LATE BHAUSAHEB HIRAY S.S. TRUST'S INSTITUTE OF COMPUTER APPLICATION

ISO 9001-2008 CERTIFIED

S.N. 341, Next to New English School, Govt.Colony,
Bandra (East), Mumbai – 400051,
Tel: 91-22-26570892/3181

Date: 12/08/2022

CERTIFICATE

This is to certify that Mr. Saurabh Bhausaheb Gawali

Roll No. 2021105 is a student of MCA of 1st year Semester-II has completed successfully full-semester practical/assignments of subject AIML Lab for the academic year 2021 – 22

Subject In-Charge **External Examiner**

Director

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1	Implementation of Logic programming using PROLOG	27-jun-2022	
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3	Implementation of 1)Linear Regression 2)Logistic regression 3)KNN- classification.	11-july-2022	
4	Implementation of Bagging Algorithm: Decision Tree.	13-july-2022	
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7	Implementation of Classifying data using Support Vector Machines (SVMs).	21-july-2022	

Practical 1

Aim : Study of Logical Programming with Prolog.

Steps :- 1. Create one file in notepad with .pl extension and **file type =All type.**

```
studnet(neeta).
loves_to_eat(noodles).
loves_to_eat(vijeta,noodles).
intelligent(suchita).
cat(tom).
freinds(jack,jill).
```

Go to GNU → File → Change dir → Select the folder where notepad file is saved.

```
GNU Prolog console
File  Edit  Terminal  Prolog  Help
GNU Prolog 1.4.5 (64 bits)
Compiled Jul 14 2018, 12:58:46 with cl
By Daniel Diaz
Copyright (C) 1999-2018 Daniel Diaz
| ?- |
```

```
GNU Prolog console
File  Edit  Terminal  Prolog  Help
GNU Prolog 1.4.5 (64 bits)
Compiled Jul 14 2018, 12:58:46 with cl
By Daniel Diaz
Copyright (C) 1999-2018 Daniel Diaz
compiling D:/Documents/Sem-2/AI & ML/lab/p1.pl for byte code...
D:/Documents/Sem-2/AI & ML/lab/p1.pl compiled, 5 lines read - 953 bytes written, 301 ms
| ?- |
```

Code:-

→[p1].
→ Student(X).
Intelligent(Y).

```
GNU Prolog console
File  Edit  Terminal  Prolog  Help
GNU Prolog 1.4.5 (64 bits)
Compiled Jul 14 2018, 12:58:46 with cl
By Daniel Diaz
Copyright (C) 1999-2018 Daniel Diaz
| ?- change_directory('D:/AI & ML').

yes
| ?- [p1].
compiling D:/AI & ML/p1.pl for byte code...
D:/AI & ML/p1.pl:1: warning: singleton variables [Sameer] for student/1
D:/AI & ML/p1.pl:3: warning: singleton variables [Krishna] for loves_to_eat/2
D:/AI & ML/p1.pl:4: warning: singleton variables [Ritvik] for intelligent/1
D:/AI & ML/p1.pl compiled, 5 lines read - 826 bytes written, 390 ms

yes
| ?- student(X).

yes
| ?- intelligent(Y)
.

yes
| ?- |
```

2. AND(;) & OR(,) Function

Create new notepad file.

→likes(pooja,geeta).
likes(geeta,pooja).
likes(neha,aliya).
freindship(X,Y) :- likes(X,Y);likes(Y,X).

```
| ?- [p2].
compiling D:/AI & ML/p2.pl for byte code...
D:/AI & ML/p2.pl compiled, 5 lines read - 884 bytes written, 17 ms

yes
| ?- freindship(X,Y).

X = pooja
Y = geeta ? ;

X = geeta
Y = pooja ? ;

X = neha
Y = aliya ? ;

X = geeta
Y = pooja ? ;

X = pooja
Y = geeta ? ;

X = aliya
Y = neha

(46 ms) yes
| ?- |
```

→ likes(pooja,geeta).
likes(geeta,pooja).
likes(neha,aliya).

freindship(X,Y) :- likes(X,Y),likes(Y,X).

```
| ?- [p2].
compiling D:/AI & ML/p2.pl for byte code...
D:/AI & ML/p2.pl compiled, 5 lines read - 763 bytes written, 16 ms

yes
| ?- freindship(X,Y).

X = pooja
Y = geeta ? ;

X = geeta
Y = pooja ? ;

no
| ?- |
```

→ next_to(mumbai,pune).
next_to(pune,satara).
next_to(mumbai,nashik).
travel(A,C) :- next_to(A,B),next_to(B,C).

```
| ?- [p2].
compiling D:/AI & ML/p2.pl for byte code...
D:/AI & ML/p2.pl compiled, 5 lines read - 738 bytes written, 16 ms

yes
| ?- freindship(X,Y).

X = pooja
Y = geeta ? ;

X = geeta
Y = pooja ? ;

(31 ms) no
```

3. Relationship in prolog: - specify relationship between object and properties of objects. Relationship can also be a rule.

Create new notepad file.

→ p3.pl
female(scarlet).
female(alice).
female(katherine).
female(fiona).

male(bob).
male(sean).
male(chris).
male(dravis).

```
parent(bob, alice).
parent(bob, sean).
parent(scarlet,alice).
parent(scarlet, sean).

parent(alice, katherine).
parent(sean, chris).

parent(katherine,fiona).
parent(chris,dravis).

granparent(X,Y) :- parent(X,Z),parent(Z,Y).

sister(X,Y) :- parent(Z,X), parent(Z,Y), female(X), X\=Y.

brother(X,Y) :- parent(Z,X), parent(Z,Y), male(X), female(Y).

uncle(X,Y) :- parent(Z,Y), brother(X,Z).

aunt(X,Y) :- parent(Z,Y),sister(X,Z).

daughter(X,Y) :- parent(Y,X), female(X).

son(X,Y) :- parent(Y,X), male(X).

mother(X,Y) :- parent(X,Y), female(X).

father(X,Y) :- parent(X,Y), male(X).
```

GNU Prolog console

File Edit Terminal Prolog Help

```
GNU Prolog 1.4.5 (64 bits)
Compiled Jul 14 2018, 12:58:46 with cl
By Daniel Diaz
Copyright (C) 1999-2018 Daniel Diaz
| ?- change_directory('D:/AI & ML').

yes
| ?- [p3].
compiling D:/AI & ML/p3.pl for byte code...
D:/AI & ML/p3.pl compiled, 38 lines read - 4475 bytes written, 354 ms

(31 ms) yes
| ?- parent(X,Y)
.

X = bob
Y = alice ? ;

X = bob
Y = sean ? ;

X = scarlet
Y = alice ? ;

X = scarlet
Y = sean ? ;

X = alice
Y = katherine ? ;

X = sean
Y = chris ? ;

X = katherine
Y = fiona ? ;

X = chris
Y = dravis
```

```
| ?- brother(X,Y).

X = sean
Y = alice ? ;

X = sean
Y = alice ? ;

no
| ?- sister(X,Y).

X = alice
Y = sean ? ;

X = alice
Y = sean ? ;

(16 ms) no
| ?- grandparent(X,Y).

X = bob
Y = katherine ? ;

X = bob
Y = chris ? ;

X = scarlet
Y = katherine ? ;

X = scarlet
Y = chris ? ;

X = alice
Y = fiona ? ;

X = sean
Y = dravis ? ;
```

```
| ?- uncle(X,Y).

X = sean
Y = katherine ? ;

X = sean
Y = katherine ? ;

(15 ms) no
| ?- aunt(X,Y).

X = alice
Y = chris ? ;

X = alice
Y = chris ? ;

(31 ms) no
| ?- mother(X,Y).

X = scarlet
Y = alice ? ;

X = scarlet
Y = sean ? ;

X = alice
Y = katherine ? ;

X = katherine
Y = fiona ? ;

(47 ms) no
```

```
| ?- father(X,Y).

X = bob
Y = alice ? ;

X = bob
Y = sean ? ;

X = sean
Y = chris ? ;

X = chris
Y = dravis

yes
| ?- son(X,Y).

X = sean
Y = bob ? ;

X = sean
Y = scarlet ? ;

X = chris
Y = sean ? ;

X = dravis
Y = chris
```

```
| ?- daughter(X,Y).

X = alice
Y = bob ? ;

X = alice
Y = scarlet ? ;

X = katherine
Y = alice ? ;

X = fiona
Y = katherine ? ;

(31 ms) no
| ?- |
```

Practical NO: 2

Aim : Study of Python Libraries

a) NumPy b) Pandas c)Matplotlib.

NumPy :

```
import numpy as np
l = ['dog', 'cat', 'horse']
l
```

Output: ['dog', 'cat', 'horse']

```
type(l)
```

Output: list

```
l.sort()
l
```

Output: ['cat', 'dog', 'horse']

```
li = list(range(6))
li
```

Output: [0, 1, 2, 3, 4, 5]

```
while li:
    p=li.pop()
    print('p:', p)
    print('li:', li)
```

Output:

```
p: 5
li: [0, 1, 2, 3, 4]
p: 4
li: [0, 1, 2, 3]
p: 3
li: [0, 1, 2]
p: 2
li: [0, 1]
p: 1
li: [0]
p: 0
li: []
```

```
a = ('Ryan', 33, True)
b = 'Takaya', 25, False
```

type(b)
Output: tuple

type(a)
type(b)
Output: tuple

print(a[1])
Output: 33

print(b[0])
Output: Takaya

a = np.array([2,4,6,8])
a
Output: array([2, 4, 6, 8])

a.dtype
Output: dtype('int32')

a = np.array([2,4,6,8], np.int64)
a
Output: array([2, 4, 6, 8], dtype=int64)

a = np.array([[2,4,6,8]])
a
Output: array([[2, 4, 6, 8]])

a[0][3]
Output: 8

a.shape
Output: (1, 4)

listarr = np.array([[1,1,1],[2,2,2],[3,3,3]])
listarr
Output:

```
array([[1, 1, 1],
       [2, 2, 2],
       [3, 3, 3]])
```

listarr.shape
Output: (3, 3)

listarr.size
Output: 9

z = np.zeros((2,4))
z
Output:

```
array([[0., 0., 0., 0.],
       [0., 0., 0., 0.]])
```

z.shape
Output: (2, 4)

y = np.ones((3,4))
y
Output:

```
array([[1., 1., 1., 1.],
       [1., 1., 1., 1.],
```

```
       [1., 1., 1., 1.]])
```

```
y = np.ones((2,3,4))
y
```

Output:

```
array([[[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]],

       [[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]]])
```

```
x = np.arange(10)
x
```

Output: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

```
m = np.linspace(1,5,4)
m
```

Output: array([1. , 2.33333333, 3.66666667, 5.])

```
m = np.linspace(1,7,3)
```

Output: Type Markdown and LaTeX: α2

```
m
```

Output: array([1., 4., 7.])

```
y
```

Output:

```
array([[[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]],

       [[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]]])
```

```
c = np.ones_like(y)
c
```

Output:

```
array([[[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]],

       [[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]]])
```

```
g = np.ones((2,3,4))
g
```

Output:

```
array([[[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]],   [[1., 1., 1., 1.],  [1., 1., 1., 1.],
        [1., 1., 1., 1.]]])
```

```
g.reshape
```

