

Week – 2

Explore machine learning tool “WEKA” Study the arff file format Explore the available data sets in WEKA. Load a data set (ex. Weather dataset, Iris dataset, etc.) Load each dataset and observe the following:

1. List the attribute names and they types
 2. Number of records in each dataset
 3. Identify the class attribute (if any)
 4. Plot Histogram
 5. Determine the number of records for each class.
 6. Visualize the data in various dimensions
- ### Introduction to WEKA

WEKA - an open source software provides tools for data preprocessing, implementation of several Machine Learning algorithms, and visualization tools so that you can develop machine learning techniques and apply them to real-world data mining problems.

features:

- i) Preprocess
- ii) Classify
- iii) Cluster
- iv) Associate
- v) Select Attributes
- vi) Visualise



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The screenshot shows the Weka Explorer interface. The 'Preprocess' tab is selected. The 'Filter' section shows 'Choose' set to 'None'. The 'Current relation' section shows 'Relation: None', 'Instances: None', 'Attributes: None', and 'Sum of weights: None'. The 'Selected attribute' section shows 'Name: None', 'Weight: None', 'Type: None', 'Missing: None', 'Distinct: None', and 'Unique: None'. The 'Attributes' list is empty. The 'Status' bar shows 'Welcome to the Weka Explorer'.

The 'Open' dialog box is open, showing the file 'bank-data (5).csv' selected. The 'File Name' field contains 'bank-data (5).csv' and the 'Files of Type' dropdown is set to 'All Files'. The 'Open' button is highlighted.

The 'Weka Explorer' window shows the 'bank-data (5)' relation loaded. The 'Attributes' list contains 12 attributes: id, age, sex, region, income, married, children, car, save_act, current_act, mortgage, and pep. The 'Selected attribute' section shows the 'id' attribute selected. The 'Status' bar shows 'OK'.

Available data sets in weka:

- 1.airline
- 2.breast cancer
- 3.contact lenses
- 4.cpu
- 5.cpu with vendor
- 6.iris
- 7.weather.nominal
- 8.weather.numeric
- 9.diabetes
- 10.glass

WEATHER.ARF:

```
@relation weather
@attribute outlook {sunny, overcast, rainy}
@attribute temperature numeric
@attribute humidity numeric
@attribute windy {TRUE, FALSE}
@attribute play {yes, no}
@data
sunny,85,85,FALSE,
no
sunny,80,90,TRUE,n
o
overcast,83,86,FALS
E,yes
rainy,70,96,FALSE,y
es
rainy,68,80,FALSE,y
es
rainy,65,70,TRUE,no
overcast,64,65,TRUE
,yes
sunny,72,95,FALSE,
no
sunny,69,70,FALSE,
yes
rainy,75,80,FALSE,y
es
sunny,75,70,TRUE,y
es
overcast,72,90,TRUE
,yes
overcast,81,75,FALS
E,yes
rainy,71,91,TRUE,no
```

IRIS.ARFF:

% 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

%

% 3. Past Usage:

% - Publications: too many to mention!!! Here are a few.

% 1. Fisher, R.A. "The use of multiple measurements
in taxonomic problems"

% Annual Eugenics, 7, Part II, 179-188 (1936);
also in "Contributions

% to Mathematical Statistics" (John Wiley, NY,
1950).

% 2. Duda, R.O., & Hart, P.E. (1973) Pattern
Classification and Scene Analysis.

% (Q327.D83) John Wiley & Sons. ISBN 0-471-
22361-1. See page 218.

5. Number of Instances: 150 (50 in each of three classes)

%

% 6. Number of Attributes: 4 numeric, predictive
attributes and the class

%

% 7. Attribute Information:

% 1. sepal length in cm

% 2. sepal width in cm

% 3. Petal length in cm

% 4. Petal width in cm

% 5. class:

% -- Iris Setosa

% -- Iris Versicolour

% -- Iris Virginica

%

% 8. Missing Attribute Values: None

%

% Summary Statistics:

	Min	Max	Mean	SD	Class	Correlation
sepal length:	4.3	7.9	5.84	0.83	0.7826	
sepal width:	2.0	4.4	3.05	0.43	-0.4194	

```
% petal length: 1.0 6.9 3.76 1.76 0.9490 (high!)
% petal width: 0.1 2.5 1.20 0.76 0.9565 (high!)
%
```

```
% 9. Class Distribution: 33.3% for each of 3 classes.
```

```
@RELATION iris
```

```
@ATTRIBUTE sepallength REAL
```

```
@ATTRIBUTE sepalwidth REAL
```

```
@ATTRIBUTE petallength REAL
```

```
@ATTRIBUTE petalwidth REAL
```

```
@ATTRIBUTE class {Iris-setosa,Iris-versicolor,Iris-
virginica}
```

```
@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
7.0,3.2,4.7,1.4,Iris-versicolor
6.4,3.2,4.5,1.5,Iris-versicolor
6.9,3.1,4.9,1.5,Iris-versicolor
5.5,2.3,4.0,1.3,Iris-versicolor
6.3,3.3,6.0,2.5,Iris-virginica
5.8,2.7,5.1,1.9,Iris-virginica
7.1,3.0,5.9,2.1,Iris-virginica
6.3,2.9,5.6,1.8,Iris-virginica
6.5,3.0,5.8,2.2,Iris-virginica
```

AIRLINE.ARFF:

%% Monthly totals of international airline passengers
(in thousands) for %% 1949-1960.

@relation airline_passengers

@attribute passenger_numbers numeric

@attribute Date date 'yyyy-MM-dd'

@data

112,1949-01-01
118,1949-02-01
132,1949-03-01
129,1949-04-01
121,1949-05-01
135,1949-06-01
148,1949-07-01
148,1949-08-01
136,1949-09-01
119,1949-10-01
104,1949-11-01
118,1949-12-01
115,1950-01-01
126,1950-02-01
141,1950-03-01
135,1950-04-01
125,1950-05-01
149,1950-06-01
170,1950-07-01
170,1950-08-01
158,1950-09-01
133,1950-10-01

CPU.ARFF:

%

% As used by Kilpatrick, D. & Cameron-Jones, M.
(1998). Numeric prediction

% using instance-based learning with encoding length
selection. In Progress

% in Connectionist-Based Information Systems.
Singapore: Springer-Verlag.

%

% Deleted "vendor" attribute to make data
consistent with what we % used in the data
mining book.

%

@relation 'cpu'

@attribute MYCT numeric

@attribute MMIN numeric

@attribute MMAX numeric

@attribute CACH numeric

@attribute CHMIN numeric

@attribute CHMAX numeric

@attribute class numeric

@data

125,256,6000,256,16,128,198

29,8000,32000,32,8,32,269

29,8000,32000,32,8,32,220

29,8000,32000,32,8,32,172

29,8000,16000,32,8,16,132

26,8000,32000,64,8,32,318

23,16000,32000,64,16,32,367

23,16000,32000,64,16,32,489

23,16000,64000,64,16,32,636

23,32000,64000,128,32,64,1144

400,1000,3000,0,1,2,38

CONTACT-LENSES.ARFF:

@relation contact-lenses

@attribute age {young, pre-presbyopic,
presbyopic}

@attribute spectacle-prescrip {myope, hypermetrope}

@attribute astigmatism {no, yes}

@attribute tear-production-rate {reduced, normal}

@attribute contact-lenses {soft, hard, none}

@data

%

% 24

instances %

young,myope,no,reduced,none

young,myope,no,normal,soft

young,myope,yes,reduced,none

young,myope,yes,normal,hard

young,hypermetrope,no,reduced,none

young,hypermetrope,no,normal,soft

LOAD DATA SETS IN WEKA

DESCRIPTION:

Step 1: open weka

Step 2: Go to file explorer

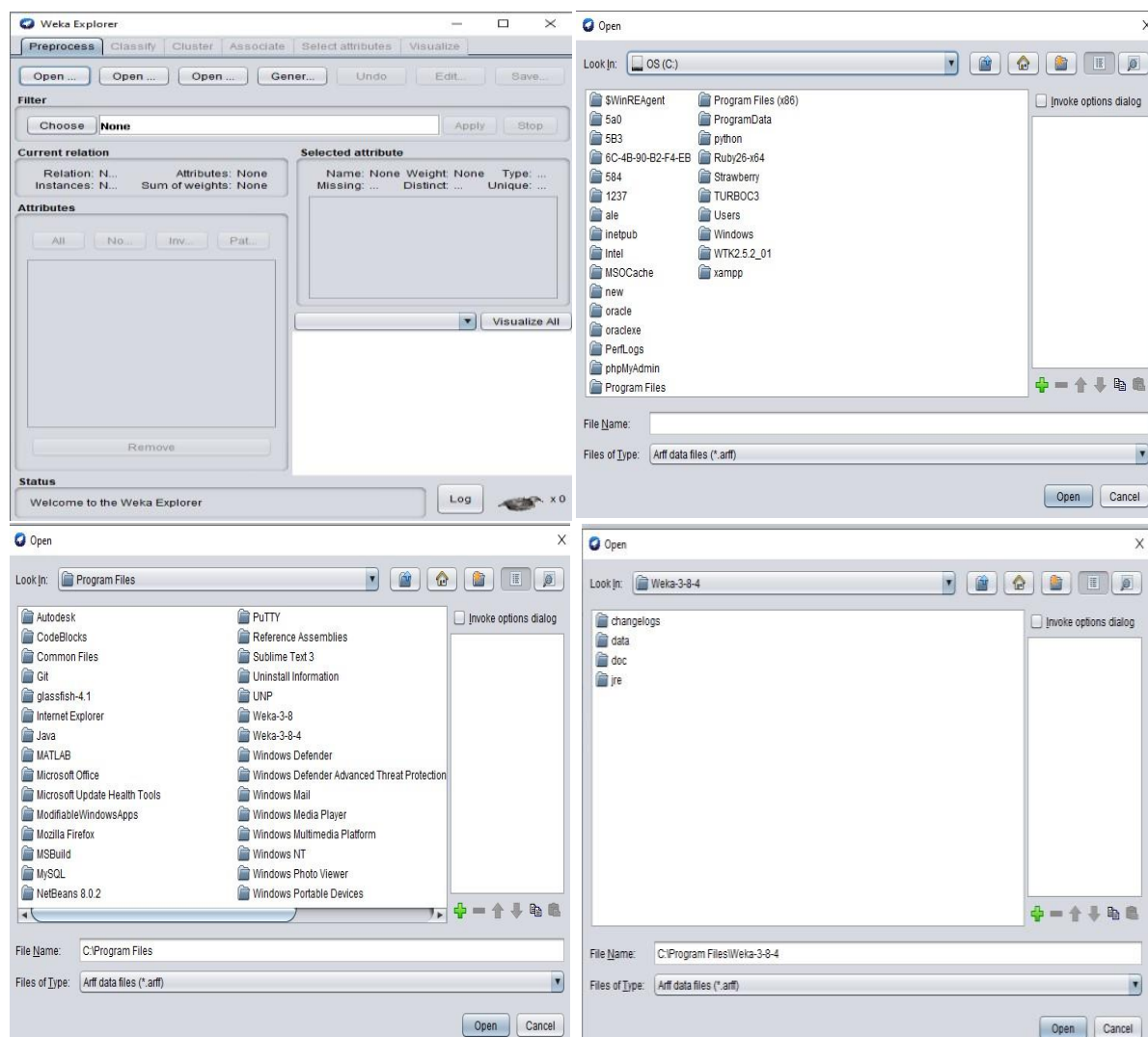
Step 3: Select open file under preprocess

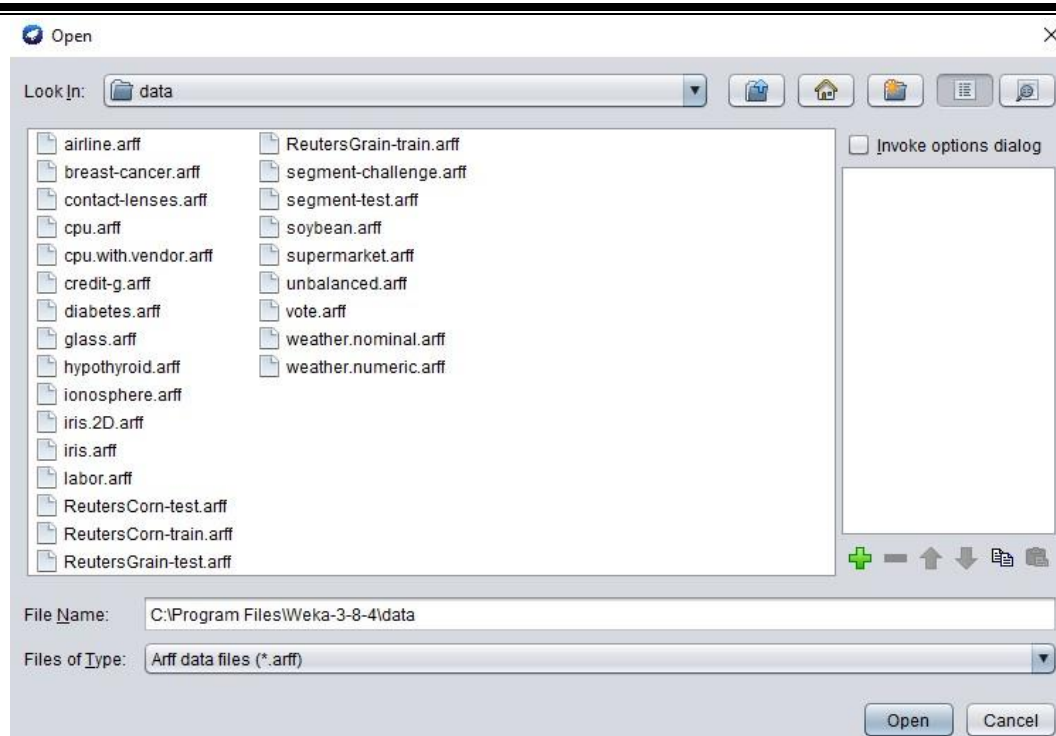
Step 4: Select the folder where the arff file is located

Step 5: Open the file

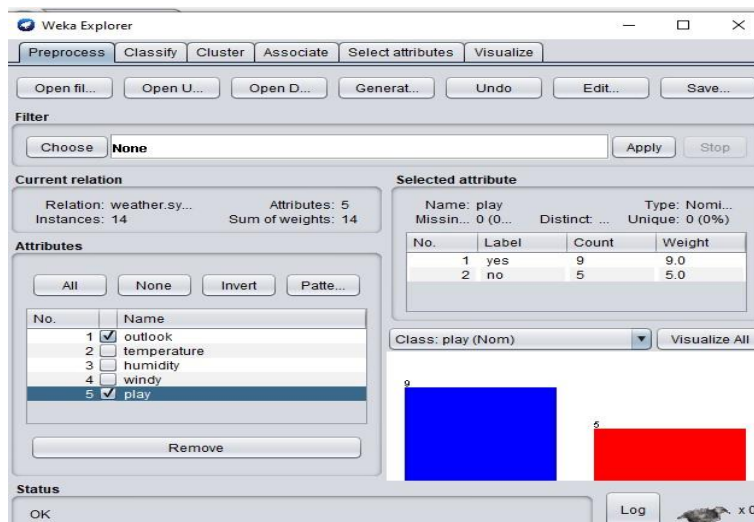
Step 6: observe attributes names, types, class attribute

1.WEATHER.ARFF:





UPLOADING WEATHER.ARFF FILE:



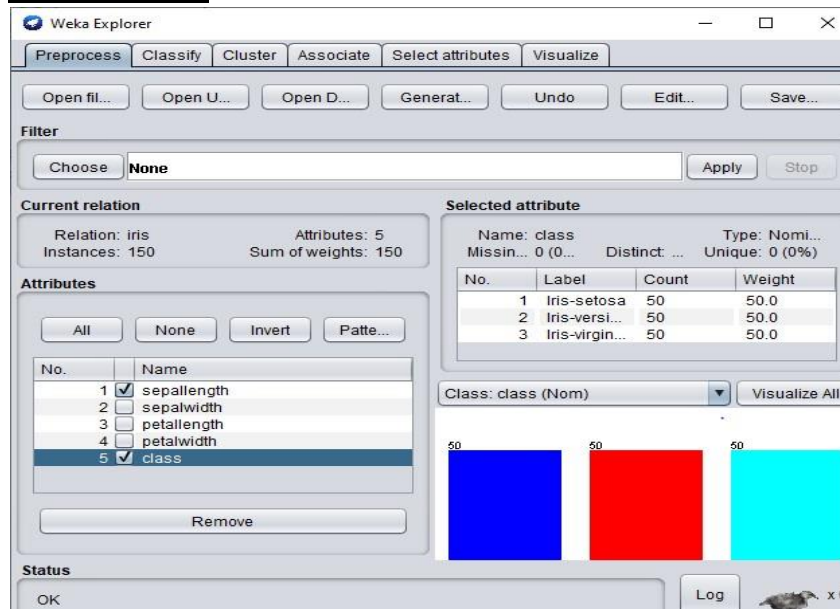
1. List the attribute names and their types
Attributes are outlook, temperature, humidity, windy, play.
2. Number of records in each dataset
number of records are 14
3. Identify the class attribute (if any)
class attribute is play
4. Histogram

