4. **Conduct investigations of complex problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
5. **Modern tool usage**: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
6. **The engineer and society**: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
7. **Environment and sustainability**: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
8. **Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
9. **Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
10. **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
11. **Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multi disciplinary environments.
12. **Life- long learning**: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

MALLA REDDY COLLEGE OF ENGINEERING & TECHNOLOGY

Maisammaguda, Dhulapally Post, Via Hakimpet, Secunderabad – 500100

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

GENERAL LABORATORY INSTRUCTIONS

1. Students are advised to come to the laboratory at least 5 minutes before (to the starting time), those who come after 5 minutes will not be allowed into the lab.
2. Plan your task properly much before to the commencement, come prepared to the lab with the synopsis / program / experiment details.
3. Student should enter into the laboratory with:

a. Laboratory observation notes with all the details (Problem statement, Aim, Algorithm, Procedure, Program, Expected Output, etc.,) filled in for the lab session.

b. Laboratory Record updated up to the last session experiments and other utensils (if any) needed in the lab.

c. Proper Dress code and Identity card.

4. Sign in the laboratory login register, write the TIME-IN, and occupy the computer system allotted to you by the faculty.
5. Execute your task in the laboratory, and record the results / output in the lab observation note book, and get certified by the concerned faculty.
6. All the students should be polite and cooperative with the laboratory staff, must maintain the discipline and decency in the laboratory.
7. Computer labs are established with sophisticated and high end branded systems, which should be utilized properly.
8. Students / Faculty must keep their mobile phones in SWITCHED OFF mode during the lab sessions.Misuse of the equipment, misbehaviors with the staff and systems etc., will attract severe punishment.
9. Students must take the permission of the faculty in case of any urgency to go out; if anybody found loitering outside the lab / class without permission during working hours will be treated seriously and punished appropriately.
10. Students should LOG OFF/ SHUT DOWN the computer system before he/she leaves the lab after completing the task (experiment) in all aspects. He/she must ensure the system / seat is kept properly.

Head of the Department **Principal**

COURSE NAME: DATA WAREHOUSING AND MINING LAB

COURSE CODE: A70595

COURSE OBJECTIVES:

1. Learn how to build a data warehouse and query it (using open source tools like Pentaho Data Integration Tool, Pentaho Business Analytics).
2. Learn to perform data mining tasks using a data mining toolkit (such as open source WEKA).
3. Understand the data sets and data preprocessing.
4. Demonstrate the working of algorithms for data mining tasks such association rule mining, classification, clustering and regression.
5. Exercise the data mining techniques with varied input values for different parameters.
6. To obtain Practical Experience Working with all real data sets.
7. Emphasize hands-on experience working with all real data sets.

COURSE OUTCOMES:

1. Ability to understand the various kinds of tools.
2. Demonstrate the classification, clustering and etc. in large data sets.
3. Ability to add mining algorithms as a component to the exiting tools.
4. Ability to apply mining techniques for realistic data.

MAPPING OF COURSE OUTCOMES WITH PROGRAM OUTCOMES:

COURSE OUTCOMES	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	P09	PO10	PO11				
Ability to add mining algorithms as a component to the exiting tools. Ability to apply mining techniques for realistic data.	√	√	√												√

DATAWARE HOUSE TOOLS

ParAccel (Actian)

Cloudera

Talend

Query surge

Amazon Redshift

Teradata

Oracle

TabLeau

Open Source Data Mining Tools

WEKA

Orange

KNIME

R-Programming

Rapid Miner

Apache Mahout

Tanagra

XL Miner

DATA WAREHOUSING AND MINING LAB- INDEX

Unit-I Build Data Warehouse and Explore WEKA

A. Build Data Warehouse/Daata Mart (using open source tools like Pentaho Data Integration Tool, Pentaho Business Analytics; or other data warehouse tools like Microsoft-SSIS,Informatica,Business Objects,etc.,)

A.(i) Identify source tables and populate sample data.

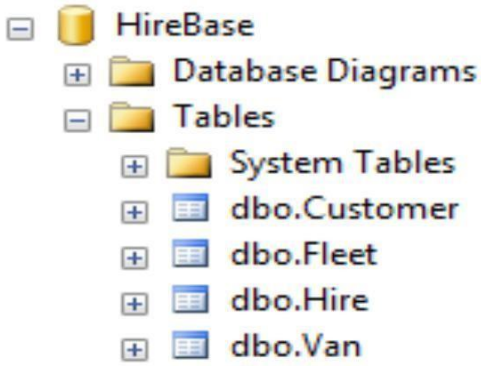
The data warehouse contains 4 **ta**bles:

1. Date dimension: contain**s** every single date from 2006 to 2016.
2. Customer dimension: co**n**tains 100 customers. To be simple we'll make **it** type 1 so we don't create a new row f**o**r each change.
3. Van dimension: contains 20 vans. To be simple we'll make it type 1 so **w**e don't create a new row for each change.
4. Hire fact table: contains **1**000 hire transactions since 1st Jan 2011. It is a **d**aily snapshot fact table so that every day w**e** insert 1000 rows into this fact table. So over t**i**me we can track the changes of total bill, **v**an charges, satnav income, etc.

Create the source tables and populate them

So now we are going to create t**h**e 3 tables in HireBase database: Customer, Va**n, a**nd Hire. Then we populate them.

First I'll show you how it l**o**oks when it's done:



Customer table:

	CustomerId	CustomerName	DateOfBirth	Town	TelephoneNo	DrivingLicenceNo	Occupation
1	N00	Customer00	2000-04-09	Town00	Phone00	Licence00	Occupation00
2	N01	Customer01	2000-01-01	Town01	Phone01	Licence01	Occupation01
3	N02	Customer02	2000-01-02	Town02	Phone02	Licence02	Occupation02
4	N03	Customer03	2000-01-03	Town03	Phone03	Licence03	Occupation03
5	N04	Customer04	2000-01-04	Town04	Phone04	Licence04	Occupation04
6	N05	Customer05	2000-01-05	Town05	Phone05	Licence05	Occupation05

Van table:

	RegNo	Make	Model	Year	Colour	CC	Class
1	Reg1	Make1	Model1	2009	White	2500	Medium
2	Reg10	Make10	Model10	2010	White	2500	Medium
3	Reg11	Make11	Model11	2011	White	3000	Large
4	Reg12	Make12	Model12	2008	White	2000	Small
5	Reg13	Make13	Model13	2009	Black	2500	Medium

Hire table:

HireId	HireDate	CustomerId	RegNo	NoOfDays	VanHire	SatNavHire	Insurance	DamageWaiver	TotalBill
H0001	2011-01-01	N01	Reg1	1	100.00	10.00	20.00	40.00	170.00
H0002	2011-01-02	N02	Reg2	2	200.00	20.00	40.00	80.00	340.00
H0003	2011-01-03	N03	Reg3	3	300.00	30.00	60.00	120.00	510.00
H0004	2011-01-04	N04	Reg4	1	100.00	10.00	20.00	40.00	170.00
H0005	2011-01-05	N05	Reg5	2	200.00	20.00	40.00	80.00	340.00

And here is the script to create and populate them:

```
-- Create database
create database HireBase
go
use HireBase
go

-- Create customer table
if exists (select * from sys.tables where name = 'Customer')
drop table Customer
go

create table Customer
( CustomerId varchar(20) not null primary key,
 CustomerName varchar(30), DateOfBirth date, Town varchar(50),
 TelephoneNo varchar(30), DrivingLicenceNo varchar(30), Occupation varchar(30)
)
go

-- Populate
Customer truncate
table Customer go

declare @i int, @si varchar(10), @startdate date
set @i = 1
while @i <= 100
begin
 set @si = right('0'+CONVERT(varchar(10), @i),2)
 insert into Customer
 ( CustomerId, CustomerName, DateOfBirth, Town, TelephoneNo, DrivingLicenceNo,
Occupation)
 values
 ( 'N'+@si, 'Customer'+@si, DATEADD(d,@i-1,'2000-01-01'), 'Town'+@si, 'Phone'+@si,
'Licence'+@si, 'Occupation'+@si)
 set @i = @i + 1
end
go

select * from Customer

-- Create Van table
if exists (select * from sys.tables where name = 'Van')
drop table Van
go
```

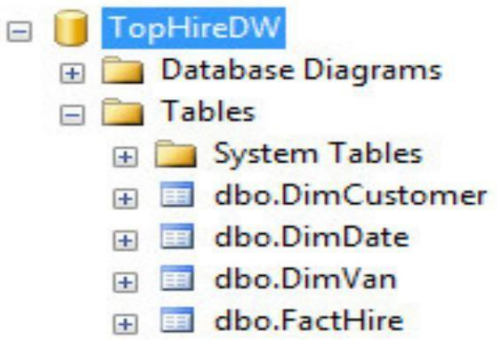
```
create table Van
( RegNo varchar(10) not null primary key,
 Make varchar(30), Model varchar(30), [Year] varchar(4),
Colour varchar(20), CC int, Class varchar(10) )

go

-- Populate Van
table truncate table
Van go

declare @i int, @si varchar(10)
set @i = 1
while @i <= 20
begin
 set @si = convert(varchar, @i)
 insert into Van
 ( RegNo, Make, Model, [Year], Colour, CC, Class)
 values
 ( 'Reg'+@si, 'Make'+@si, 'Model'+@si,
 case @i%4 when 0 then 2008 when 1 then 2009 when 2 then 2010 when 3 then 2011 end,
 case when @i%5<3 then 'White' else 'Black' end,
 case @i%3 when 0 then 2000 when 1 then 2500 when 2 then 3000 end,
 case @i%3 when 0 then 'Small' when 1 then 'Medium' when 2 then 'Large' end)
 set @i = @i + 1
end
go

select * from Van

-- Create Hire table
if exists (select * from sys.tables where name = 'Hire')
drop table Hire
go

create table Hire
( HireId varchar(10) not null primary key,
 HireDate date not null,
 CustomerId varchar(20) not null,
 RegNo varchar(10), NoOfDays int, VanHire money, SatNavHire money,
Insurance money, DamageWaiver money, TotalBill money )

go
```

```
-- Populate Hire table
truncate table Hire
go

declare @i int, @si varchar(10), @DaysFrom1stJan int, @CustomerId int, @RegNo int, @mi int
set @i = 1
while @i <= 1000
begin
 set @si = right('000'+convert(varchar(10), @i),4) -- string of i
 set @DaysFrom1stJan = (@i-1)%200 --The Hire Date is derived from i modulo
 200 set @CustomerId = (@i-1)%100+1 --The CustomerId is derived from i modulo
 100 set @RegNo = (@i-1)%20+1 --The Van RegNo is derived from i modulo 20
 set @mi = (@i-1)%3+1 --i modulo 3
 insert into Hire (HireId, HireDate, CustomerId, RegNo, NoOfDays, VanHire,
SatNavHire, Insurance, DamageWaiver, TotalBill)
 values ('H'+@si, DateAdd(d, @DaysFrom1stJan, '2011-01-01'),
 left('N0'+CONVERT(varchar(10),@CustomerId),3), 'Reg'+CONVERT(varchar(10),
 @RegNo), @mi, @mi*100, @mi*10, @mi*20, @mi*40, @mi*170) set @i += 1

end
go

select * from Hire
```

Create the Data Warehouse

So now we are going to create the 3 dimension tables and 1 fact table in the data warehouse: DimDate, DimCustomer, DimVan and FactHire. We are going to populate the 3 dimensions but we'll leave the fact table empty. The purpose of this article is to show how to populate the fact table using SSIS.

First I'll show you how it looks when it's done:



Date Dimension:

	DateKey	Year	Month	Date	DateString
1	0	Unknown	Unknown	0001-01-01	Unknown
2	20060101	2006	2006-01	2006-01-01	2006-01-01
3	20060102	2006	2006-01	2006-01-02	2006-01-02
4	20060103	2006	2006-01	2006-01-03	2006-01-03
5	20060104	2006	2006-01	2006-01-04	2006-01-04
6	20060105	2006	2006-01	2006-01-05	2006-01-05

Customer Dimension:

	CustomerKey	CustomerId	CustomerName	DateOfBirth	Town	TelephoneNo	DrivingLicenceNo	Occupation
1	1	N01	Customer01	2000-01-01	Town01	Phone01	Licence01	Occupation01
2	2	N02	Customer02	2000-01-02	Town02	Phone02	Licence02	Occupation02
3	3	N03	Customer03	2000-01-03	Town03	Phone03	Licence03	Occupation03
4	4	N04	Customer04	2000-01-04	Town04	Phone04	Licence04	Occupation04
5	5	N05	Customer05	2000-01-05	Town05	Phone05	Licence05	Occupation05

Van Dimension:

	VanKey	RegNo	Make	Model	Year	Colour	CC	Class
1	1	Reg1	Make1	Model1	2009	White	2500	Medium
2	2	Reg10	Make10	Model10	2010	White	2500	Medium
3	3	Reg11	Make11	Model11	2011	White	3000	Large
4	4	Reg12	Make12	Model12	2008	White	2000	Small
5	5	Reg13	Make13	Model13	2009	Black	2500	Medium

And then we do it. This is the script to create and populate those dim and fact tables:

```
-- Create the data
warehouse create database
TopHireDW go
use
TopHireDW go

-- Create Date Dimension
if exists (select * from sys.tables where name = 'DimDate')
drop table DimDate
go

create table DimDate
( DateKey int not null primary key,
 [Year] varchar(7), [Month] varchar(7), [Date] date, DateString varchar(10))
go

-- Populate Date Dimension
truncate table DimDate
go

declare @i int, @Date date, @StartDate date, @EndDate date, @DateKey
 int, @DateString varchar(10), @Year varchar(4), @Month varchar(7),
 @Date1 varchar(20)
set @StartDate = '2006-01-01'
set @EndDate = '2016-12-31'
set @Date = @StartDate

insert into DimDate (DateKey, [Year], [Month], [Date], DateString)
 values (0, 'Unknown', 'Unknown', '0001-01-01', 'Unknown') --The unknown row

while @Date <= @EndDate
begin
 set @DateString = convert(varchar(10), @Date, 20)
 set @DateKey = convert(int, replace(@DateString,'-',''))
 set @Year = left(@DateString,4)
 set @Month = left(@DateString, 7)
 insert into DimDate (DateKey, [Year], [Month], [Date], DateString)
 values (@DateKey, @Year, @Month, @Date, @DateString)
 set @Date = dateadd(d, 1, @Date)
end
go

select * from DimDate
```

```
-- Create Customer dimension
if exists (select * from sys.tables where name = 'DimCustomer')
drop table DimCustomer
go

create table DimCustomer
( CustomerKey int not null identity(1,1) primary
 key, CustomerId varchar(20) not null,
 CustomerName varchar(30), DateOfBirth date, Town varchar(50),
 TelephoneNo varchar(30), DrivingLicenceNo varchar(30), Occupation varchar(30)
)
go

insert into DimCustomer (CustomerId, CustomerName, DateOfBirth, Town, TelephoneNo,
 DrivingLicenceNo, Occupation)
select * from HireBase.dbo.Customer

select * from DimCustomer

-- Create Van dimension
if exists (select * from sys.tables where name = 'DimVan')
drop table DimVan
go

create table DimVan
( VanKey int not null identity(1,1) primary key,
 RegNo varchar(10) not null,
 Make varchar(30), Model varchar(30), [Year] varchar(4),
Colour varchar(20), CC int, Class varchar(10) )

go

insert into DimVan (RegNo, Make, Model, [Year], Colour, CC, Class)
select * from HireBase.dbo.Van
go

select * from DimVan

-- Create Hire fact table
if exists (select * from sys.tables where name = 'FactHire')
drop table FactHire
go
```

```
create table FactHire
( SnapshotDateKey int not null, --Daily periodic snapshot fact table
 HireDateKey int not null, CustomerKey int not null, VanKey int not null, --Dimension Keys
 HireId varchar(10) not null, --Degenerate Dimension
 NoOfDays int, VanHire money, SatNavHire money,
Insurance money, DamageWaiver money, TotalBill money
)
go

select * from FactHire
```

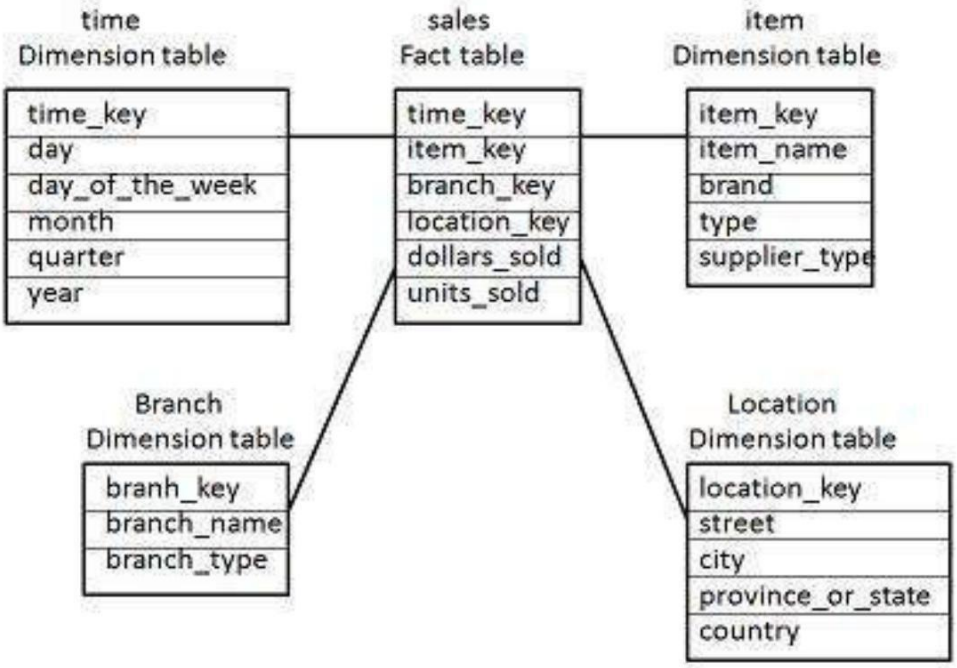
A.(ii). Design multi-demesional data models namely Star, Snowflake and Fact Constellation schemas for any one enterprise (ex. Banking,Insurance, Finance, Healthcare, manufacturing, Automobiles,sales etc).

Ans: **Schema Definition**

Multidimensional schema is defined using Data Mining Query Language (DMQL). The two primitives, cube definition and dimension definition, can be used for defining the data warehouses and data marts.

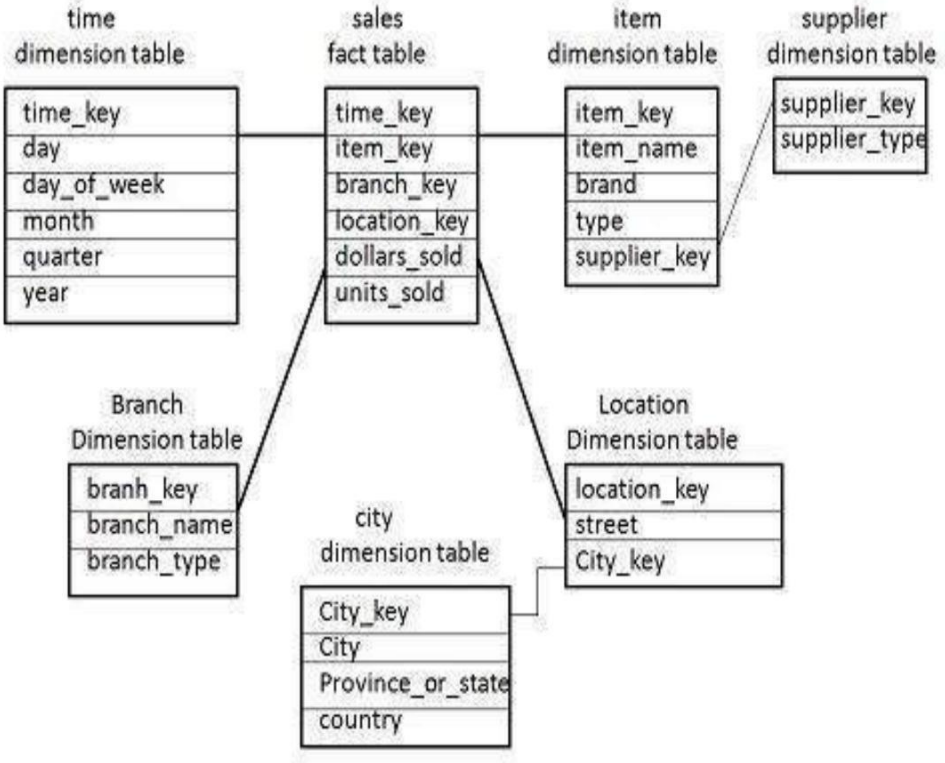
Star Schema

- Each dimension in a star schema is represented with only one-dimension table.
- This dimension table contains the set of attributes.
- The following diagram shows the sales data of a company with respect to the four dimensions, namely time, item, branch, and location.
- There is a fact table at the center. It contains the keys to each of four dimensions.
- The fact table also contains the attributes, namely dollars sold and units sold.



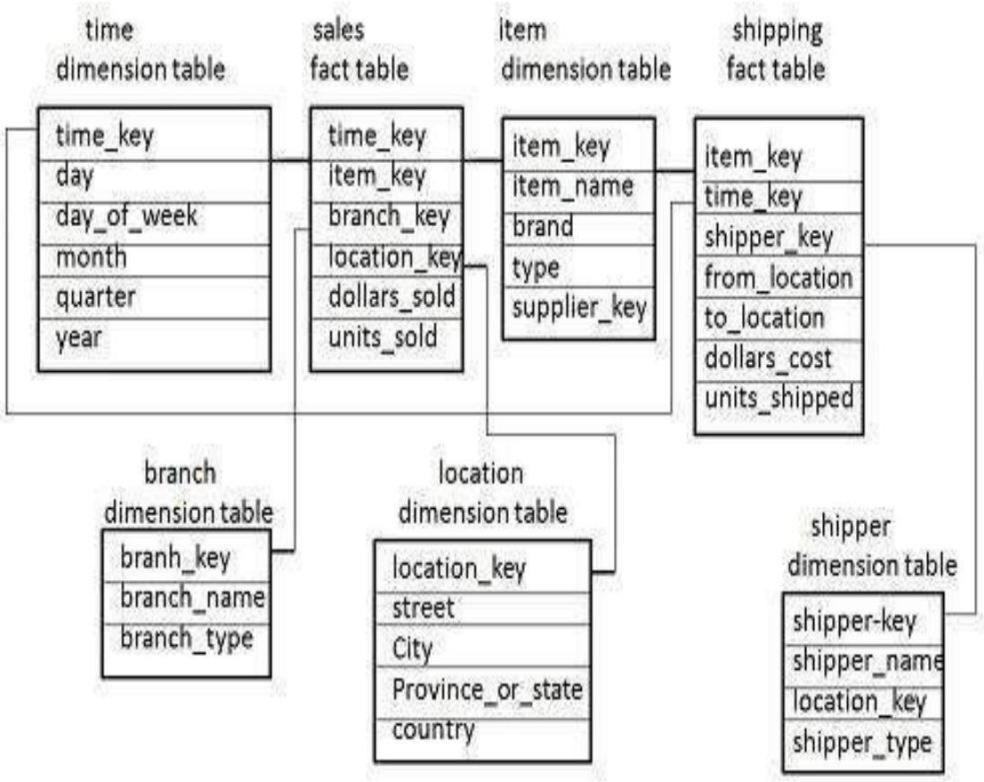
Snowflake Schema

- Some dimension tables in the Snowflake schema are normalized.
- The normalization splits up the data into additional tables.
- Unlike Star schema, the dimensions table in a snowflake schema is normalized. For example, the item dimension table in star schema is normalized and split into two dimension tables, namely item and supplier table.
- Now the item dimension table contains the attributes item_key, item_name, type, brand, and supplier-key.
- The supplier key is linked to the supplier dimension table. The supplier dimension table contains the attributes supplier_key and supplier_type.



Fact Constellation Schema

- A fact constellation has multiple fact tables. It is also known as galaxy schema.
- The following diagram shows two fact tables, namely sales and shipping.
- The sales fact table is same as that in the star schema.
- The shipping fact table has the five dimensions, namely item_key, time_key, shipper_key, from_location, to_location.
- The shipping fact table also contains two measures, namely dollars sold and units sold.
- It is also possible to share dimension tables between fact tables. For example, time, item, and location dimension tables are shared between the sales and shipping fact table.



A.(iii) Write ETL scripts and implement using data warehouse tools.

Ans:

ETL comes from Data Warehousing and stands for Extract-Transform-Load. ETL covers a process of how the data are loaded from the source system to the data warehouse. Extraction–transformation–loading (ETL) tools are pieces of software responsible for the extraction of data from several sources, its cleansing, customization, reformatting, integration, and insertion into a data warehouse.

Building the ETL process is potentially one of the biggest tasks of building a warehouse; it is complex, time consuming, and consumes most of data warehouse project‘s implementation efforts, costs, and resources.

Building a data warehouse requires focusing closely on understanding three main areas:

1. Source Area- The source area has standard models such as entity relationship diagram.

2. Destination Area- The destination area has standard models such as star schema.

3. Mapping Area- But the mapping area has not a standard model till now.

Abbreviations

- ETL-extraction–transformation–loading
- DW-data warehouse
- DM- data mart
- OLAP- on-line analytical processing
- DS-data sources
- ODS- operational data store
- DSA- data staging area
- DBMS- database management system
- OLTP-on-line transaction processing
- CDC-change data capture
- SCD-slowly changing dimension
- FCME- first-class modeling elements
- EMD-entity mapping diagram
- DSA-data storage area

ETL Process:

Extract

The Extract step covers the data extraction from the source system and makes it accessible for further processing. The main objective of the extract step is to retrieve all the required data from the source system with as little resources as possible. The extract step should be designed in a way that it does not negatively affect the source system in terms or performance, response time or any kind of locking.

There are several ways to perform the extract:

- Update notification - if the source system is able to provide a notification that a record has been changed and describe the change, this is the easiest way to get the data.
- Incremental extract - some systems may not be able to provide notification that an update has occurred, but they are able to identify which records have been modified and provide an extract of such records. During further ETL steps, the system needs to identify changes and propagate it down. Note, that by using daily extract, we may not be able to handle deleted records properly.
- Full extract - some systems are not able to identify which data has been changed at all, so a full extract is the only way one can get the data out of the system. The full extract requires keeping a copy of the last extract in the same format in order to be able to identify changes. Full extract handles deletions as well.

Transform

The transform step applies a set of rules to transform the data from the source to the target. This includes converting any measured data to the same dimension (i.e. conformed dimension) using the same units so that they can later be joined. The transformation step also requires joining data from several sources, generating aggregates, generating surrogate keys, sorting, deriving new calculated values, and applying advanced validation rules.

Load

During the load step, it is necessary to ensure that the load is performed correctly and with as little resources as possible. The target of the Load process is often a database. In order to make the load process efficient, it is helpful to disable any constraints and indexes before the load and enable them back only after the load completes. The referential integrity needs to be maintained by ETL tool to ensure consistency.

ETL method – nothin' but SQL

ETL as scripts that can just be run on the database.These scripts must be re-runnable: they should be able to be run without modification to pick up any changes in the legacy data, and automatically work out how to merge the changes into the new schema.

In order to meet the requirements, my scripts must:

1. INSERT rows in the new tables based on any data in the source that hasn't already been created in the destination
2. UPDATE rows in the new tables based on any data in the source that has already been inserted in the destination
3. DELETE rows in the new tables where the source data has been deleted

Now, instead of writing a whole lot of INSERT, UPDATE and DELETE statements, I thought ―surely MERGE would be both faster and better‖ – and in fact, that has turned out to be the case. By writing all the transformations as MERGE statements, I've satisfied all the criteria, while also making my code very easily modified, updated, fixed and rerun. If I discover a bug or a change in requirements, I simply change the way the column is transformed in the MERGE statement, and re-run the statement. It then takes care of working out whether to insert, update or delete each row.

My next step was to design the architecture for my custom ETL solution. I went to the dba with the following design, which was approved and created for me:

1. create two new schemas on the new 11g database: LEGACY and MIGRATE
2. take a snapshot of all data in the legacy database, and load it as tables in the LEGACY schema
3. grant read-only on all tables in LEGACY to MIGRATE
4. grant CRUD on all tables in the target schema to MIGRATE.

For example, in the legacy database we have a table:

```
LEGACY.BMS_PARTIES(
 par_id            NUMBER       PRIMARY KEY,
 par_domain        VARCHAR2(10) NOT NULL,
 par_first_name VARCHAR2(100) ,
 par_last_name    VARCHAR2(100),
 par_dob           DATE,
 par_business_name VARCHAR2(250),
 created_by        VARCHAR2(30) NOT NULL,
 creation_date     DATE         NOT NULL,
 last_updated_by   VARCHAR2(30),
 last_update_date DATE)
```

In the new model, we have a new table that represents the same kind of information:

```
NEW.TBMS_PARTY(
 party_id          NUMBER(9)     PRIMARY KEY,
 party_type_code   VARCHAR2(10) NOT NULL,
 first_name        VARCHAR2(50),
 surname           VARCHAR2(100),
```

```
date_of_birth      DATE,
business_name      VARCHAR2(300),
db_created_by      VARCHAR2(50) NOT NULL,
db_created_on      DATE         DEFAULT SYSDATE NOT NULL,
db_modified_by  VARCHAR2(50),
db_modified_on     DATE,
version_id         NUMBER(12)    DEFAULT 1 NOT NULL)
```

This was the simplest transformation you could possibly think of – the mapping from one to the other is 1:1, and the columns almost mean the same thing.

The solution scripts start by creating an intermediary table:

```
MIGRATE.TBMS_PARTY(
old_par_id         NUMBER        PRIMARY KEY,
party_id           NUMBER(9)     NOT NULL,
party_type_code    VARCHAR2(10) NOT NULL,
first_name         VARCHAR2(50),
surname            VARCHAR2(100),
date_of_birth      DATE,
business_name      VARCHAR2(300),
db_created_by      VARCHAR2(50),
```

```
db_created_on      DATE,
db_modified_by     VARCHAR2(50),
db_modified_on     DATE,
deleted            CHAR(1))
```

The second step is the E and T parts of –ETL‖: I query the legacy table, transform the data right there in the query, and insert it into the intermediary table. However, since I want to be able to re-run this script as often as I want, I wrote this as a MERGE statement:

```
MERGE INTO MIGRATE.TBMS_PARTY dest
USING (
  SELECT par_id            AS old_par_id,
         par_id            AS party_id,
         CASE par_domain
           WHEN 'P' THEN 'PE' /*Person*/
           WHEN 'O' THEN 'BU' /*Business*/
         END               AS party_type_code,
         par_first_name AS first_name,
         par_last_name       AS surname,
         par_dob           AS date_of_birth,
         par_business_name AS business_name,
```

```
        created_by        AS db_created_by,
        creation_date     AS db_created_on,
        last_updated_by AS db_modified_by,
        last_update_date AS db_modified_on
  FROM LEGACY.BMS_PARTIES s
  WHERE NOT EXISTS (
    SELECT null
    FROM MIGRATE.TBMS_PARTY d
    WHERE d.old_par_id = s.par_id
    AND    (d.db_modified_on = s.last_update_date
          OR (d.db_modified_on IS NULL
            AND s.last_update_date IS NULL))
    )
  ) src
ON (src.OLD_PAR_ID = dest.OLD_PAR_ID)
WHEN MATCHED THEN UPDATE SET
  party_id        = src.party_id        ,
  party_type_code = src.party_type_code ,
  first_name      = src.first_name      ,
```

```
surname        = src.surname        ,
date_of_birth  = src.date_of_birth  ,
business_name  = src.business_name  ,
db_created_by  = src.db_created_by  ,
db_created_on  = src.db_created_on  ,
db_modified_by = src.db_modified_by ,
```

A.(iv) Perform Various OLAP operations such slice, dice, roll up, drill up and pivot.