Output: <function ndarray.reshape>

```
g
```

Output:
array([[[1., 1., 1., 1.], [1., 1., 1., 1.],
        [1., 1., 1., 1.]], [[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]]])

h = np.arange(50)
h
Output:
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
       34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49])

h.reshape(2,25)
Output:
array([[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,
        16, 17, 18, 19, 20, 21, 22, 23, 24],
       [25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40,
        41, 42, 43, 44, 45, 46, 47, 48, 49]])

h.ravel()
Output:
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
       34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49])

b = np.arange(3,10,2, dtype=np.int32)
b.itemsize
b
Output: 4

b = np.arange(3.4,10,2)
b.itemsize
Output: 8

b.shape
Output: (4,)
b.itemsize
Output: 8

t = np.linspace(3,10,3, dtype=np.int32)
t
Output: array([3. , 4.75, 6.5 , 8.25, 10.])

t = np.linspace(3,10,5, dtype=np.int32)
t
Output: array([3, 4, 6, 8, 10])
m = np.arange(6)
m
Output: array([0, 1, 2, 3, 4, 5])
m.reshape(2,3)

Output:
array([[0, 1, 2],
       [3, 4, 5]])
m.reshape(3,2)
Output:
array([[0, 1],[2, 3], [4, 5]])

Pandas :

```
import numpy as np
import pandas as pd
dict = {"name":['aa', 'bb', 'cc'],
        "class":['fy','sy','ty'],
       "roll":[11, 22, 33]}
dict
```

Output: {'name': ['aa', 'bb', 'cc'], 'class': ['fy', 'sy', 'ty'], 'roll': [11, 22, 33]}

```
df = pd.DataFrame(dict)
df
```

Output:

name	class	roll	
0	aa	fy	11
1	bb	sy	22
2	cc	ty	33

```
df.to_csv('student.csv')
df.to_csv('index_false_student.csv', index=False)
df.head()
```

Output:

name	class	roll	
0	aa	fy	11
1	bb	sy	22
2	cc	ty	33

```
df.tail()
```

Output:

name	class	roll	
0	aa	fy	11
1	bb	sy	22
2	cc	ty	33

```
df.describe()
```

Output:

roll	
count	3.0
mean	22.0
std	11.0
min	11.0
25%	16.5
50%	22.0
75%	27.5
max	33.0

```
df.head(3)
```

Output:

	name	class	roll
0	aa	fy	11
1	bb	sy	22
2	cc	ty	33

```
df.to_csv('index.csv', index=False)
df
```

Output:

	name	class	roll

```
0    aa    fy    11
1    bb    sy    22
2    cc    ty    33
```

```
df.to_csv('index1.csv', index=False)
demo = pd.read_csv('index2.csv')
demo
```

Output:

	prod_id	name	area
0	2200	apple	andheri
1	3300	mango	parle
2	4400	orange	santacruz

```
demo['name']
```

Output:

```
0   apple
1   mango
2   orange
Name: name, dtype: object
```

```
demo['name'][1]
```

Output: 'mango'

```
demo['prod_id']
```

Output:

```
0   2200
1   3300
2   4400
Name: prod_id, dtype: int64
```

```
demo['prod_id'][2]
```

Output: 4400

```
demo['prod_id'][2] = 4004
```

Output: warning

```
<ipython-input-64-0c3a9eb8bc8c>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
demo['prod_id'][2] = 4004
demo['prod_id']
```

Output:

```
0   2200
1   3300
2   4004
Name: prod_id, dtype: int64
```

```
demo.to_csv('new.csv')
demo
```

Output:

prod_id		name	area
0	2200	apple	andheri
1	3300	mango	parle
2	4004	orange	santacruz

```
demo.index = ['one', 'two', 'three']
demo
```

Output:

	prod_id	name	area

```
one      2200    apple   andheri
two      3300    mango parle
three    4004    orange Santacruz
```

```
s = pd.Series([2,3,4,5,6,7,8,9,10])
s
```

Output:

```
0    2
1    3
2    4
3    5
4    6
5    7
6    8
7    9
8   10
dtype: int64
```

```
s1 = pd.Series(np.random.rand(20))
s1
```

Output:

```
0     0.476242
1     0.332118
2     0.265113
3     0.722535
4     0.210917
5     0.204344
6     0.557794
7     0.585600
8     0.775989
9     0.555856
10    0.669544
11    0.874442
12    0.534156
13    0.260446
14    0.519634
15    0.776713
16    0.660476
17    0.748030
18    0.814161
19    0.366974
dtype: float64
```

```
df1 = pd.DataFrame(np.random.rand(20,10))
df1
```

Output:

```
         0        1        2        3        4        5        6        7        8        9
0        0.889829         0.217723         0.950464         0.114454         0.175260         0.171785
         0.502882         0.431306         0.585802         0.824907
1        0.815695         0.961605         0.734357         0.617062         0.778672         0.737305
         0.224034         0.792681         0.043488         0.755798
2        0.300321         0.297326         0.667170         0.810632         0.954124         0.527148
         0.697780         0.679426         0.251948         0.124489
3        0.648760         0.770672         0.254008         0.025945         0.110265         0.602699
         0.498752         0.413338         0.312994         0.293970
```

4	0.538527	0.630472	0.851454	0.061778	0.659211	0.565140	0.876626	0.598274	0.997209	0.087594
5	0.541544	0.934696	0.424254	0.602228	0.491561	0.614428	0.120711	0.491124	0.204725	0.973860
6	0.628961	0.302158	0.846598	0.068880	0.285089	0.233620	0.408571	0.277139	0.119807	0.524263
7	0.120473	0.407693	0.207758	0.042455	0.203260	0.605364	0.230598	0.450066	0.450713	0.003687
8	0.558722	0.927035	0.777533	0.483478	0.847846	0.096667	0.910407	0.327488	0.254891	0.337679
9	0.427066	0.629416	0.845941	0.008152	0.927802	0.945599	0.783255	0.626967	0.922936	0.155402
10	0.748707	0.909395	0.492470	0.046778	0.203244	0.102367	0.242721	0.370299	0.525937	0.410644
11	0.190404	0.602494	0.196155	0.650595	0.986109	0.680599	0.886406	0.262964	0.956797	0.719145
12	0.240944	0.520401	0.174845	0.756972	0.198388	0.355310	0.419668	0.514867	0.761939	0.560055
13	0.627101	0.535762	0.842373	0.963862	0.816623	0.052924	0.211294	0.368572	0.167157	0.388588
14	0.978139	0.237486	0.077492	0.209904	0.650783	0.663827	0.352613	0.130673	0.536371	0.074908
15	0.488940	0.336477	0.495782	0.341456	0.425742	0.461244	0.142852	0.294217	0.499867	0.226806
16	0.024142	0.726993	0.602587	0.815984	0.753234	0.515214	0.982483	0.124366	0.452646	0.757576
17	0.428680	0.481441	0.671396	0.437300	0.565147	0.387528	0.174145	0.295377	0.683534	0.326617
18	0.529209	0.236979	0.605650	0.002481	0.898732	0.043005	0.464004	0.849748	0.056447	0.424221
19	0.884170	0.725553	0.001559	0.273916	0.643806	0.102261	0.280440	0.360105	0.760108	0.674790

```
type(df1)
df1.describe()
```

Output:

	0	1	2	3	4	5	6	7	8	9
count	20.000000	20.000000	20.000000	20.000000	20.000000	20.000000	20.000000	20.000000	20.000000	20.000000
mean	0.530517	0.569589	0.535992	0.366716	0.578745	0.423202	0.470512	0.432950	0.477266	0.432250
std	0.263312	0.252397	0.294265	0.323563	0.296716	0.265350	0.286197	0.197626	0.300232	0.281850
min	0.024142	0.217723	0.001559	0.002481	0.110265	0.043005	0.120711	0.124366	0.043488	0.003687
25%	0.395380	0.327897	0.242445	0.058028	0.264632	0.154430	0.228957	0.295087	0.240142	0.208955
50%	0.540035	0.569128	0.604118	0.307686	0.647295	0.488229	0.414119	0.391818	0.476257	0.399616
75%	0.673747	0.737913	0.793743	0.625445	0.824429	0.607630	0.719149	0.535718	0.702677	0.685879
max	0.978139	0.961605	0.950464	0.963862	0.986109	0.945599	0.982483	0.849748	0.997209	0.973860

```
df1 [0][1] = "abc"
df1.head(10)
```

Output:

```
0	1	2	3	4	5	6	7	8	9
0	0.889829	0.217723	0.950464	0.114454	0.175260	0.171785
	0.502882	0.431306	0.585802	0.824907
1	abc	0.961605	0.734357	0.617062	0.778672	0.737305
	0.224034	0.792681	0.043488	0.755798
2	0.300321	0.297326	0.667170	0.810632	0.954124	0.527148
	0.697780	0.679426	0.251948	0.124489
3	0.64876	0.770672	0.254008	0.025945	0.110265	0.602699
	0.498752	0.413338	0.312994	0.293970
4	0.538527	0.630472	0.851454	0.061778	0.659211	0.565140
	0.876626	0.598274	0.997209	0.087594
5	0.541544	0.934696	0.424254	0.602228	0.491561	0.614428
	0.120711	0.491124	0.204725	0.973860
6	0.628961	0.302158	0.846598	0.068880	0.285089	0.233620
	0.408571	0.277139	0.119807	0.524263
7	0.120473	0.407693	0.207758	0.042455	0.203260	0.605364
	0.230598	0.450066	0.450713	0.003687
8	0.558722	0.927035	0.777533	0.483478	0.847846	0.096667
	0.910407	0.327488	0.254891	0.337679
9	0.427066	0.629416	0.845941	0.008152	0.927802	0.945599
	0.783255	0.626967	0.922936	0.155402
```

```
df1.head(4)
```

Output:

```
0	1	2	3	4	5	6	7	8	9
0	0.889829	efg	0.950464	0.114454	0.175260	0.171785
	0.502882	0.431306	0.585802	0.824907
1	abc	0.961605	0.734357	0.617062	0.778672	0.737305
	0.224034	0.792681	0.043488	0.755798
2	pqr	0.297326	0.667170	0.810632	0.954124	0.527148
	0.697780	0.679426	0.251948	0.124489
3	0.64876	0.770672	0.254008	0.025945	0.110265	0.602699
	0.498752	0.413338	0.312994	0.293970
```

```
df1[2][1]="aaa"
```

Output:

```
<ipython-input-95-93449a955d64>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

```
df1
```

Output:

```
0	1	2	3	4	5	6	7	8	9
0	0.889829	efg	0.950464	0.114454	0.175260	0.171785
	0.502882	0.431306	0.585802	0.824907
1	abc	0.961605	aaa	0.617062	0.778672	0.737305	0.224034
	0.792681	0.043488	0.755798
2	pqr	0.297326	0.66717	0.810632	0.954124	0.527148
	0.697780	0.679426	0.251948	0.124489
3	0.64876	0.770672	0.254008	0.025945	0.110265	0.602699
	0.498752	0.413338	0.312994	0.293970
4	0.538527	0.630472	0.851454	0.061778	0.659211	0.565140
	0.876626	0.598274	0.997209	0.087594
```

5	0.541544	0.934696	0.424254	0.602228	0.491561	0.614428	0.120711	0.491124	0.204725	0.973860
6	0.628961	0.302158	0.846598	0.068880	0.285089	0.233620	0.408571	0.277139	0.119807	0.524263
7	0.120473	0.407693	0.207758	0.042455	0.203260	0.605364	0.230598	0.450066	0.450713	0.003687
8	0.558722	0.927035	0.777533	0.483478	0.847846	0.096667	0.910407	0.327488	0.254891	0.337679
9	0.427066	0.629416	0.845941	0.008152	0.927802	0.945599	0.783255	0.626967	0.922936	0.155402
10	0.748707	0.909395	0.49247	0.046778	0.203244	0.102367	0.242721	0.370299	0.525937	0.410644
11	0.190404	0.602494	0.196155	0.650595	0.986109	0.680599	0.886406	0.262964	0.956797	0.719145
12	0.240944	0.520401	0.174845	0.756972	0.198388	0.355310	0.419668	0.514867	0.761939	0.560055
13	0.627101	0.535762	0.842373	0.963862	0.816623	0.052924	0.211294	0.368572	0.167157	0.388588
14	0.978139	0.237486	0.077492	0.209904	0.650783	0.663827	0.352613	0.130673	0.536371	0.074908
15	0.48894	0.336477	0.495782	0.341456	0.425742	0.461244	0.142852	0.294217	0.499867	0.226806
16	0.024142	0.726993	0.602587	0.815984	0.753234	0.515214	0.982483	0.124366	0.452646	0.757576
17	0.42868	0.481441	0.671396	0.437300	0.565147	0.387528	0.174145	0.295377	0.683534	0.326617
18	0.529209	0.236979	0.60565	0.002481	0.898732	0.043005	0.464004	0.849748	0.056447	0.424221
19	0.88417	0.725553	0.001559	0.273916	0.643806	0.102261	0.280440	0.360105	0.760108	0.674790

demo

Output:

	prod_id	name	area
one	2200	apple	andheri
two	3300	mango	parle
three	4004	grapes	santacruz

demo['prod_id'][1] = 5005

<ipython-input-98-547956110199>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

demo['prod_id'][1] = 5005
demo

Output:

	prod_id	name	area
one	2200	apple	andheri
two	5005	mango	parle
three	4004	grapes	santacruz

demo.dtypes

Output:

prod_id int64
name object
area object
dtype: object

df1.dtypes

Output:

```
0     object
1     object
2     object
3    float64
4    float64
5    float64
6    float64
7    float64
8    float64
9    float64
dtype: object
```

df1

Output:

	0	1	2	3	4	5	6	7	8	9
0	0.889829	efg	0.950464	0.114454	0.175260	0.171785	0.502882	0.431306	0.585802	0.824907
1	abc	0.961605	aaa	0.617062	0.778672	0.737305	0.224034	0.792681	0.043488	0.755798
2	pqr	0.297326	0.66717	0.810632	0.954124	0.527148	0.697780	0.679426	0.251948	0.124489
3	0.64876	0.770672	0.254008	0.025945	0.110265	0.602699	0.498752	0.413338	0.312994	0.293970
4	0.538527	0.630472	0.851454	0.061778	0.659211	0.565140	0.876626	0.598274	0.997209	0.087594
5	0.541544	0.934696	0.424254	0.602228	0.491561	0.614428	0.120711	0.491124	0.204725	0.973860
6	0.628961	0.302158	0.846598	0.068880	0.285089	0.233620	0.408571	0.277139	0.119807	0.524263
7	0.120473	0.407693	0.207758	0.042455	0.203260	0.605364	0.230598	0.450066	0.450713	0.003687
8	0.558722	0.927035	0.777533	0.483478	0.847846	0.096667	0.910407	0.327488	0.254891	0.337679
9	0.427066	0.629416	0.845941	0.008152	0.927802	0.945599	0.783255	0.626967	0.922936	0.155402
10	0.748707	0.909395	0.49247	0.046778	0.203244	0.102367	0.242721	0.370299	0.525937	0.410644
11	0.190404	0.602494	0.196155	0.650595	0.986109	0.680599	0.886406	0.262964	0.956797	0.719145
12	0.240944	0.520401	0.174845	0.756972	0.198388	0.355310	0.419668	0.514867	0.761939	0.560055
13	0.627101	0.535762	0.842373	0.963862	0.816623	0.052924	0.211294	0.368572	0.167157	0.388588
14	0.978139	0.237486	0.077492	0.209904	0.650783	0.663827	0.352613	0.130673	0.536371	0.074908
15	0.48894	0.336477	0.495782	0.341456	0.425742	0.461244	0.142852	0.294217	0.499867	0.226806
16	0.024142	0.726993	0.602587	0.815984	0.753234	0.515214	0.982483	0.124366	0.452646	0.757576
17	0.42868	0.481441	0.671396	0.437300	0.565147	0.387528	0.174145	0.295377	0.683534	0.326617

18	0.529209	0.236979	0.60565	0.002481	0.898732	0.043005	0.464004	0.849748	0.056447	0.424221
19	0.88417	0.725553	0.001559	0.273916	0.643806	0.102261	0.280440	0.360105	0.760108	0.674790

```
df1.to_numpy()
```

Output:

```
array([[0.8898290587574625, 'efg', 0.9504637009415536,
        0.11445350753707939, 0.1752600347199531, 0.17178486545231497,
        0.5028824898103187, 0.431305684264646, 0.5858017094187148,
        0.8249071762869403],
       ['abc', 0.9616049518794304, 'aaa', 0.6170616309044902,
        0.7786715778059061, 0.7373050333549065, 0.22403425159455848,
        0.7926807836787797, 0.04348811153552434, 0.7557984441046045],
       ['pqr', 0.29732601721264285, 0.6671699248305508,
        0.8106324766594586, 0.9541240643323579, 0.5271480185664397,
        0.6977800757136665, 0.6794261624792959, 0.25194753570017625,
        0.12448932434428084],
       [0.6487599631982358, 0.7706715150467816, 0.2540076701928634,
        0.02594477872312806, 0.11026541677027257, 0.6026986958103315,
        0.4987517228774331, 0.4133382664044277, 0.31299444322854375,
        0.2939702728123903],
       [0.5385269288296717, 0.6304722606997493, 0.8514542001716628,
        0.06177752739395137, 0.6592108981215252, 0.5651400220152262,
        0.8766258842206889, 0.5982735952347097, 0.9972089870133152,
        0.08759388187127126],
       [0.7487069527367622, 0.9093947236386258, 0.49246977663430314,
        0.04677816297810866, 0.20324374999174266, 0.1023672526008913,
        0.24272067170750022, 0.3702986708319129, 0.5259374157967004,
        0.41064368110825533],
        [0.48894020892946477, 0.33647710082718496, 0.4957819333797754,
          0.2268061817643775],
       [0.02414249471968255, 0.7269933849502771, 0.6025866134022627,
        0.8159838725163027, 0.7532337808624099, 0.5152143189684777,
        0.9824832756390718, 0.12436628539572403, 0.4526464668408925,
        0.7575758731905909],
       [0.4286800832564034, 0.48144143422024277, 0.6713958370200016,
        0.43730039897594153, 0.5651468661339273, 0.38752775998992894,
        0.1741454366748063, 0.2953770888681998, 0.6835335205019395,
        0.32661688397358923],
       [0.5292085630387563, 0.23697946207749765, 0.6056501407655644,
        0.0024813922441588865, 0.8987318909075309, 0.04300455769905975,
        0.46400399742872456, 0.8497477915770419, 0.05644742404326131,
        0.4242205865280846],
       [0.8841697571458046, 0.7255526457480526, 0.0015591409819755153,
        0.2739157678767543, 0.6438064650372433, 0.10226113788566826,
        0.2804404425187115, 0.36010547725733033, 0.7601084640428719,
        0.6747895650580462]], dtype=object)
```

```
df1
```

Output:

	0	1	2	3	4	5	6	7	8	9
0	0.889829	efg	0.950464	0.114454	0.175260	0.171785	0.502882	0.431306	0.585802	0.824907

1 abc 0.961605 aaa 0.617062 0.778672 0.737305 0.224034
0.792681 0.043488 0.755798
2 pqr 0.297326 0.66717 0.810632 0.954124 0.527148
0.697780 0.679426 0.251948 0.124489
3 0.64876 0.770672 0.254008 0.025945 0.110265 0.602699
0.498752 0.413338 0.312994 0.293970
4 0.538527 0.630472 0.851454 0.061778 0.659211 0.565140
0.876626 0.598274 0.997209 0.087594
5 0.541544 0.934696 0.424254 0.602228 0.491561 0.614428
0.120711 0.491124 0.204725 0.973860
6 0.628961 0.302158 0.846598 0.068880 0.285089 0.233620
0.408571 0.277139 0.119807 0.524263
7 0.120473 0.407693 0.207758 0.042455 0.203260 0.605364
0.230598 0.450066 0.450713 0.003687
10 0.748707 0.909395 0.49247 0.046778 0.203244 0.102367
0.242721 0.370299 0.525937 0.410644
11 0.190404 0.602494 0.196155 0.650595 0.986109 0.680599
0.886406 0.262964 0.956797 0.719145
12 0.240944 0.520401 0.174845 0.756972 0.198388 0.355310
0.419668 0.514867 0.761939 0.560055
13 0.627101 0.535762 0.842373 0.963862 0.816623 0.052924
0.211294 0.368572 0.167157 0.388588
14 0.978139 0.237486 0.077492 0.209904 0.650783 0.663827
0.352613 0.130673 0.536371 0.074908
15 0.48894 0.336477 0.495782 0.341456 0.425742 0.461244
0.142852 0.294217 0.499867 0.226806
16 0.024142 0.726993 0.602587 0.815984 0.753234 0.515214
0.982483 0.124366 0.452646 0.757576
17 0.42868 0.481441 0.671396 0.437300 0.565147 0.387528
0.174145 0.295377 0.683534 0.326617
18 0.529209 0.236979 0.60565 0.002481 0.898732 0.043005
0.464004 0.849748 0.056447 0.424221
19 0.88417 0.725553 0.001559 0.273916 0.643806 0.102261
0.280440 0.360105 0.760108 0.674790

```
demo
```

Output:

	prod_id	name	area
one	2200	apple	andheri
two	5005	mango	parle
three	4004	grapes	santacruz

```
demo.T
```

Output:

	One	two	three
prod_id	2200	5005	4004
name	apple	mango	grapes
area	andheri	parle	santacruz

```
df2 = pd.DataFrame(np.random.rand(10,5))
df2
```

Output:

	0	1	2	3	4
0	0.988782	0.155982	0.163659	0.216378	0.338656
1	0.922171	0.810851	0.249822	0.283435	0.181059

2	0.069235	0.844811	0.165427	0.086819	0.301486
3	0.789741	0.358560	0.738854	0.373372	0.934196
4	0.405396	0.146483	0.516349	0.259770	0.846987
5	0.929204	0.212274	0.604740	0.422453	0.722843
6	0.247970	0.452907	0.853457	0.639186	0.590882
7	0.672903	0.397623	0.773096	0.071042	0.135975
8	0.139015	0.843306	0.936715	0.941274	0.551718
9	0.052673	0.486642	0.234463	0.257344	0.981282