DATE:



```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
data=pd.read_csv("/Iris.csv")
print(data.head(10)) data.info()
plt.figure(figsize=(10,7))
```

IRIS.ARFF:



Current relation
Relation: iris
Instances: 150
Attributes: 5
Sum of weights: 150

Selected attribute
Name: class
Missin... 0 (0...
Distinct: ...
Unique: 0 (0%)

No.	Label	Count	Weight
1	Iris-setosa	50	50.0
2	Iris-versi...	50	50.0
3	Iris-virgin...	50	50.0

Class: class (Nom) Visualize All

1. List the attribute names and they types

sepalwidth

REAL

sepalwidth

REAL

petalwidth

REAL

petalwidth

REAL

class {Iris-setosa, Iris-versicolor, Iris-virginica}

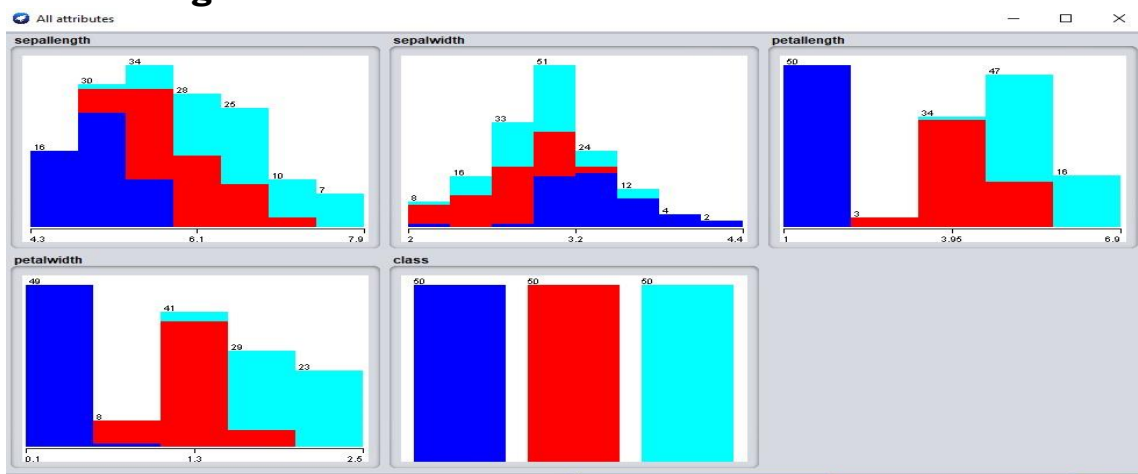
2. Number of records in each dataset

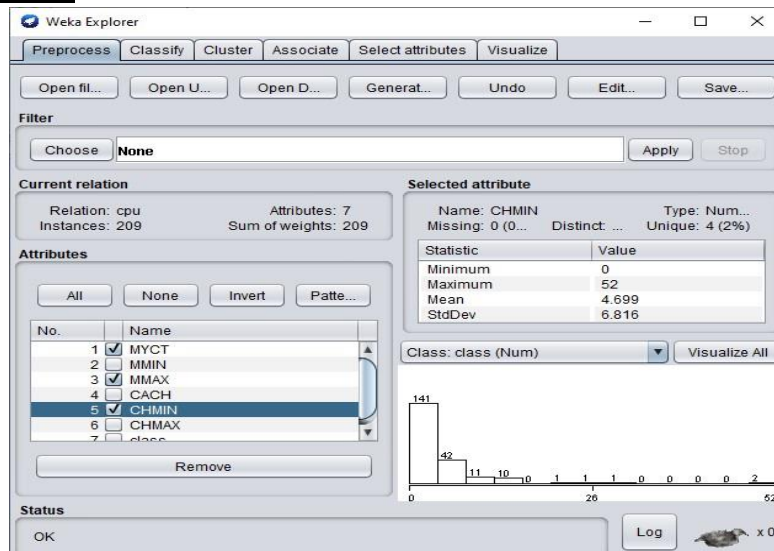
Number of records = 150

3. Identify the class attribute (if any)

Class {Iris-setosa, Iris-versicolor, Iris-virginica}

4. Plot Histogram



CPU.ARFF:**1.List the attribute names and they types**

attribute MYCT

numeric MMIN

numeric

MMAX numeric

@attribute CACH numeric

@attribute CHMIN numeric

@attribute CHMAX numeric

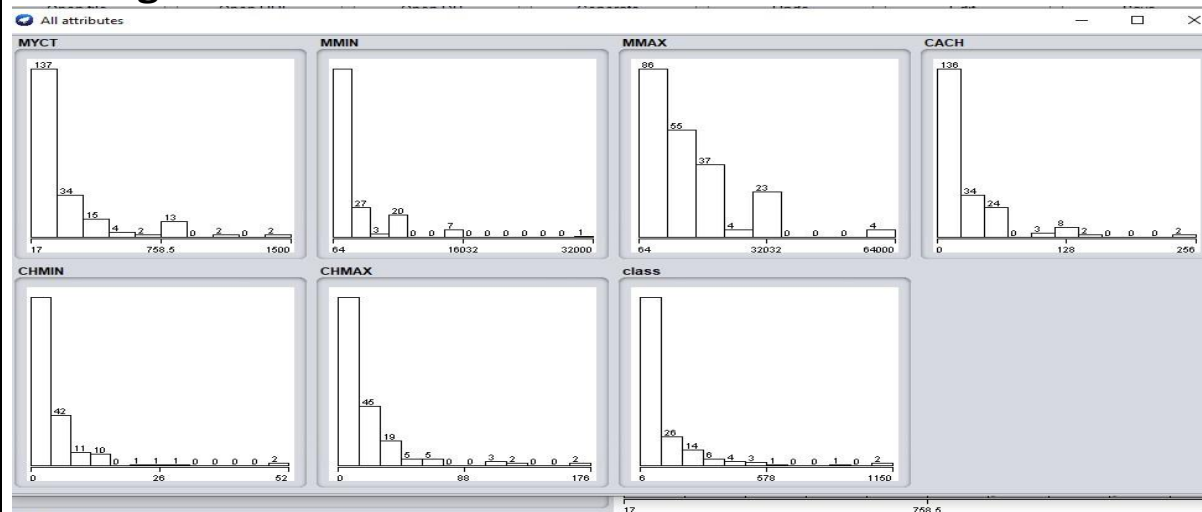
@attribute class numeric

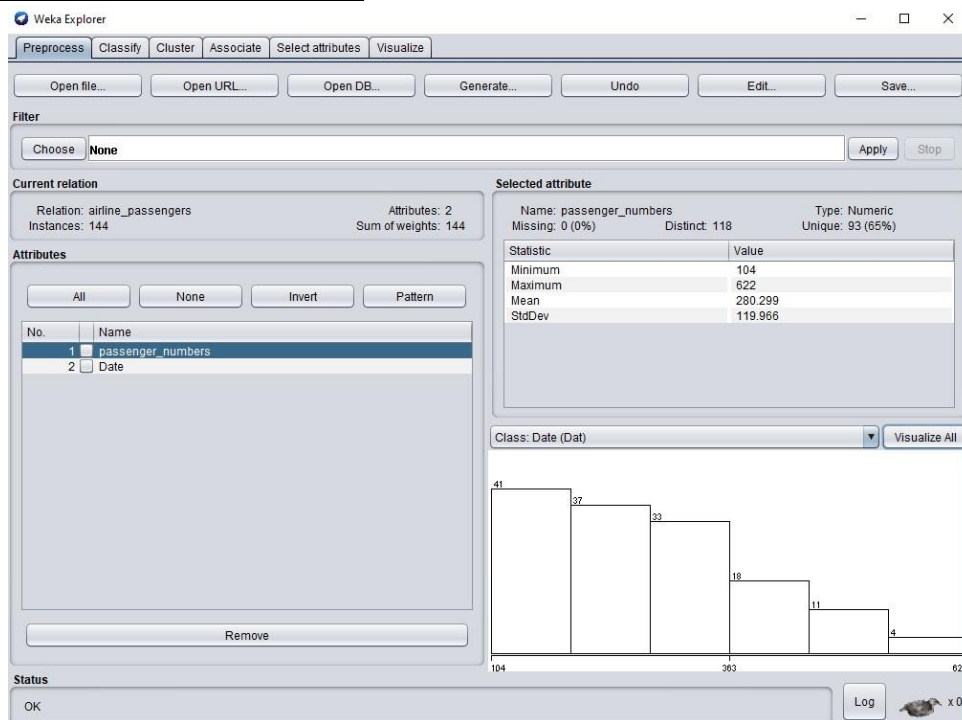
2.Number of records in each dataset

Number of records : 11

3.Identify the class attribute (if any)

class numeric

4.histogram:

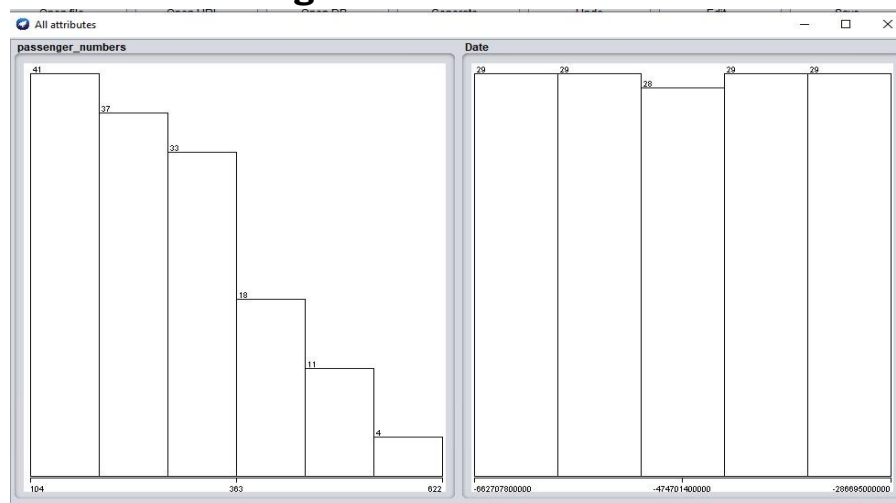
AIRLINE.ARFF File:**1.List the attribute names and they types**

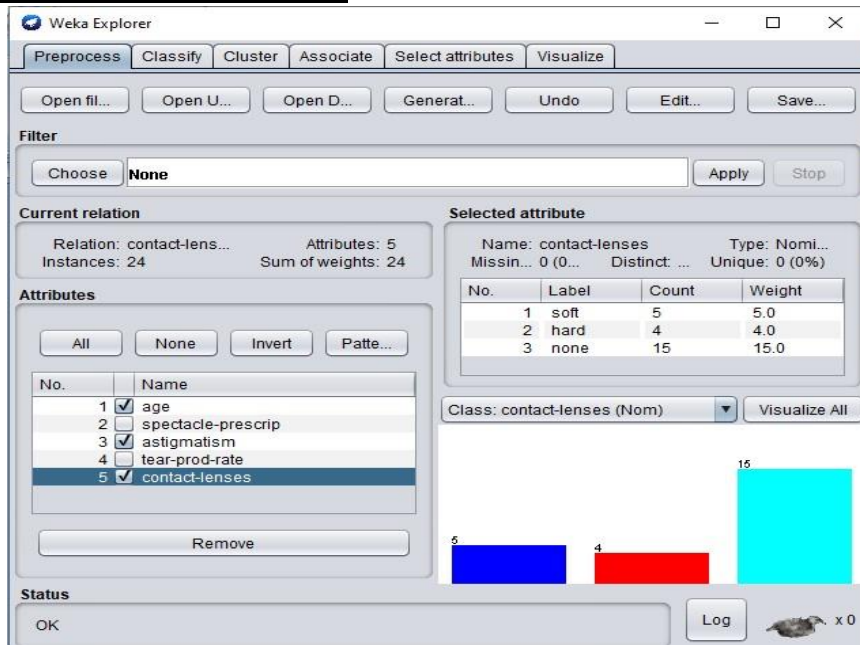
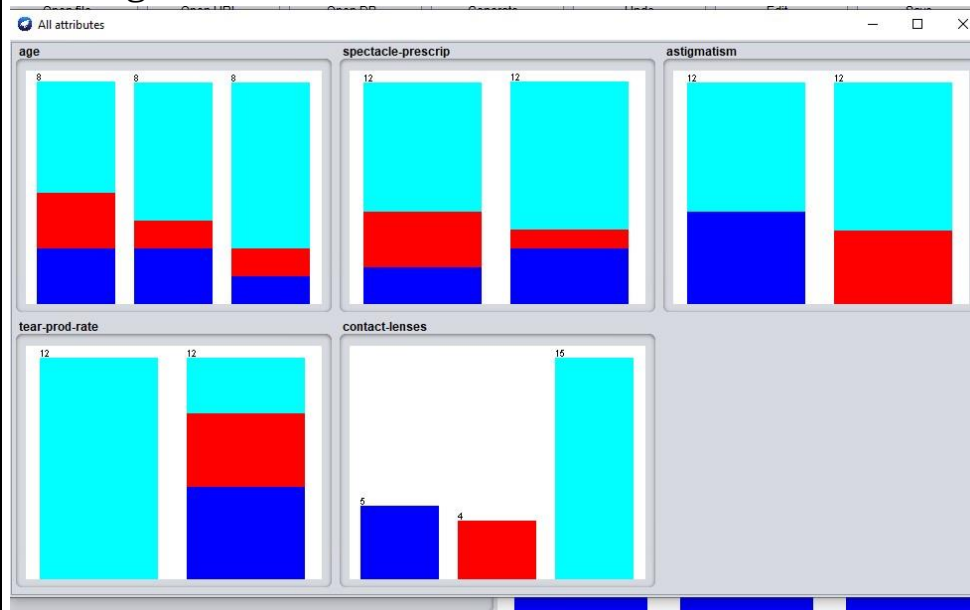
Passengers number

DATE

2.Number of data records: 22**3.Identify the class attribute (if any)**

No class attribute

4.Plot the Histogram

Contact-lenses.arff:**4.histogram:**

numpy:

NumPy is a Python library used for working with arrays.

It also has functions for working in domain of linear algebra, fourier transform, and matrices.

NumPy was created in 2005 by Travis Oliphant. It is an open source project and you can use it freely. NumPy stands for Numerical Python.

pandas:

pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real-world data analysis in Python

matplotlib:

Matplotlib is a cross-platform, data visualization and graphical plotting library for Python and its numerical extension NumPy. As such, it offers a viable open source alternative to MATLAB. Developers can also use matplotlib's APIs (Application Programming Interfaces) to embed plots in GUI applications

Program:



```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
[ ] data=pd.read_csv("/content/Iris (1).csv")
```

```
[ ] print(data.head(10))
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
5	6	5.4	3.9	1.7	0.4	Iris-setosa
6	7	4.6	3.4	1.4	0.3	Iris-setosa
7	8	5.0	3.4	1.5	0.2	Iris-setosa
8	9	4.4	2.9	1.4	0.2	Iris-setosa
9	10	4.9	3.1	1.5	0.1	Iris-setosa

```
[ ] data.describe()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161

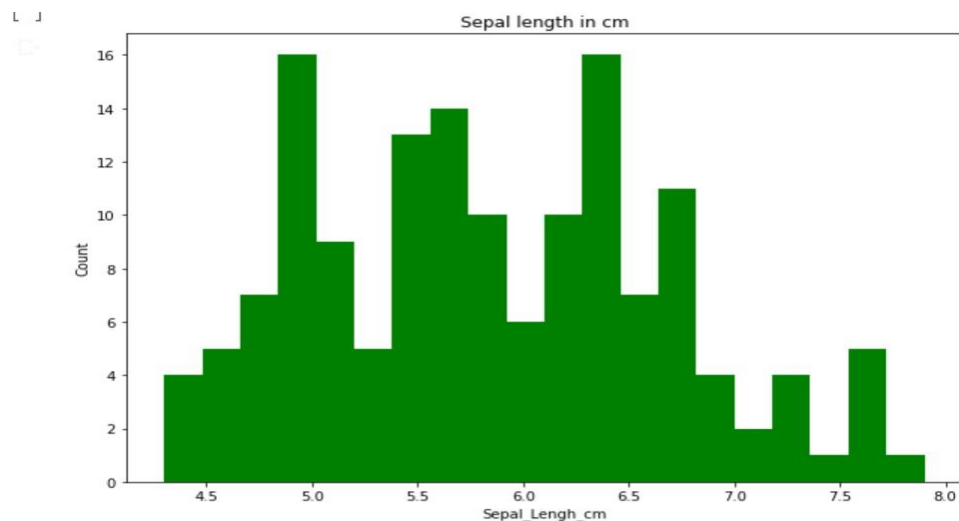
[]	min	1.000000	4.300000	2.000000	1.000000	0.100000
	25%	38.250000	5.100000	2.800000	1.600000	0.300000
	50%	75.500000	5.800000	3.000000	4.350000	1.300000
	75%	112.750000	6.400000	3.300000	5.100000	1.800000
	max	150.000000	7.900000	4.400000	6.900000	2.500000

```
[ ] data.info()
```