Ans: **OLAP OPERATIONS**

Online Analytical Processing Server (OLAP) is based on the multidimensional data model. It allows managers, and analysts to get an insight of the information through fast, consistent, and interactive access to information.

OLAP operations in multidimensional data.

Here is the list of OLAP operations:

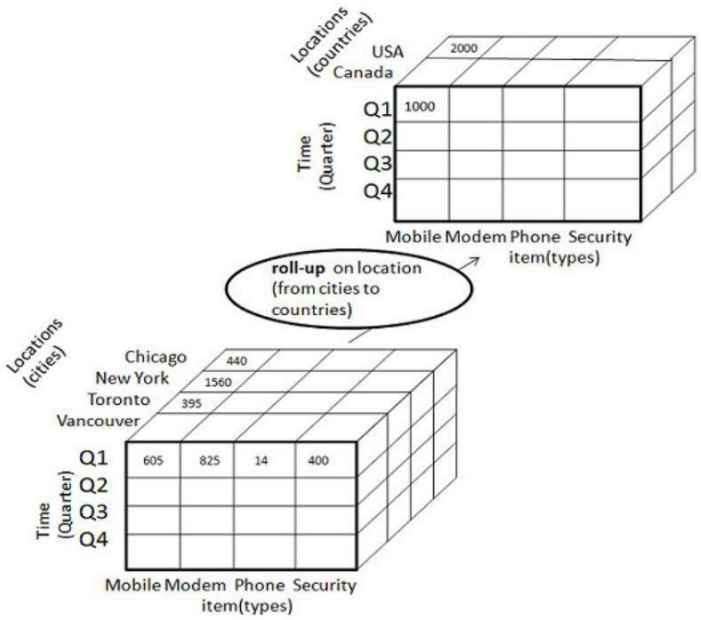
- Roll-up
- Drill-down
- Slice and dice
- Pivot (rotate)

Roll-up

Roll-up performs aggregation on a data cube in any of the following ways:

- By climbing up a concept hierarchy for a dimension
- By dimension reduction

The following diagram illustrates how roll-up works.



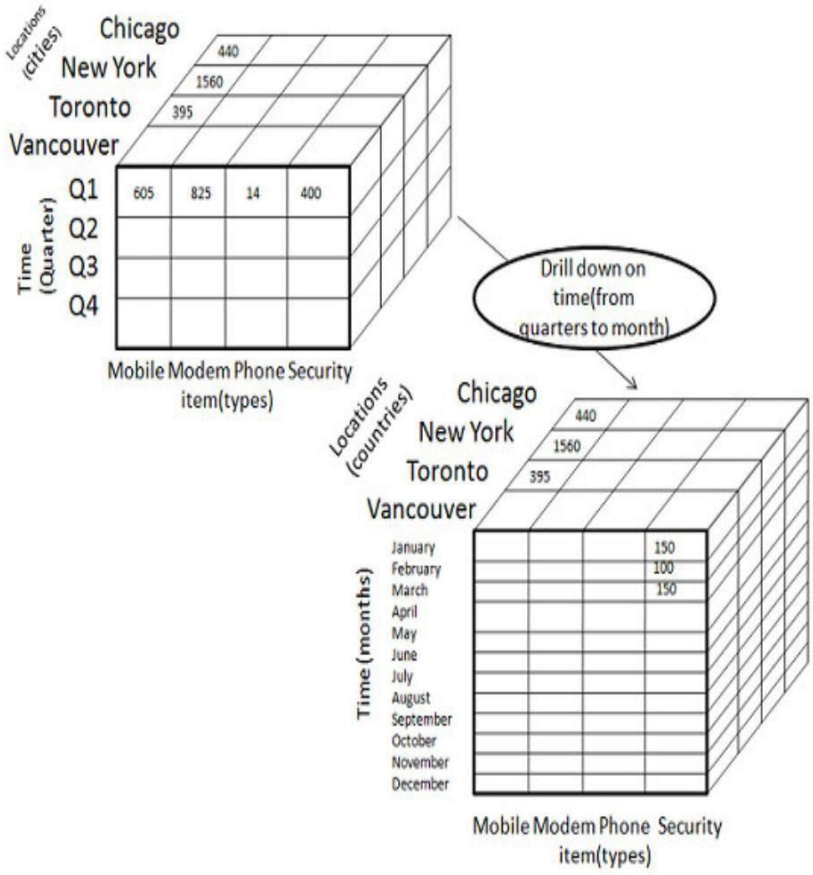
- Roll-up is performed by climbing up a concept hierarchy for the dimension location.
- Initially the concept hierarchy was "street < city < province < country".
- On rolling up, the data is aggregated by ascending the location hierarchy from the level of city to the level of country.
- The data is grouped into cities rather than countries.
- When roll-up is performed, one or more dimensions from the data cube are removed.

Drill-down

Drill-down is the reverse operation of roll-up. It is performed by either of the following ways:

- By stepping down a concept hierarchy for a dimension
- By introducing a new dimension.

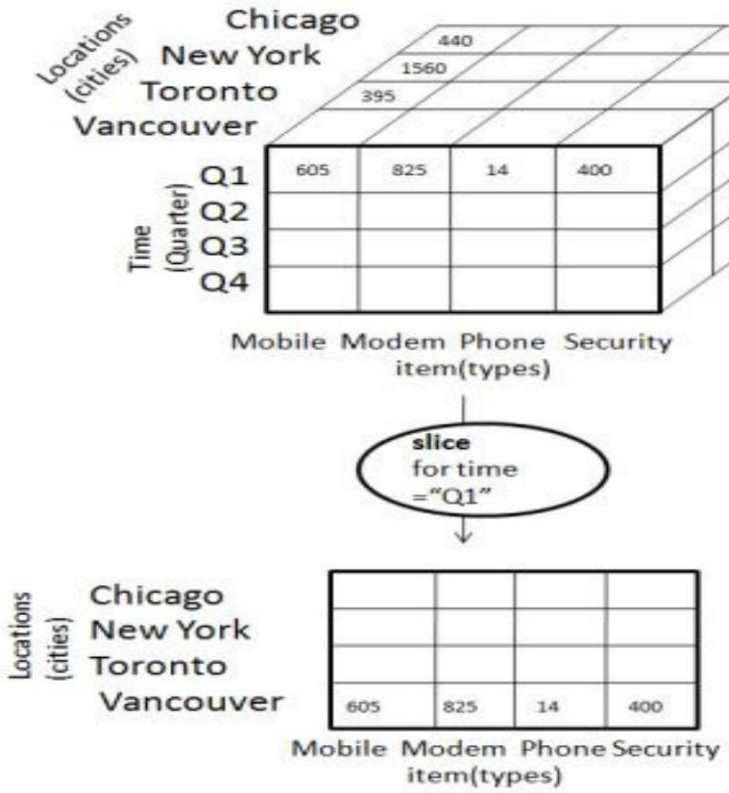
The following diagram illustrates how drill-down works:



- Drill-down is performed by stepping down a concept hierarchy for the dimension time.
- Initially the concept hierarchy was "day < month < quarter < year."
- On drilling down, the time dimension is descended from the level of quarter to the level of month.
- When drill-down is performed, one or more dimensions from the data cube are added.
- It navigates the data from less detailed data to highly detailed data.

Slice

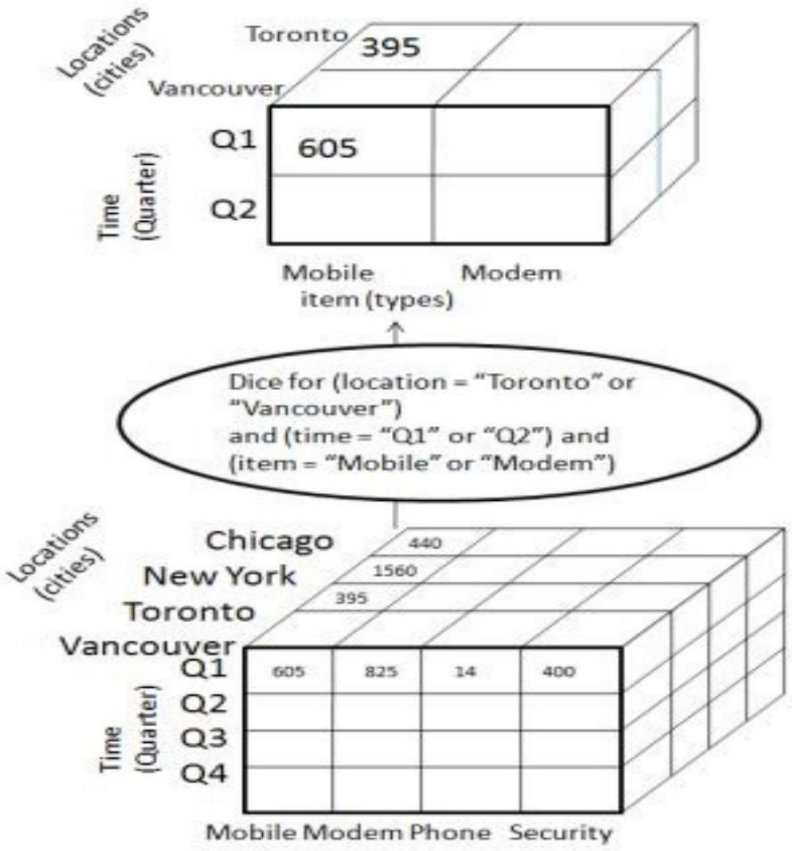
The slice operation selects one particular dimension from a given cube and provides a new sub-cube. Consider the following diagram that shows how slice works.



- Here Slice is performed for the dimension "time" using the criterion time = "Q1".
- It will form a new sub-cube by selecting one or more dimensions.

Dice

Dice selects two or more dimensions from a given cube and provides a new sub-cube. Consider the following diagram that shows the dice operation.

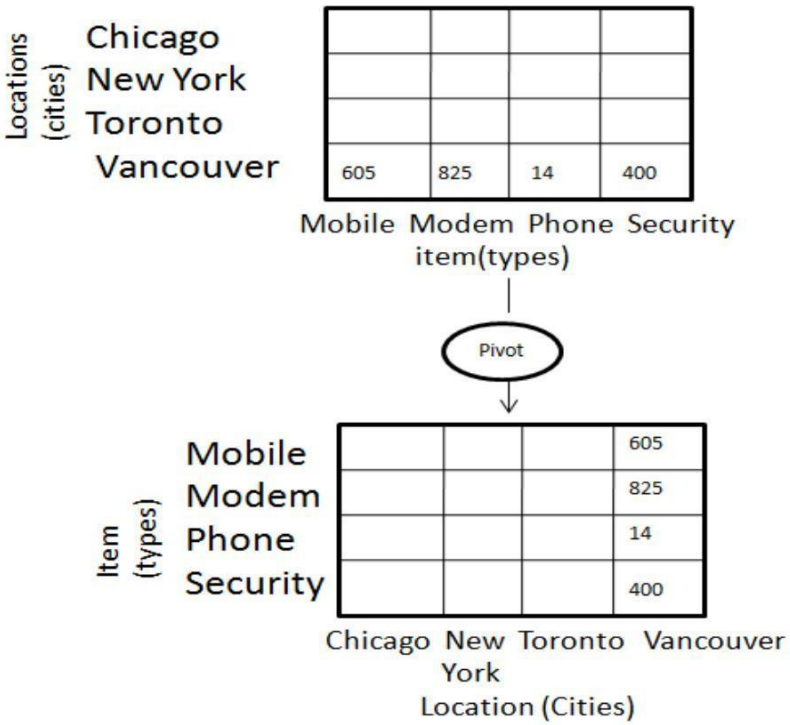


The dice operation on the cube based on the following selection criteria involves three dimensions.

- (location = "Toronto" or "Vancouver")
- (time = "Q1" or "Q2")
- (item =" Mobile" or "Modem")

Pivot

The pivot operation is also known as rotation. It rotates the data axes in view in order to provide an alternative presentation of data. Consider the following diagram that shows the pivot operation.



A. (v). Explore visualization features of the tool for analysis like identifying trends etc.

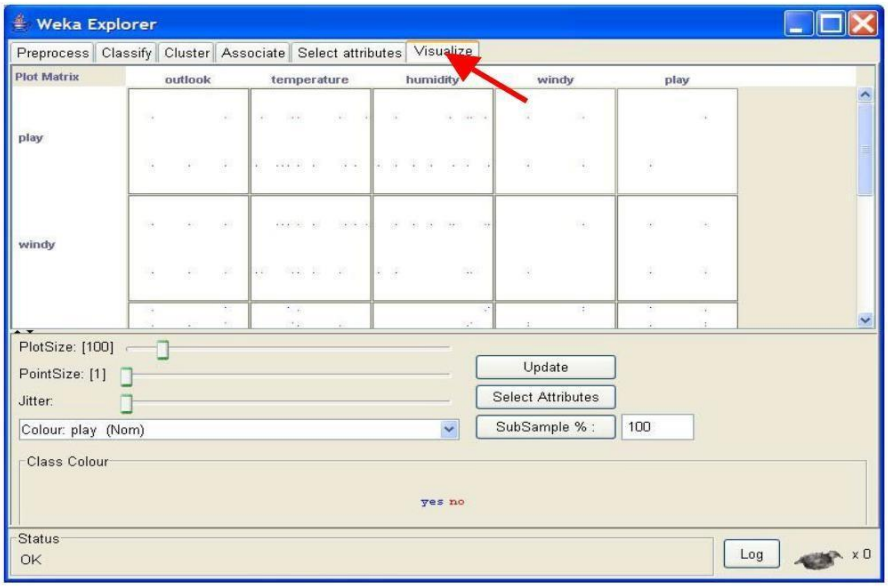
Ans:

Visualization Features:

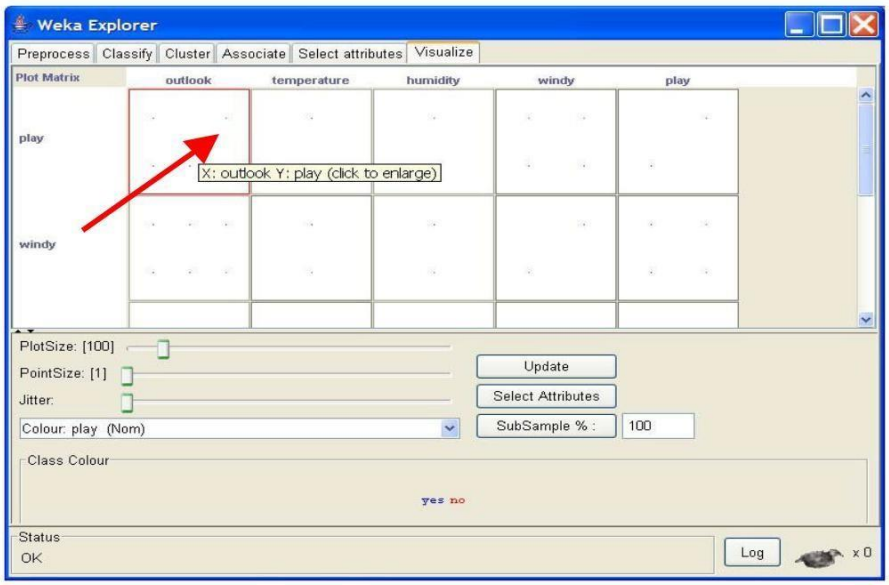
WEKA's visualization allows you to visualize a 2-D plot of the current working relation. Visualization is very useful in practice, it helps to determine difficulty of the learning problem. WEKA can visualize single attributes (1-d) and pairs of attributes (2-d), rotate 3-d visualizations (Xgobi-style).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

- Access To **Visualization** From The *Classifier*, *Cluster* And *Attribute Selection* Panel Is Available From A Popup Menu. Click The Right Mouse Button Over An Entry In The Result List To Bring Up The Menu. You Will Be Presented With Options For Viewing Or Saving The Text Output And --- Depending On The Scheme --- Further Options For Visualizing Errors, Clusters, Trees Etc.

To open Visualization screen, click _Visualize‘ tab.



Select a square that corresponds to the attributes you would like to visualize. For example, let‘s choose _outlook‘ for X – axis and _play‘ for Y – axis. Click anywhere inside the square that corresponds to _play on the left and _outlook‘ at the top



Changing the View:

In the visualization window, beneath the X-axis selector there is a drop-down list,

_Colour‘, for choosing the color scheme. This allows you to choose the color of points based on the attribute selected. Below the plot area, there is a legend that describes what values the colors correspond to. In your example, red represents _no‘, while blue represents _yes‘. For better visibility you should change the color of label _yes‘. Left-click on _yes‘ in the _Class colour‘ box and select lighter color from the color palette.

To the right of the plot area there are series of horizontal strips. Each strip represents an attribute, and the dots within it show the distribution values of the attribute. You can choose

what axes are used in the main graph by clicking on these strips (left-click changes X-axis, right-click changes Y-axis).

The software sets X - axis to _Outlook‘ attribute and Y - axis to _Play‘. The instances are spread out in the plot area and concentration points are not visible. Keep sliding _Jitter‘, a random displacement given to all points in the plot, to the right, until you can spot concentration points.

The results are shown below. But on this screen we changed _Colour‘ to temperature. Besides _outlook‘ and _play‘, this allows you to see the _temperature‘ corresponding to the

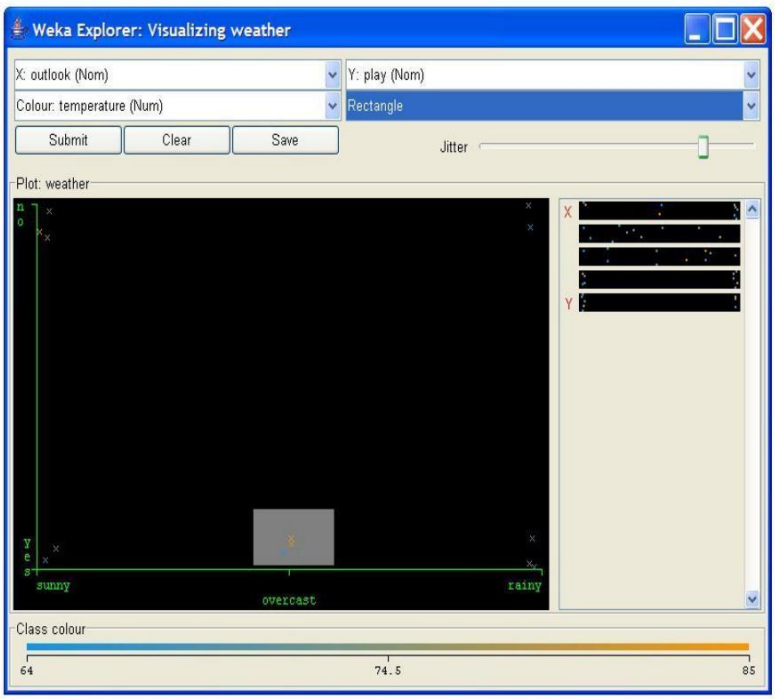
_outlook‘. It will affect your result because if you see _outlook‘ = _sunny‘ and _play‘ = _no‘ to explain the result, you need to see the _temperature‘ – if it is too hot, you do not want to play. Change _Colour‘ to _windy‘, you can see that if it is windy, you do not want to play as well.

Selecting Instances

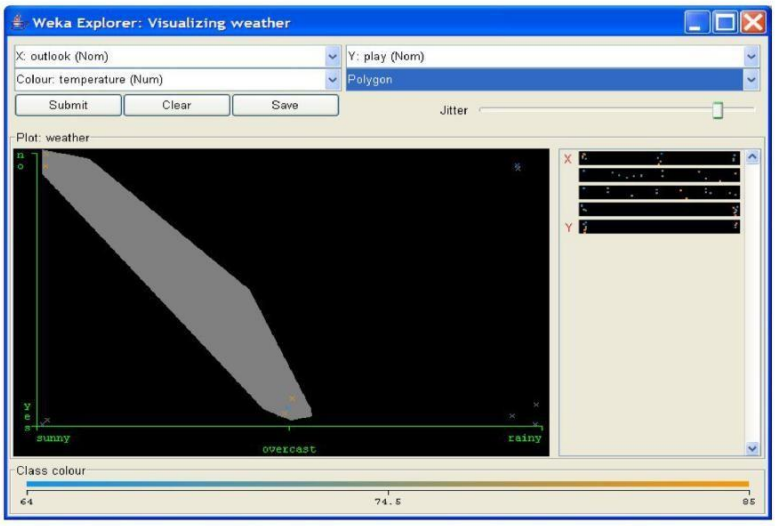
Sometimes it is helpful to select a subset of the data using visualization tool. A special case is the _UserClassifier‘, which lets you to build your own classifier by interactively selecting instances. Below the Y – axis there is a drop-down list that allows you to choose a selection method. A group of points on the graph can be selected in four ways [2]:

1. **Select Instance**. Click on an individual data point. It brings up a window listing attributes of the point. If more than one point will appear at the same location, more than one set of attributes will be shown.

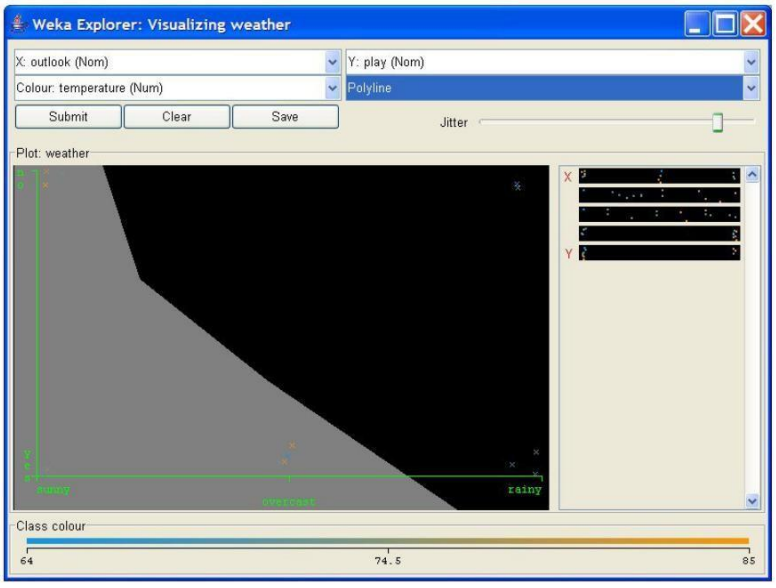
2. **Rectangle**. You can create a rectangle by dragging it around the point.



3. **Polygon**. You can select several points by building a free-form polygon. Left-click on the graph to add vertices to the polygon and right-click to complete it.



4. **Polyline**. To distinguish the points on one side from the once on another, you can build a polyline. Left-click on the graph to add vertices to the polyline and right-click to finish.

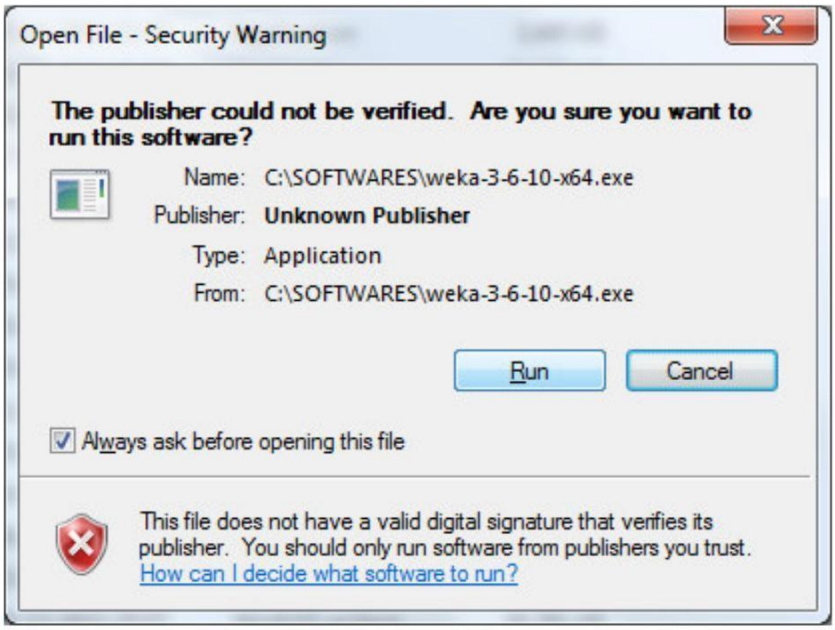


B.Explore WEKA Data Mining/Machine Learning Toolkit

B.(i) Downloading and/or installation of WEKA data mining toolkit.

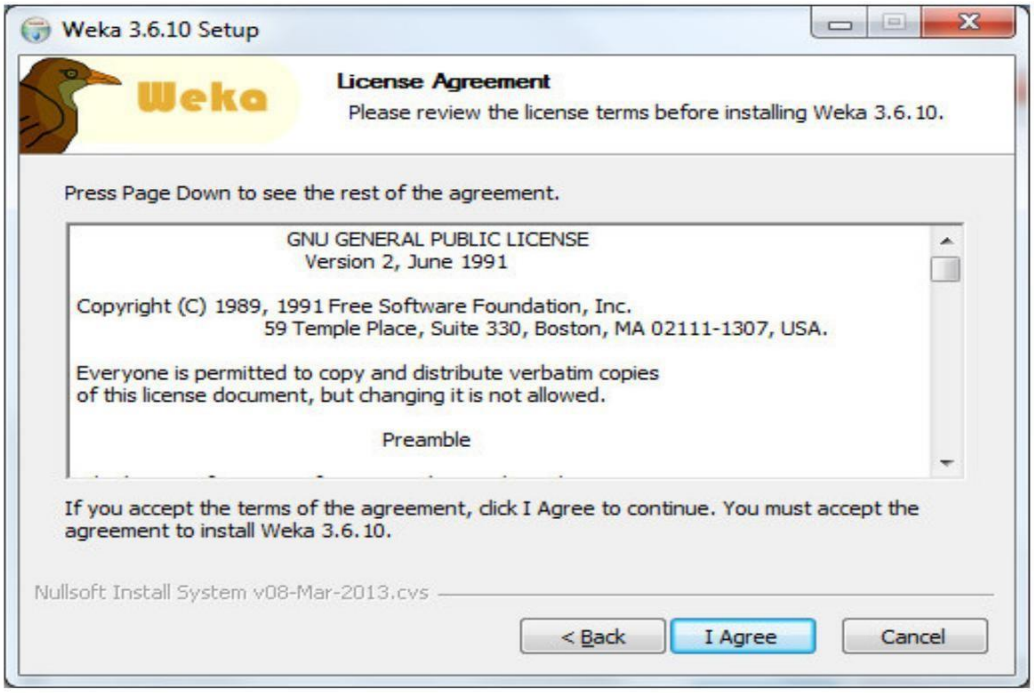
Ans: **Install Steps for WEKA a Data Mining Tool**

1. Download the software as your requirements from the below given link.
   http://www.cs.waikato.ac.nz/ml/weka/downloading.html
2. The Java is mandatory for installation of WEKA so if you have already Java on your machine then download only WEKA else download the software with JVM.
3. Then open the file location and double click on the file

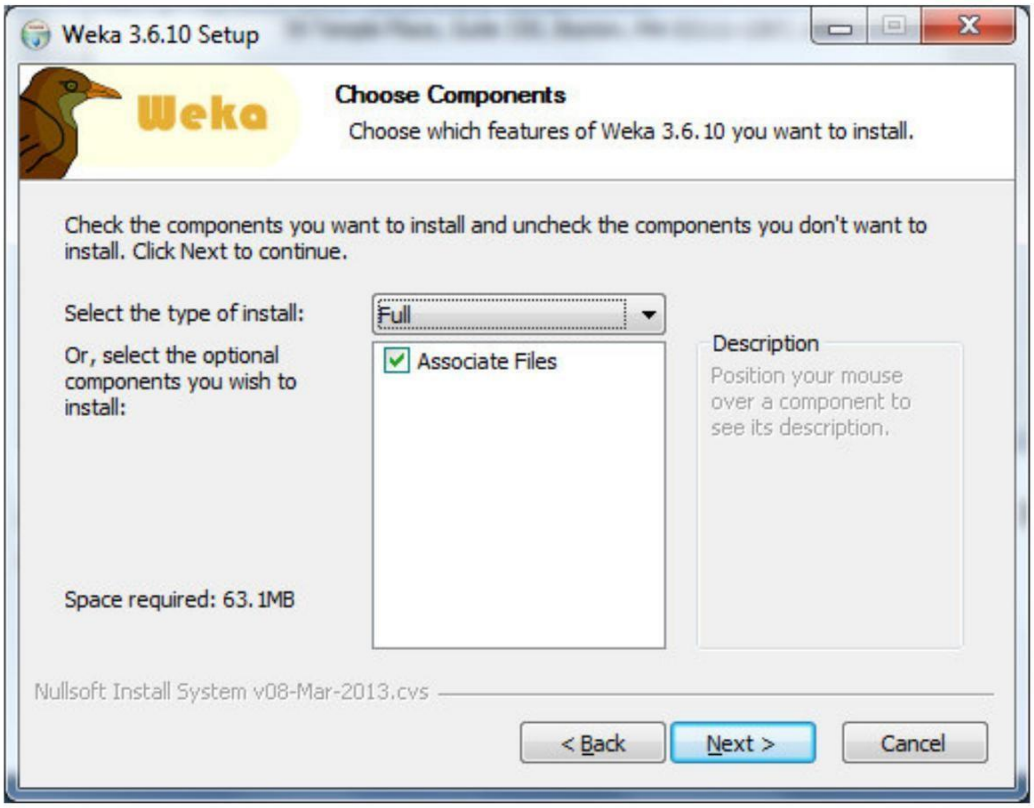


4. Click Next

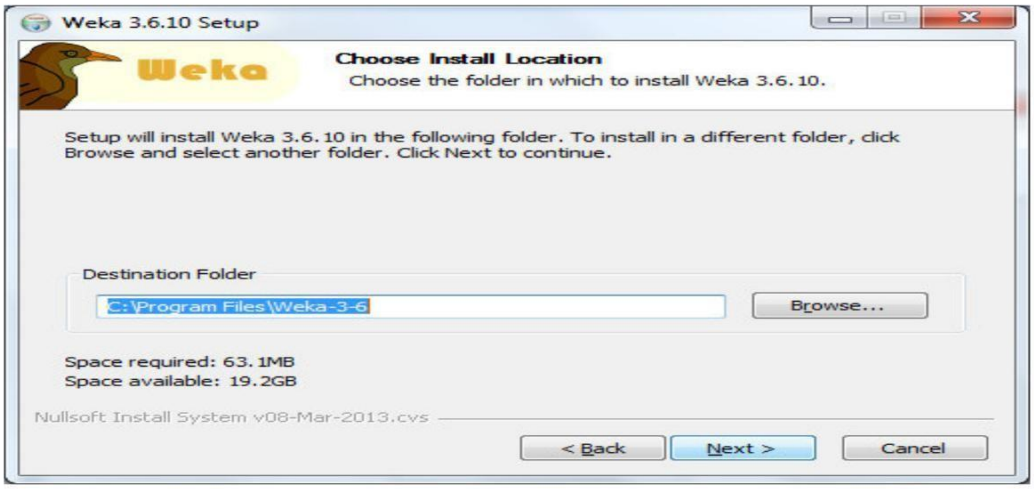
5. Click I Agree.