```
df2.sort_index(axis=1, ascending=False)
```
Output:

4	3	2	1	0	
0	0.338656	0.216378	0.163659	0.155982	0.988782
1	0.181059	0.283435	0.249822	0.810851	0.922171
2	0.301486	0.086819	0.165427	0.844811	0.069235
3	0.934196	0.373372	0.738854	0.358560	0.789741
4	0.846987	0.259770	0.516349	0.146483	0.405396
5	0.722843	0.422453	0.604740	0.212274	0.929204
6	0.590882	0.639186	0.853457	0.452907	0.247970
7	0.135975	0.071042	0.773096	0.397623	0.672903
8	0.551718	0.941274	0.936715	0.843306	0.139015
9	0.981282	0.257344	0.234463	0.486642	0.052673

```
demo
```
Output:

	prod_id	name	area
one	2200	apple	andheri
two	5005	mango	parle
three	4004	grapes	santacruz

```
p = demo.sort_values('name')
p
```
Output:

	prod_id	name	area
one	2200	apple	andheri
three	4004	grapes	santacruz
two	5005	mango	parle

```
q = demo.groupby('prod_id')
q
```
Output:

<pandas.core.groupby.generic.DataFrameGroupBy object at 0x000001EE05FE2A30>

```
import numpy as np
from matplotlib import pyplot as plt
```

```
demo.hist('prod_id', bins=20)
ax = plt.gca()
ax.set_yscale('log')
```
Output: (graph)

```
demo.info()
```
Output:

<class 'pandas.core.frame.DataFrame'>

```
Index: 3 entries, one to three
Data columns (total 3 columns):
 #  Column   Non-Null Count  Dtype
--  -------  ---------- ------
 0   prod_id  3 non-null      int64
 1   name     3 non-null      object
 2   area     3 non-null      object
dtypes: int64(1), object(2)
memory usage: 204.0+ bytes
```

df1

Output:

	0	1	2	3	4	5	6	7	8	9
0	0.889829	efg	0.950464	0.114454	0.175260	0.171785	0.502882	0.431306	0.585802	0.824907
1	abc	0.961605	aaa	0.617062	0.778672	0.737305	0.224034	0.792681	0.043488	0.755798
2	pqr	0.297326	0.66717	0.810632	0.954124	0.527148	0.697780	0.679426	0.251948	0.124489
3	0.64876	0.770672	0.254008	0.025945	0.110265	0.602699	0.498752	0.413338	0.312994	0.293970
4	0.538527	0.630472	0.851454	0.061778	0.659211	0.565140	0.876626	0.598274	0.997209	0.087594
5	0.541544	0.934696	0.424254	0.602228	0.491561	0.614428	0.120711	0.491124	0.204725	0.973860
6	0.628961	0.302158	0.846598	0.068880	0.285089	0.233620	0.408571	0.277139	0.119807	0.524263
7	0.120473	0.407693	0.207758	0.042455	0.203260	0.605364	0.230598	0.450066	0.450713	0.003687
8	0.558722	0.927035	0.777533	0.483478	0.847846	0.096667	0.910407	0.327488	0.254891	0.337679
9	0.427066	0.629416	0.845941	0.008152	0.927802	0.945599	0.783255	0.626967	0.922936	0.155402
10	0.748707	0.909395	0.49247	0.046778	0.203244	0.102367	0.242721	0.370299	0.525937	0.410644
11	0.190404	0.602494	0.196155	0.650595	0.986109	0.680599	0.886406	0.262964	0.956797	0.719145
12	0.240944	0.520401	0.174845	0.756972	0.198388	0.355310	0.419668	0.514867	0.761939	0.560055
13	0.627101	0.535762	0.842373	0.963862	0.816623	0.052924	0.211294	0.368572	0.167157	0.388588
14	0.978139	0.237486	0.077492	0.209904	0.650783	0.663827	0.352613	0.130673	0.536371	0.074908
15	0.48894	0.336477	0.495782	0.341456	0.425742	0.461244	0.142852	0.294217	0.499867	0.226806
16	0.024142	0.726993	0.602587	0.815984	0.753234	0.515214	0.982483	0.124366	0.452646	0.757576
17	0.42868	0.481441	0.671396	0.437300	0.565147	0.387528	0.174145	0.295377	0.683534	0.326617
18	0.529209	0.236979	0.60565	0.002481	0.898732	0.043005	0.464004	0.849748	0.056447	0.424221
19	0.88417	0.725553	0.001559	0.273916	0.643806	0.102261	0.280440	0.360105	0.760108	0.674790

df1.loc[0,0]=990
df1

Output:

	0	1	2	3	4	5	6	7	8	9
0	990	efg	0.950464	0.114454	0.175260	0.171785	0.502882	0.431306	0.585802	0.824907
1	abc	0.961605	aaa	0.617062	0.778672	0.737305	0.224034	0.792681	0.043488	0.755798
2	pqr	0.297326	0.66717	0.810632	0.954124	0.527148	0.697780	0.679426	0.251948	0.124489
3	0.64876	0.770672	0.254008	0.025945	0.110265	0.602699	0.498752	0.413338	0.312994	0.293970
4	0.538527	0.630472	0.851454	0.061778	0.659211	0.565140	0.876626	0.598274	0.997209	0.087594
5	0.541544	0.934696	0.424254	0.602228	0.491561	0.614428	0.120711	0.491124	0.204725	0.973860
6	0.628961	0.302158	0.846598	0.068880	0.285089	0.233620	0.408571	0.277139	0.119807	0.524263
7	0.120473	0.407693	0.207758	0.042455	0.203260	0.605364	0.230598	0.450066	0.450713	0.003687
8	0.558722	0.927035	0.777533	0.483478	0.847846	0.096667	0.910407	0.327488	0.254891	0.337679
9	0.427066	0.629416	0.845941	0.008152	0.927802	0.945599	0.783255	0.626967	0.922936	0.155402
10	0.748707	0.909395	0.49247	0.046778	0.203244	0.102367	0.242721	0.370299	0.525937	0.410644
11	0.190404	0.602494	0.196155	0.650595	0.986109	0.680599	0.886406	0.262964	0.956797	0.719145
12	0.240944	0.520401	0.174845	0.756972	0.198388	0.355310	0.419668	0.514867	0.761939	0.560055
13	0.627101	0.535762	0.842373	0.963862	0.816623	0.052924	0.211294	0.368572	0.167157	0.388588
14	0.978139	0.237486	0.077492	0.209904	0.650783	0.663827	0.352613	0.130673	0.536371	0.074908
15	0.48894	0.336477	0.495782	0.341456	0.425742	0.461244	0.142852	0.294217	0.499867	0.226806
16	0.024142	0.726993	0.602587	0.815984	0.753234	0.515214	0.982483	0.124366	0.452646	0.757576
17	0.42868	0.481441	0.671396	0.437300	0.565147	0.387528	0.174145	0.295377	0.683534	0.326617
18	0.529209	0.236979	0.60565	0.002481	0.898732	0.043005	0.464004	0.849748	0.056447	0.424221
19	0.88417	0.725553	0.001559	0.273916	0.643806	0.102261	0.280440	0.360105	0.760108	0.674790

df2

Output:

	0	1	2	3	4
0	0.988782	0.155982	0.163659	0.216378	0.338656
1	0.922171	0.810851	0.249822	0.283435	0.181059
2	0.069235	0.844811	0.165427	0.086819	0.301486
3	0.789741	0.358560	0.738854	0.373372	0.934196
4	0.405396	0.146483	0.516349	0.259770	0.846987
5	0.929204	0.212274	0.604740	0.422453	0.722843

6	0.247970	0.452907	0.853457	0.639186	0.590882
7	0.672903	0.397623	0.773096	0.071042	0.135975
8	0.139015	0.843306	0.936715	0.941274	0.551718
9	0.052673	0.486642	0.234463	0.257344	0.981282

```
df2.loc[0,0]=990
df2
```

Output:

	0	1	2	3	4
0	990.000000	0.155982	0.163659	0.216378	0.338656
1	0.922171	0.810851	0.249822	0.283435	0.181059
2	0.069235	0.844811	0.165427	0.086819	0.301486
3	0.789741	0.358560	0.738854	0.373372	0.934196
4	0.405396	0.146483	0.516349	0.259770	0.846987
5	0.929204	0.212274	0.604740	0.422453	0.722843
6	0.247970	0.452907	0.853457	0.639186	0.590882
7	0.672903	0.397623	0.773096	0.071042	0.135975
8	0.139015	0.843306	0.936715	0.941274	0.551718
9	0.052673	0.486642	0.234463	0.257344	0.981282

```
df2.columns = list("ABCDE")
df2
```

Output:

	A	B	C	D	E
0	990.000000	0.155982	0.163659	0.216378	0.338656
1	0.922171	0.810851	0.249822	0.283435	0.181059
2	0.069235	0.844811	0.165427	0.086819	0.301486
3	0.789741	0.358560	0.738854	0.373372	0.934196
4	0.405396	0.146483	0.516349	0.259770	0.846987
5	0.929204	0.212274	0.604740	0.422453	0.722843
6	0.247970	0.452907	0.853457	0.639186	0.590882
7	0.672903	0.397623	0.773096	0.071042	0.135975
8	0.139015	0.843306	0.936715	0.941274	0.551718
9	0.052673	0.486642	0.234463	0.257344	0.981282

```
df2.loc[0,'A']=89
df2
```

Output:

	A	B	C	D	E
0	89.000000	899.000000	0.163659	0.216378	0.338656
1	0.922171	0.810851	0.249822	0.283435	0.181059
2	0.069235	0.844811	0.165427	0.086819	0.301486
3	0.789741	0.358560	0.738854	0.373372	0.934196
4	0.405396	0.146483	0.516349	0.259770	0.846987
5	0.929204	0.212274	0.604740	0.422453	0.722843
6	0.247970	0.452907	0.853457	0.639186	0.590882
7	0.672903	0.397623	0.773096	0.071042	0.135975
8	0.139015	0.843306	0.936715	0.941274	0.551718
9	0.052673	0.486642	0.234463	0.257344	0.981282

```
dt = pd.DataFrame(np.random.rand(10,5))
dt
```

Ouput:

0 1 2 3 4

0	0.514973	0.132473	0.662300	0.870011	0.099254
1	0.505812	0.655760	0.709748	0.459002	0.258930
2	0.446541	0.850593	0.959236	0.653753	0.742279
3	0.364539	0.001264	0.233297	0.904143	0.396865
4	0.214473	0.344468	0.010521	0.403364	0.834405
5	0.543493	0.511075	0.517688	0.971037	0.386030
6	0.757976	0.310684	0.385691	0.767525	0.537692
7	0.532578	0.294248	0.438818	0.581528	0.483544
8	0.383618	0.366597	0.258645	0.600649	0.044865
9	0.649240	0.894046	0.534226	0.551215	0.025614