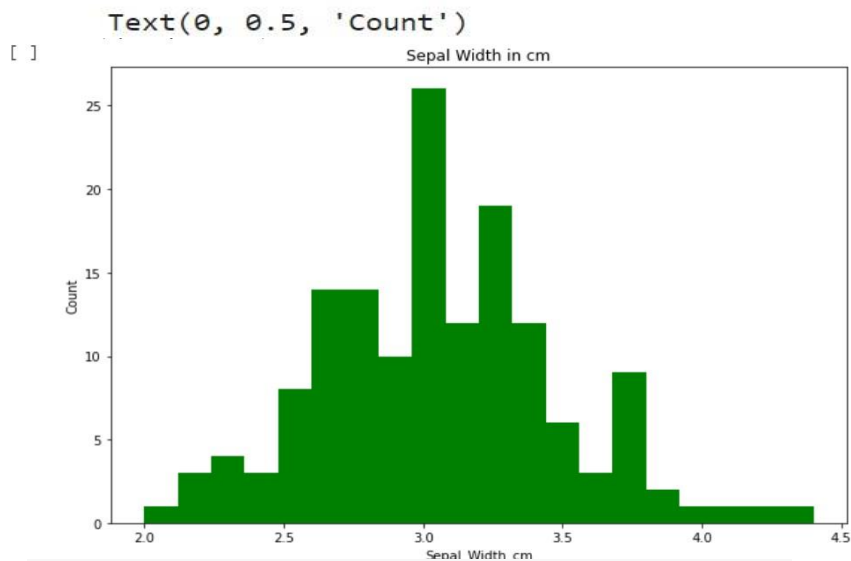
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Id              150 non-null   int64
1   SepalLengthCm   150 non-null   float64
2   SepalWidthCm    150 non-null   float64
3   PetalLengthCm   150 non-null   float64
4   PetalWidthCm    150 non-null   float64
5   Species         150 non-null   object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

```
[ ] plt.figure(figsize=(10,7))
x=data["SepalLengthCm"]
plt.hist(x,bins=20,color="green")
plt.title("Sepal length in cm")
plt.xlabel("Sepal_Length_cm")
plt.ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```

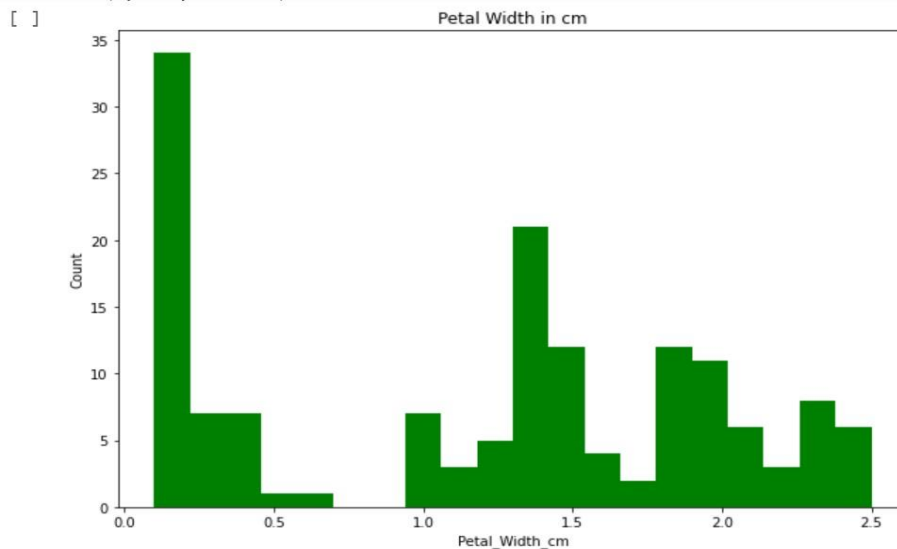


```
[ ] plt.figure(figsize=(10,7))
x=data["SepalWidthCm"]
plt.hist(x,bins=20,color="green")
plt.title("Sepal Width in cm")
plt.xlabel("Sepal_Width_cm")
plt.ylabel("Count")
```



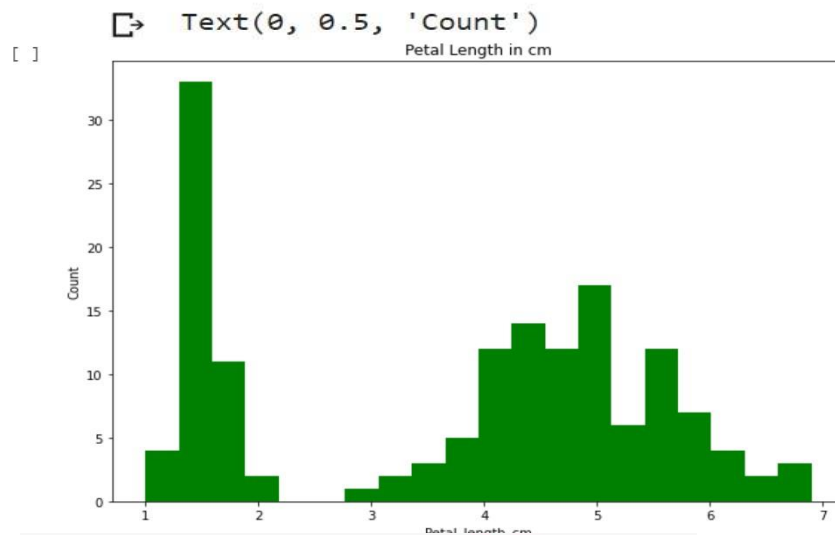
```
[ ] plt.figure(figsize=(10,7))
x=data["PetalWidthCm"]
plt.hist(x,bins=20,color="green")
plt.title("Petal Width in cm")
plt.xlabel("Petal_Width_cm")
plt.ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```



▶

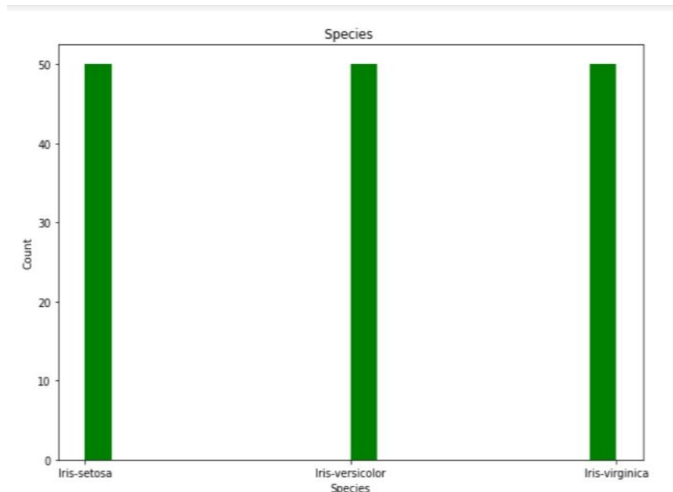
```
plt.figure(figsize=(10,7))
x=data["PetalLengthCm"]
plt.hist(x,bins=20,color="green")
plt.title("Petal Length in cm")
plt.xlabel("Petal_length_cm")
plt.ylabel("Count")
```



[]

```
plt.figure(figsize=(10,7))
x=data.Species
plt.hist(x,bins=20,color="green")
plt.title("Species ")
plt.xlabel("Species")
plt.ylabel("Count")
plt.show()
```

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5.Determine the number of records for each class.