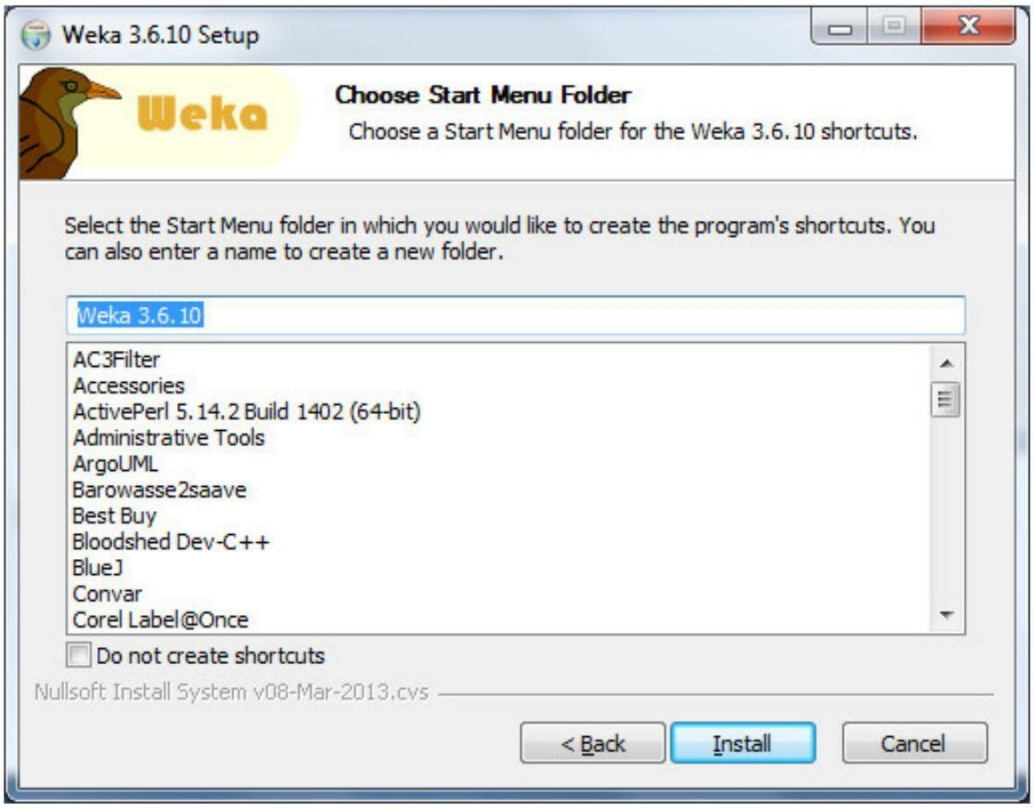
6. As your requirement do the necessary changes of settings and click Next. Full and Associate files are the recommended settings.



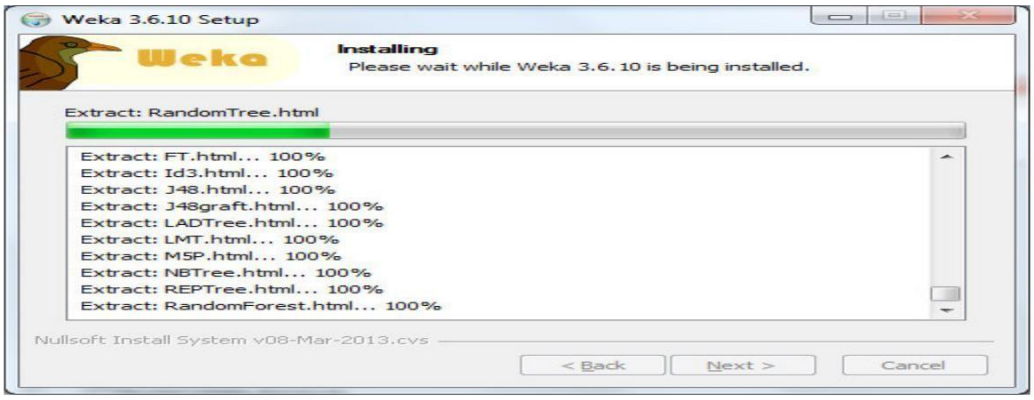
7. Change to your desire installation location.



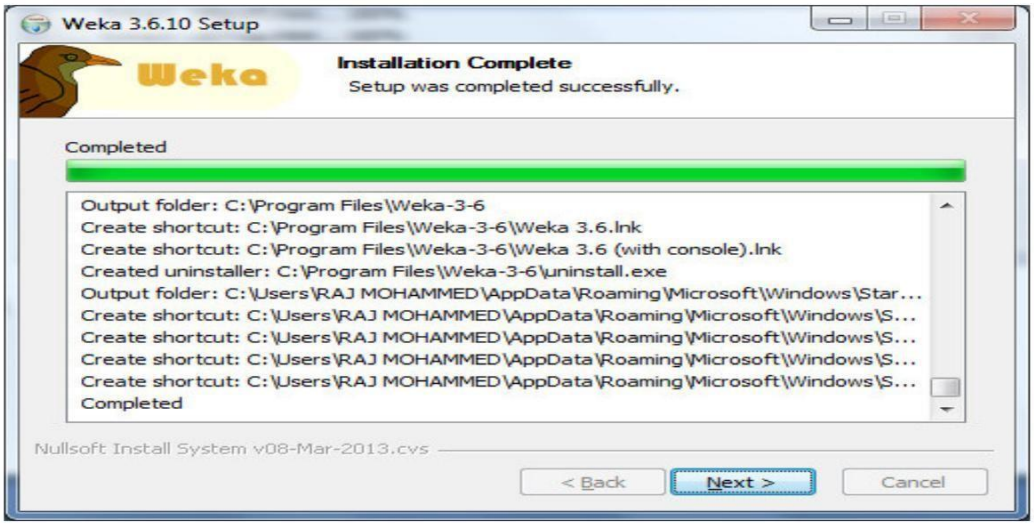
8. If you want a shortcut then check the box and click Install.



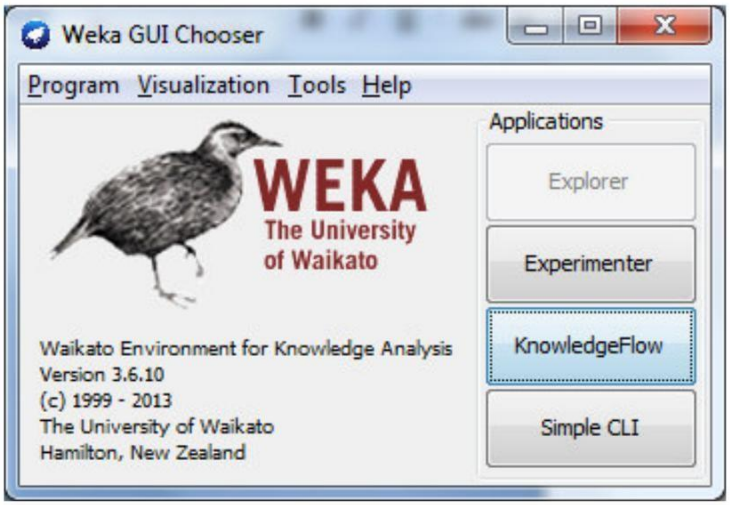
9. The Installation will start wait for a while it will finish within a minute.



10. After complete installation click on Next.



11. Hurray !!!!!!! That‘s all click on the Finish and take a shovel and start Mining. Best of Luck.



This is the GUI you get when started. You have 4 options Explorer, Experimenter, KnowledgeFlow and Simple CLI.

B.(ii)Understand the features of WEKA tool kit such as Explorer, Knowledge flow interface, Experimenter, command-line interface.

Ans: **WEKA**

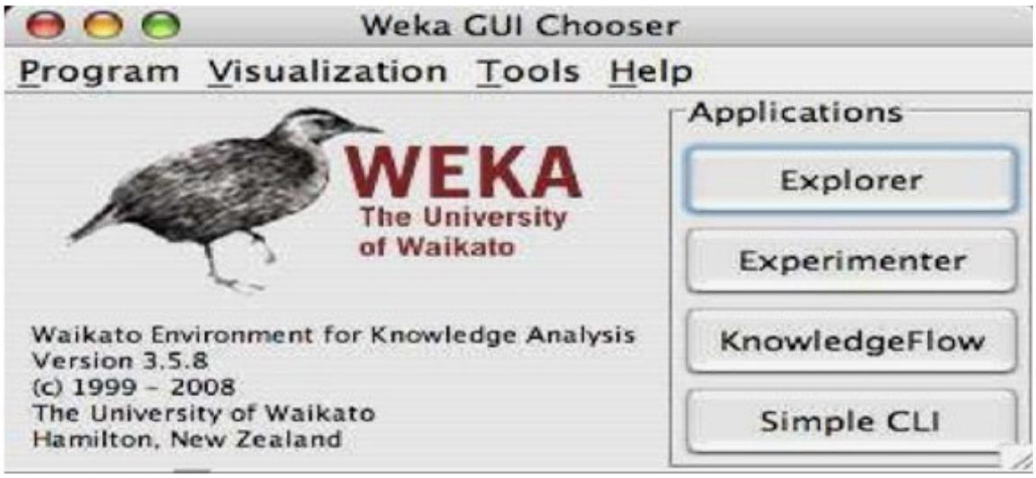
Weka is created by researchers at the university WIKATO in New Zealand. University of Waikato, Hamilton, New Zealand Alex Seewald (original Command-line primer) David Scuse (original Experimenter tutorial)

- It is java based application.
- It is collection often source, Machine Learning Algorithm.
- The routines (functions) are implemented as classes and logically arranged in packages.
- It comes with an extensive GUI Interface.
- Weka routines can be used standalone via the command line interface.

The Graphical User Interface;-

The Weka GUI Chooser (class weka.gui.GUIChooser) provides a starting point for launching Weka‘s main GUI applications and supporting tools. If one prefers a MDI (―multiple document interface‖) appearance, then this is provided by an alternative launcher called ―Main‖

(class weka.gui.Main). The GUI Chooser consists of four buttons—one for each of the four major Weka applications—and four menus.



The buttons can be used to start the following applications:

- **Explorer An environment** for exploring data with WEKA (the rest of this Documentation deals with this application in more detail).
- **Experimenter** An environment for performing experiments and conducting statistical tests between learning schemes.
- **Knowledge Flow** This environment supports essentially the same functions as the Explorer but with a drag-and-drop interface. One advantage is that it supports incremental learning.
- **SimpleCLI Provides** a simple command-line interface that allows direct execution of WEKA commands for operating systems that do not provide their own command line interface.

1. Explorer

The Graphical user interface

1.1 Section Tabs

At the very top of the window, just below the title bar, is a row of tabs. When the Explorer is first started only the first tab is active; the others are grayed out. This is because it is necessary to open (and potentially pre-process) a data set before starting to explore the data.

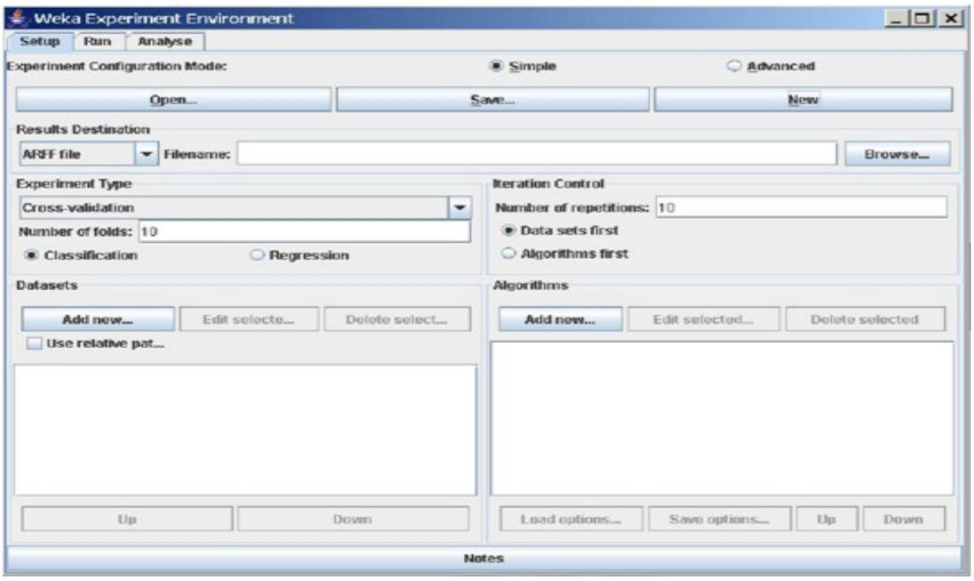
The tabs are as follows:

1. **Preprocess.** Choose and modify the data being acted on.
2. **Classify.** Train & test learning schemes that classify or perform regression
3. **Cluster.** Learn clusters for the data.
4. **Associate.** Learn association rules for the data.
5. **Select attributes.** Select the most relevant attributes in the data.
6. **Visualize.** View an interactive 2D plot of the data.

Once the tabs are active, clicking on them flicks between different screens, on which the respective actions can be performed. The bottom area of the window (including the status box, the log button, and the Weka bird) stays visible regardless of which section you are in. The Explorer can be easily extended with custom tabs. The Wiki article **―Adding tabs in the Explorer‖ explains this in detail.**

2. Weka Experimenter:-

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.



The Experiment Environment can be run from the command line using the Simple CLI. For example, the following commands could be typed into the CLI to run the OneR scheme on the Iris dataset using a basic train and test process. (Note that the commands would be typed on one line into the CLI.) While commands can be typed directly into the CLI, this technique is not particularly convenient and the experiments are not easy to modify. The Experimenter comes in two flavors', either with a simple interface that provides most of the functionality one needs for experiments, or with an interface **with full access to the Experimenter's capabilities. You can** choose between those two with the Experiment Configuration Mode radio buttons:

- Simple
- Advanced

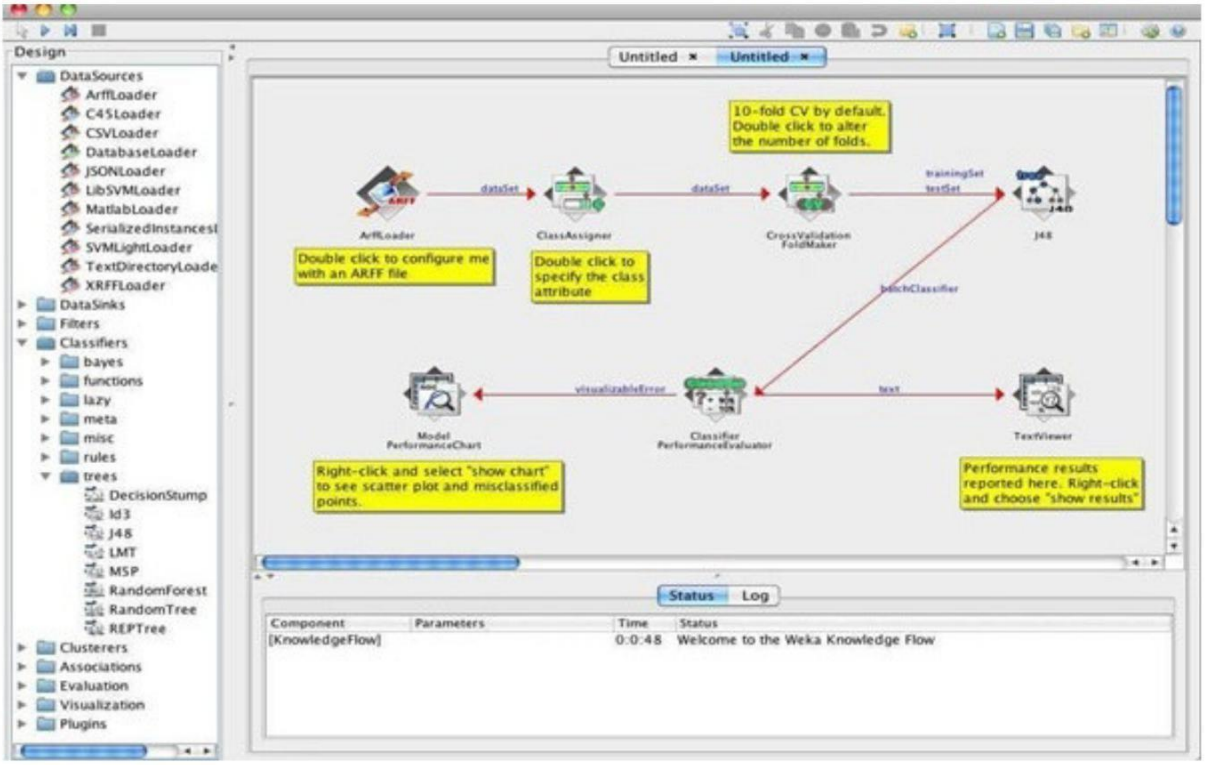
Both setups allow you to setup standard experiments, that are run locally on a single machine, or remote experiments, which are distributed between several hosts. The distribution of experiments cuts down the time the experiments will take until completion, but on the other hand the setup takes more time. The next section covers the standard experiments (both, simple and advanced), followed by the remote experiments and finally the analyzing of the results.

3. Knowledge Flow

Introduction

The Knowledge Flow provides an alternative to the Explorer as a graphical front end to **WEKA's core algorithms.**

The Knowledge Flow presents a data-flow inspired interface to WEKA. The user can select WEKA components from a palette, place them on a layout canvas and connect them together in order to form a knowledge flow for processing and analyzing data. At present, all of **WEKA's classifiers, filters, clusterers, associators, loaders and savers a**re available in the Knowledge Flow along with some extra tools.



The Knowledge Flow can handle data either incrementally or in batches (the Explorer handles batch data only). Of course learning from data incremen- tally requires a classifier that can

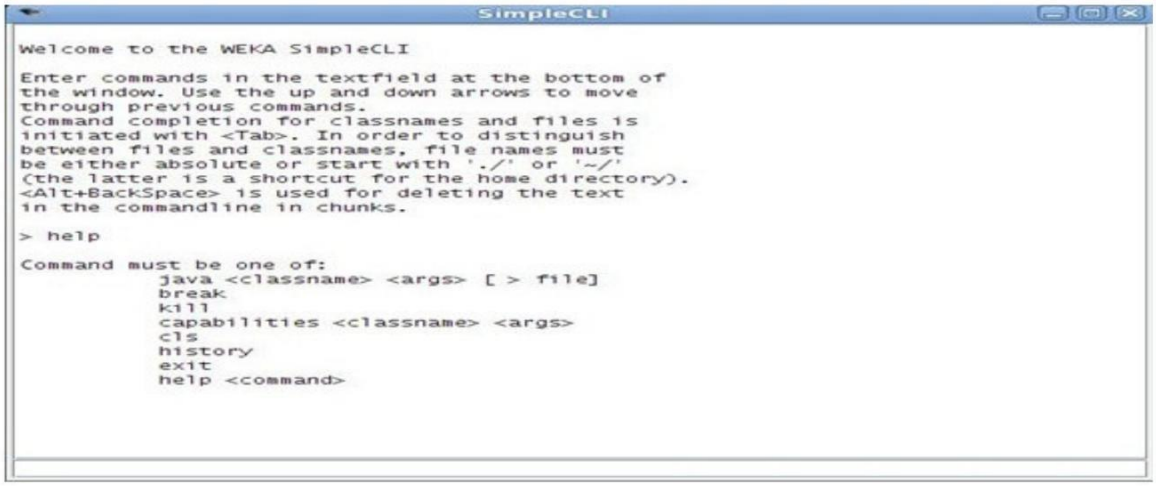
be updated on an instance by instance basis. Currently in WEKA there are ten classifiers that can handle data incrementally.

The Knowledge Flow offers the following features:

- **Intuitive** data flow style layout.
- **Process** data in batches or incrementally.
- **Process multiple batches** or streams in parallel (each separate flow executes in its own thread) .
- **Process multiple streams sequentially** via a user-specified order of execution.
- **Chain filters** together.
- **View models** produced by classifiers for each fold in a cross validation.
- **Visualize performance** of incremental classifiers during processing (scrolling plots of classification accuracy, RMS error, predictions etc.).
- **Plugin —perspectives‖ that add major new functionality (e.g. 3D data** visualization, time series forecasting environment etc.).

4. Simple CLI

The Simple CLI provides full access to all Weka classes, i.e., classifiers, filters, clusterers, etc., but without the hassle of the CLASSPATH (it facilitates the one, with which Weka was started). It offers a simple Weka shell with separated command line and output.



Commands

The following commands are available in the Simple CLI:

- Java <classname> [<args>]

  Invokes a java class with the given arguments (if any).

- Break

  Stops the current thread, e.g., a running classifier, in a friendly manner kill stops the current thread in an unfriendly fashion.

- Cls

  Clears the output area

- Capabilities <classname> [<args>]

  Lists the capabilities of the specified class, e.g., for a classifier with its.

- option:

  Capabilities weka.classifiers.meta.Bagging -W weka.classifiers.trees.Id3

- exit

  Exits the Simple CLI

- help [<command>]

  Provides an overview of the available commands if without a command name as argument, otherwise more help on the specified command

Invocation

In order to invoke a Weka class, one has only to prefix the class with ljavall. This command tells the Simple CLI to load a class and execute it with any given parameters. E.g., the J48 classifier can be invoked on the iris dataset with the following command:

java weka.classifiers.trees.J48 -t c:/temp/iris.arff

This results in the following output:

Command redirection

Starting with this version of Weka one can perform a basic redirection: java weka.classifiers.trees.J48 -t test.arff > j48.txt

Note: the > must be preceded and followed by a space, otherwise it is not recognized as redirection, but part of another parameter.

Command completion

Commands starting with java support completion for classnames and filenames via Tab (Alt+BackSpace deletes parts of the command again). In case that there are several matches, Weka lists all possible matches.

- Package Name Completion java weka.cl<Tab>

Results in the following output of possible matches of

package names: Possible matches:

weka.classifiers
weka.clusterers

- Classname completion

java weka.classifiers.meta.A<Tab> lists the following classes

Possible matches:
weka.classifiers.meta.AdaBoostM1
weka.classifiers.meta.AdditiveRegression
weka.classifiers.meta.AttributeSelectedClassifier

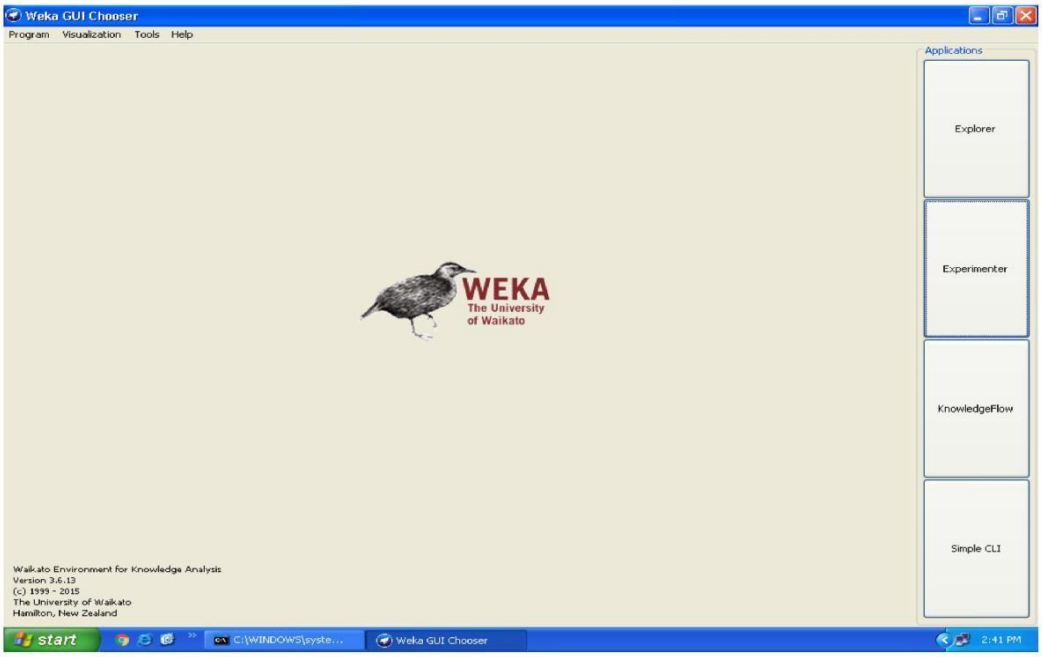
- Filename Completion

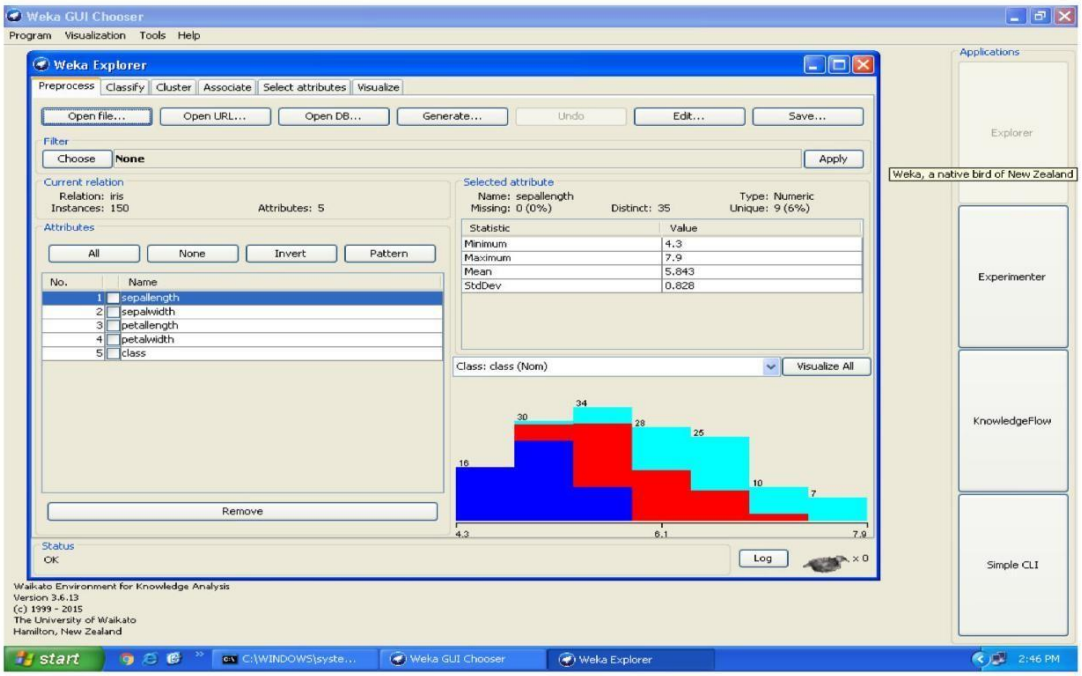
In order for Weka to determine whether a the string under the cursor is a classname or a filename, filenames need to be absolute (Unix/Linx: /some/path/file;Windows: C:\Some\Path\file) or relative and starting with a dot (Unix/Linux:./some/other/path/file; Windows: .\Some\Other\Path\file).

B.(iii)Navigate the options available in the WEKA(ex.select attributes panel,preprocess panel,classify panel,cluster panel,associate panel and visualize)

Ans: Steps for identify options in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose iris data set and open file.
8. All tabs available in WEKA home page.


Weka GUI Chooser
Program Visualization Tools Help
Applications
Explorer
Experimenter
KnowledgeFlow
Simple CLI
WEKA
The University of Waikato
Waikato Environment for Knowledge Analysis
Version 3.6.13
(c) 1999 - 2015
The University of Waikato
Hamilton, New Zealand
start
Weka GUI Chooser
2:41 PM


Weka GUI Chooser
Program Visualization Tools Help
Weka Explorer
Preprocess Classify Cluster Associate Select attributes Visualize
Open file... Open URL... Open DB... Generate... Undo Edit... Save...
Filter
Choose None Apply
Current relation
Relation: iris
Instances: 150
Attributes: 5
Selected attribute
Name: sepallength
Missing: 0 (0%)
Distinct: 35
Type: Numeric
Unique: 9 (6%)
Attributes
All None Invert Pattern
No. Name
1 sepallength
2 sepalwidth
3 petallength
4 petalwidth
5 class
Statistic Value
Minimum 4.3
Maximum 7.9
Mean 5.843
StdDev 0.828
Class: class (Nom)
Visualize All
Remove
Status
OK
Log
Applications
Explorer
Weka, a native bird of New Zealand
Experimenter
KnowledgeFlow
Simple CLI
Waikato Environment for Knowledge Analysis
Version 3.6.13
(c) 1999 - 2015
The University of Waikato
Hamilton, New Zealand
start
Weka GUI Chooser
Weka Explorer
2:46 PM

B. (iv) Study the ARFF file format

Ans: ARFF File Format

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 are not the only format one can load, but all files that can be converted with **Weka's —core converters‖. The following formats are currently** supported:

- ARFF (+ compressed)
- C4.5
- CSV
- libsvm
- binary serialized instances
- XRFF (+ compressed)

Overview

ARFF files have two distinct sections. The first section is the **Header** information, which is followed the **Data** information. The Header of the ARFF file contains the name of the relation, a list of the attributes (the columns in the data), and their types.

An example header on the standard IRIS dataset looks like this:

1. Title: Iris Plants Database

2. Sources:

(a) Creator: R.A. Fisher
(b) Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
(c) Date: July, 1988

@RELATION iris

@ATTRIBUTE sepal length NUMERIC
@ATTRIBUTE sepal width NUMERIC
@ATTRIBUTE petal length NUMERIC
@ATTRIBUTE petal width NUMERIC
@ATTRIBUTE class {Iris-setosa, Iris-versicolor, Iris-irginica} The Data of the ARFF file looks like the following:

@DATA

5.1,3.5,1.4,0.2,Iris-setosa
4.9,3.0,1.4,0.2,Iris-setosa
4.7,3.2,1.3,0.2,Iris-setosa
4.6,3.1,1.5,0.2,Iris-setosa
5.0,3.6,1.4,0.2,Iris-setosa
5.4,3.9,1.7,0.4,Iris-setosa
4.6,3.4,1.4,0.3,Iris-setosa
5.0,3.4,1.5,0.2,Iris-setosa
4.4,2.9,1.4,0.2,Iris-setosa
4.9,3.1,1.5,0.1,Iris-setosa

Lines that begin with a % are comments.
The @RELATION, @ATTRIBUTE and @DATA declarations are case insensitive.