```
dt[0][0]=88
dt
```

Output:

	0	1	2	3	4
0	88.000000	0.132473	0.662300	0.870011	0.099254
1	0.505812	0.655760	0.709748	0.459002	0.258930
2	0.446541	0.850593	0.959236	0.653753	0.742279
3	0.364539	0.001264	0.233297	0.904143	0.396865
4	0.214473	0.344468	0.010521	0.403364	0.834405
5	0.543493	0.511075	0.517688	0.971037	0.386030
6	0.757976	0.310684	0.385691	0.767525	0.537692
7	0.532578	0.294248	0.438818	0.581528	0.483544
8	0.383618	0.366597	0.258645	0.600649	0.044865
9	0.649240	0.894046	0.534226	0.551215	0.025614

```
dt.sort_index(axis=1, ascending=False)
```

Output:

	4	3	2	1	0
0	0.099254	0.870011	0.662300	0.132473	88.000000
1	0.258930	0.459002	0.709748	0.655760	0.505812
2	0.742279	0.653753	0.959236	0.850593	0.446541
3	0.396865	0.904143	0.233297	0.001264	0.364539
4	0.834405	0.403364	0.010521	0.344468	0.214473
5	0.386030	0.971037	0.517688	0.511075	0.543493
6	0.537692	0.767525	0.385691	0.310684	0.757976
7	0.483544	0.581528	0.438818	0.294248	0.532578
8	0.044865	0.600649	0.258645	0.366597	0.383618
9	0.025614	0.551215	0.534226	0.894046	0.649240

```
dt[0][0]=0.9
dt
```

Output:

	0	1	2	3	4
0	0.900000	0.132473	0.662300	0.870011	0.099254
1	0.505812	0.655760	0.709748	0.459002	0.258930
2	0.446541	0.850593	0.959236	0.653753	0.742279
3	0.364539	0.001264	0.233297	0.904143	0.396865
4	0.214473	0.344468	0.010521	0.403364	0.834405
5	0.543493	0.511075	0.517688	0.971037	0.386030
6	0.757976	0.310684	0.385691	0.767525	0.537692
7	0.532578	0.294248	0.438818	0.581528	0.483544
8	0.383618	0.366597	0.258645	0.600649	0.044865
9	0.649240	0.894046	0.534226	0.551215	0.025614

```
dt.columns = list("abcde")
dt
```

Output:

a	b	c	d	e	
0	0.900000	0.132473	0.662300	0.870011	0.099254
1	0.505812	0.655760	0.709748	0.459002	0.258930
2	0.446541	0.850593	0.959236	0.653753	0.742279
3	0.364539	0.001264	0.233297	0.904143	0.396865
4	0.214473	0.344468	0.010521	0.403364	0.834405
5	0.543493	0.511075	0.517688	0.971037	0.386030
6	0.757976	0.310684	0.385691	0.767525	0.537692
7	0.532578	0.294248	0.438818	0.581528	0.483544
8	0.383618	0.366597	0.258645	0.600649	0.044865
9	0.649240	0.894046	0.534226	0.551215	0.025

```
dt.loc[0,'b']=68
dt
```

Output:

a	b	c	d	e	
0	0.900000	68.000000	0.662300	0.870011	0.099254
1	0.505812	0.655760	0.709748	0.459002	0.258930
2	0.446541	0.850593	0.959236	0.653753	0.742279
3	0.364539	0.001264	0.233297	0.904143	0.396865
4	0.214473	0.344468	0.010521	0.403364	0.834405
5	0.543493	0.511075	0.517688	0.971037	0.386030
6	0.757976	0.310684	0.385691	0.767525	0.537692
7	0.532578	0.294248	0.438818	0.581528	0.483544
8	0.383618	0.366597	0.258645	0.600649	0.044865
9	0.649240	0.894046	0.534226	0.551215	0.025614

```
dt.loc[0,0]=98
dt
```

Output:

a	b	c	d	e	0	
0	0.900000	68.000000	0.662300	0.870011	0.099254	98.0
1	0.505812	0.655760	0.709748	0.459002	0.258930	NaN
2	0.446541	0.850593	0.959236	0.653753	0.742279	NaN
3	0.364539	0.001264	0.233297	0.904143	0.396865	NaN
4	0.214473	0.344468	0.010521	0.403364	0.834405	NaN
5	0.543493	0.511075	0.517688	0.971037	0.386030	NaN
6	0.757976	0.310684	0.385691	0.767525	0.537692	NaN
7	0.532578	0.294248	0.438818	0.581528	0.483544	NaN
8	0.383618	0.366597	0.258645	0.600649	0.044865	NaN
9	0.649240	0.894046	0.534226	0.551215	0.025614	NaN

```
dt.drop(0,axis=1)
```

Output:

a	b	c	d	e	
0	0.900000	68.000000	0.662300	0.870011	0.099254
1	0.505812	0.655760	0.709748	0.459002	0.258930
2	0.446541	0.850593	0.959236	0.653753	0.742279
3	0.364539	0.001264	0.233297	0.904143	0.396865
4	0.214473	0.344468	0.010521	0.403364	0.834405

5	0.543493	0.511075	0.517688	0.971037	0.386030
6	0.757976	0.310684	0.385691	0.767525	0.537692
7	0.532578	0.294248	0.438818	0.581528	0.483544
8	0.383618	0.366597	0.258645	0.600649	0.044865
9	0.649240	0.894046	0.534226	0.551215	0.025614

```
newdt = dt.drop(0,axis=1)
newdt
```

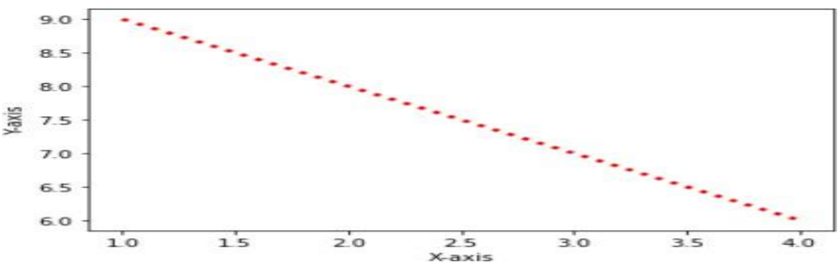
Output:

a	b	c	d	e	
0	0.900000	68.000000	0.662300	0.870011	0.099254
1	0.505812	0.655760	0.709748	0.459002	0.258930
2	0.446541	0.850593	0.959236	0.653753	0.742279
3	0.364539	0.001264	0.233297	0.904143	0.396865
4	0.214473	0.344468	0.010521	0.403364	0.834405
5	0.543493	0.511075	0.517688	0.971037	0.386030
6	0.757976	0.310684	0.385691	0.767525	0.537692
7	0.532578	0.294248	0.438818	0.581528	0.483544
8	0.383618	0.366597	0.258645	0.600649	0.044865
9	0.649240	0.894046	0.534226	0.551215	0.025614

Matplotlib :

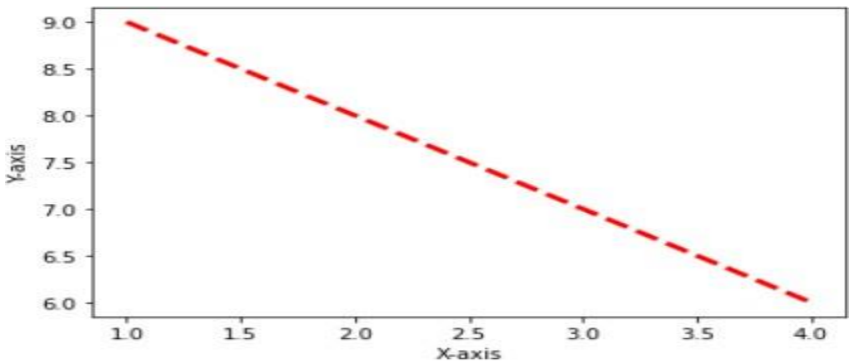
```
import matplotlib.pyplot as pl
x = [1, 2, 3, 4]
y = [9, 8, 7, 6]
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,'r',linewidth = 3, linestyle = 'dashdot')
pl.show()
```

Output:



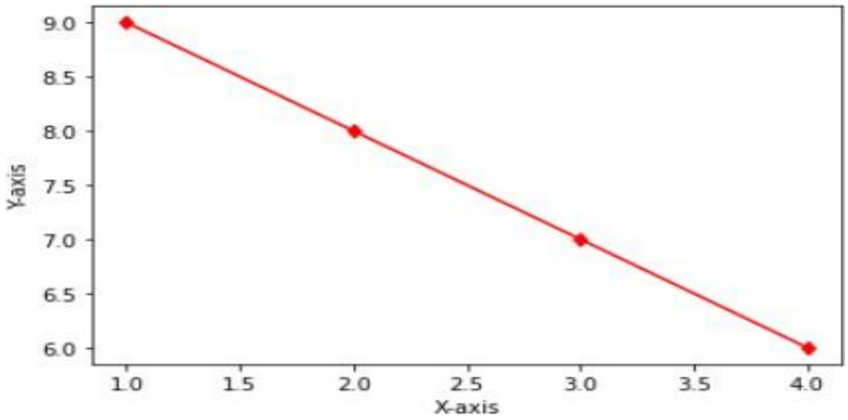

```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,'r',linewidth = 3, linestyle = 'dashed')
pl.show()
```

Output:



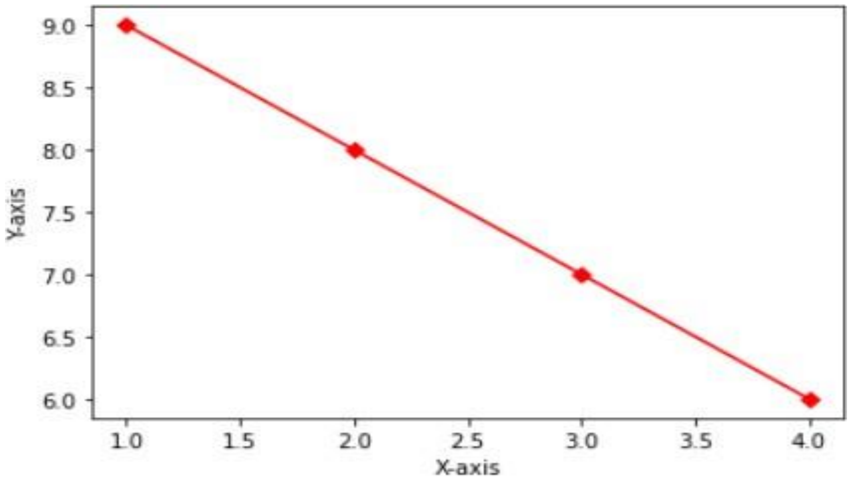
```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,'r',marker='d')
pl.show()
```

Output:



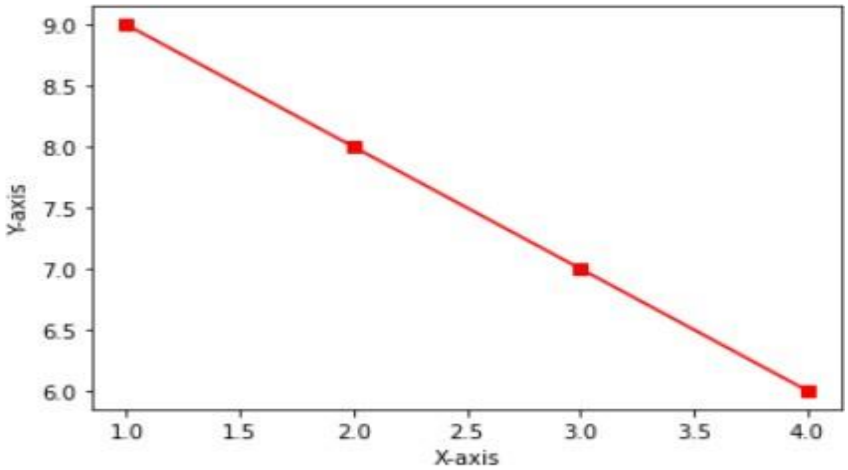