Iris-data set

Iris-setosa : 50 records

Iris-versicolor : 50 records

Iris virginica : 50 records

Weather.nominal set

9 records : yes

5 records : no

total 14 records

Diabetes:

500 records : tested_negative diabetes

268 records : tested_positive diabetes

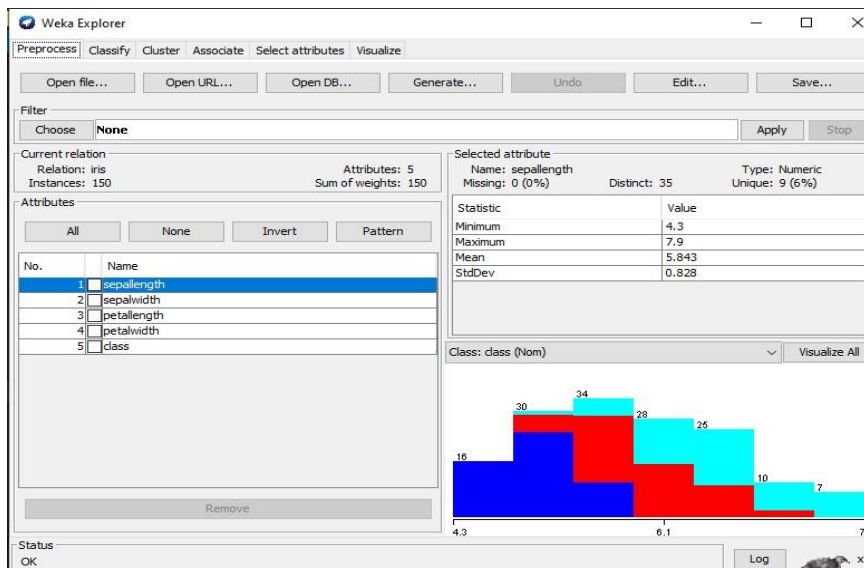
Breast Cancer

201 records : no recurrence events

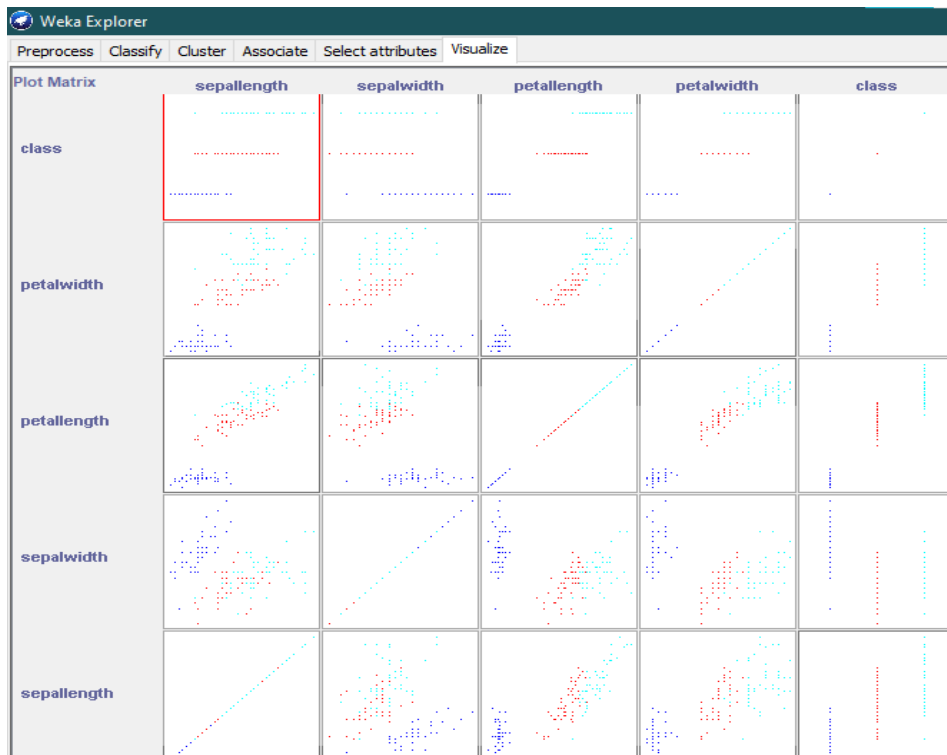
85 records : recurrence events

6.Visualize the data in various dimensions

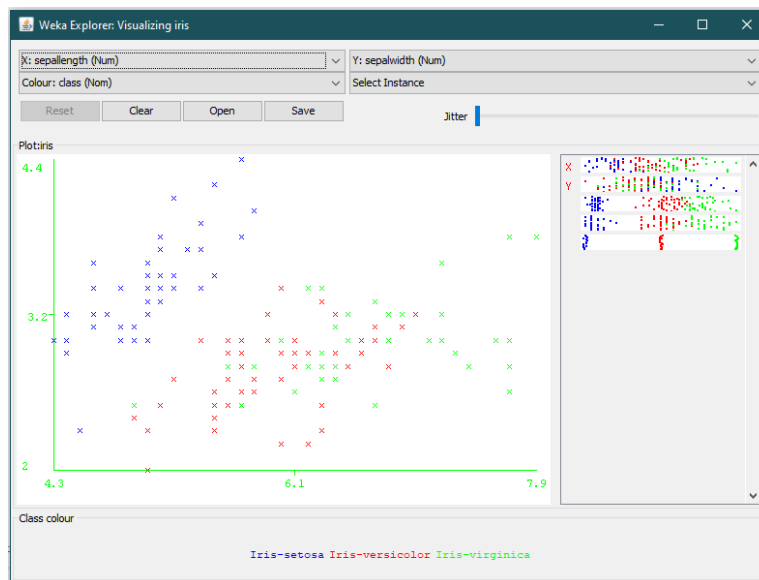
Load iris data set into weka



click on visualize tab (next to select attributes)



i) sepal_length vs sepal_width

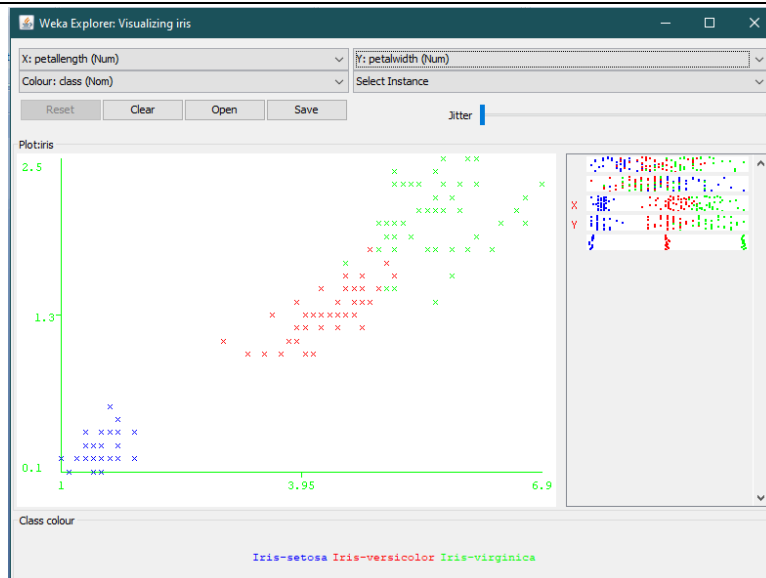


ii) petal_length vs petal_width

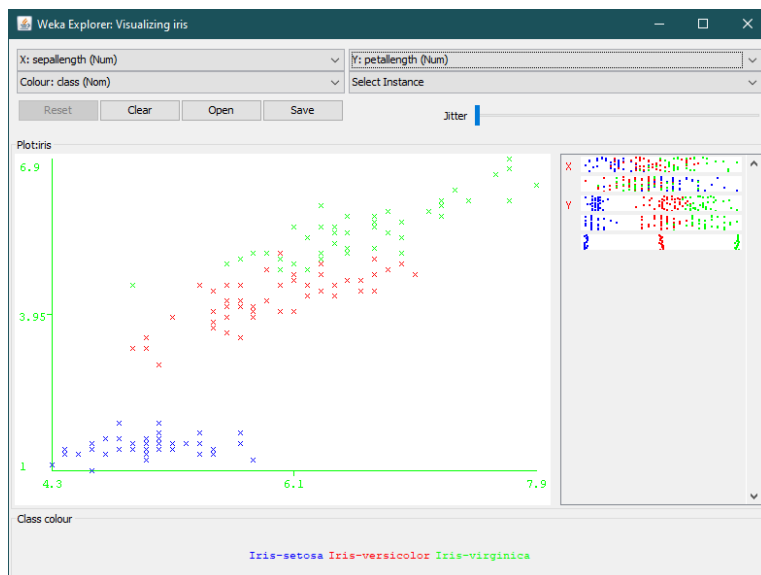
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Data Mining Lab