The ARFF Header Section

The ARFF Header section of the file contains the relation declaration and attribute declarations.

The @relation Declaration

The relation name is defined as the first line in the ARFF file. The format is: @relation <relation-name>
where <relation-name> is a string. The string must be quoted if the name includes spaces.

The @attribute Declarations

Attribute declarations take the form of an ordered sequence of @attribute statements. Each attribute in the data set has its own @attribute statement which uniquely defines the name **of that attribute and it's data type. The order** the attributes are declared indicates the column position in the data section of the file. For example, if an attribute is the third one declared then Weka expects that all that attributes values will be found in the third comma delimited column.

The format for the @attribute statement is:

@attribute <attribute-name> <datatype>

where the <attribute-name> must start with an alphabetic character. If spaces are to be included in the name then the entire name must be quoted.

The <datatype> can be any of the four types supported by Weka:

- numeric
- integer is treated as numeric
- real is treated as numeric
- <nominal-specification>
- string
- date [<date-format>]
- relational for multi-instance data (for future use)

where <nominal-specification> and <date-format> are defined below. The keywords numeric, real, integer, string and date are case insensitive.

Numeric attributes

Numeric attributes can be real or integer numbers.

Nominal attributes

Nominal values are defined by providing an <nominal-specification> listing the possible values: <nominal-name1>, <nominal-name2>, <nominal-name3>,

For example, the class value of the Iris dataset can be defined as follows: @ATTRIBUTE class {Iris-setosa,Iris-versicolor,Iris-virginica} Values that contain spaces must be quoted.

String attributes

String attributes allow us to create attributes containing arbitrary textual values. This is very useful in text-mining applications, as we can create datasets with string attributes, then write Weka Filters to manipulate strings (like String- ToWordVectorFilter). String attributes are declared as follows:

@ATTRIBUTE LCC string

Date attributes

Date attribute declarations take the form: @attribute <name> date [<date-format>] where <name> is the name for the attribute and <date-format> is an optional string specifying how date values should be parsed and printed (this is the same format used by SimpleDateFormat). The default format string accepts the ISO-8601 combined date and time format: yyyy-MM-**dd'T'HH:mm:ss.** Dates must be specified in the data section as the corresponding string representations of the date/time (see example below).

Relational attributes

Relational attribute declarations take the form: @attribute <name> relational <further attribute definitions> @end <name>

For the multi-instance dataset MUSK1 the definition would look like thi**s (ll...ll** denotes an omission):

@attribute molecule_name {MUSK-jf78,...,NON-MUSK-199} @attribute bag relational

@attribute f1 numeric

...

@attribute f166 numeric @end bag

@attribute class {0,1}

The ARFF Data Section

The ARFF Data section of the file contains the data declaration line and the actual instance lines.

The @data Declaration

The @data declaration is a single line denoting the start of the data segment in the file. The format is:

@data

The instance data

Each instance is represented on a single line, with carriage returns denoting the end of the instance. A percent sign (%) introduces a comment, which continues to the end of the line.

Attribute values for each instance are delimited by commas. They must appear in the order that they were declared in the header section (i.e. the data corresponding to the nth @attribute declaration is always the nth field of the attribute).

Missing values are represented by a single question mark, as in:

@data 4.4,?,1.5,?,Iris-setosa

Values of string and nominal attributes are case sensitive, and any that contain space or the comment-delimiter character % must be quoted. (The code suggests that double-quotes are acceptable and that a backslash will escape individual characters.)

An example follows: @relation LCCvsLCSH @attribute LCC string @attribute LCSH string

@data

AG5, 'Encyclopedias and dictionaries.;Twentieth century.' AS262, 'Science -- Soviet Union -- **History.'**
AE5, 'Encyclopedias and dictionaries.'
AS281, 'Astronomy, Assyro-Babylonian.;Moon -- **Phases.'**
AS28**1, 'Astronomy, Assyro**-Babylonian.;Moon -- **Tables.'**

Dates must be specified in the data section using the string representation specified in the attribute declaration.

For example:
@RELATION Timestamps
@ATTRIBUTE timestamp DATE "yyyy-MM-dd HH:mm:ss" @DATA

"2001-04-03 12:12:12"
"2001-05-03 12:59:55"

Relational data must be enclosed within double quotes ||. For example an instance of the MUSK1 **dataset (||...|| denotes an omission):**

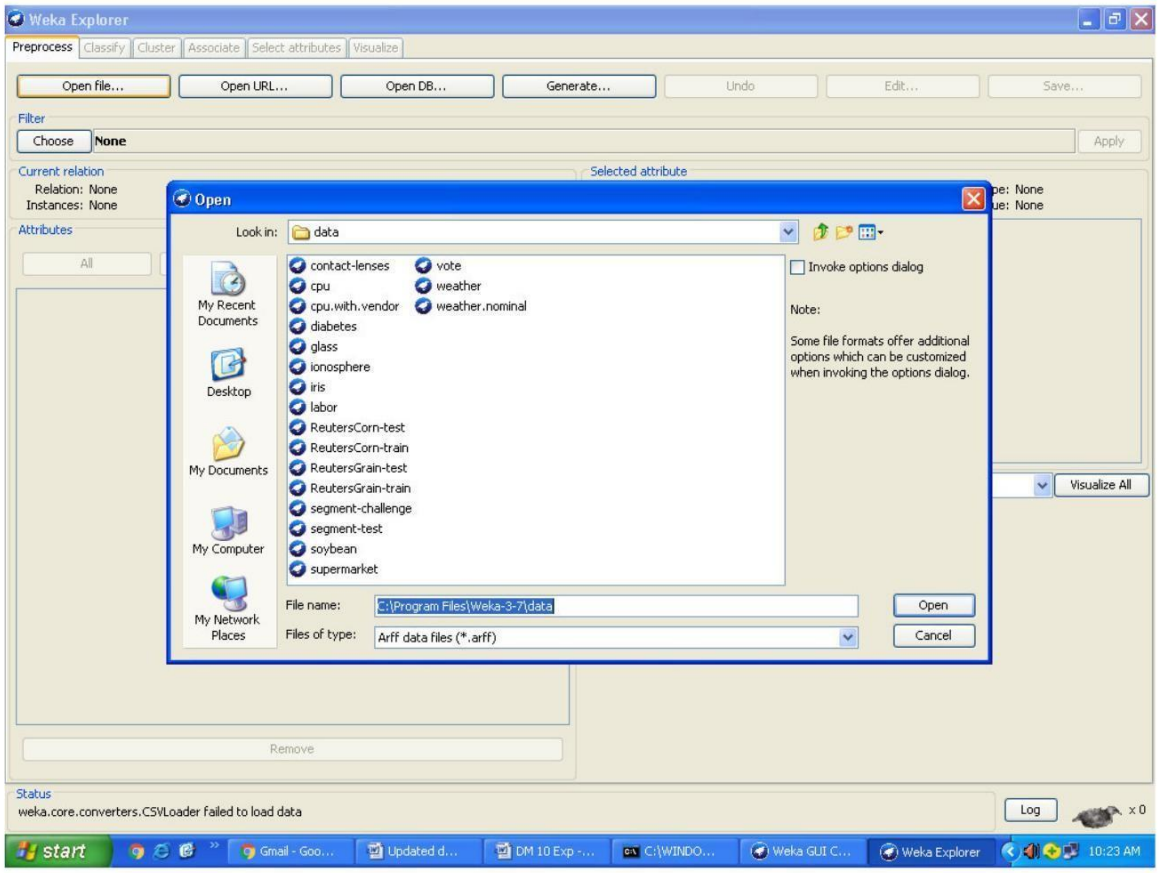
MUSK-188,"42,...,30",1

B.(v) Explore the available data sets in WEKA.

Ans: Steps for identifying data sets in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on open file button.
4. Choose WEKA folder in C drive.
5. Select and Click on data option button.

Exercise: 1)Perform data preprocessing tasks and Demonstrate to categorical data
2)Perform data preprocessing tasks and Demonstrate to categorical data and nominal data.



.

Sample Weka Data Sets

Below are some sample WEKA data sets, in arff format.

- contact-lens.arff
- cpu.arff
- cpu.with-vendor.arff
- diabetes.arff
- glass.arff
- ionospehre.arff
- iris.arff
- labor.arff
- ReutersCorn-train.arff

- ReutersCorn-test.arff
- ReutersGrain-train.arff
- ReutersGrain-test.arff
- segment-challenge.arff
- segment-test.arff
- soybean.arff
- supermarket.arff
- vote.arff
- weather.arff
- weather.nominal.arff

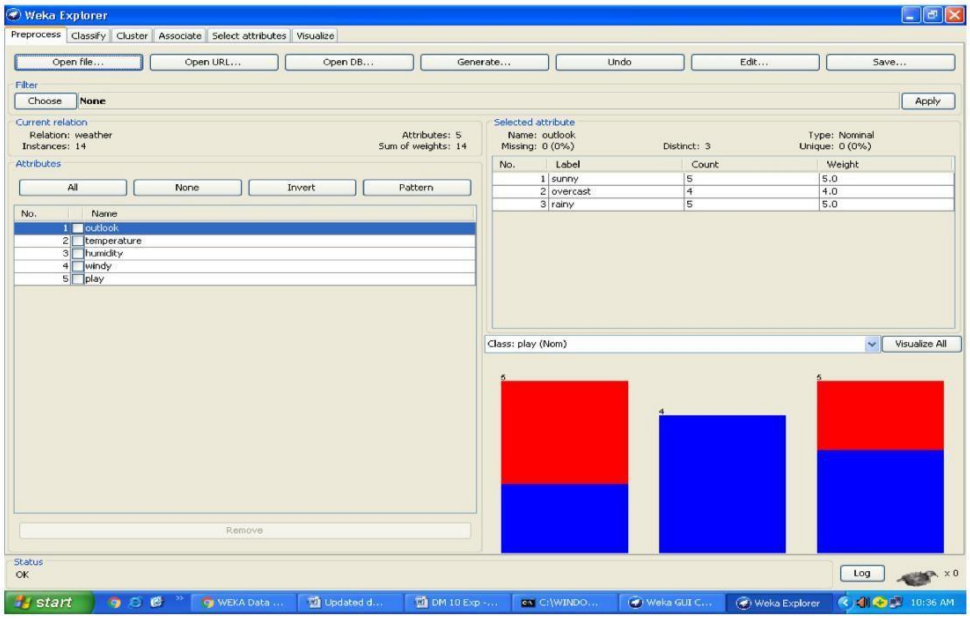
B. (vi) Load a data set (ex.Weather dataset,Iris dataset,etc.)

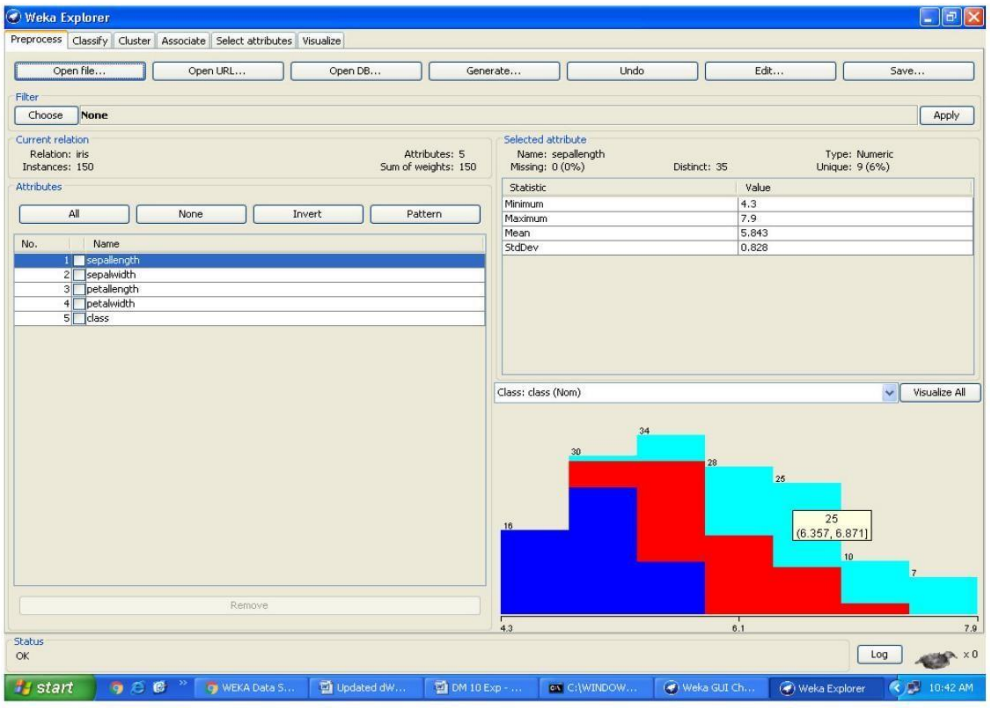
Ans: Steps for load the Weather data set.

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on open file button.
4. Choose WEKA folder in C drive.
5. Select and Click on data option button.
6. Choose Weather.arff file and Open the file.

Steps for load the Iris data set.

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on open file button.
4. Choose WEKA folder in C drive.
5. Select and Click on data option button.
6. Choose Iris.arff file and Open the file.


Weka Explorer
Preprocess
Classify
Cluster
Associate
Select attributes
Visualize
Open file...
Open URL...
Open DB...
Generate...
Undo
Edit...
Save...
Filter
Choose
None
Apply
Current relation
Relation: weather
Instances: 14
Attributes: 5
Sum of weights: 14
Attributes
All
None
Invert
Pattern
No.
Name
1 outlook
2 temperature
3 humidity
4 windy
5 play
Remove
Selected attribute
Name: outlook
Missing: 0 (0%)
Distinct: 3
Type: Nominal
Unique: 0 (0%)
No.
Label
Count
Weight
1 sunny 5 5.0
2 overcast 4 4.0
3 rainy 5 5.0
Class: play (Nom)
Visualize All
Status
OK
Log
x 0
start
10:36 AM


Weka Explorer
Preprocess
Classify
Cluster
Associate
Select attributes
Visualize
Open file...
Open URL...
Open DB...
Generate...
Undo
Edit...
Save...
Filter
Choose
None
Apply
Current relation
Relation: iris
Instances: 150
Attributes: 5
Sum of weights: 150
Attributes
All
None
Invert
Pattern
No.
Name
1 sepallength
2 sepalwidth
3 petallength
4 petalwidth
5 class
Remove
Selected attribute
Name: sepallength
Missing: 0 (0%)
Distinct: 35
Type: Numeric
Unique: 9 (6%)
Statistic
Value
Minimum 4.3
Maximum 7.9
Mean 5.843
StdDev 0.828
Class: class (Nom)
Visualize All
34
30
28
25
16
10
7
25
(6.357, 6.871)
4.3
6.1
7.9
Status
OK
Log
x 0
start
10:42 AM

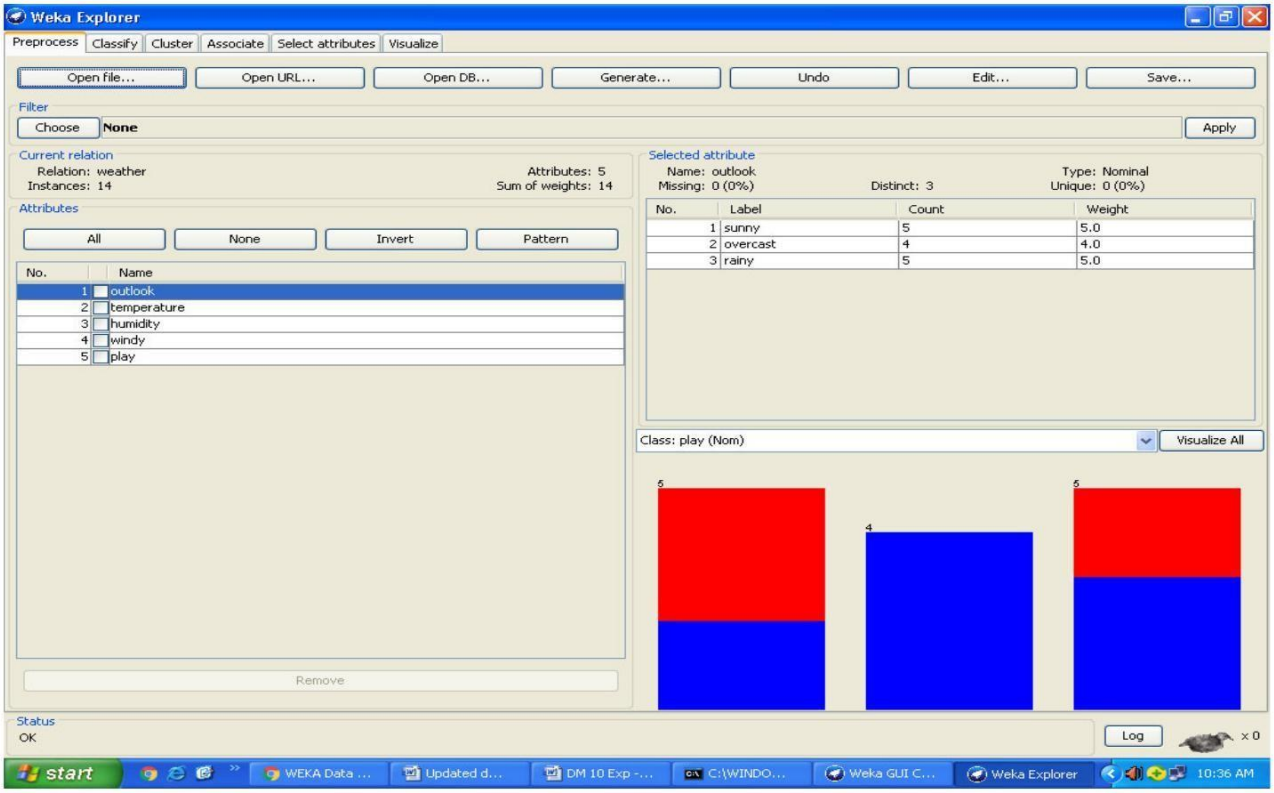
B. (vii) Load each dataset and observe the following:

B. (vii.i) List attribute names and they types

Ans: Example dataset-Weather.arff

List out the attribute names:

1. outlook
2. temperature
3. humidity
4. windy
5. play



B. (vii.ii) Number of records in each dataset.

Ans: @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

B. (vii.iii) Identify the class attribute (if any)

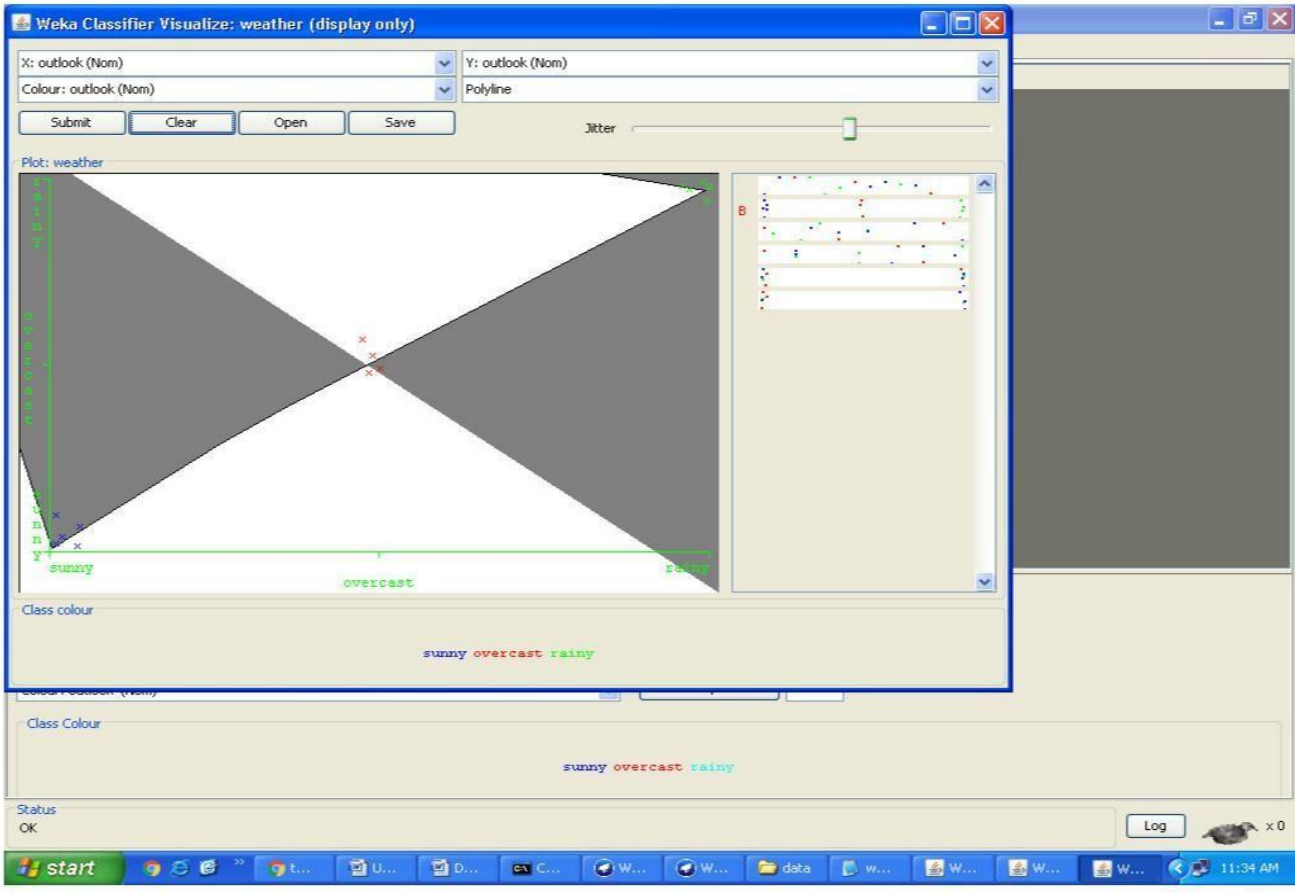
Ans: class attributes

1. sunny
2. overcast
3. rainy

B. (vii.iv) Plot Histogram

Ans: Steps for identify the plot histogram

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Visualize button.
4. Click on right click button.
5. Select and Click on polyline option button.



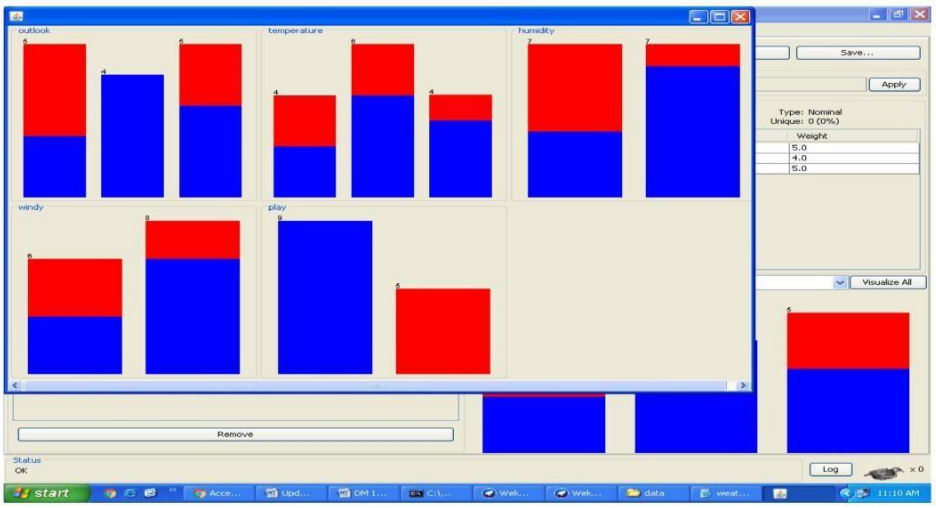
B. (vii.v) Determine the number of records for each class

Ans: @relation weather.symbolic
@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

B. (vii.vi) Visualize the data in various dimensions

Click on Visualize All button in WEKA Explorer.



Unit-II Perform data preprocessing tasks and Demonstrate performing association rule mining on data sets

A. Explore various options in Weka for Preprocessing data and apply (like Discretization Filters, Resample filter, etc.) n each dataset.

Ans:

Preprocess Tab

1. Loading Data

The first four buttons at the top of the preprocess section enable you to load data into WEKA:

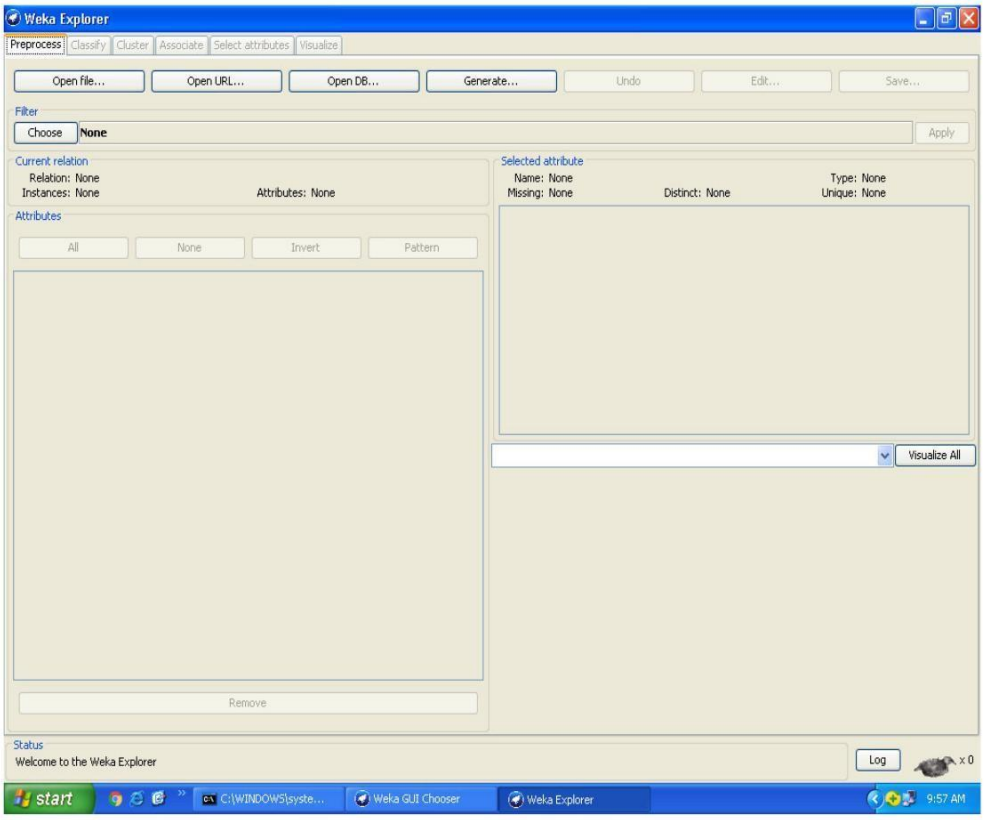
1. Open file..... Brings up a dialog box allowing you to browse for the data file on the local file system.

2. Open URL.... Asks for a Uniform Resource Locator address for where the data is stored.

3. Open DB.... Reads data from a database. (Note that to make this work you might have to edit the file in weka/experiment/DatabaseUtils.props.)

4. Generate .... Enables you to generate artificial data from a variety of Data Generators. Using the Open file ...button you can read files in a variety of formats: **WEKA's ARFF format, CSV**

format, C4.5 format, or serialized Instances format. ARFF files typically have a .arff extension, CSV files a .csv extension, C4.5 files a .data and .names extension, and serialized Instances objects a .bsi extension.



Current Relation: Once some data has been loaded, the Preprocess panel shows a variety of in**formation. The Current relation box (the —current relationll is the** currently loaded data, which can be interpreted as a single relational table in database terminology) has three entries:

1. Relation. The name of the relation, as given in the file it was loaded from. Filters (described below) modify the name of a relation.

2. Instances. The number of instances (data points/records) in the data.

3. Attributes. The number of attributes (features) in the data.

Working With Attributes

Below the Current relation box is a box titled Attributes. There are four buttons, and beneath them is a list of the attributes in the current relation.

The list has three columns:

1. No.. A number that identifies the attribute in the order they are specified in the data file.

2. Selection tick boxes. These allow you select which attributes are present in the relation.

3. Name. The name of the attribute, as it was declared in the data file. When you click on different rows in the list of attributes, the fields change in the box to the right titled Selected attribute.

This box displays the characteristics of the currently highlighted attribute in the list:

1. Name. The name of the attribute, the same as that given in the attribute list.

2. Type. The type of attribute, most commonly Nominal or Numeric.

3. Missing. The number (and percentage) of instances in the data for which this attribute is missing (unspecified).

4. Distinct. The number of different values that the data contains for this attribute.

5. Unique. The number (and percentage) of instances in the data having a value for this attribute that no other instances have.

Below these statistics is a list showing more information about the values stored in this attribute, which differ depending on its type. If the attribute is nominal, the list consists of each possible value for the attribute along with the number of instances that have that value. If the attribute is numeric, the list gives four statistics describing the distribution of values in the data—the minimum, maximum, mean and standard deviation. And below these statistics there is a coloured histogram, colour-coded according to the attribute chosen as the Class using the box above the histogram. (This box will bring up a drop-down list of available selections when clicked.) Note that only nominal Class attributes will result in a colour-coding. Finally, after pressing the Visualize All button, histograms for all the attributes in the data are shown in a separate window.

Returning to the attribute list, to begin with all the tick boxes are unticked.

They can be toggled on/off by clicking on them individually. The four buttons above can also be used to change the selection:

PREPROCESSING

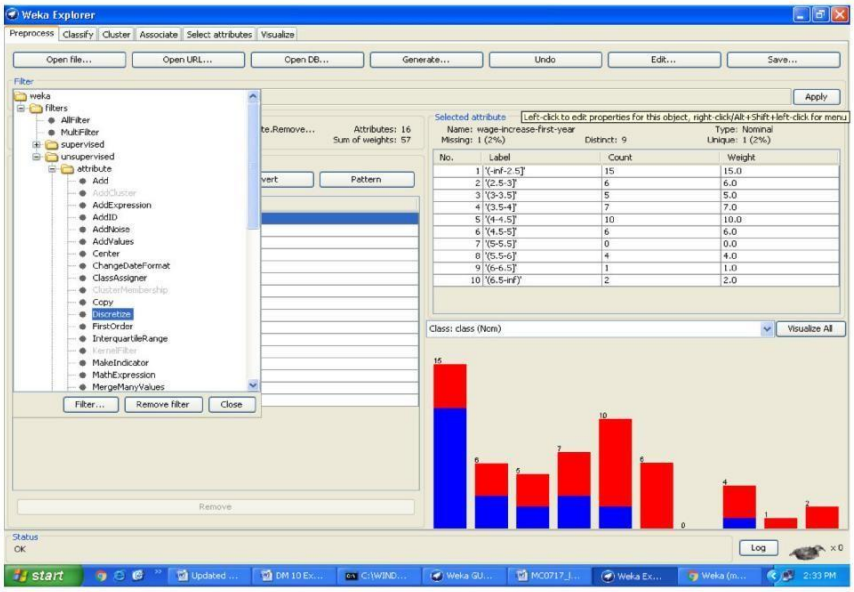
1. **All.** All boxes are ticked.
2. **None.** All boxes are cleared (unticked).
3. **Invert.** Boxes that are ticked become unticked and vice versa.