```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,'r',marker='D')
pl.show()
```

Output:



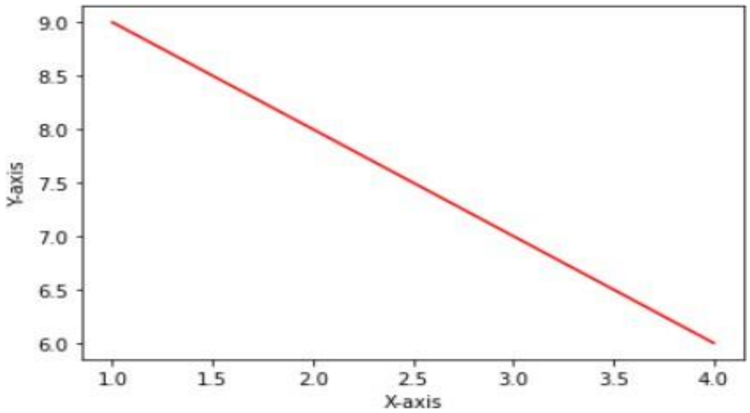

```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,'r',marker='s')
pl.show()
```

Output:



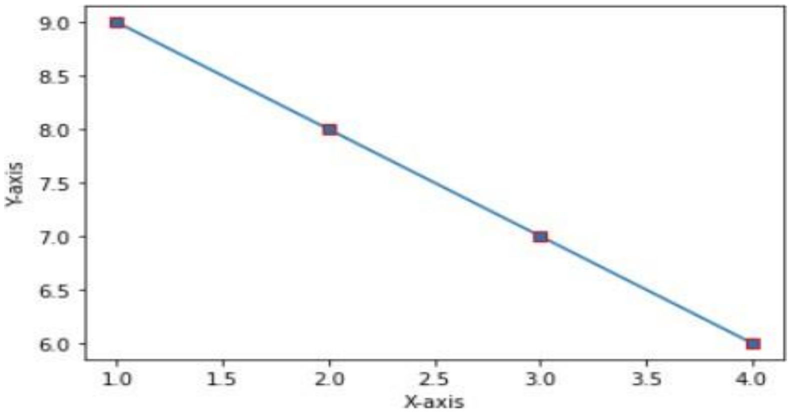
```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,'r',marker='')
pl.show()
```

Output:



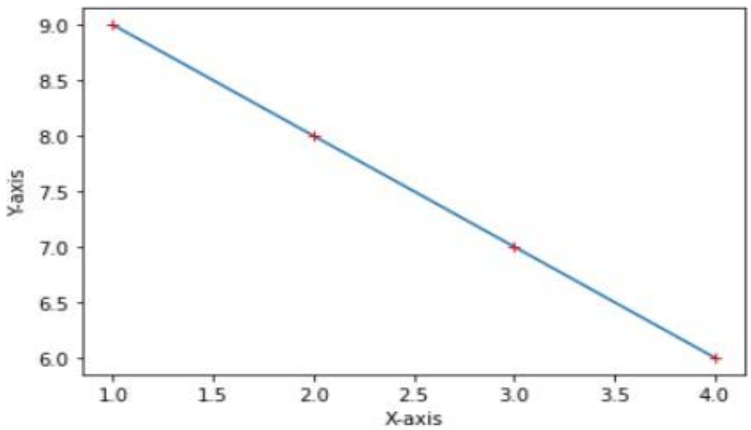

```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,marker='s', markeredgecolor='red')
pl.show()
```

Output:



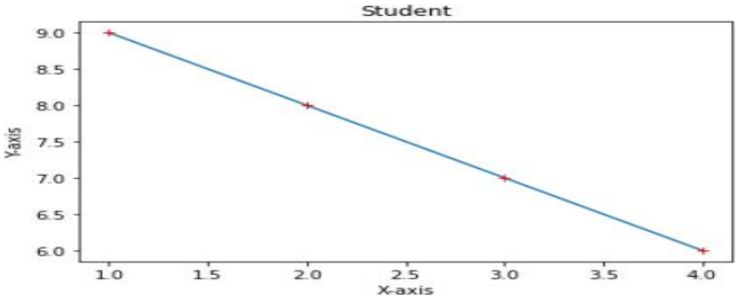

```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,marker='+', markeredgecolor='red')
pl.show()
```

Output:



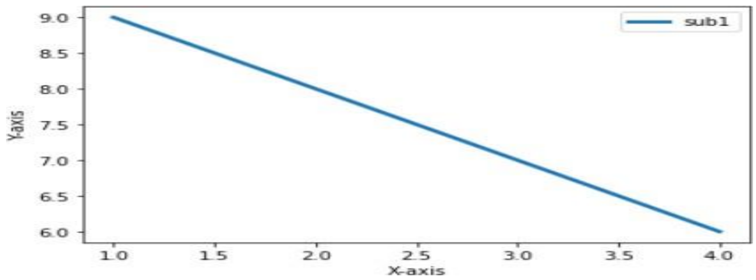
```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.title("Student")
pl.plot(x,y,marker='+', markeredgecolor='red')
pl.show()
```

Output:




```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,linewidth=3, label="sub1")
pl.legend()
pl.show()
```

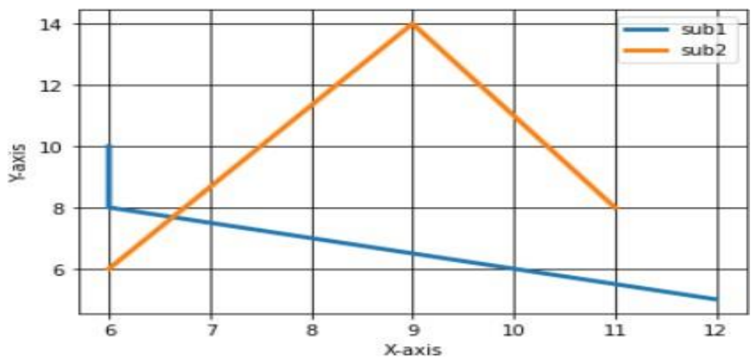
Output:




```
x2 = [6, 9, 11]
y = [5, 8, 10]
x = [12, 6, 6]
y2 = [6, 14, 8]
```

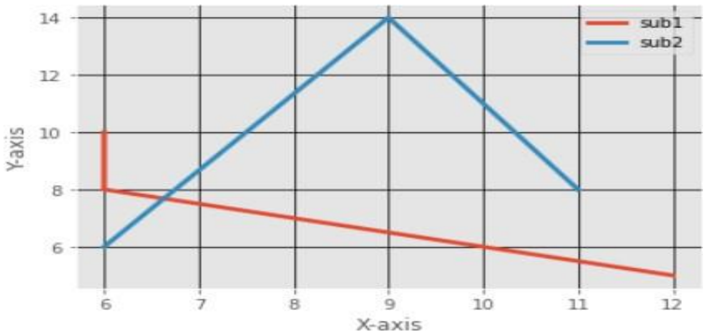
```
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.plot(x,y,linewidth=3, label="sub1")
pl.plot(x2,y2,linewidth=3, label="sub2")
pl.legend()
pl.show()
```

Output:



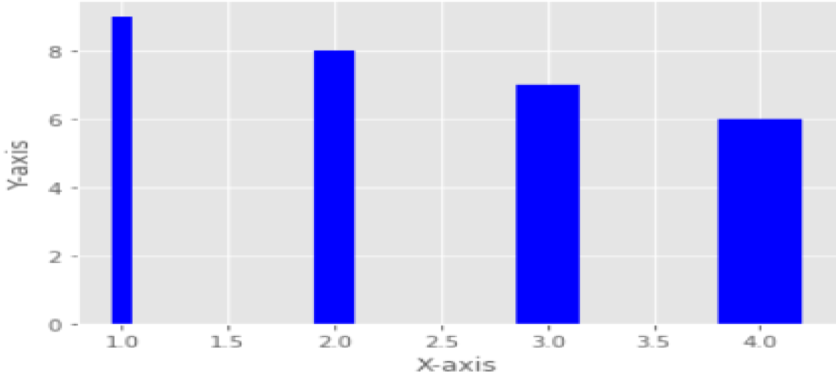

```
from matplotlib import style
style.use('ggplot')
pl.xlabel("X-axis")
```

```
pl.ylabel("Y-axis")
pl.plot(x,y,linewidth=3, label="sub1")
pl.plot(x2,y2,linewidth=3, label="sub2")
pl.legend()
pl.grid(True, color = 'k')
pl.show()
```



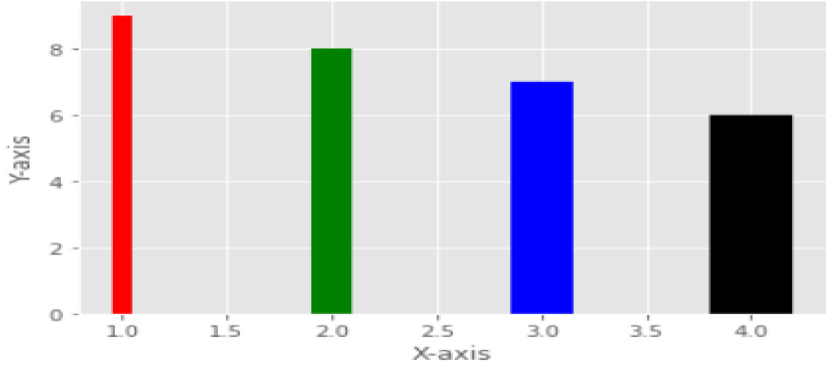

```
x = [1,2,3,4]
y = [9,8,7,6]
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.bar(x,y, width=[0.1,0.2,0.3,0.4], color = 'b')
pl.show()
```

Output:



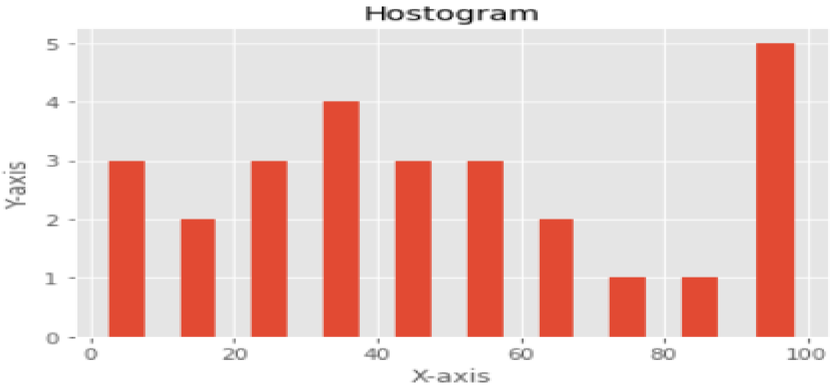