iii) sepal_length vs petal_length



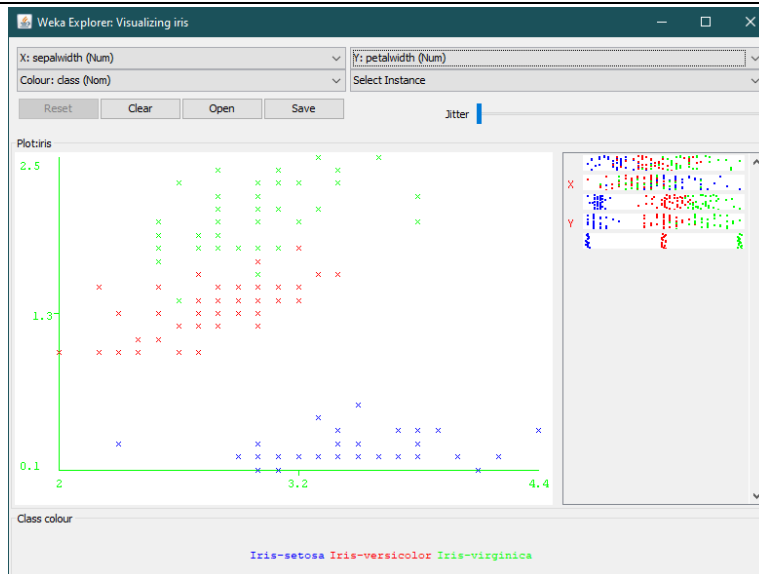
iv) sepal_width vs petal_width

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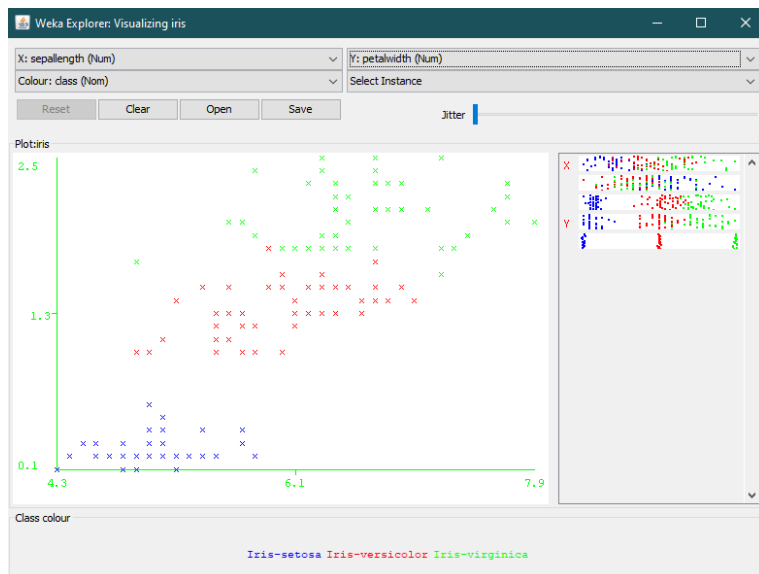
DATE:



Data Mining Lab



v) sepal_length vs petal_width



Week – 3

Perform following data preprocessing tasks using Python

i) Rescale Data ii) Binarize Data iii) Standardize Data

Aim:

To Perform following data preprocessing tasks using Python i) Rescale Data ii) Binarize Data iii) Standardize data

Normalization:

Normalization is used to scale the data of an attribute so that it falls in a smaller range, such as -1.0 to 1.0 or 0.0 to 1.0. It is generally useful for classification algorithms.

Min-Max Normalization :

In this technique of knowledge normalization, a linear transformation is performed on the first data. Minimum and maximum value from data is fetched and each value is replaced according to the following formula.

Min-Max Normalization preserves the relationships among the original data values. It will encounter an out-of-bounds error if a future input case for normalization falls outside the first data range for A. The formula is given below

$$V' = V - \min(A) | \max(A) - \min(A) (new_{\max}(A) - new_{\min}(A)) + new_{\min}(A)$$

Where A is the attribute data represent as follows.

Min(A) - It is the minimum absolute value A.

Max(A) - It is the maximum absolute value A.

v' - It is the new value of each attribute data.

v - It is the old value of each attribute data.

new_max(A), new_min(A) is the max and min value within the range

(i.e boundary value of range required) respectively.

Example :

Here, we will discuss an example as follows.

Normalize the following group of data –

1000,2000,3000,9000

using min-max normalization by setting min:0 and max:1

Solution –

As given in question

here, new_max(A)=1

max=1 new_min(A)=0,

min=0

max(A)=9000

as the maximum data among
1000,2000,3000,9000 is 9000

min(A)=1000

as the minimum data among
1000,2000,3000,9000 is 1000

Case-1:

normalizing 1000 –

v = 1000 ,

putting all values in the formula,we
get

$$v' = \frac{(1000-1000) \times (1-0)}{9000-1000} + 0 = 0$$

Case-2:

normalizing 2000 –

v = 2000,

putting all values in the formula,we
get

$$v' = \frac{(2000-1000) \times (1-0)}{9000-1000} + 0 = 0.125$$

Case-3:

normalizing 3000 –

v=3000,

putting all values in the formula,we get

$$v' = \frac{(3000-1000) \times (1-0)}{9000-1000} + 0 = 0.25$$

Case-4:

normalizing 9000 –

v=9000,

putting all values in the formula, we get

$$v' = \frac{(9000-1000) \times (1-0)}{9000-1000} + 0 = 1$$

Outcome :

Hence, the normalized values of 1000,2000,3000,9000 are 0, 0.125, .25, 1.

PROGRAM:

```

▶ from numpy import asarray
  from sklearn.preprocessing import MinMaxScaler

  data = asarray([[100,150],[800,500],[500,750],[880,600],[400,100]])
  print(data)
  scaler = MinMaxScaler()
  scaled = scaler.fit_transform(data)
  print(scaled)

```

```

[[100 150]
 [800 500]
 [500 750]
 [880 600]
 [400 100]]
[[0.         0.07692308]
 [0.8974359  0.61538462]
 [0.51282051 1.         ]
 [1.         0.76923077]
 [0.38461538 0.         ]]

```

```

[3] from sklearn import datasets
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import MinMaxScaler

```

```

[4] iris = datasets.load_iris()
    X = iris.data
    Y = iris.target

```

```

[5] print(X)

```

```

[5.8 2.6 4.  1.2]
[5.  2.3 3.3 1. ]
[5.6 2.7 4.2 1.3]
[5.7 3.  4.2 1.2]
[5.7 2.9 4.2 1.3]
[6.2 2.9 4.3 1.3]
[5.1 2.5 3.  1.1]
[5.7 2.8 4.1 1.3]
[6.3 3.3 6.  2.5]
[5.8 2.7 5.1 1.9]
[7.1 3.  5.9 2.1]
[6.3 2.9 5.6 1.8]
[6.5 3.  5.8 2.2]
[7.6 3.  6.6 2.1]
[4.9 2.5 4.5 1.7]
[7.3 2.9 6.3 1.8]
[6.7 2.5 5.8 1.8]

```

```
[7] print(Y)
```

[illegible]

```
[8] X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.3,random_state = 1,stratify = Y)
```

```
[9] mmScaler = MinMaxScaler()
X_train_norm = mmScaler.fit_transform(X_train)
X_test_norm = mmScaler.transform(X_train)
```

```
[11] print(X_test_norm)
```

```
[0.19444444 0.54545455 0.03389831 0.04166667]
[0.66666667 0.5          0.77966102 0.95833333]
[0.91666667 0.45454545 0.94915254 0.83333333]
[0.41666667 0.90909091 0.03389831 0.04166667]
[0.80555556 0.45454545 0.81355932 0.625      ]
[0.63888889 0.40909091 0.61016949 0.5        ]
[0.19444444 0.13636364 0.38983051 0.375      ]
[0.25        0.31818182 0.49152542 0.54166667]
[0.11111111 0.54545455 0.05084746 0.04166667]
[0.5         0.36363636 0.62711864 0.45833333]
```

ii) Binarize data

sklearn.preprocessing

Binarizer() is a method which belongs to preprocessing module. It plays a key role in the discretization of continuous feature values

Example #1:

A continuous data of pixels values of an 8-bit grayscale image have values ranging between 0 (black) and 255 (white) and one needs it to be black and white.

So, using Binarizer() one can set a threshold converting pixel values from 0 – 127 to 0 and 128 – 255 as 1.