4. **Pattern.** Enables the user to select attributes based on a Perl 5 Regular Expression. E.g., .* id selects all attributes which name ends with id.

Once the desired attributes have been selected, they can be removed by clicking the Remove button below the list of attributes. Note that this can be undone by clicking the Undo button, which is located next to the Edit button in the top-right corner of the Preprocess panel.

Working with Filters:-

The preprocess section allows filters to be defined that transform the data in various ways. The Filter box is used to set up the filters that are required. At the left of the Filter box is a Choose button. By clicking this button it is possible to select one of the filters in WEKA. Once a filter has been selected, its name and options are shown in the field next to the Choose button. Clicking on this box with the left mouse button brings up a GenericObjectEditor dialog box. A click with the right mouse button (or Alt+Shift+left click) brings up a menu where you can choose, either to display the properties in a GenericObjectEditor dialog box, or to copy the current setup string to the clipboard.



The GenericObjectEditor Dialog Box

The GenericObjectEditor dialog box lets you configure a filter. The same kind of dialog box is used to configure other objects, such as classifiers and clusterers

(see below). The fields in the window reflect the available options.

Right-clicking (or Alt+Shift+Left-Click) on such a field will bring up a popup menu, listing the following options:

1. **Show properties...** has the same effect as left-clicking on the field, i.e., a dialog appears allowing you to alter the settings.

2. **Copy configuration** to clipboard copies the currently displayed configuration string to the **system's clipboar**d and therefore can be used anywhere else in WEKA or in the console. This is rather handy if you have to setup complicated, nested schemes.

3. **Enter configuration... is the —receiving‖ end for configurations that** got copied to the clipboard earlier on. In this dialog you can enter a class name followed by options (if the class supports these). This also allows you to transfer a filter setting from the Preprocess panel to a Filtered Classifier used in the Classify panel.

Left-Clicking on any of these gives an opportunity to alter the filters settings. For example, the setting may take a text string, in which case you type the string into the text field provided. Or it may give a drop-down box listing several states to choose from. Or it may do something else, depending on the information required. Information on the options is provided in a tool tip if you let the mouse pointer hover of the corresponding field. More information on the filter and its options can be obtained by clicking on the More button in the About panel at the top of the GenericObjectEditor window.

Applying Filters

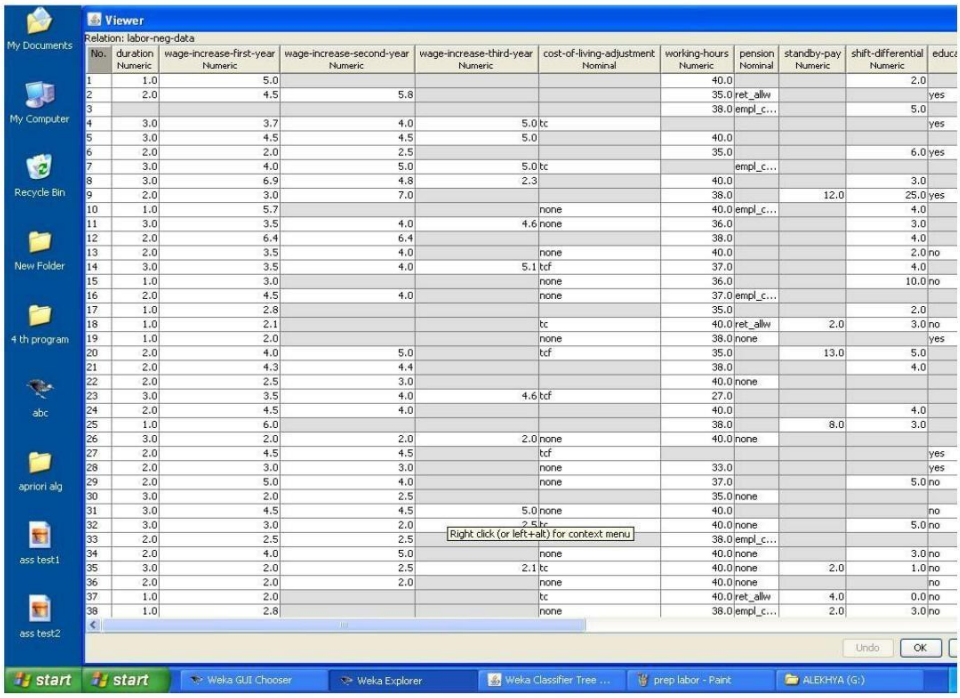
Once you have selected and configured a filter, you can apply it to the data by pressing the Apply button at the right end of the Filter panel in the Preprocess panel. The Preprocess panel will then show the transformed data. The change can be undone by pressing the Undo button. You can also use the Edit...button to modify your data manually in a dataset editor. Finally, the Save...

button at the top right of the Preprocess panel saves the current version of the relation in file formats that can represent the relation, allowing it to be kept for future use.

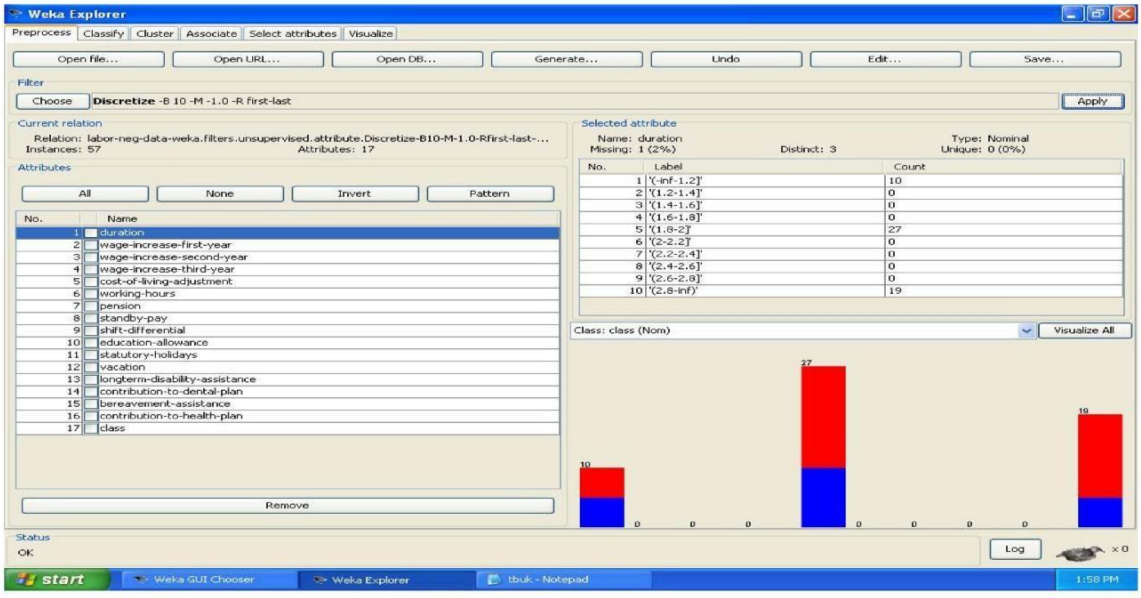
- Steps for run preprocessing tab in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose labor data set and open file.
8. Choose filter button and select the Unsupervised-Discritize option and apply

Dataset labor.arff



The following screenshot shows the effect of discretization



B.Load each dataset into Weka and run Aprior algorithm with different support and confidence values. Study the rules generated.

Ans:

Steps for run Aprior algorithm in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose Weather data set and open file.
8. Click on Associate tab and Choose Aprior algorithm
9. Click on start button.

Output : === Run information ===

Scheme: weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
Relation: weather.symbolic
Instances: 14
Attributes: 5
outlook
temperature
humidity
windy
play
=== Associator model (full training set) ===
Apriori
=======

Minimum support: 0.15 (2 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 17

Generated sets of large itemsets:

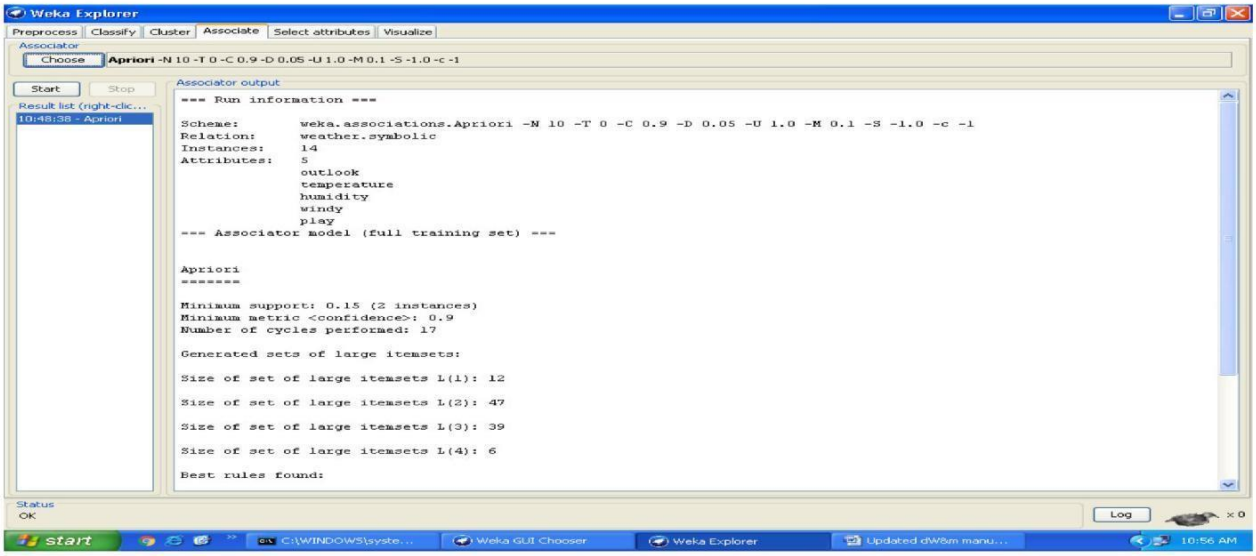
Size of set of large itemsets L(1): 12

Size of set of large itemsets L(2): 47
Size of set of large itemsets L(3): 39

Size of set of large itemsets L(4): 6

Best rules found:

1. outlook=overcast 4 ==> play=yes 4 conf:(1)
2. temperature=cool 4 ==> humidity=normal 4 conf:(1)
3. humidity=normal windy=FALSE 4 ==> play=yes 4 conf:(1)
4. outlook=sunny play=no 3 ==> humidity=high 3 conf:(1)
5. outlook=sunny humidity=high 3 ==> play=no 3 conf:(1)
6. outlook=rainy play=yes 3 ==> windy=FALSE 3 conf:(1)
7. outlook=rainy windy=FALSE 3 ==> play=yes 3 conf:(1)
8. temperature=cool play=yes 3 ==> humidity=normal 3 conf:(1)
9. outlook=sunny temperature=hot 2 ==> humidity=high 2 conf:(1)
10. temperature=hot play=no 2 ==> outlook=sunny 2 conf:(1)



Association Rule:

An association rule has two parts, an antecedent (if) and a consequent (then). An antecedent is an item found in the data. A consequent is an item that is found in combination with the antecedent.

Association rules are created by analyzing data for frequent if/then patterns and using the criteriasupport and confidence to identify the most important relationships. Support is an indication of how frequently the items appear in the database. Confidence indicates the number of times the if/then statements have been found to be true.

In data mining, association rules are useful for analyzing and predicting customer behavior. They play an important part in shopping basket data analysis, product clustering, catalog design and store layout.

Support and Confidence values:

- Support count: The support count of an itemset X, denoted by $X.count$, in a data set T is the number of transactions in T that contain X. Assume T has n transactions.
- Then,

$$support = \frac{(X \cup Y).count}{n}$$

$$confidence = \frac{(X \cup Y).count}{X.count}$$

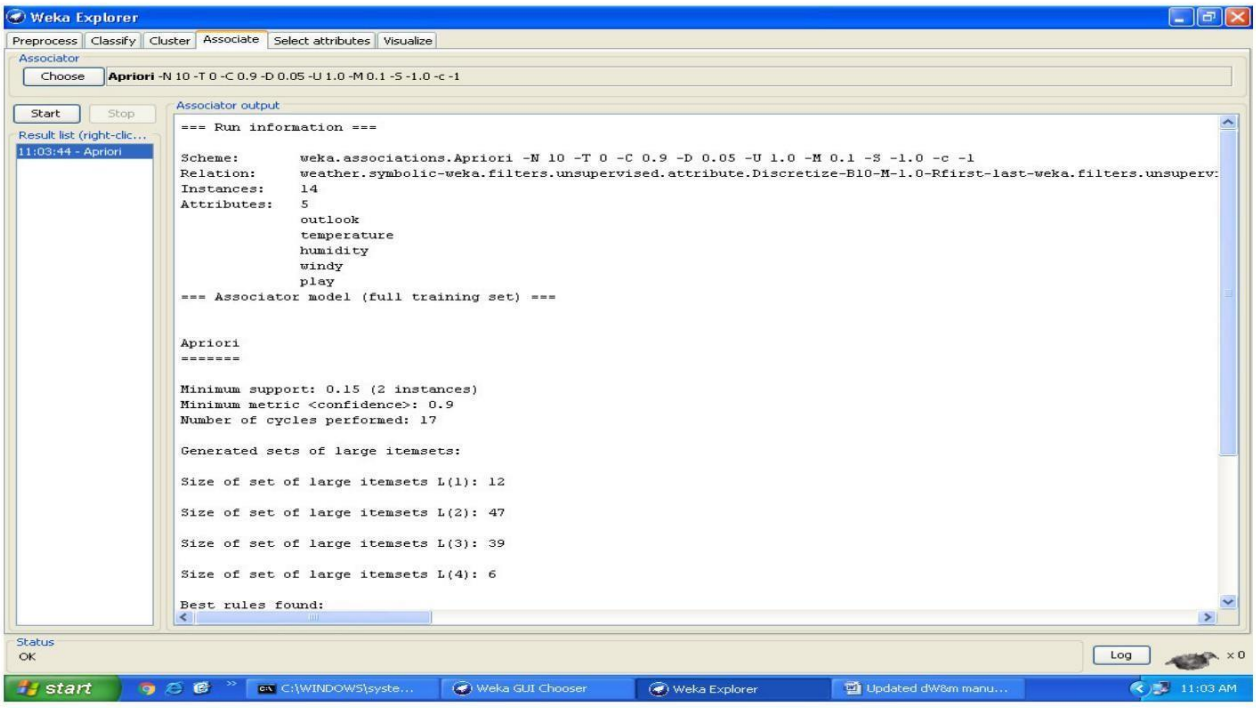
support = support({A U C})

confidence = support({A U C})/support({A})

C. Apply different discretization filters on numerical attributes and run the Aprior association rule algorithm. Study the rules generated. Derive interesting insights and observe the effect of discretization in the rule generation process.

Ans: Steps for run Aprior algorithm in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose Weather data set and open file.
8. Choose filter button and select the Unsupervised-Discritize option and apply
9. Click on Associate tab and Choose Aprior algorithm
10. Click on start button.



Output : === Run information ===

Scheme: weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
Relation: weather.symbolic
Instances: 14
Attributes: 5
outlook
temperature
humidity
windy
play
=== Associator model (full training set) ===
Apriori
=======
Minimum support: 0.15 (2 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 17

Generated sets of large itemsets:

Size of set of large itemsets L(1): 12

Size of set of large itemsets L(2): 47
Size of set of large itemsets L(3): 39

Size of set of large itemsets L(4): 6

Best rules found:

1. outlook=overcast 4 ==> play=yes 4 conf:(1)
2. temperature=cool 4 ==> humidity=normal 4 conf:(1)
3. humidity=normal windy=FALSE 4 ==> play=yes 4 conf:(1)
4. outlook=sunny play=no 3 ==> humidity=high 3 conf:(1)
5. outlook=sunny humidity=high 3 ==> play=no 3 conf:(1)
6. outlook=rainy play=yes 3 ==> windy=FALSE 3 conf:(1)
7. outlook=rainy windy=FALSE 3 ==> play=yes 3 conf:(1)

Unit – III Demonstrate performing classification on data sets.

Classification Tab

Selecting a Classifier

At the top of the classify section is the Classifier box. This box has a text fieldthat gives the name of the currently selected classifier, and its options. Clicking on the text box with the left mouse button brings up a GenericObjectEditor dialog box, just the same as for filters, that you can use to configure the options of the current classifier. With a right click (or Alt+Shift+left click) you can once again copy the setup string to the clipboard or display the properties in a GenericObjectEditor dialog box. The Choose button allows you to choose one of the classifiers that are available in WEKA.

Exercise:1)performing APRIOIRI Algorithm mining on data sets
2) performing FP-Growth Algorithm mining on data sets
3) performing Vertical FormatAlgorithm mining on data sets

1. Use training set. The classifier is evaluated on how well it predicts the class of the instances it was trained on.

2. Supplied test set. The classifier is evaluated on how well it predicts the class of a set of instances loaded from a file. Clicking the Set... button brings up a dialog allowing you to choose the file to test on.

3. Cross-validation. The classifier is evaluated by cross-validation, using the number of folds that are entered in the Folds text field.

4. Percentage split. The classifier is evaluated on how well it predicts a certain percentage of the data which is held out for testing. The amount of data held out depends on the value entered in the % field.

Classifier Evaluation Options:

1. Output model. The classification model on the full training set is output so that it can be viewed, visualized, etc. This option is selected by default.

2. Output per-class stats. The precision/recall and true/false statistics for each class are output. This option is also selected by default.

3. Output entropy evaluation measures. Entropy evaluation measures are included in the output. This option is not selected by default.

4. Output confusion matrix. The confusion matrix of the classifier's predictions is included in the output. This option is selected by default.

5. Store predictions for visualization. Th**e classifier's predictions are** remembered so that they can be visualized. This option is selected by default.

6. Output predictions. The predictions on the evaluation data are output.

Note that in the case of a cross-validation the instance numbers do not correspond to the location in the data!

7. Output additional attributes. If additional attributes need to be output alongside the

predictions, e.g., an ID attribute for tracking misclassifications, then the index of this attribute can be specified here. The usual **Weka ranges are supported,—first‖ and —last‖ are therefore valid** indices as **well (example: —first**-3,6,8,12-**last‖).**

8. Cost-sensitive evaluation. The errors is evaluated with respect to a cost matrix. The Set... button allows you to specify the cost matrix used.

9. Random seed for xval / % Split. This specifies the random seed used when randomizing the data before it is divided up for evaluation purposes.

10. Preserve order for % Split. This suppresses the randomization of the data before splitting into train and test set.

11. Output source code. If the classifier can output the built model as Java source code, you can specify the class name here. The code will be printed **in the —Classifier output‖ area.**

attribute, which is the target for prediction. Some classifiers can only learn nominal classes; others can only learn numeric classes (regression problems) still others can learn both.

By default, the class is taken to be the last attribute in the data. If you want

to train a classifier to predict a different attribute, click on the box below the Test options box to bring up a drop-down list of attributes to choose from.

Training a Classifier

Once the classifier, test options and class have all been set, the learning process is started by clicking on the Start button. While the classifier is busy being trained, the little bird moves around. You can stop the training process at any time by clicking on the Stop button. When training is complete, several things happen. The Classifier output area to the right of the display is filled with text describing the results of training and testing. A new entry appears in the Result list box. We look at the result list below; but first we investigate the text that has been output.

A. Load each dataset into Weka and run id3, j48 classification algorithm, study the classifier output. Compute entropy values, Kappa ststistic.

Ans:

- Steps for run ID3 and J48 Classification algorithms in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose iris data set and open file.
8. Click on classify tab and Choose J48 algorithm and select use training set test option.
9. Click on start button.
10. Click on classify tab and Choose ID3 algorithm and select use training set test option.
11. Click on start button.

Output:

```
=== Run information ===

Scheme:weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     iris
Instances:    150
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode:evaluate on training data

=== Classifier model (full training set) ===

J48 pruned tree
------------------

petalwidth <= 0.6: Iris-setosa (50.0)
petalwidth > 0.6
| petalwidth <= 1.7
| | petallength <= 4.9: Iris-versicolor (48.0/1.0)
| | petallength > 4.9
| | | petalwidth <= 1.5: Iris-virginica (3.0)
| | | petalwidth > 1.5: Iris-versicolor (3.0/1.0)
| petalwidth > 1.7: Iris-virginica (46.0/1.0)

Number of Leaves :      5

Size of the tree :          9


Time taken to build model: 0 seconds

=== Evaluation on training set ===
=== Summary ===
```

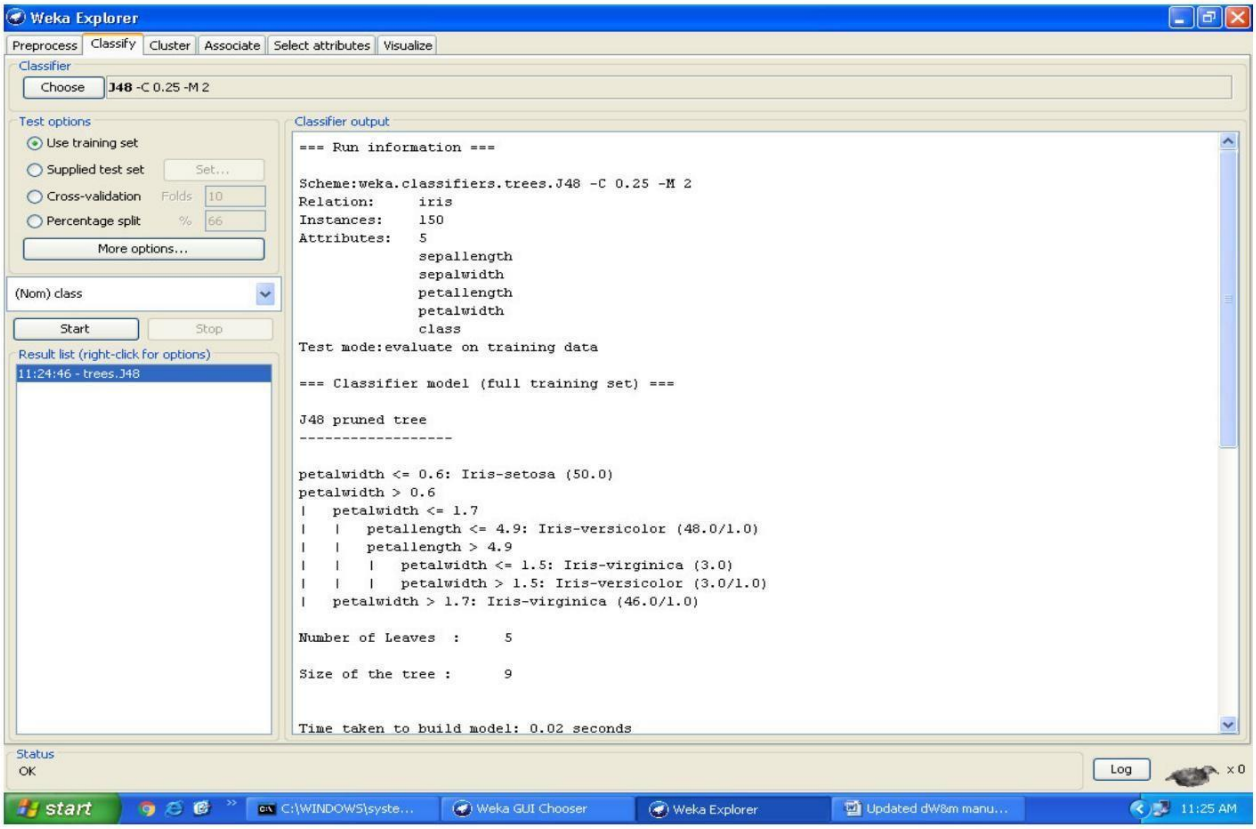
Correctly Classified Instances	147	98	%
Incorrectly Classified Instances	3	2	%
Kappa statistic	0.97		
K&B Relative Info Score	14376.1925 %		
K&B Information Score	227.8573 bits	1.519	bits/instance
Class complexity | order 0	237.7444 bits	1.585	bits/instance
Class complexity | scheme	16.7179 bits	0.1115	bits/instance
Complexity improvement (Sf)	221.0265 bits	1.4735	bits/instance
Mean absolute error	0.0233		
Root mean squared error	0.108		
Relative absolute error	5.2482 %		
Root relative squared error	22.9089 %		
Total Number of Instances	150		

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	Iris-setosa
0.98	0.02	0.961	0.98	0.97	0.99	Iris-versicolor
0.96	0.01	0.98	0.96	0.97	0.99	Iris-virginica
Weighted Avg.	0.98	0.01	0.98	0.98	0.98	0.993

=== Confusion Matrix ===

```
a b c   <-- classified as
50 0 0 | a = Iris-setosa
0 49 1 | b = Iris-versicolor
0 2 48 | c = Iris-virginica
```



The Classifier Output Text

The text in the Classifier output area has scroll bars allowing you to browse the results. Clicking with the left mouse button into the text area, while holding Alt and Shift, brings up a dialog that enables you to save the displayed output

in a variety of formats (currently, BMP, EPS, JPEG and PNG). Of course, you can also resize the Explorer window to get a larger display area.

The output is

Split into several sections:

1. Run information. A list of information giving the learning scheme options, relation name, instances, attributes and test mode that were involved in the process.

2. Classifier model (full training set). A textual representation of the classification model that was produced on the full training data.

3. The results of the chosen test mode are broken down thus.

4. Summary. A list of statistics summarizing how accurately the classifier was able to predict the true class of the instances under the chosen test mode.

5. Detailed Accuracy By Class. A more detailed per-class break down **of the classifier's** prediction accuracy.

6. Confusion Matrix. Shows how many instances have been assigned to each class. Elements show the number of test examples whose actual class is the row and whose predicted class is the column.

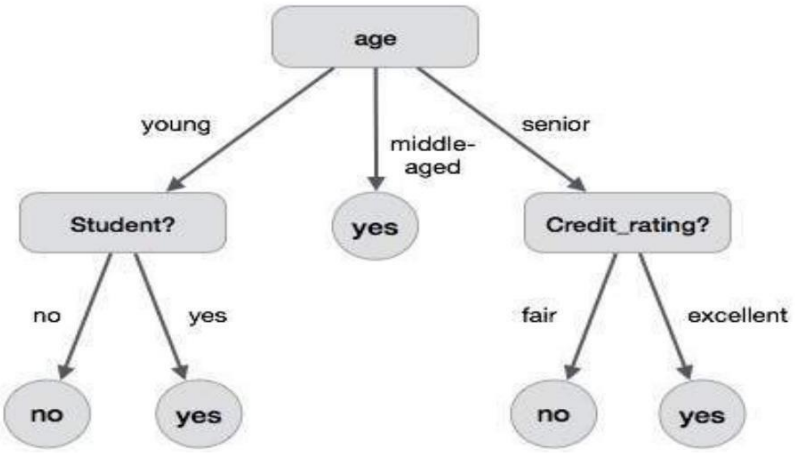
7. Source code (optional). This section lists the Java source code if one
chose —Output source code‖ in the —More options‖ dialog.

B.E xtract if-then rues from decision tree gentrated by classifier, Observe the confusion matrix and derive Accuracy, F- measure, TPrate, FPrate , Precision and recall values. Apply cross-validation strategy with various fold levels and compare the accuracy results.

Ans:

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.

IF-THEN Rules:

Rule-based classifier makes use of a set of IF-THEN rules for classification. We can express a rule in the following from −

IF condition THEN conclusion

Let us consider a rule R1,

R1: IF age=youth AND student=yes

THEN buy_computer=yes

Points to remember −

- The IF part of the rule is called **rule antecedent** or**precondition**.
- The THEN part of the rule is called **rule consequent**.
- The antecedent part the condition consist of one or more attribute tests and these tests are logically ANDed.
- The consequent part consists of class prediction.

Note − We can also write rule R1 as follows:

R1: (age = youth) ^ (student = yes))(buys computer = yes)

If the condition holds true for a given tuple, then the antecedent is satisfied.

Rule Extraction

Here we will learn how to build a rule-based classifier by extracting IF-THEN rules from a decision tree.

Points to remember −

- One rule is created for each path from the root to the leaf node.
- To form a rule antecedent, each splitting criterion is logically ANDed.
- The leaf node holds the class prediction, forming the rule consequent.

Rule Induction Using Sequential Covering Algorithm

Sequential Covering Algorithm can be used to extract IF-THEN rules form the training data. We do not require to generate a decision tree first. In this algorithm, each rule for a given class covers many of the tuples of that class.

Some of the sequential Covering Algorithms are AQ, CN2, and RIPPER. As per the general strategy the rules are learned one at a time. For each time rules are learned, a tuple covered by the rule is removed and the process continues for the rest of the tuples. This is because the path to each leaf in a decision tree corresponds to a rule.

Note − The Decision tree induction can be considered as learning a set of rules simultaneously.

The Following is the sequential learning Algorithm where rules are learned for one class at a time. When learning a rule from a class Ci, we want the rule to cover all the tuples from class C only and no tuple form any other class.

Algorithm: Sequential Covering

Input:
D, a data set class-labeled tuples,
Att_vals, the set of all attributes and their possible values.

```
Output: A Set of IF-THEN rules.
Method:
Rule_set={ }; // initial set of rules learned is empty

for each class c do

repeat
Rule = Learn_One_Rule(D, Att_valls, c);
remove tuples covered by Rule form D;
until termination condition;

Rule_set=Rule_set+Rule; // add a new rule to rule-set
end for
return Rule_Set;
```

Rule Pruning

The rule is pruned is due to the following reason −

- The Assessment of quality is made on the original set of training data. The rule may perform well on training data but less well on subsequent data. That's why the rule pruning is required.
- The rule is pruned by removing conjunct. The rule R is pruned, if pruned version of R has greater quality than what was assessed on an independent set of tuples.

FOIL is one of the simple and effective method for rule pruning. For a given rule R,

FOIL_Prune = pos - neg / pos + neg

where pos and neg is the number of positive tuples covered by R, respectively.

Note − This value will increase with the accuracy of R on the pruning set. Hence, if the FOIL_Prune value is higher for the pruned version of R, then we prune R.

- Steps for run decision tree algorithms in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.

4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose iris data set and open file.
8. Click on classify tab and Choose decision table algorithm and select cross-validation folds value-10 test option.
9. Click on start button.