```
x = [1,2,3,4]
y = [9,8,7,6]
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.bar(x,y, width=[0.1,0.2,0.3,0.4], color = ['r','g','b','k'])
pl.show()
```

Output:



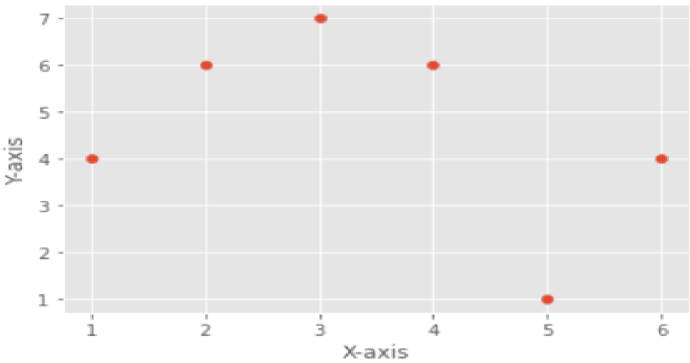
```
population_age = [50,30,60,76,34,29,90,100,9,8,5,23,65,34,21,54,87,98,43,56,
45,99,12,10,44,35,101]
bins = [0,10,20,30,40,50,60,70,80,90,101]
pl.hist(population_age,bins,histtype = 'bar', rwidth=0.5)
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.title("Hostogram")
pl.show()
```

Output:




```
x = [1,2,3,4,5,6]
y = [4,6,7,6,1,4]
pl.scatter(x,y)
pl.xlabel("X-axis")
pl.ylabel("Y-axis")
pl.show()
```

Output:



Practical No : 3

Aim : Study of Supervised Learning

a) Linear Regression
b) Logistic Regression
c) K Nearest Neighbour Algorithm

a) Linear Regression

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as pl
from sklearn import linear_model
df = pd.read_csv("dataset1.csv")
df
```

Output:

	area	price
0	2600	550000
1	3000	565000
2	3200	610000
3	3600	680000
4	4000	725000

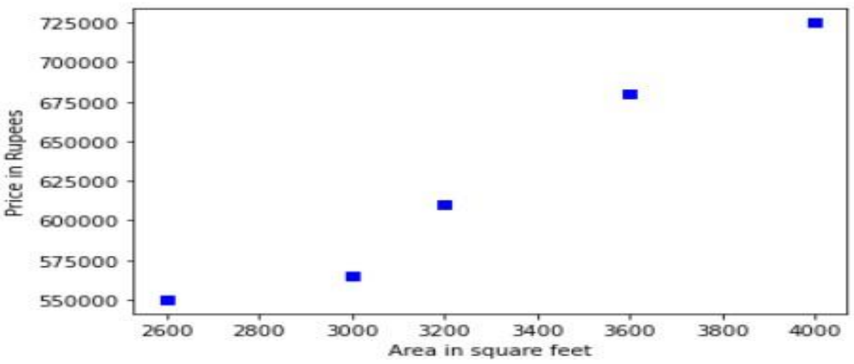
```
df.shape
```

Output: (5, 2)

```
%matplotlib inline
pl.xlabel('Area in square feet')
pl.ylabel('Price in Rupees')
pl.scatter(df.area,df.price, color='b', marker='s')
```

Output:

```
[24]:  <matplotlib.collections.PathCollection at 0x13360421a90>
```




```
reg = linear_model.LinearRegression()
reg.fit(df[['area']],df.price)
```

Output: LinearRegression()

```
reg.coef_                    #coef is m (slope)
```

Output: array([135.78767123])

```
reg.predict([[3300]])
```

Output: array([628715.75342466])

```
reg.intercept_              #intercept is b
```

Output: 180616.43835616432

```
# y = m * x + b
135.78767123 * 3300 + 180616.43835616432
```

Output: 628715.7534151643

b) Logistic Regression

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as pl
```

```
df1 = pd.read_csv("loan.csv")
df1.head()
```

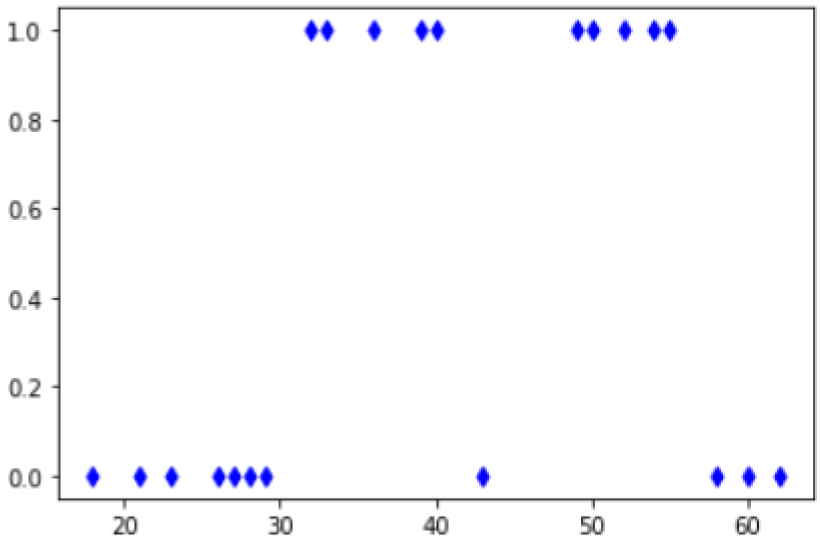
Output:

	age	bought_loan
0	23	0
1	18	0
2	55	1
3	43	0
4	36	1

```
pl.scatter(df1.age,df1.bought_loan, marker='d', color='b')
```

Output:

```
<matplotlib.collections.PathCollection at 0x25b5e99d160>
```




```
from sklearn.model_selection import train_test_split
x_train, x_test,y_train,y_test = train_test_split(df1[['age']], df1.bought_loan, train_size=0.9, shuffle=False)
x_test
```

Output:

	age
18	33
19	60
20	52

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(x_train,y_train)
```

Output: LogisticRegression()

```
logreg.predict(x_test)
```

Output: array([0, 1, 1], dtype=int64)

c)K Nearest Neighbour Algorithm

```
import numpy as np
import pandas as pd
ds = pd.read_csv("iris.csv")
ds
```

Output:

	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
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

```
ds.iloc[: ,1:5]
```

Output:

	SepalLengthCm	SepalWidthCm	PetalLengthCm
0	5.1	3.5	1.4
1	4.9	3.0	1.4
2	4.7	3.2	1.3
3	4.6	3.1	1.5
4	5.0	3.6	1.4
...	...	...	...
145	6.7	3.0	5.2
146	6.3	2.5	5.0
147	6.5	3.0	5.2
148	6.2	3.4	5.4
149	5.9	3.0	5.1

150 rows × 3 columns

```
x = ds.iloc[:, 1:5].values
y = ds.iloc[:, 5].values
from sklearn.preprocessing import LabelEncoder    #0 and nclass-1
lblenc_y = LabelEncoder()
y = lblenc_y.fit_transform(y)
y
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2)
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(x_train, y_train)
```

Output: KNeighborsClassifier()

```
y_predict = knn_model.predict(x_test)
from sklearn.metrics import confusion_matrix, classification_report
print(confusion_matrix(y_test,y_predict))
```

Output:

```
[[13  0  0]
 [ 0  7  2]
 [ 0  0  8]]
```

```
#accuracy
print(28/30)
```

Output: 0.9333333333333333

```
print(classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         9
           1       0.91      0.91      0.91        11
           2       0.90      0.90      0.90        10

    accuracy                           0.93        30
   macro avg       0.94      0.94      0.94        30
weighted avg       0.93      0.93      0.93        30
```

Practical No : 4.

Aim : Implementation of Bagging Algorithm: Decision Tree**.**

a) Decision Tree classifier

```
import pandas as pd
ds = pd.read_csv("IrisNew.csv")
ds.head()
```

	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

```
X = ds.iloc[:,1:5]
y = ds.iloc[:,5]
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # 70% training and 30% test
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier()
dt_classifier.fit(X_train, y_train)
```

DecisionTreeClassifier()

```
y_pred = dt_classifier.predict(X_test)
from sklearn.metrics import confusion_matrix, accuracy_score
cf = confusion_matrix(y_test, y_pred)
cf
```

```
array([[14,  0,  0],
       [ 0, 17,  1],
       [ 0,  3, 10]], dtype=int64)
```

```
ac = accuracy_score(y_test, y_pred)
ac
```

0.9111111111111111

b) Bagging classifier

```
import pandas as pd
ds = pd.read_csv("IrisNew.csv")
ds.head()
```

	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

```
X = ds.iloc[:,1:5]
y = ds.iloc[:,5]
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # 70% training and 30% test
from sklearn.ensemble import BaggingClassifier
bagclassifier = BaggingClassifier()
bagclassifier.fit(X_train, y_train)
```

BaggingClassifier()

```
y_pred = bagclassifier.predict(X_test)
from sklearn.metrics import confusion_matrix, accuracy_score
bag_cs = confusion_matrix(y_test, y_pred)
bag_cs
```

```
array([[15,  0,  0],
       [ 0, 13,  1],
       [ 0,  2, 14]], dtype=int64)
```

```
bag_ac = accuracy_score(y_test, y_pred)
bag_ac
```

0.9333333333333333

```
import pickle
with open('bagModelIris.pkl','wb') as file:
    pickle.dump(bagclassifier, file)
import flask
from flask import Flask, request
model_bagging = pickle.load(open('bagModelIris.pkl','rb'))
app = Flask(_name_)
# Two parts (base address + route address)
@app.route('/', methods = ['GET','POST'])
def main():
    return "Begging Flask API Development"
@app.route('/classify', methods = ['GET'])
def classify():
    if flask.request.method == 'GET':
        SepalLengthCm = request.args.get('sl')
        SepalWidthCm = request.args.get('sw')
        PetalLengthCm = request.args.get('pl')
        PetalWidthCm = request.args.get('pw')

        prediction = model_bagging.predict([[SepalLengthCm, SepalWidthCm, PetalLengthCm,
PetalWidthCm]])

        return 'Class of species is '+str(prediction)
if__name__== '_main_':
    app.run()
```

```
 * Serving Flask app "__main__" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: off
 * Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
127.0.0.1 - - [15/Aug/2021 22:55:00] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [15/Aug/2021 22:56:36] "GET /classify?sl=1.2&sw=3.1&pl=2.4&pw=5.6 HTTP/1.1" 200 -
```