Syntax:

```
sklearn.preprocessing.Binarizer(threshold, copy)
```

Parameters :

threshold :[float, optional] Values less than or equal to threshold is mapped to 0, else to 1.

By default threshold value is 0.0.

copy : [boolean, optional] If set to False, it avoids a copy.

By default it is True.

PROGRAM

```
[1] from sklearn.preprocessing import Binarizer
import pandas
import numpy as np
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
```

```
[6] col_name = ['preg', 'plasma', 'pres', 'skin', 'test', 'BMI', 'pedi', 'age', 'class']
```

```
[7] print(col_name)
```

```
['preg', 'plasma', 'pres', 'skin', 'test', 'BMI', 'pedi', 'age', 'class']
```

```
[12] data = pandas.read_csv(url, names = col_name) #dataset is converted to data frame
```

```
[10] print(data)
```

	preg	plasma	pres	skin	test	BMI	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
..
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

```
[768 rows x 9 columns]
```

```
[11] array = data.values
```

```
[14] array
```

```
array([[ 6. , 148. , 72. , ..., 0.627, 50. , 1. ],
       [ 1. , 85. , 66. , ..., 0.351, 31. , 0. ],
       [ 8. , 183. , 64. , ..., 0.672, 32. , 1. ],
       ...,
       [ 5. , 121. , 72. , ..., 0.245, 30. , 0. ],
       [ 1. , 126. , 60. , ..., 0.349, 47. , 1. ],
       [ 1. , 93. , 70. , ..., 0.315, 23. , 0. ]])
```

```
[15] X = array[:,0:8]
      Y = array[:,8]
```

```
[16] print(X)
```

```
[[ 6.   148.   72.   ...  33.6   0.627  50.   ]
 [ 1.    85.   66.   ...  26.6   0.351  31.   ]
 [ 8.   183.   64.   ...  23.3   0.672  32.   ]
 ...
 [ 5.   121.   72.   ...  26.2   0.245  30.   ]
 [ 1.   126.   60.   ...  30.1   0.349  47.   ]
 [ 1.    93.   70.   ...  30.4   0.315  23.   ]]
```

```
[18] print(Y) #original outcome
```

```
[1. 0. 1. 0. 1. 0. 1. 0. 1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 0. 1. 1.
 1. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 0. 1. 0. 1. 0. 0.
 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0.
 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0.
 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0.
 1. 0. 0. 0. 1. 1. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.
 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 0. 0.
 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 1. 1. 0. 0.
 1. 1. 0. 1. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 1. 1. 1.
 1. 0. 1. 1. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 1. 1. 1. 0.
 0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 0.
 1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 1.
 0. 0. 0. 1. 1. 1. 0. 0. 1. 0. 1. 0. 1. 1. 0. 1. 0. 0. 1. 0. 1. 1. 0. 0.
 1. 0. 1. 0. 0. 1. 0. 1. 0. 1. 1. 1. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 0.
 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 0. 1.
 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 0.]
```

```
[19] binarizer = Binarizer(threshold = 0.0).fit(X)
      binaryX = binarizer.transform(X)
```

```
[22] print(binaryX[0:10,:]) #binarised data outcome converted to 0,1
```

```
[[1. 1. 1. 1. 0. 1. 1. 1.]
 [1. 1. 1. 1. 0. 1. 1. 1.]
 [1. 1. 1. 0. 0. 1. 1. 1.]
 [1. 1. 1. 1. 1. 1. 1. 1.]
 [0. 1. 1. 1. 1. 1. 1. 1.]
 [1. 1. 1. 0. 0. 1. 1. 1.]
 [1. 1. 1. 1. 1. 1. 1. 1.]
 [1. 1. 0. 0. 0. 1. 1. 1.]
 [1. 1. 1. 1. 1. 1. 1. 1.]
 [1. 1. 1. 0. 0. 0. 1. 1.]]
```

iii) Standardise data

Data standardization is **the process of rescaling the attributes so that they have mean as 0 and variance as 1**. The ultimate goal to perform standardization is to bring down all the features to a common scale without distorting the differences in the range of the values.

```
[1] from sklearn.preprocessing import StandardScaler
import pandas
import numpy as np
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
```

```
[2] col_name = ['preg', 'plasma', 'pres', 'skin', 'test', 'BMI', 'pedi', 'age', 'class']
```

```
[3] print(col_name)
```

```
['preg', 'plasma', 'pres', 'skin', 'test', 'BMI', 'pedi', 'age', 'class']
```

```
[4] data = pandas.read_csv(url, names = col_name)
```

```
[5] print(data)
```

	preg	plasma	pres	skin	test	BMI	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

```
[768 rows x 9 columns]
```

```
[6] array = data.values
```

```
[7] array
```

```
array([[ 6., 148., 72., ..., 0.627, 50., 1. ],
       [ 1., 85., 66., ..., 0.351, 31., 0. ],
       [ 8., 183., 64., ..., 0.672, 32., 1. ],
       ...,
       [ 5., 121., 72., ..., 0.245, 30., 0. ],
       [ 1., 126., 60., ..., 0.349, 47., 1. ],
       [ 1., 93., 70., ..., 0.315, 23., 0.]])
```

```
[8] X = array[:,0:8]
Y = array[:,8]
```


```
[9] print(X)
```

```
[[ 6. 148. 72. ... 33.6 0.627 50. ]
 [ 1. 85. 66. ... 26.6 0.351 31. ]
 [ 8. 183. 64. ... 23.3 0.672 32. ]
 ...
 [ 5. 121. 72. ... 26.2 0.245 30. ]
 [ 1. 126. 60. ... 30.1 0.349 47. ]
 [ 1. 93. 70. ... 30.4 0.315 23. ]]
```

 print(Y)

```
[1. 0. 1. 0. 1. 0. 1. 0. 1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 0. 1. 1.
1. 1. 1. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 1. 0. 1. 0. 0.
1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0.
1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0.
0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 1. 0. 0. 1. 1. 1. 0. 0. 0.
1. 0. 0. 0. 1. 1. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.
0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 1. 0. 0.
0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 1. 1. 0. 0.
1. 1. 0. 1. 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 1. 1. 1.
1. 0. 1. 1. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 1. 1. 1. 0.
0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 0.
1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 1. 1. 0. 1.
0. 0. 0. 1. 1. 1. 0. 0. 1. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0. 1. 1. 0. 0.
1. 0. 1. 0. 0. 1. 0. 1. 0. 1. 1. 1. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 0.
0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1. 1. 1. 0. 1.
1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 0.
0. 0. 1. 1. 1. 0. 0. 1. 0. 0. 1. 0. 0. 1. 0. 1. 1. 0. 1. 0. 1. 0. 1. 0.
1. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0. 1. 0. 0.
0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 1. 1. 0. 0. 1. 0. 0. 1. 0. 0. 0. 1.
0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0.
1. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0.
0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0.
0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 1. 1. 1. 0. 0. 1. 1. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.
0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 1. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0.
0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 1. 1. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 1. 1.]
```

```
[12] scaler = StandardScaler().fit(X)
rescaledX = scaler.transform(X)
```

 print(rescaledX[0:10,:])

```
[[ 0.63994726  0.84832379  0.14964075  0.90726993 -0.69289057  0.20401277
  0.46849198  1.4259954 ]
 [-0.84488505 -1.12339636 -0.16054575  0.53090156 -0.69289057 -0.68442195
 -0.36506078 -0.19067191]
 [ 1.23388019  1.94372388 -0.26394125 -1.28821221 -0.69289057 -1.10325546
  0.60439732 -0.10558415]
 [-0.84488505 -0.99820778 -0.16054575  0.15453319  0.12330164 -0.49404308
 -0.92076261 -1.04154944]
 [-1.14185152  0.5040552 -1.50468724  0.90726993  0.76583594  1.4097456
  5.4849091 -0.0204964 ]
 [ 0.3429808 -0.15318486  0.25303625 -1.28821221 -0.69289057 -0.81134119
 -0.81807858 -0.27575966]
 [-0.25095213 -1.34247638 -0.98770975  0.71908574  0.07120427 -0.12597727
 -0.676133 -0.61611067]
 [ 1.82781311 -0.184482 -3.57259724 -1.28821221 -0.69289057  0.41977549
 -1.02042653 -0.36084741]
 [-0.54791859  2.38188392  0.04624525  1.53455054  4.02192191 -0.18943689
 -0.94794368  1.68125866]
 [ 1.23388019  0.12848945  1.39038675 -1.28821221 -0.69289057 -4.06047387
 -0.7244549  1.76634642]]
```


EXP NO:

DATE:



Data Mining Lab