Output:

=== Run information ===
Scheme:weka.classifiers.rules.DecisionTable -X 1 -S "weka.attributeSelection.BestFirst -D 1 -N 5"
Relation: iris
Instances: 150
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode:10-fold cross-validation

=== Classifier model (full training set) ===

Decision Table:

Number of training instances: 150
Number of Rules : 3
Non matches covered by Majority class.
Best first.
Start set: no attributes
Search direction: forward
Stale search after 5 node expansions
Total number of subsets evaluated: 12
Merit of best subset found: 96
Evaluation (for feature selection): CV (leave one out)
Feature set: 4,5

Time taken to build model: 0.02 seconds

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

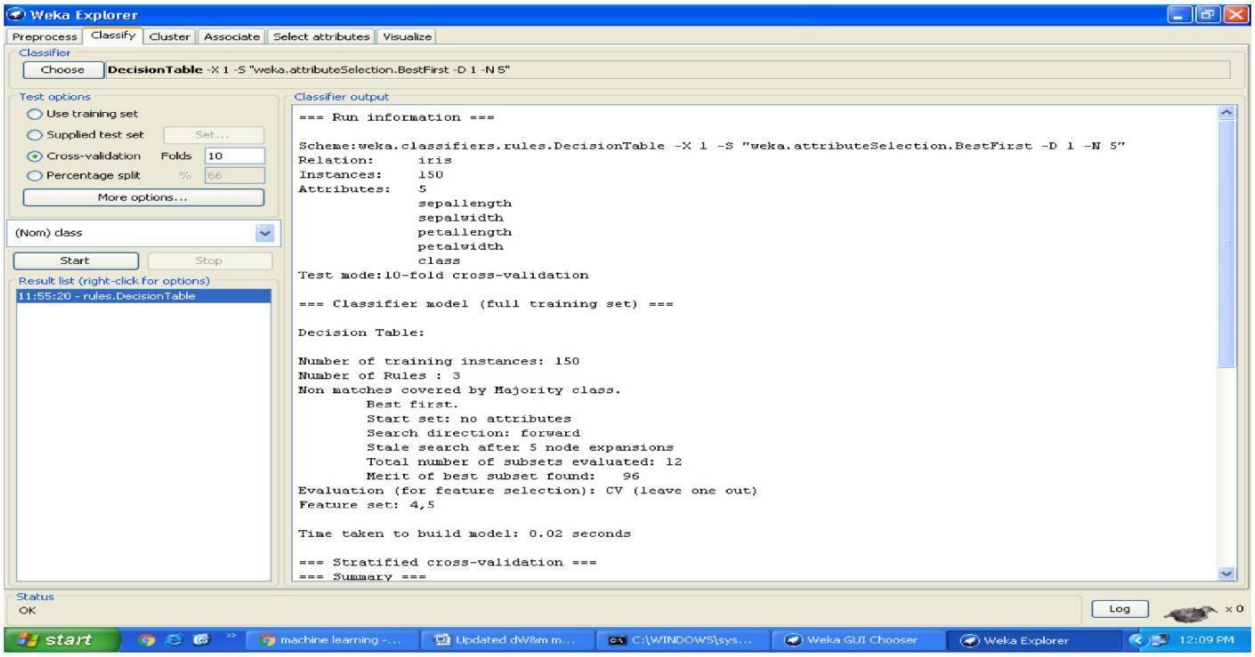
Correctly Classified Instances	139	92.6667 %
Incorrectly Classified Instances	11	7.3333 %
Kappa statistic	0.89	
Mean absolute error	0.092	
Root mean squared error	0.2087	
Relative absolute error	20.6978 %	
Root relative squared error	44.2707 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	Iris-setosa
0.88	0.05	0.898	0.88	0.889	0.946	Iris-versicolor
0.9	0.06	0.882	0.9	0.891	0.947	Iris-virginica
Weighted Avg.	0.927	0.037	0.927	0.927	0.927	0.964

=== Confusion Matrix ===

```
a b c   <-- classified as
50 0 0 | a = Iris-setosa
0 44 6 | b = Iris-versicolor
0 5 45 | c = Iris-virginica
```



C. Load each dataset into Weka and perform Naïve-bayes classification and k-Nearest Neighbor classification, Interpret the results obtained.

Ans:

➊ Steps for run Naïve-bayes and k-nearest neighbor Classification algorithms in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose iris data set and open file.
8. Click on classify tab and Choose Naïve-bayes algorithm and select use training set test option.
9. Click on start button.
10. Click on classify tab and Choose k-nearest neighbor and select use training set test option.
11. Click on start button.

Output: Naïve Bayes

=== Run information ===

Scheme:weka.classifiers.bayes.NaiveBayes
Relation: iris
Instances: 150
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode:evaluate on training data

=== Classifier model (full training set)

=== Naive Bayes Classifier

Class Attribute	Iris-setosa (0.33)	Iris-versicolor (0.33)	Iris-virginica (0.33)
sepallength			
mean	4.9913	5.9379	6.5795
std. dev.	0.355	0.5042	0.6353
weight sum	50	50	50
precision	0.1059	0.1059	0.1059
sepalwidth			
mean	3.4015	2.7687	2.9629
std. dev.	0.3925	0.3038	0.3088
weight sum	50	50	50
precision	0.1091	0.1091	0.1091
petallength			

mean	1.4694	4.2452	5.5516
std. dev.	0.1782	0.4712	0.5529
weight sum	50	50	50
precision	0.1405	0.1405	0.1405

petalwidth

mean	0.2743	1.3097	2.0343
std. dev.	0.1096	0.1915	0.2646
weight sum	50	50	50
precision	0.1143	0.1143	0.1143

Time taken to build model: 0 seconds

=== Evaluation on training set ===

=== Summary ===

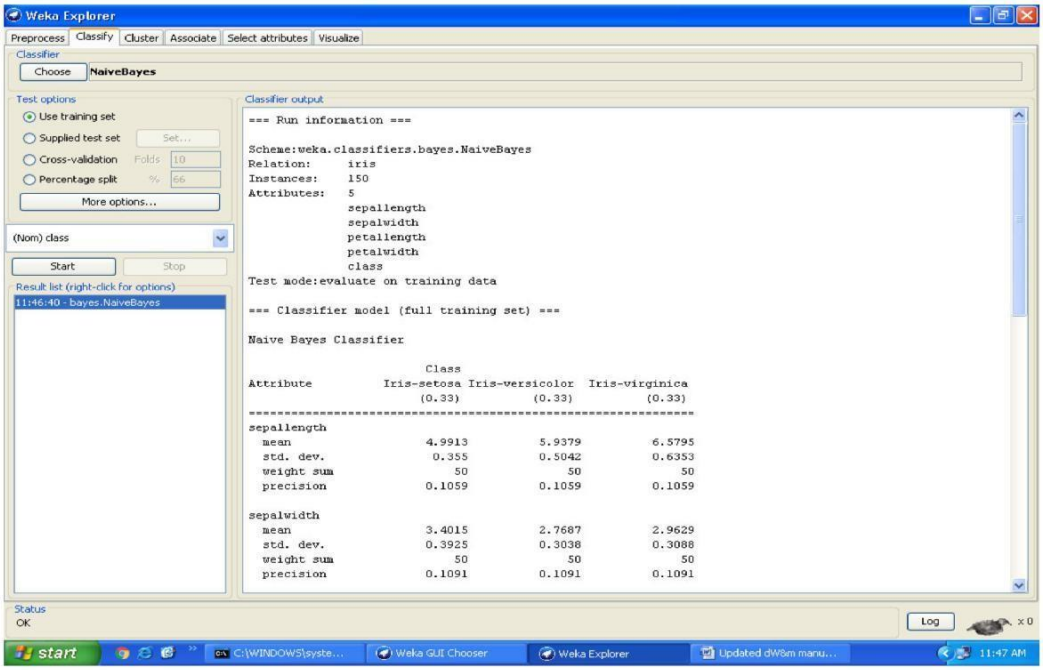
Correctly Classified Instances	144	96 %
Incorrectly Classified Instances	6	4 %
Kappa statistic	0.94	
Mean absolute error	0.0324	
Root mean squared error	0.1495	
Relative absolute error	7.2883 %	
Root relative squared error	31.7089 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	Iris-setosa
0.96	0.04	0.923	0.96	0.941	0.993	Iris-versicolor
0.92	0.02	0.958	0.92	0.939	0.993	Iris-virginica
Weighted Avg.	0.96	0.02	0.96	0.96	0.96	0.995

=== Confusion Matrix ===

a b c <-- classified as
50 0 0 | a = Iris-setosa
0 48 2 | b = Iris-versicolor
0 4 46 | c = Iris-virginica.



Output: KNN (IBK)

=== Run information ===

Scheme:weka.classifiers.lazy.IBk -K 1 -W 0 -A "weka.core.neighboursearch.LinearNNSearch -A \"weka.core.EuclideanDistance -R first-last\""
Relation: iris
Instances: 150
Attributes: 5
sepallength
sepalwidth
petallength

petalwidth
class
Test mode:evaluate on training data

=== Classifier model (full training set) ===

IB1 instance-based classifier
using 1 nearest neighbour(s) for classification

Time taken to build model: 0 seconds

=== Evaluation on training set ===
=== Summary ===

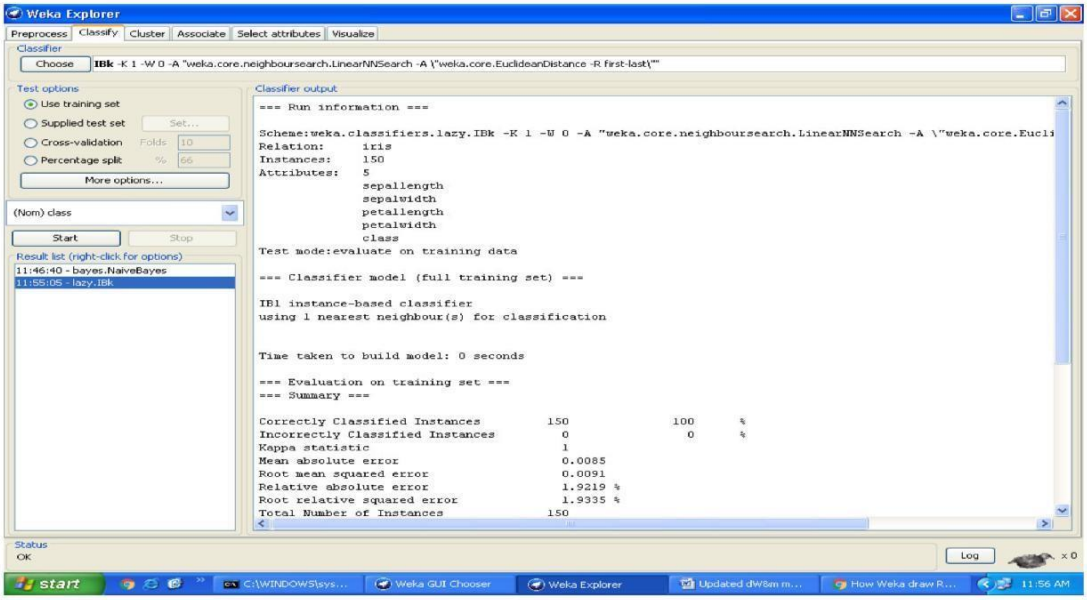
Correctly Classified Instances	150	100 %
Incorrectly Classified Instances	0	0 %
Kappa statistic	1	
Mean absolute error	0.0085	
Root mean squared error	0.0091	
Relative absolute error	1.9219 %	
Root relative squared error	1.9335 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	Iris-setosa
1	0	1	1	1	1	Iris-versicolor
1	0	1	1	1	1	Iris-virginica
Weighted Avg. 1	0	1	1	1	1	

=== Confusion Matrix ===

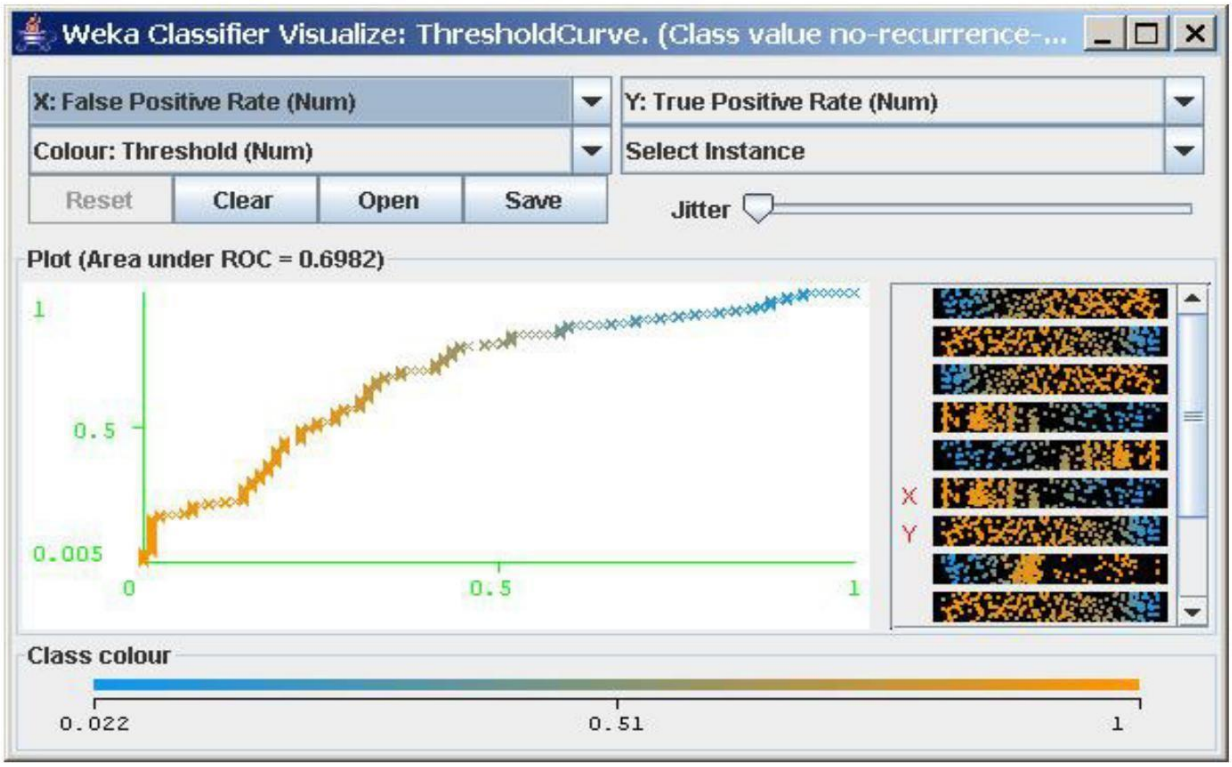
a	b	c	<-- classified as
50	0	0	a = Iris-setosa
0	50	0	b = Iris-versicolor
0	0	50	c = Iris-virginica



D. Plot RoC Curves.

Ans: Steps for identify the plot RoC Curves.

Exercise:1)performing Decision Trees-Decision tree Construction mining on data sets
2) performing Naive-Bayes Classifier mining on data sets
3)performing K- Nearest neighbor classification mining on data sets



E. Compare classification results of ID3,J48, Naïve-Bayes and k-NN classifiers for each dataset, and reduce which classifier is performing best and poor for each dataset and justify.

Ans:

➊ Steps for run ID3 and J48 Classification algorithms in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose iris data set and open file.
8. Click on classify tab and Choose J48 algorithm and select use training set test option.

9. Click on start button.
10. Click on classify tab and Choose ID3 algorithm and select use training set test option.
11. Click on start button.
12. Click on classify tab and Choose Naïve-bayes algorithm and select use training set test option.
13. Click on start button.
14. Click on classify tab and Choose k-nearest neighbor and select use training set test option.
15. Click on start button.

J48:

=== Run information ===

Scheme:weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: iris
Instances: 150
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode:evaluate on training data

=== Classifier model (full training set) ===
J48 pruned tree
---
petalwidth <= 0.6: Iris-setosa (50.0)
petalwidth > 0.6
| petalwidth <= 1.7
| | petallength <= 4.9: Iris-versicolor (48.0/1.0)
| | petallength > 4.9
| | | petalwidth <= 1.5: Iris-virginica (3.0)
| | | petalwidth > 1.5: Iris-versicolor (3.0/1.0)
| petalwidth > 1.7: Iris-virginica (46.0/1.0)

Number of Leaves : 5

Size of the tree : 9

Time taken to build model: 0 seconds

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	147	98 %
Incorrectly Classified Instances	3	2 %
Kappa statistic	0.97	
Mean absolute error	0.0233	
Root mean squared error	0.108	
Relative absolute error	5.2482 %	
Root relative squared error	22.9089 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	Iris-setosa
0.98	0.02	0.961	0.98	0.97	0.99	Iris-versicolor
0.96	0.01	0.98	0.96	0.97	0.99	Iris-virginica
Weighted Avg.	0.98	0.01	0.98	0.98	0.98	0.993

=== Confusion Matrix ===

a	b	c	<-- classified as
50	0	0	a = Iris-setosa
0	49	1	b = Iris-versicolor
0	2	48	c = Iris-virginica

Naïve-bayes:

=== Run information ===

Scheme:weka.classifiers.bayes.NaiveBayes
Relation: iris
Instances: 150
Attributes: 5
sepallength

sepalwidth
petallength
petalwidth
class
Test mode:evaluate on training data
=== Classifier model (full training set) ===
Naive Bayes Classifier
Class
Attribute Iris-setosa Iris-versicolor Iris-virginica
(0.33) (0.33) (0.33)
==========

sepallength			
mean	4.9913	5.9379	6.5795
std. dev.	0.355	0.5042	0.6353
weight sum	50	50	50
precision	0.1059	0.1059	0.1059
sepalwidth			
mean	3.4015	2.7687	2.9629
std. dev.	0.3925	0.3038	0.3088
weight sum	50	50	50
precision	0.1091	0.1091	0.1091
petallength			
mean	1.4694	4.2452	5.5516
std. dev.	0.1782	0.4712	0.5529
weight sum	50	50	50
precision	0.1405	0.1405	0.1405
petalwidth			
mean	0.2743	1.3097	2.0343
std. dev.	0.1096	0.1915	0.2646
weight sum	50	50	50
precision	0.1143	0.1143	0.1143

Time taken to build model: 0 seconds

=== Evaluation on training set ===

=== Summary ===

Correctly Classified Instances	144	96 %
Incorrectly Classified Instances	6	4 %
Kappa statistic	0.94	
Mean absolute error	0.0324	
Root mean squared error	0.1495	
Relative absolute error	7.2883 %	
Root relative squared error	31.7089 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	Iris-setosa
0.96	0.04	0.923	0.96	0.941	0.993	Iris-versicolor
0.92	0.02	0.958	0.92	0.939	0.993	Iris-virginica
Weighted Avg.	0.96	0.02	0.96	0.96	0.96	0.995

=== Confusion Matrix ===

a b c <-- classified as
50 0 0 | a = Iris-setosa
0 48 2 | b = Iris-versicolor
0 4 46 | c = Iris-virginica

K-Nearest Neighbor (IBK):

=== Run information ===

Scheme:weka.classifiers.lazy.IBk -K 1 -W 0 -A "weka.core.neighboursearch.LinearNNSearch -A \"weka.core.EuclideanDistance -R first-last\""
Relation: iris
Instances: 150
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode:evaluate on training data

=== Classifier model (full training set) ===

IB1 instance-based classifier
using 1 nearest neighbour(s) for classification

Time taken to build model: 0 seconds
=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	150	100 %
Incorrectly Classified Instances	0	0 %
Kappa statistic	1	
Mean absolute error	0.0085	
Root mean squared error	0.0091	
Relative absolute error	1.9219 %	
Root relative squared error	1.9335 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	Iris-setosa
1	0	1	1	1	1	Iris-versicolor
1	0	1	1	1	1	Iris-virginica
Weighted Avg. 1	0	1	1	1	1	

=== Confusion Matrix ===

a b c <-- classified as
50 0 0 | a = Iris-setosa
0 50 0 | b = Iris-versicolor
0 0 50 | c = Iris-virginica

Unit – IV demonstrate performing clustering on data sets Clustering Tab

Selecting a Clusterer

By now you will be familiar with the process of selecting and configuring objects. Clicking on the clustering scheme listed in the Clusterer box at the top of the

window brings up a GenericObjectEditor dialog with which to choose a new clustering scheme.

Cluster Modes

The Cluster mode box is used to choose what to cluster and how to evaluate

the results. The first three options are the same as for classification: Use training set, Supplied test set and Percentage split (Section 5.3.1)—except that now the data is assigned to clusters instead of trying to predict a specific class. The fourth mode, Classes to clusters evaluation, compares how well the chosen clusters match up with a pre-assigned class in the data. The drop-down box below this option selects the class, just as in the Classify panel.

An additional option in the Cluster mode box, the Store clusters for visualization tick box, determines whether or not it will be possible to visualize the clusters once training is complete. When dealing with datasets that are so large that memory becomes a problem it may be helpful to disable this option.

Ignoring Attributes

Often, some attributes in the data should be ignored when clustering. The Ignore attributes button brings up a small window that allows you to select which attributes are ignored. Clicking on an attribute in the window highlights it, holding down the SHIFT key selects a range

of consecutive attributes, and holding down CTRL toggles individual attributes on and off. To cancel the selection, back out with the Cancel button. To activate it, click the Select button. The next time clustering is invoked, the selected attributes are ignored.

Working with Filters

The Filtered Clusterer meta-clusterer offers the user the possibility to apply filters directly before the clusterer is learned. This approach eliminates the manual application of a filter in the Preprocess panel, since the data gets processed on the fly. Useful if one needs to try out different filter setups.

Learning Clusters

The Cluster section, like the Classify section, has Start/Stop buttons, a result text area and a result list. These all behave just like their classification counterparts. Right-clicking an entry in the result list brings up a similar menu, except that it shows only two visualization options: Visualize cluster assignments and Visualize tree. The latter is grayed out when it is not applicable.

A.Load each dataset into Weka and run simple k-means clustering algorithm with different values of k(number of desired clusters). Study the clusters formed. Observe the sum of squared errors and centroids, and derive insights.

Ans:

- Steps for run K-mean Clustering algorithms in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose iris data set and open file.
8. Click on cluster tab and Choose k-mean and select use training set test option.
9. Click on start button.

Output:

=== Run information ===

Scheme:weka.clusterers.SimpleKMeans -N 2 -A "weka.core.EuclideanDistance -R first-last" -I 500 -S 10
Relation: iris

Instances: 150
Attributes: 5
sepallength
sepalwidth
petallength
petalwidth
class
Test mode:evaluate on training data

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

kMeans
======
Number of iterations: 7
Within cluster sum of squared errors: 62.1436882815797
Missing values globally replaced with mean/mode

Cluster centroids:

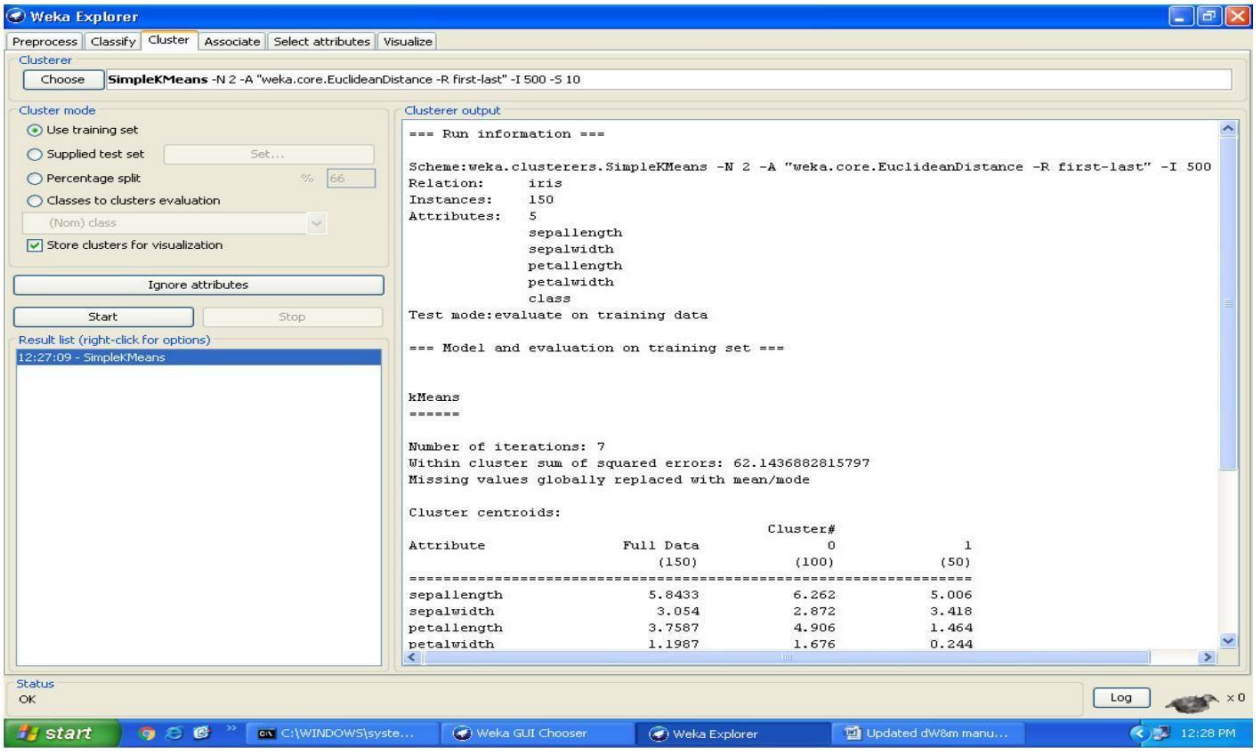
Cluster#			
Attribute	Full Data	0	1
	(150)	(100)	(50)
sepallength	5.8433	6.262	5.006
sepalwidth	3.054	2.872	3.418
petallength	3.7587	4.906	1.464
petalwidth	1.1987	1.676	0.244
class	Iris-setosa	Iris-versicolor	Iris-setosa

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

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

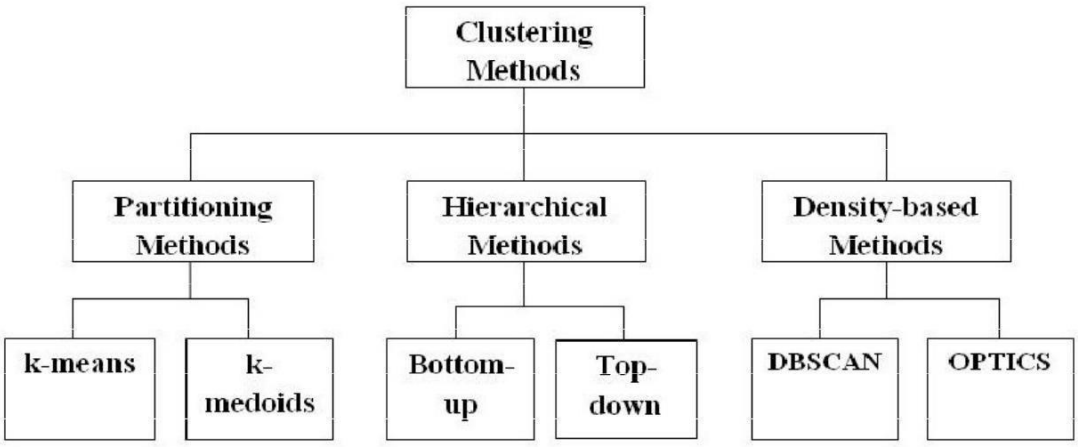
Clustered Instances

0 100 (67%)
1 50 (33%)



B.Explore other clustering techniques available in Weka.

Ans: Clustering Algorithms And Techniques in WEKA, They are



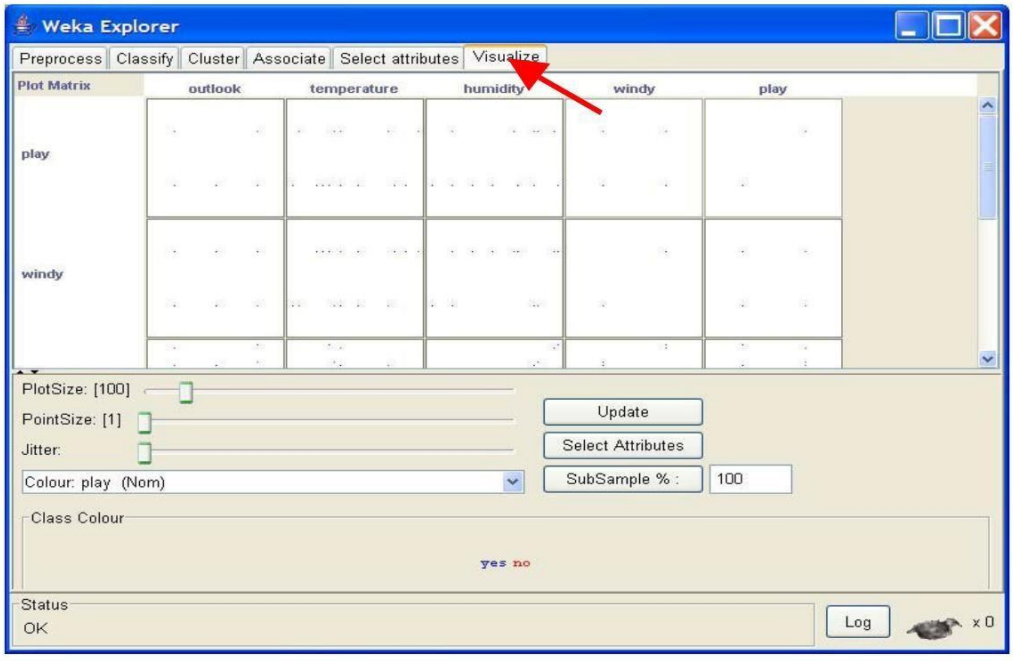
C.Explore visualization features of weka to visualize the clusters. Derive interesting insights and explain.

Ans: Visualize Features

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.

Access To **Visualization** From The *Classifier*, *Cluster* And *Attribute Selection* Panel Is Available From A Popup Menu. Click The Right Mouse Button Over An Entry In The Result List To Bring Up The Menu. You Will Be Presented With Options For Viewing Or Saving The Text Output And --- Depending On The Scheme --- Further Options For Visualizing Errors, Clusters, Trees Etc.

To open Visualization screen, click _Visualize' tab.



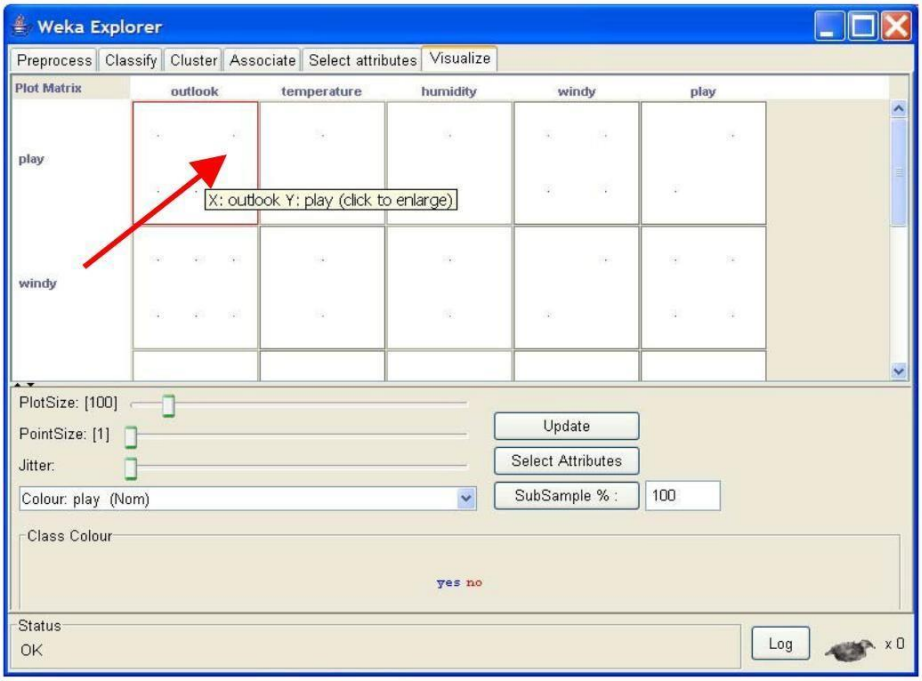
Select a square that corresponds to the attributes you would like to visualize. For example, let‘s choose _outlook‘ for X – axis and _play‘ for Y – axis. Click anywhere inside the square that corresponds to _play o

Changing the View:

In the visualization window, beneath the X-axis selector there is a drop-down list,

_Colour‘, for choosing the color scheme. This allows you to choose the color of points based on the attribute selected. Below the plot area, there is a legend that describes what values the colors correspond to. In your example, red represents _no‘, while blue represents _yes‘. For better visibility you should change the color of label _yes‘. Left-click on _yes‘ in the _Class colour‘ box and select lighter color from the color palette.

n the left and _outlook‘ at the top.

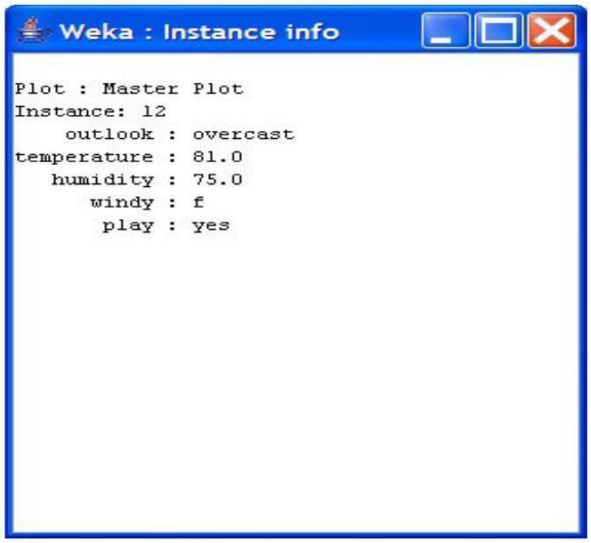


Selecting Instances

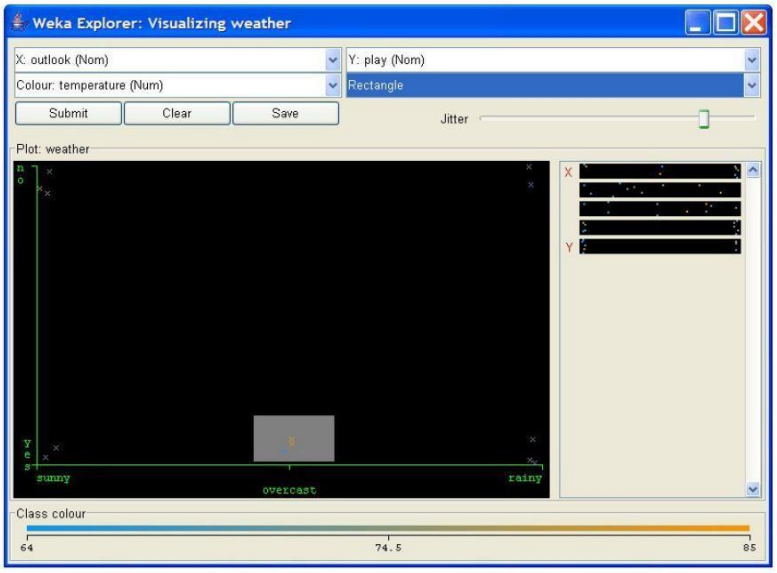
Sometimes it is helpful to select a subset of the data using visualization tool. A special case is the _UserClassifier‘, which lets you to build your own classifier by interactively selecting instances. Below the Y – axis there is a drop-down list that allows you to choose a selection method. A group of points on the graph can be selected in four ways [2]:

1. **Select Instance**. Click on an individual data point. It brings up a window listing

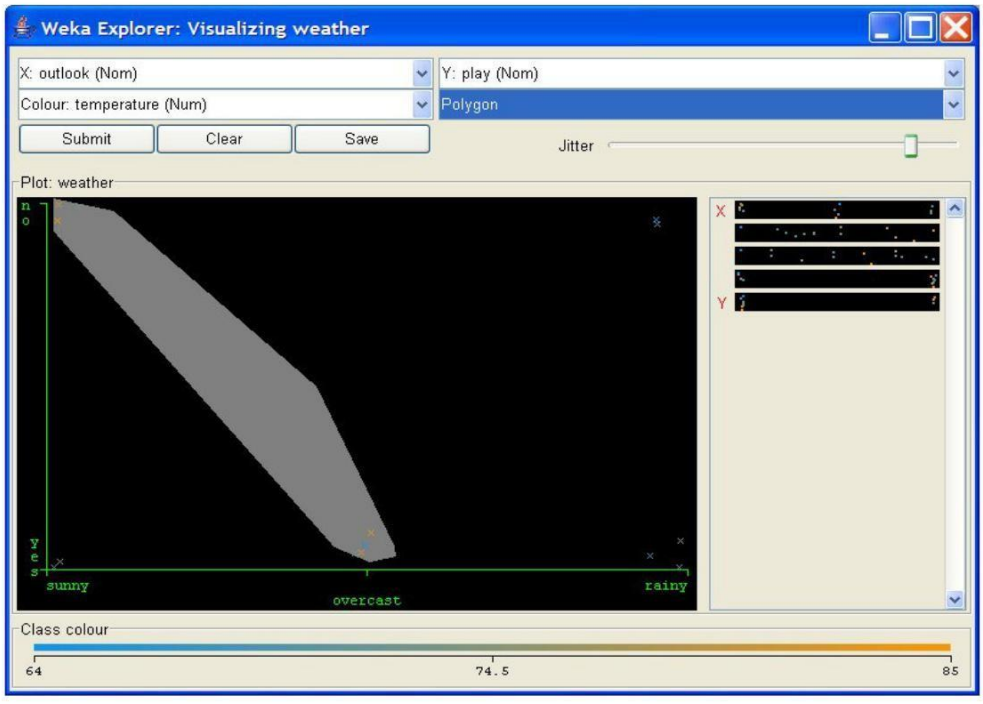
   attributes of the point. If more than one point will appear at the same location, more than one set of attributes will be shown.



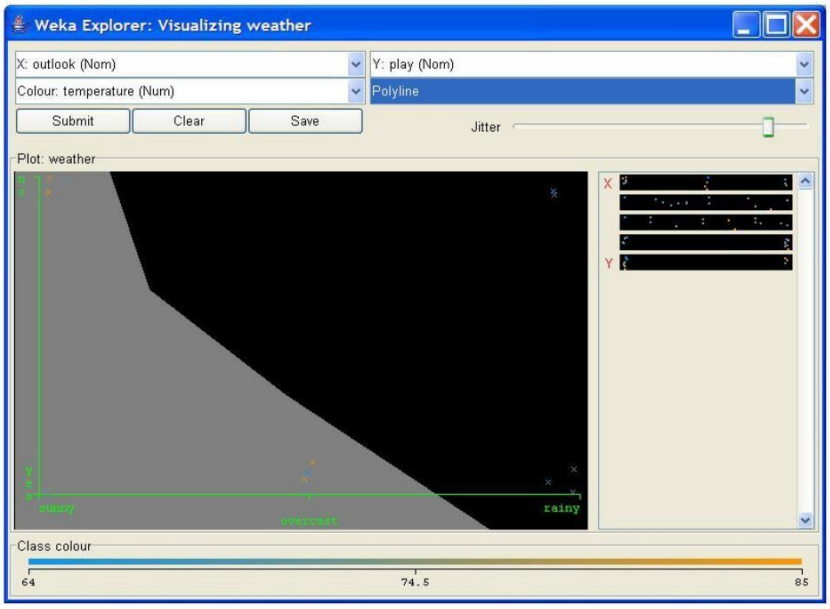
2. **Rectangle**. You can create a rectangle by dragging it around the point.

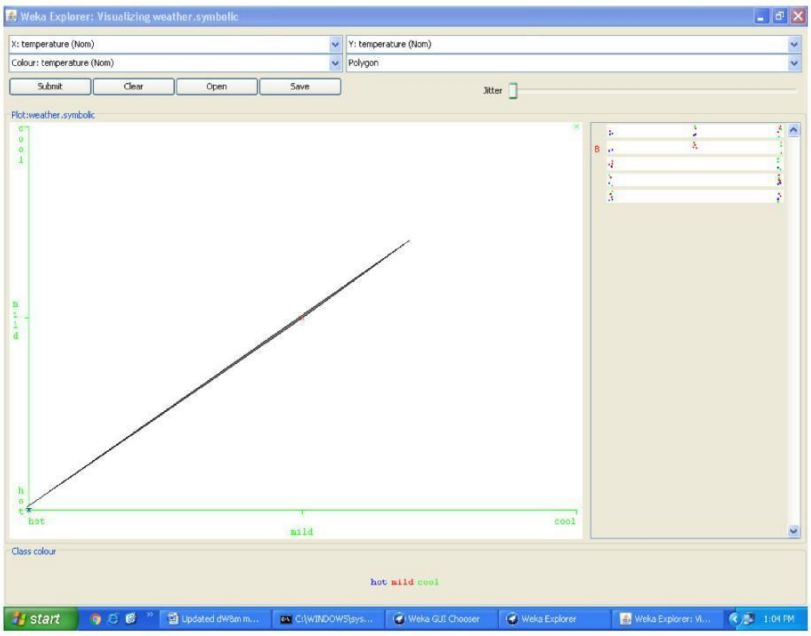


3. **Polygon**. You can select several points by building a free-form polygon. Left-click on the graph to add vertices to the polygon and right-click to complete it.



4. **Polyline**. To distinguish the points on one side from the once on another, you can build a polyline. Left-click on the graph to add vertices to the polyline and right-click to finish.





Unit-V Demonstrate performing regression on data sets.

Regression:

Regression is a data mining function that predicts a number. Age, weight, distance, temperature, income, or sales could all be predicted using regression techniques. For example, a regression model could be used to predict children's height, given their age, weight, and other factors.

A regression task begins with a data set in which the target values are known. For example, a regression model that predicts children's height could be developed based on observed data for many children over a period of time. The data might track age, height, weight, developmental milestones, family history, and so on. Height would be the target, the other attributes would be the predictors, and the data for each child would constitute a case.

In the model build (training) process, a regression algorithm estimates the value of the target as a function of the predictors for each case in the build data. These relationships between predictors and target are summarized in a model, which can then be applied to a different data set in which the target values are unknown.

Regression models are tested by computing various statistics that measure the difference between the predicted values and the expected values. See "Testing a Regression Model".

Common Applications of Regression

Regression modeling has many applications in trend analysis, business planning, marketing, financial forecasting, time series prediction, biomedical and drug response modeling, and environmental modeling.

Exercise: 1)performing clustering on Partitioning Methods a)K-Mean mining on data sets

1)b)K-Mediod mining on datasets

2)a)Agglomerative clustering on datasets

2)b)Divisive clustering mining on datasets

$y = F(\mathbf{x},\theta) + e$

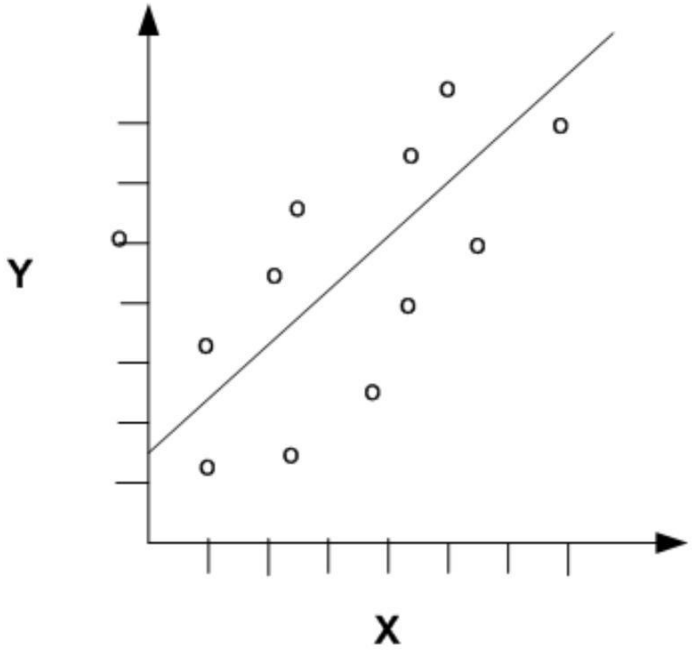
The process of training a regression model involves finding the best parameter values for the function that minimize a measure of the error, for example, the sum of squared errors.

There are different families of regression functions and different ways of measuring the error.

Linear Regression

The simplest form of regression to visualize is linear regression with a single predictor. A linear regression technique can be used if the relationship between x and y can be approximated with a straight line, as shown in Figure 4-1.

Figure 4-1 Linear Relationship Between x and y



Description of "Figure :Linear Relationship Between x and y"

In a linear regression scenario with a single predictor ($y = \theta_2 x + \theta_1$), the regression parameters (also called coefficients) are:

The **slope** of the line (θ_2) — the angle between a data point and the regression line and

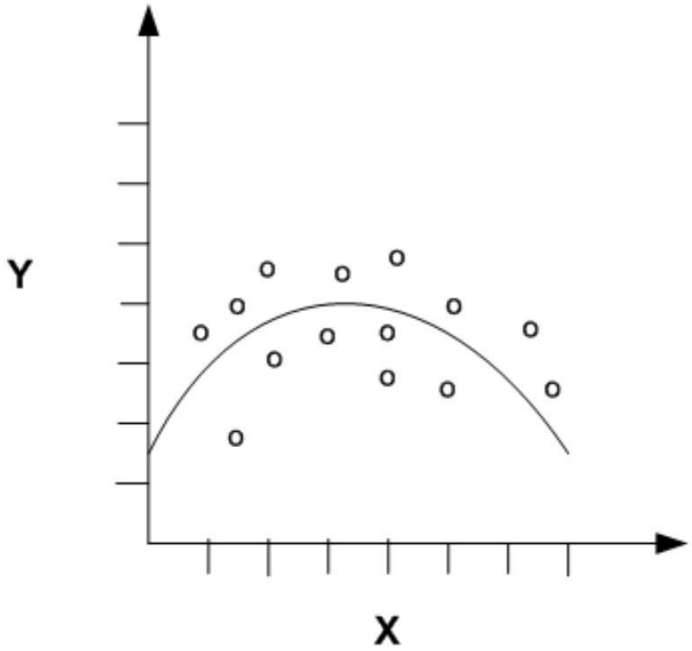
The **y intercept** (θ_1) — the point where x crosses the y axis (x = 0)

Nonlinear Regression

Often the relationship between x and y cannot be approximated with a straight line. In this case, a nonlinear regression technique may be used. Alternatively, the data could be preprocessed to make the relationship linear.

In Figure 4-2, x and y have a nonlinear relationship. Oracle Data Mining supports nonlinear regression via the gaussian kernel of SVM. (See "Kernel-Based Learning".)

Figure: Nonlinear Relationship Between x and y



Description of "Figure:Nonlinear Relationship Between x and y"

Multivariate Regression

Multivariate regression refers to regression with multiple predictors (x_1 , x_2 , ..., x_n). For purposes of illustration, Figure 4-1and Figure 4-2 show regression with a single predictor. Multivariate regression is also referred to as **multiple regression**.

Regression Algorithms

Oracle Data Mining provides the following algorithms for regression:

- **Generalized Linear Models**

  Generalized Linear Models (GLM) is a popular statistical technique for linear modeling. Oracle Data Mining implements GLM for regression and classification. See Chapter 12, "Generalized Linear Models"

- **Support Vector Machines**

  Support Vector Machines (SVM) is a powerful, state-of-the-art algorithm for linear and nonlinear regression. Oracle Data Mining implements SVM for regression and other mining functions. See Chapter 18, "Support Vector Machines"

Note:

Both GLM and SVM, as implemented by Oracle Data Mining, are particularly suited for mining data that includes many predictors (wide data).

Testing a Regression Model

The Root Mean Squared Error and the Mean Absolute Error are statistics for evaluating the overall quality of a regression model. Different statistics may also be available depending on the regression methods used by the algorithm.

Root Mean Squared Error

The Root Mean Squared Error (RMSE) is the square root of the average squared distance of a data point from the fitted line.Figure 4-3 shows the formula for the RMSE.

Figure 4-3 Root Mean Squared Error

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

Description of "Figure 4-3 Root Mean Squared Error"

This SQL expression calculates the RMSE.

SQRT(AVG((predicted_value - actual_value) * (predicted_value - actual_value)))

Mean Absolute Error

The Mean Absolute Error (MAE) is the average of the absolute value of the residuals. The MAE is very similar to the RMSE but is less sensitive to large errors. Figure 4-4 shows the formula for the MAE.

Figure:Mean Absolute Error

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

A. Load each dataset into Weka and build Linear Regression model. Study the cluster formed. Use training set option. Interpret the regression model and derive patterns and conclusions from the regression results.

Ans:

- Steps for run Aprior algorithm in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose labor data set and open file.
8. Click on Classify tab and Click the Choose button then expand the functions branch.
9. Select the LinearRegression leaf ans select use training set test option.
10. Click on start button.

Output:

=== Run information ===

Scheme: weka.classifiers.functions.LinearRegression -S 0 -R 1.0E-8

Relation: labor-neg-data

Instances: 57

Attributes: 17

duration

wage-increase-first-year

wage-increase-second-year

wage-increase-third-year

cost-of-living-adjustment

working-hours

pension

standby-pay

shift-differential

education-allowance

statutory-holidays

vacation

longterm-disability-assistance

contribution-to-dental-plan

bereavement-assistance

contribution-to-health-plan

class

Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Linear Regression Model

duration =

0.4689 * cost-of-living-adjustment=tc,tcf +

0.6523 * pension=none,empl_contr +

1.0321 * bereavement-assistance=yes +

0.3904 * contribution-to-health-plan=full +

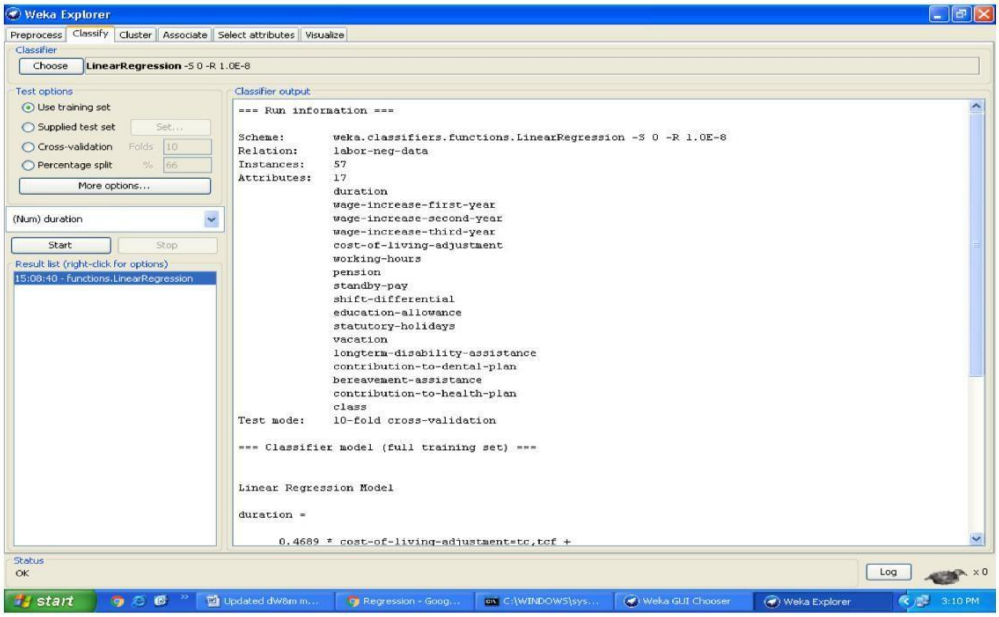
0.2765

Time taken to build model: 0 seconds

=== Cross-validation ===

=== Summary ===

Correlation coefficient	0.1967
Mean absolute error	0.6499
Root mean squared error	0.777
Relative absolute error	111.6598 %
Root relative squared error	108.8152 %
Total Number of Instances	56
Ignored Class Unknown Instances	1



B. Use options cross-validation and percentage split and repeat running the Linear Regression Model. Observe the results and derive meaningful results.

Ans: Steps for run Aprior algorithm in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose labor data set and open file.
8. Click on Classify tab and Click the Choose button then expand the functions branch.
9. Select the LinearRegression leaf and select test options cross-validation.
10. Click on start button.
11. Select the LinearRegression leaf and select test options percentage split.
12. Click on start button.

Output: cross-validation

=== Run information ===

Scheme: weka.classifiers.functions.LinearRegression -S 0 -R 1.0E-8
Relation: labor-neg-data
Instances: 57
Attributes: 17
duration
wage-increase-first-year
wage-increase-second-year
wage-increase-third-year
cost-of-living-adjustment
working-hours
pension
standby-pay
shift-differential
education-allowance
statutory-holidays

vacation
longterm-disability-assistance
contribution-to-dental-plan
bereavement-assistance
contribution-to-health-plan
class

Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Linear Regression Model

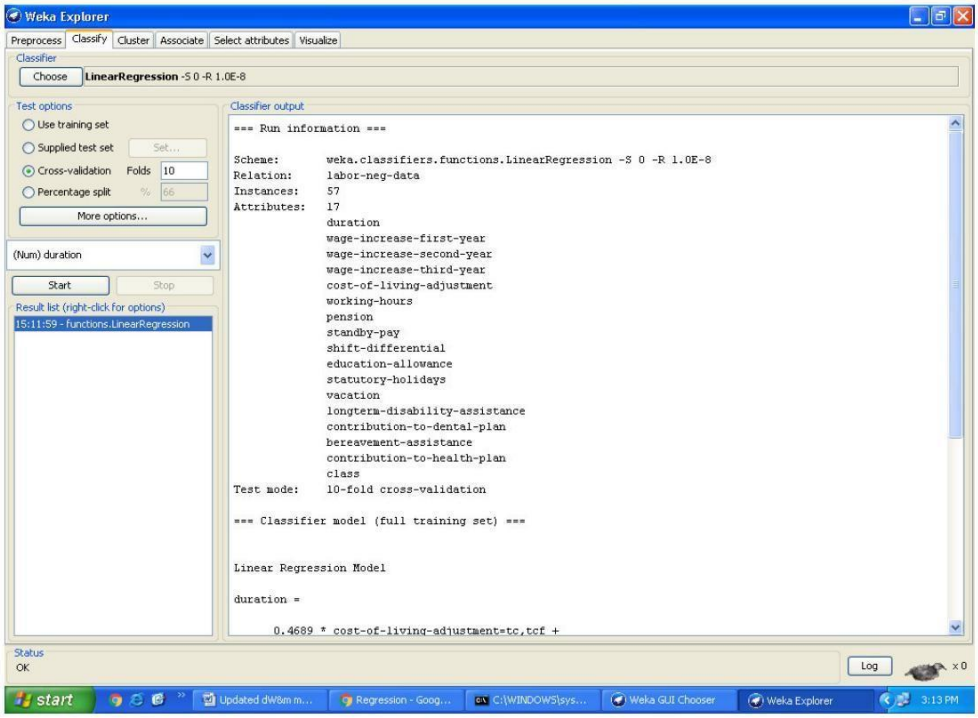
duration =

0.4689 * cost-of-living-adjustment=tc,tcf +
0.6523 * pension=none,empl_contr +
1.0321 * bereavement-assistance=yes +
0.3904 * contribution-to-health-plan=full +
0.2765

Time taken to build model: 0.02 seconds

=== Cross-validation ===
=== Summary ===

Correlation coefficient	0.1967
Mean absolute error	0.6499
Root mean squared error	0.777
Relative absolute error	111.6598 %
Root relative squared error	108.8152 %
Total Number of Instances	56
Ignored Class Unknown Instances	1



Output: percentage split

=== Run information ===

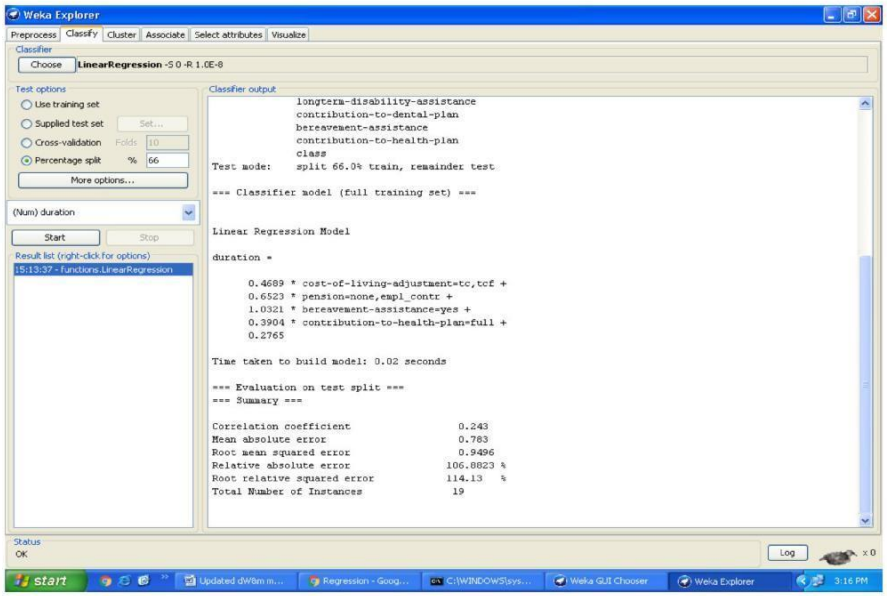
Scheme: weka.classifiers.functions.LinearRegression -S 0 -R 1.0E-8
Relation: labor-neg-data
Instances: 57
Attributes: 17
duration
wage-increase-first-year
wage-increase-second-year
wage-increase-third-year
cost-of-living-adjustment
working-hours
pension
standby-pay
shift-differential
education-allowance
statutory-holidays
vacation
longterm-disability-assistance

contribution-to-dental-plan
bereavement-assistance
contribution-to-health-plan
class
Test mode: split 66.0% train, remainder test

=== Classifier model (full training set) ===

Linear Regression Model
duration =
0.4689 * cost-of-living-adjustment=tc,tcf +
0.6523 * pension=none,empl_contr +
1.0321 * bereavement-assistance=yes +
0.3904 * contribution-to-health-plan=full +
0.2765
Time taken to build model: 0.02 seconds
=== Evaluation on test split ===
=== Summary ===

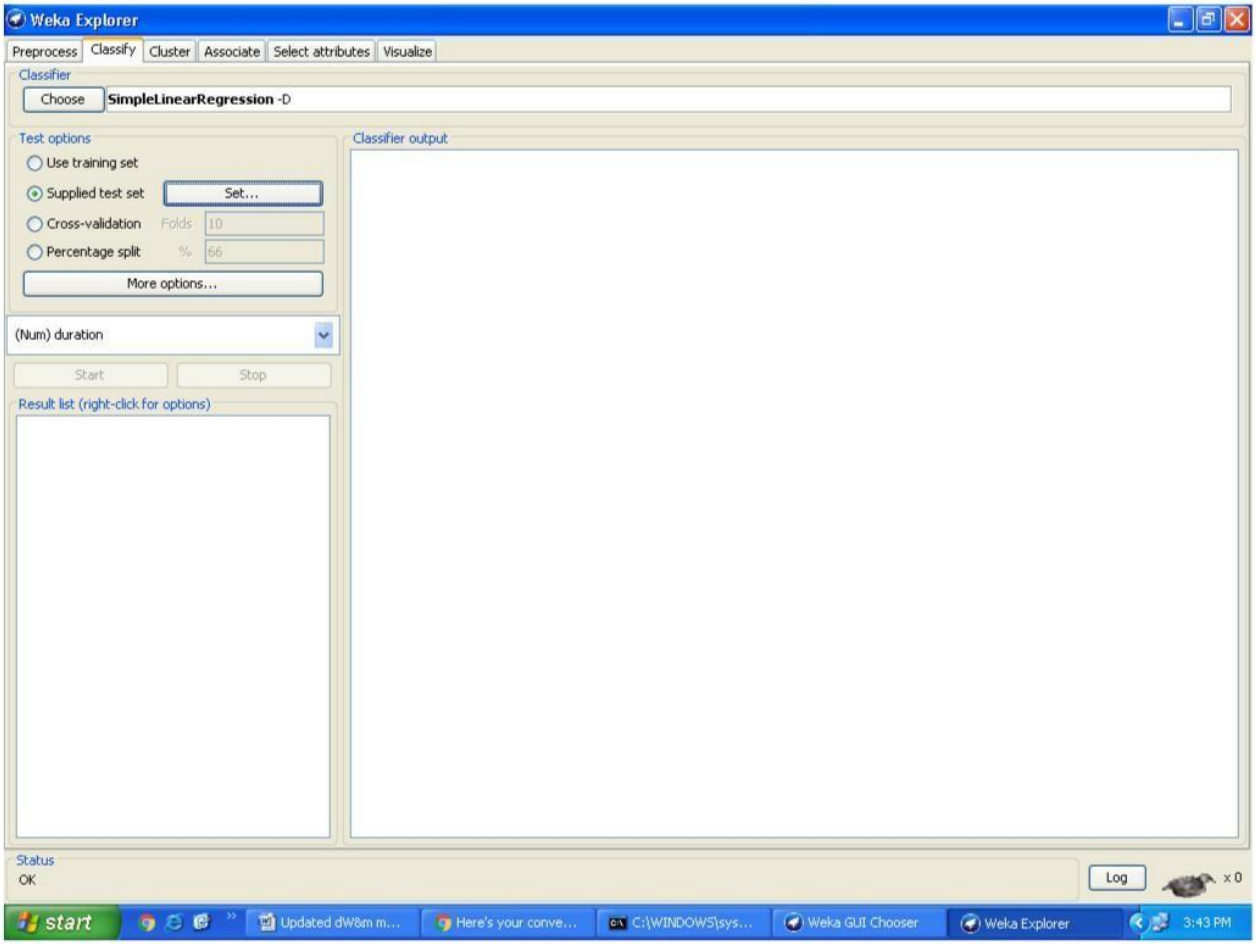
Correlation coefficient	0.243
Mean absolute error	0.783
Root mean squared error	0.9496
Relative absolute error	106.8823 %
Root relative squared error	114.13 %
Total Number of Instances	19



C.Explore Simple linear regression techniques that only looks at one variable.

Ans: Steps for run Aprior algorithm in WEKA

1. Open WEKA Tool.
2. Click on WEKA Explorer.
3. Click on Preprocessing tab button.
4. Click on open file button.
5. Choose WEKA folder in C drive.
6. Select and Click on data option button.
7. Choose labor data set and open file.
8. Click on Classify tab and Click the Choose button then expand the functions branch.
9. Select the S i m p l e Linear Regression leaf and select test options cross-validation.
10. Click on start button.



6. Sample Programs using German Credit Data.

Task 1: Credit Risk Assessment

Description: The business of banks is making loans. Assessing the credit worthiness of an applicant is of crucial importance. You have to develop a system to help a loan officer decide **whether the credit of a customer is good. Or bad. A bank's business rules regarding loans must** consider two opposing factors. On th one han, a bank wants to make as many loans as possible.

Interest on these loans is the banks profit source. On the other hand, a bank can not afford to make too many bad loans. Too many bad loans could lead to the collapse of the bank. Th**e bank's** loan policy must involved a compromise. Not too strict and not too lenient.

To do the assignment, you first and foremost need some knowledge about the world of credit. You can acquire such knowledge in a number of ways.

1. Knowledge engineering: Find a loan officer who is willing to talk. Interview her and try to represent her knowledge in a number of ways.

2. Books: Find some training manuals for loan officers or perhaps a suitable textbook on finance. Translate this knowledge from text from to production rule form.

3. Common sense: Imagine yourself as a loan officer and make up reasonable rules which can be used to judge the credit worthiness of a loan applicant.

4. Case histories: Find records of actual cases where competent loan officers correctly judged when and not to. Approve a loan application.

The German Credit Data

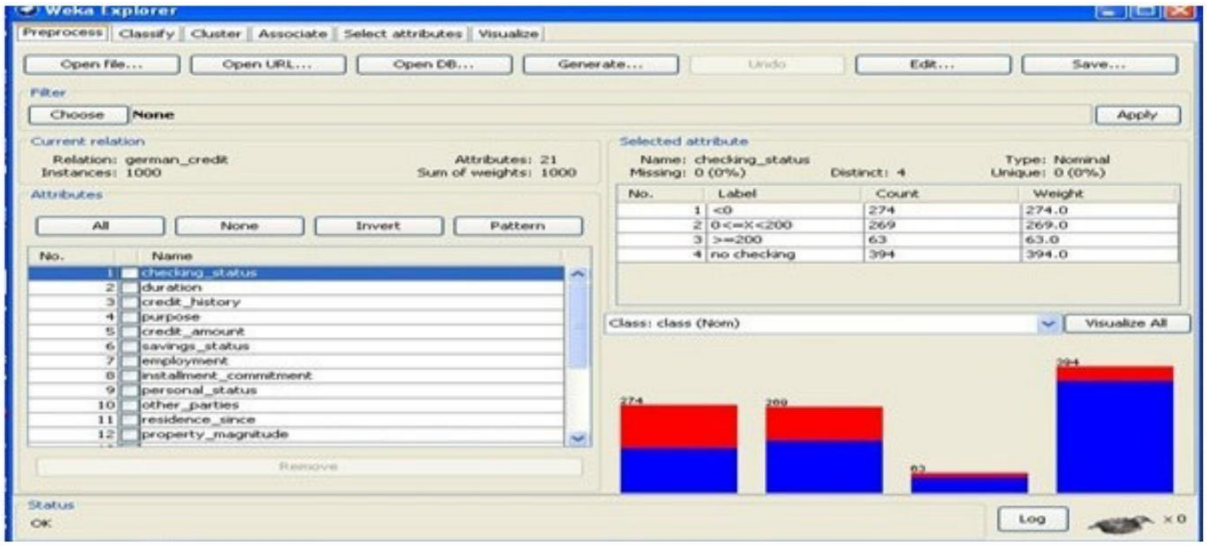
Actual historical credit data is not always easy to come by because of confidentiality rules. Here is one such data set. Consisting of **1000** actual cases collected in Germany.

In spite of the fact that the data is German, you should probably make use of it for this assignment(Unless you really can consult a real loan officer!)

There are 20 attributes used in judging a loan applicant(ie., 7 Numerical attributes and 13 Categoricl or Nominal attributes). The goal is the classify the applicant into one of two categories. Good or Bad.

The total number of attributes present in German credit data are.

1. Checking_Status
2. Duration
3. Credit_history
4. Purpose
5. Credit_amout
6. Savings_status
7. Employment
8. Installment_Commitment
9. Personal_status
10. Other_parties
11. Residence_since
12. Property_Magnitude
13. Age
14. Other_payment_plans
15. Housing
16. Existing_credits
17. Job
18. Num_dependents
19. Own_telephone
20. Foreign_worker
21. Class



Tasks(Turn in your answers to the following taks)

1. List all the categorical (or nominal) attributes and the real valued attributes separately.

Ans) Steps for identifying categorical attributes

1. Double click on credit-g.arff file.
2. Select all categorical attributes.
3. Click on invert.
4. Then we get all real valued attributes selected
5. Click on remove
6. Click on visualize all.

Steps for identifying real valued attributes

1. Double click on credit-g.arff file.
2. Select all real valued attributes.
3. Click on invert.
4. Then we get all categorial attributes selected
5. Click on remove
6. Click on visualize all.

The following are the Categorical (or Nominal) attributes)

1. Checking_Status
2. Credit_history
3. Purpose
4. Savings_status
5. Employment
6. Personal_status
7. Other_parties
8. Property_Magnitude
9. Other_payment_plans
10. Housing
11. Job

12. Own_telephone
13. Foreign_worker

The following are the Numerical attributes)

1. Duration
2. Credit_amout
3. Installment_Commitment
4. Residence_since
5. Age
6. Existing_credits
7. Num_dependents

2. What attributes do you think might be crucial in making the credit assessment? Come up with some simple rules in plain English using your selected attributes.

Ans) The following are the attributes may be crucial in making the credit assessment.

1. Credit_amount
2. Age
3. Job
4. Savings_status
5. Existing_credits
6. Installment_commitment
7. Property_magnitude

3. One type of model that you can create is a Decision tree . train a Decision tree using the complete data set as the training data. Report the model obtained after training.

Ans) Steps to model decision tree.

1. Double click on credit-g.arff file.
2. Consider all the 21 attributes for making decision tree.
3. Click on classify tab.
4. Click on choose button.
5. Expand tree folder and select J48
6. Click on use training set in test options.
7. Click on start button.
8. Right click on result list and choose the visualize tree to get decision tree.

We created a decision tree by using J48 Technique for the complete dataset as the training data.

The following model obtained after training.

Output:

=== Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: german_credit
Instances: 1000
Attributes: 21

Checking_status duration credit_history purpose credit_amount savings_status employment installment_commitment personal_status other_parties residence_since property_magnitude age other_payment_plans housing existing_credits job num_dependents own_telephone foreign_worker class

Test mode: evaluate on training data

=== Classifier model (full training set)

=== J48 pruned tree

Number of Leaves : 103

Size of the tree : 140

Time taken to build model: 0.08 seconds

=== **Evaluation on training set ===**

=== **Summary ===**

Correctly Classified Instances	855	85.5 %
Incorrectly Classified Instances	145	14.5 %

Kappa statistic	0.6251
Mean absolute error	0.2312
Root mean squared error	0.34
Relative absolute error	55.0377 %
Root relative squared error	74.2015 %
Coverage of cases (0.95 level)	100 %
Mean rel. region size (0.95 level)	93.3 %
Total Number of Instances	1000

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.956	0.38	0.854	0.956	0.902	0.857	good
	0.62	0.044	0.857	0.62	0.72	0.857	bad
WeightedAvg.	0.855	0.279	0.855	0.855	0.847	0.857	

=== Confusion Matrix ===

```
  a b <-- classified as 669
 31 | a = good

 114 186 | b = bad
```

4. Suppose you use your above model trained on the complete dataset, and classify credit good/bad for each of the examples in the dataset. What % of examples can you classify correctly?(This is also called testing on the training set) why do you think can not get 100% training accuracy?

Ans) Steps followed are:

1. Double click on credit-g.arff file.
2. Click on classify tab.
3. Click on choose button.
4. Expand tree folder and select J48
5. Click on use training set in test options.
6. Click on start button.
7. On right side we find confusion matrix
8. Note the correctly classified instances.

Output:

If we used our above model trained on the complete dataset and classified credit as good/bad for each of the examples in that dataset. We can not get 100% training accuracy only **85.5%** of examples, we can classify correctly.

5. Is testing on the training set as you did above a good idea? Why or why not?

Ans)It is not good idea by using 100% training data set.

6. One approach for solving the problem encountered in the previous question is using cross-validation? Describe what is cross validation briefly. Train a decision tree again using cross validation and report your results. Does accuracy increase/decrease? Why?

Ans) steps followed are:

1. Double click on credit-g.arff file.
2. Click on classify tab.
3. Click on choose button.
4. Expand tree folder and select J48
5. Click on cross validations in test options.
6. Select folds as 10
7. Click on start
8. Change the folds to 5
9. Again click on start
10. Change the folds with 2
11. Click on start.
12. Right click on blue bar under result list and go to visualize tree

Output:

Cross-Validation Definition: The classifier is evaluated by cross validation using the number of folds that are entered in the folds text field.

In Classify Tab, Select cross-validation option and folds size is 2 then Press Start Button, next time change as folds size is 5 then press start, and next time change as folds size is 10 then press start.

i) Fold Size-10

Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances	705	70.5 %
Incorrectly Classified Instances	295	29.5 %
Kappa statistic	0.2467	
Mean absolute error	0.3467	
Root mean squared error	0.4796	
Relative absolute error	82.5233 %	
Root relative squared error	104.6565 %	
Coverage of cases (0.95 level)	92.8 %	
Mean rel. region size (0.95 level)	91.7 %	
Total Number of Instances	1000	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.84	0.61	0.763	0.84	0.799	0.639	good
	0.39	0.16	0.511	0.39	0.442	0.639	bad
Weighted Avg.	0.705	0.475	0.687	0.705	0.692	0.639	

=== Confusion Matrix ===

a	b	<-- classified as
588	112	a = good
183	117	b = bad

ii) Fold Size-5

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

Correctly Classified Instances	733	73.3 %
Incorrectly Classified Instances	267	26.7 %
Kappa statistic	0.3264	
Mean absolute error	0.3293	
Root mean squared error	0.4579	
Relative absolute error	78.3705 %	
Root relative squared error	99.914 %	
Coverage of cases (0.95 level)	94.7 %	
Mean rel. region size (0.95 level)	93 %	
Total Number of Instances	1000	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.851	0.543	0.785	0.851	0.817	0.685	good
	0.457	0.149	0.568	0.457	0.506	0.685	bad
Weighted Avg.	0.733	0.425	0.72	0.733	0.724	0.685	

=== Confusion Matrix ===

a b <-- classified as
596 104 | a = good
163 137 | b = bad

iii) Fold Size-2

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

Correctly Classified Instances	721	72.1	%
Incorrectly Classified Instances	279	27.9	%
Kappa statistic	0.2443		
Mean absolute error	0.3407		
Root mean squared error	0.4669		
Relative absolute error	81.0491 %		
Root relative squared error	101.8806 %		
Coverage of cases (0.95 level)	92.8 %		
Mean rel. region size (0.95 level)	91.3 %		
Total Number of Instances	1000		

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.891	0.677	0.755	0.891	0.817	0.662	good
	0.323	0.109	0.561	0.323	0.41	0.662	bad
Weighted Avg.	0.721	0.506	0.696	0.721	0.695	0.662	

=== Confusion Matrix ===

a b <-- classified as

624 76 | a = good
203 97 | b = bad

Note: With this observation, we have seen accuracy is increased when we have folds size is 5 and accuracy is decreased when we have 10 folds.

7. Check to see if the data shows a bias against —foreign workers‖ or —personal-status‖.

One way to do this is to remove these attributes from the data set and see if the decision tree created in those cases is significantly different from the full dataset case which you have already done. Did removing these attributes have any significantly effect? Discuss.

Ans) steps followed are:

1. Double click on credit-g.arff file.
2. Click on classify tab.
3. Click on choose button.
4. Expand tree folder and select J48
5. Click on cross validations in test options.
6. Select folds as 10
7. Click on start
8. Click on visualization
9. Now click on preprocessor tab
10. Select 9th and 20th attribute
11. Click on remove button
12. Goto classify tab
13. Choose J48 tree
14. Select cross validation with 10 folds
15. Click on start button
16. Right click on blue bar under the result list and go to visualize tree.

Output:

We use the **Preprocess Tab in Weka GUI Explorer to remove an attribute —Foreign-workers‖ & —Perosnal_status‖ one by one.** In Classify Tab, Select Use Training set option then

Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

i) If Foreign_worker is removed

Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	859	85.9	%
Incorrectly Classified Instances	141	14.1	%
Kappa statistic	0.6377		
Mean absolute error	0.2233		
Root mean squared error	0.3341		
Relative absolute error	53.1347 %		
Root relative squared error	72.9074 %		
Coverage of cases (0.95 level)	100	%	
Mean rel. region size (0.95 level)	91.9	%	
Total Number of Instances	1000		

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.954	0.363	0.86	0.954	0.905	0.867	good
	0.637	0.046	0.857	0.637	0.73	0.867	bad
Weighted Avg	0.859	0.268	0.859	0.859	0.852	0.867	

=== Confusion Matrix ===

a	b	<-- classified as
668	32	a = good
109	191	b = bad

i) If Personal_status is removed

Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	866	86.6	%
Incorrectly Classified Instances	134	13.4	%
Kappa statistic	0.6582		
Mean absolute error	0.2162		
Root mean squared error	0.3288		
Relative absolute error	51.4483 %		
Root relative squared error	71.7411 %		
Coverage of cases (0.95 level)	100	%	
Mean rel. region size (0.95 level)	91.7	%	

Total Number of Instances 1000

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.954	0.34	0.868	0.954	0.909	0.868	good
	0.66	0.046	0.861	0.66	0.747	0.868	bad
Weighted Avg.	0.866	0.252	0.866	0.866	0.86	0.868	

=== Confusion Matrix ===

```
  a b <-- classified as
668 32 | a = good 102
198 | b = bad
```

Note: With this observation we have seen, **when —Foreign_worker —attribute is removed from the**

Dataset, the accuracy is decreased. So this attribute is important for classification.

8. Another question might be, do you really need to input so many attributes to get good results? May be only a few would do. For example, you could try just having attributes 2,3,5,7,10,17 and 21. Try out some combinations.(You had removed two attributes in problem 7. Remember to reload the arff data file to get all the attributes initially before you start selecting the ones you want.)

Ans) steps followed are:

1. Double click on credit-g.arff file.
2. Select 2,3,5,7,10,17,21 and tick the check boxes.
3. Click on invert
4. Click on remove
5. Click on classify tab
6. Choose trace and then algorithm as J48
7. Select cross validation folds as 2
8. Click on start.

OUTPUT:

We use the **Preprocess Tab** in Weka GUI Explorer to remove 2nd attribute (Duration). In Classify Tab, Select Use Training set option then Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

```
=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances         841               84.1      %
Incorrectly Classified Instances       159               15.9      %
Confusion Matrix ===

  a b   <-- classified as
 647  53 | a = good
 106 194 | b = bad
```

Remember to reload the previous removed attribute, press Undo option in Preprocess tab. We use the **Preprocess Tab** in Weka GUI Explorer to remove 3rd attribute (Credit_history). In Classify Tab, Select Use Training set option then Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

```
=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances         839               83.9      %
Incorrectly Classified Instances       161               16.1      %

== Confusion Matrix ===

  a b   <-- classified as
 645  55 | a = good
 106 194 | b = bad
```

Remember to reload the previous removed attribute, press Undo option in Preprocess tab. We use the **Preprocess Tab** in Weka GUI Explorer to remove 5th attribute (Credit_amount). In Classify Tab, Select Use Training set option then Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	864	86.4	%
Incorrectly Classified Instances	136	13.6	%

= Confusion Matrix ===

```
  a b   <-- classified as
675  25 | a = good
111 189 | b = bad
```

Remember to reload the previous removed attribute, press Undo option in Preprocess tab. We use the **Preprocess Tab** in Weka GUI Explorer to remove 7^{th} attribute (Employment). In Classify Tab, Select Use Training set option then Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	858	85.8	%
Incorrectly Classified Instances	142	14.2	%

== Confusion Matrix ===

```
  a b   <-- classified as
670  30 | a = good
112 188 | b = bad
```

Remember to reload the previous removed attribute, press Undo option in Preprocess tab. We use the **Preprocess Tab** in Weka GUI Explorer to remove 10^{th} attribute (Other_parties). In Classify Tab, Select Use Training set option then Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

Time taken to build model: 0.05 seconds

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	845	84.5	%

Incorrectly Classified Instances 155 15.5 %

Confusion Matrix ===

```
  a  b  <-- classified as
663 37 | a = good 118
182 | b = bad
```

Remember to reload the previous removed attribute, press Undo option in Preprocess tab. We use the **Preprocess Tab** in Weka GUI Explorer to remove 17th attribute (Job). In Classify Tab, Select Use Training set option then Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	859	85.9	%
Incorrectly Classified Instances	141	14.1	%

=== Confusion Matrix ===

```
  a  b   <-- classified as
675  25 | a = good
116 184 | b = bad
```

Remember to reload the previous removed attribute, press Undo option in Preprocess tab. We use the **Preprocess Tab** in Weka GUI Explorer to remove 21st attribute (Class). In Classify Tab, Select Use Training set option then Press Start Button, If these attributes removed from the dataset, we can see change in the accuracy compare to full data set when we removed.

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	963	96.3 %
Incorrectly Classified Instances	37	3.7 %

=== Confusion Matrix ===

```
  a  b <-- classified as
```

963 0 | a = yes
37 0 | b = no

Note: With this observation we have seen, when 3rd attribute is removed from the Dataset, the accuracy (83%) is decreased. So this attribute is important for classification. when 2nd and 10th attributes are removed from the Dataset, the accuracy(84%) is same. So we can remove any one among them. when 7th and 17th attributes are removed from the Dataset, the accuracy(85%) is same. So we can remove any one among them. If we remove 5th and 21st attributes the accuracy is increased, so these attributes may not be needed for the classification.

9. Sometimes, The cost of rejecting an applicant who actually has good credit might be higher than accepting an applicant who has bad credit. Instead of counting the misclassification equally in both cases, give a higher cost to the first case (say cost 5) and lower cost to the second case. By using a cost matrix in weak. Train your decision tree and report the Decision Tree and cross validation results. Are they significantly different from results obtained in problem 6.

Ans) steps followed are:

1. Double click on credit-g.arff file.
2. Click on classify tab.
3. Click on choose button.
4. Expand tree folder and select J48
5. Click on start
6. Note down the accuracy values
7. Now click on credit arff file
8. Click on attributes 2,3,5,7,10,17,21
9. Click on invert
10. Click on classify tab
11. Choose J48 algorithm
12. Select Cross validation fold as 2
13. Click on start and note down the accuracy values.
14. Again make cross validation folds as 10 and note down the accuracy values.
15. Again make cross validation folds as 20 and note down the accuracy values.

OUTPUT:

In Weka GUI Explorer, Select Classify Tab, In that Select **Use Training set** option . In Classify Tab then press **Choose** button in that select J48 as Decision Tree Technique. In Classify Tab then press **More options** button then we get classifier evaluation options window in that select cost sensitive evaluation the press set option Button then we get Cost Matrix Editor. In that change classes as 2 then press Resize button. Then we get 2X2 Cost matrix. In Cost Matrix (0,1) location value change as 5, then we get modified cost matrix is as follows.

0.0 5.0
1.0 0.0

Then close the cost matrix editor, then press ok button. Then press start button.

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances	855	85.5	%
Incorrectly Classified Instances	145	14.5	%

=== Confusion Matrix ===

```
  a b <-- classified as
669 31 | a = good 114
186 | b = bad
```

Note: With this observation we have seen that ,total 700 customers in that 669 classified as good customers and 31 misclassified as bad customers. In total 300cusotmers, 186 classified as bad customers and 114 misclassified as good customers.

10. Do you think it is a good idea to prefect simple decision trees instead of having long complex decision tress? How does the complexity of a Decision Tree relate to the bias of the model?

Ans)

steps followed are:-
1)click on credit arff file
2)Select all attributes
3)click on classify tab
4)click on choose and select J48 algorithm
5)select cross validation folds with 2
6)click on start

7)write down the time complexity value

It is Good idea to prefer simple Decision trees, instead of having complex Decision tree.

11. You can make your Decision Trees simpler by pruning the nodes. One approach is to use Reduced Error Pruning. Explain this idea briefly. Try reduced error pruning for training your Decision Trees using cross validation and report the Decision Trees you obtain? Also Report your accuracy using the pruned model Does your Accuracy increase?

Ans)

steps followed are:-
1)click on credit arff file
2)Select all attributes
3)click on classify tab
4)click on choose and select REP algorithm
5)select cross validation 2
6) click on start
7) Note down the results

We can make our decision tree simpler by pruning the nodes. For that In Weka GUI Explorer, Select Classify Tab, In that Select **Use Training set** option . In Classify Tab then press **Choose** button in that select J48 as Decision Tree Technique. Beside Choose Button Press on **J48 –c 0.25 –M2 text** we get Generic Object Editor. In that select **Reduced Error pruning Property** as **True then press ok.** Then press start button.

=== **Evaluation on training set ===**
=== **Summary ===**

Correctly Classified Instances	786	78.6	%
Incorrectly Classified Instances	214	21.4	%

== Confusion Matrix ===

```
  a b   <-- classified as
662  38 | a = good
176 124 | b = bad
```

By using pruned model, the accuracy decreased. Therefore by pruning the nodes we can make our decision tree simpler.

12) How can you convert a Decision Tree into —if-then-else rules‖. Make up your own small

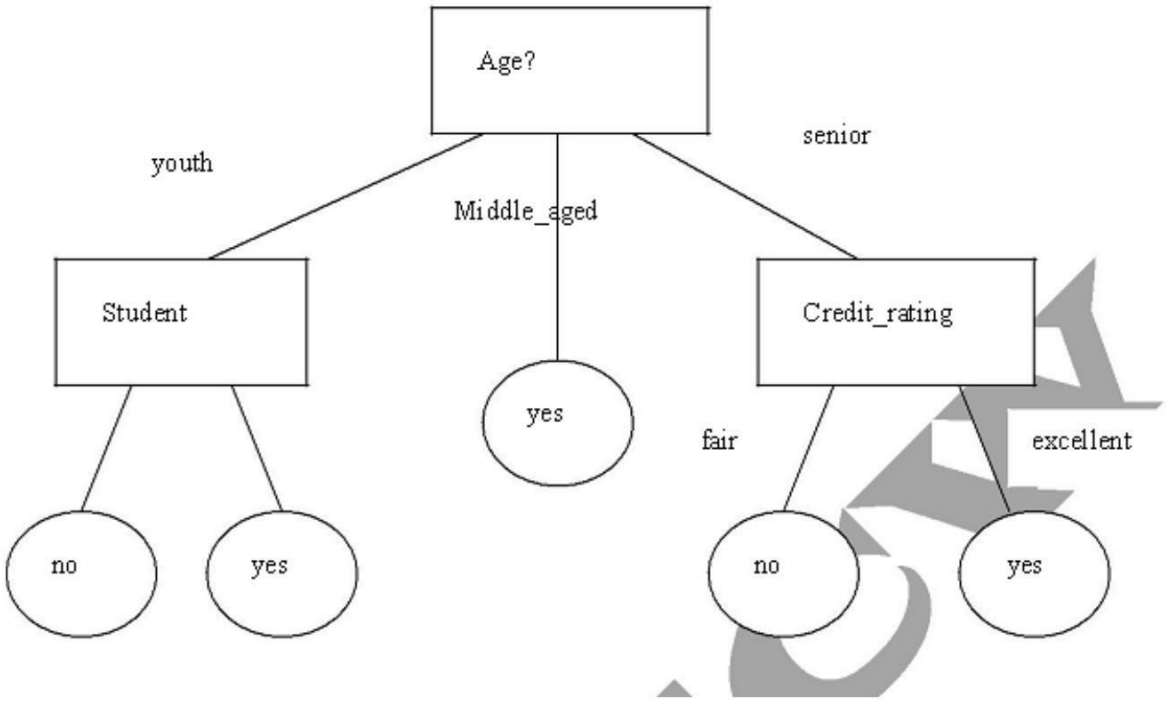
Decision Tree consisting 2-3 levels and convert into a set of rules. There also exist different classifiers that output the model in the form of rules. One such classifier in weka is rules. PART, train this model and report the set of rules obtained. Sometimes just one attribute can be good enough in making the decision, yes, just one ! Can you predict what attribute that might be in this data set? OneR classifier uses a single attribute to make decisions(it chooses the attribute based on minimum error).Report the rule obtained by training a one R classifier. Rank the performance of j48,PART,oneR.

Ans)

Steps For Analyze Decision Tree:

1)click on credit arff file
2)Select all attributes
3) click on classify tab
4) click on choose and select J48 algorithm
5)select cross validation folds with 2
6)click on start
7) note down the accuracy value
8) again goto choose tab and select PART
9)select cross validation folds with 2
10)click on start
11) note down accuracy value
12) again goto choose tab and select One R
13)select cross validation folds with 2
14)click on start
15)note down the accuracy value.

Sample Decision Tree of 2-3 levles.



Converting Decision tree into a set of rules is as follows.

Rule1: If age = youth AND student=yes THEN buys_computer=yes
Rule2: If age = youth AND student=no THEN buys_computer=no
Rule3: If age = middle_aged THEN buys_computer=yes

Rule4: If age = senior AND credit_rating=excellent THEN buys_computer=yes
Rule5: If age = senior AND credit_rating=fair THEN buys_computer=no

In Weka GUI Explorer, Select Classify Tab, In that Select **Use Training set** option .There also exist different classifiers that output the model in the form of Rules. Such classifiers in weka are

—PART‖ and ‖OneR‖ . Then go to Choose and select Rules in that select PART and press start Button.

== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances 897 89.7 %
Incorrectly Classified Instances 103 10.3 %

== Confusion Matrix ===

a b <-- classified as
653 47 | a = good
56 244 | b = bad

Then go to Choose and select Rules in that select OneR and press start Button.

== Evaluation on training set ===
=== Summary ===
Correctly Classified Instances 742 74.2 %
Incorrectly Classified Instances 258 25.8 %

=== Confusion Matrix ===

a b <-- classified as
642 58 | a = good 200
100 | b = bad

Then go to Choose and select Trees in that select J48 and press start Button.

=== Evaluation on training set ===
=== Summary ===
Correctly Classified Instances 855 85.5 %
Incorrectly Classified Instances 145 14.5 %

=== Confusion Matrix ===

a b <-- classified as
669 31 | a = good 114
186 | b = bad

Note: With this observation we have seen the performance of classifier and Rank is as follows

1. PART
2. J48 3. OneR

7. Task 2:Hospital Management System

Data warehouse consists dimension table and fact table.

REMEMBER the following

Dimension

The dimension object(dimension);

_name

_attributes(levels),with primary key

_hierarchies

One time dimension is must.

About levels and hierarchies

Dimensions objects(dimension) consists of set of levels and set of hierarchies defined over those levels.the levels represent levels of aggregation.hierarchies describe-child relationships among a set of levels.

For example .a typical calander dimension could contain five levels.two hierarchies can be defined on these levels.

H1: YearL>QuarterL>MonthL>DayL

H2: YearL>WeekL>DayL

The hierarchies are describes from parent to child,so that year is the parent of Quarter,quarter are parent of month,and so forth.

About Unique key constraints

When you create a definition for a hierarchy,warehouse builder creates an identifier key for each level of the hierarchy and unique key constraint on the lowest level (base level)

Design a hospital management system data warehouse(TARGET) consists of dimensions patient,medicine,supplier,time.where measure are _ NO UNITS‘ ,UNIT PRICE.

Assume the relational database(SOURCE)table schemas as follows TIME(day,month,year)

PATIENT(patient_name,age,address,etc)

MEDICINE(Medicine_brand_name,Drug_name,supplier,no_units,units_price,etc..,)

SUPPLIER:(Supplier_name,medicine_brand_name,address,etc..,)

If each dimension has 6 levels,decide the levels and hierarchies,assumes the level names suitably.

Design the hospital management system data warehousing using all schemas.give the example 4-D cube with assumption names.

8. Simple Project on Data Preprocessing

Data Preprocessing

Objective: Understanding the purpose of unsupervised attribute/instance filters for preprocessing the input data.

Follow the steps mentioned below to configure and apply a filter.

The preprocess section allows filters to be defined that transform the data in various ways. The Filter box is used to set up filters that are required. At the left of the Filter box is a Choose button. By clicking this button it is possible to select one of the filters in Weka. Once a filter has been selected, its name and options are shown in the field next to the Choose button. Clicking on this box brings up a GenericObjectEditor dialog box, which lets you configure a filter. Once you are happy with the settings you have chosen, click OK to return to the main Explorer window.

Now you can apply it to the data by pressing the Apply button at the right end of the Filter panel. The Preprocess panel will then show the transformed data. The change can be undone using the Undo button. Use the Edit button to view your transformed data in the dataset editor.

Try each of the following **Unsupervised Attribute Filters**. (Choose -> weka -> filters -> unsupervised -> attribute)

- Use **ReplaceMissingValues** to replace missing values in the given dataset.
- Use the filter **Add** to add the attribute Average.
- Use the filter **AddExpression** and add an attribute which is the average of attributes M1 and M2. Name this attribute as AVG.
- Understand the purpose of the attribute filter **Copy.**
- Use the attribute filters **Discretize** and **PKIDiscretize** to discretize the M1 and M2 attributes into five bins. (NOTE: Open the file afresh to apply the second filter

since there would be no numeric attribute to dicretize after you have applied the first filter.)

- Perform **Normalize** and **Standardize** on the dataset and identify the difference between these operations.
- Use the attribute filter **FirstOrder** to convert the M1 and M2 attributes into a single attribute representing the first differences between them.
- Add a nominal attribute Grade and use the filter **MakeIndicator** to convert the attribute into a Boolean attribute.
- Try if you can accomplish the task in the previous step using the filter

MergeTwoValues.

- Try the following transformation functions and identify the purpose of each
    - NumericTransform
    - NominalToBinary
    - NumericToBinary
    - Remove
    - RemoveType
    - RemoveUseless
    - ReplaceMissingValues
    - SwapValues

Try the following **Unsupervised Instance Filters.**

(Choose -> weka -> filters -> unsupervised -> instance)

- Perform **Randomize** on the given dataset and try to correlate the resultant sequence with the given one.
- Use **RemoveRange** filter to remove the last two instances.
- Use **RemovePercent** to remove 10 percent of the dataset.

- Apply the filter **RemoveWithValues** to a nominal and a numeric attribute