Testing using Postman

Practical No : 5

Aim : Implementation of K-Means Clustering

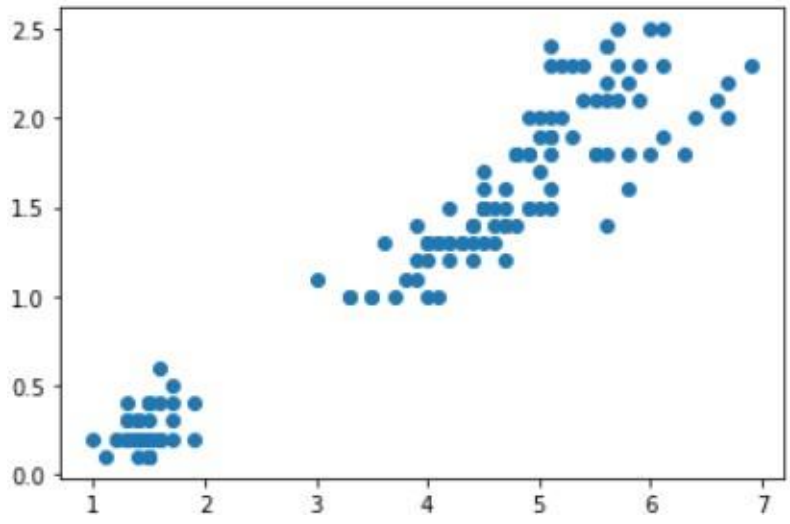
 # Find the exact / proper K
 # Elbow method

```
import pandas as pd
import numpy as np
ds = pd.read_csv("Iris.csv")
ds.head()
```

	PetalLength	PetalWidth	Species
0	1.4	0.2	Iris-setosa
1	1.4	0.2	Iris-setosa
2	1.3	0.2	Iris-setosa
3	1.5	0.2	Iris-setosa
4	1.4	0.2	Iris-setosa

```
from matplotlib import pyplot as pl
pl.scatter(ds['PetalLength'],ds['PetalWidth'])
```

```
<matplotlib.collections.PathCollection at 0x25124fdc3d0>
```




```
from sklearn.cluster import KMeans
kmean = KMeans(n_clusters = 3)
kmean
```

KMeans(n_clusters=3)

```
y_predict = kmean.fit_predict(ds[['PetalLength','PetalWidth']])
y_predict
```

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

```
ds['cluster'] = y_predict
```

ds

	PetalLength	PetalWidth	Species	cluster
0	1.4	0.2	Iris-setosa	1
1	1.4	0.2	Iris-setosa	1
2	1.3	0.2	Iris-setosa	1
3	1.5	0.2	Iris-setosa	1
4	1.4	0.2	Iris-setosa	1
...	...	...	...	...
145	5.2	2.3	Iris-virginica	2
146	5.0	1.9	Iris-virginica	2
147	5.2	2.0	Iris-virginica	2
148	5.4	2.3	Iris-virginica	2
149	5.1	1.8	Iris-virginica	2

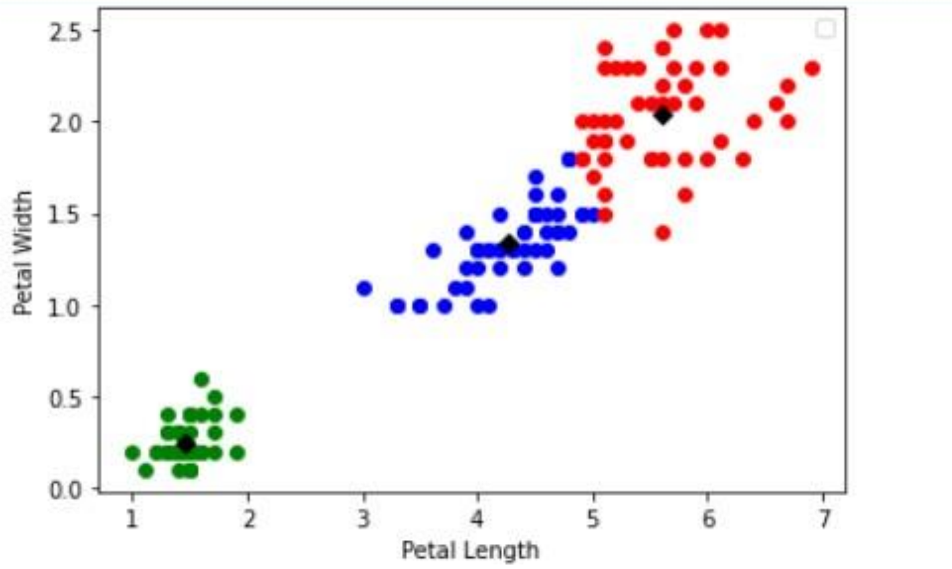
150 rows × 4 columns

kmean.cluster_centers_

```
array([[4.26923077, 1.34230769],
       [1.464     , 0.244     ],
       [5.59583333, 2.0375    ]])
```

```
ds1 = ds[ds.cluster == 0]
ds2 = ds[ds.cluster == 1]
ds3 = ds[ds.cluster == 2]

pl.scatter(ds1.PetalLength,ds1.PetalWidth, color = 'blue')
pl.scatter(ds2.PetalLength,ds2.PetalWidth, color = 'red')
pl.scatter(ds3.PetalLength,ds3.PetalWidth, color = 'green')
pl.scatter(kmean.cluster_centers_[:,0], kmean.cluster_centers_[:,1], color = 'black',
marker='D')
pl.xlabel('Petal Length')
pl.ylabel('Petal Width')
pl.legend()
pl.show()
```



 # since values of x and y are mismatch
 # so we need to scale the values

```
from sklearn.preprocessing import MinMaxScaler
scl = MinMaxScaler()
scl.fit(ds[['PetalLength']])
ds['PetalLength'] = scl.transform(ds[['PetalLength']])

scl.fit(ds[['PetalWidth']])
ds['PetalWidth'] = scl.transform(ds[['PetalWidth']])
```

 # Applying KMean once again

```
kmean = KMeans(n_clusters = 3)
y_predict = kmean.fit_predict(ds[['PetalLength', 'PetalWidth']])
y_predict
```

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

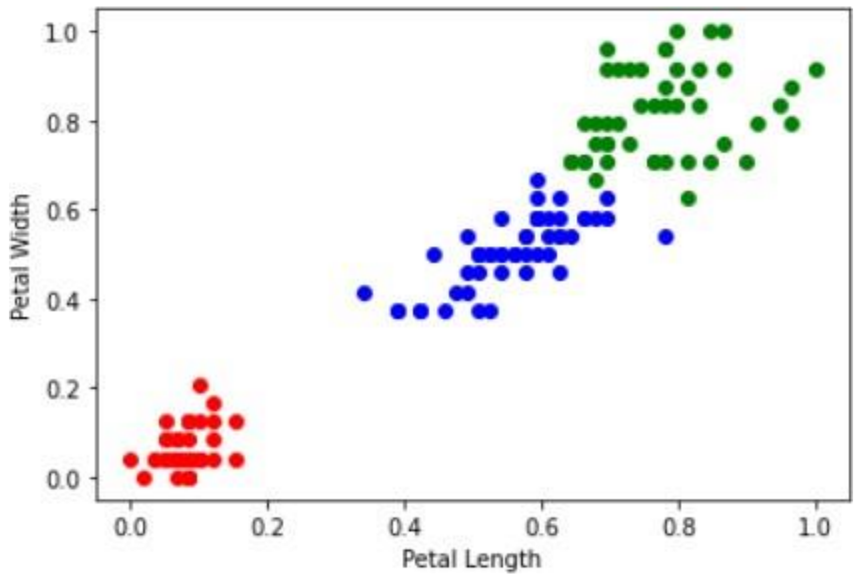
```
ds['cluster'] = y_predict
ds
```

	PetalLength	PetalWidth	Species	cluster
0	0.067797	0.041667	Iris-setosa	1
1	0.067797	0.041667	Iris-setosa	1
2	0.050847	0.041667	Iris-setosa	1
3	0.084746	0.041667	Iris-setosa	1
4	0.067797	0.041667	Iris-setosa	1
...	...	...	...	...
145	0.711864	0.916667	Iris-virginica	2
146	0.677966	0.750000	Iris-virginica	2
147	0.711864	0.791667	Iris-virginica	2
148	0.745763	0.916667	Iris-virginica	2
149	0.694915	0.708333	Iris-virginica	2

150 rows × 4 columns

```
ds1 = ds[ds.cluster == 0]
ds2 = ds[ds.cluster == 1]
ds3 = ds[ds.cluster == 2]

pl.scatter(ds1.PetalLength,ds1.PetalWidth, color = 'blue')
pl.scatter(ds2.PetalLength,ds2.PetalWidth, color = 'red')
pl.scatter(ds3.PetalLength,ds3.PetalWidth, color = 'green')
pl.xlabel('Petal Length')
pl.ylabel('Petal Width')
pl.show()
```

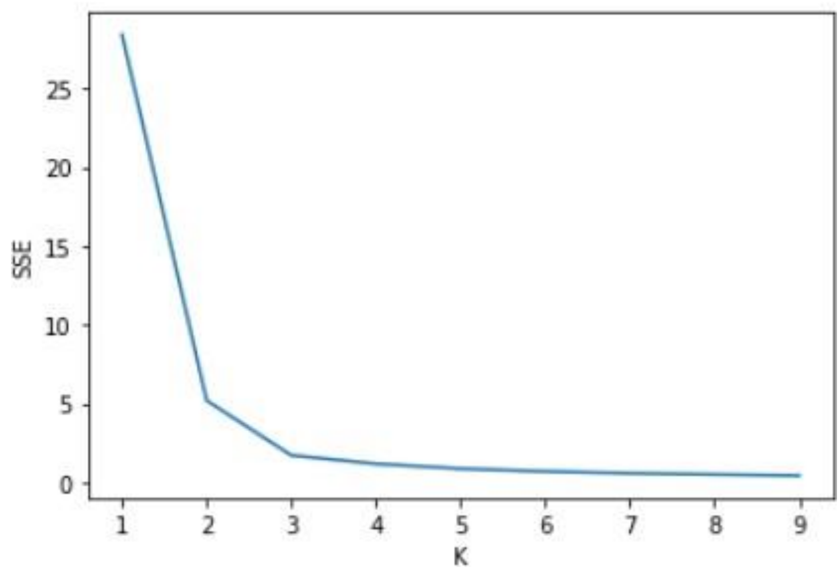



```
k_range = range(1,10)
sse = []
for k in k_range:
    kmean = KMeans(n_clusters = k)
    kmean.fit(ds[['PetalLength','PetalWidth']])
    sse.append(kmean.inertia_)
sse
```

```
[28.391514358368717,
 5.179687509974783,
 1.7050986081225123,
 1.1621031930971286,
 0.8570856553216398,
 0.6833274904190353,
 0.5683512655008139,
 0.48911635449076774,
 0.4155388630360096]
```

```
pl.xlabel('K')
pl.ylabel('SSE')
pl.plot(k_range, sse)
```

```
[<matplotlib.lines.Line2D at 0x1c46ba07d90>]
```



Practical No: 6

Aim : Implementation of dimensionality reduction techniques:
1)Normalization
2)Principal Components Analysis.

1)Normalization

```
import numpy as np
import pandas as pd
ds = pd.read_csv("FeatureSelection.csv")
ds.head()
```

	age	weight	height	cholestrol	sugar	Target
0	35	70	150	233	250	1
1	56	75	100	250	300	0
2	67	68	180	204	260	0
3	72	60	170	236	450	1
4	39	77	190	354	220	1

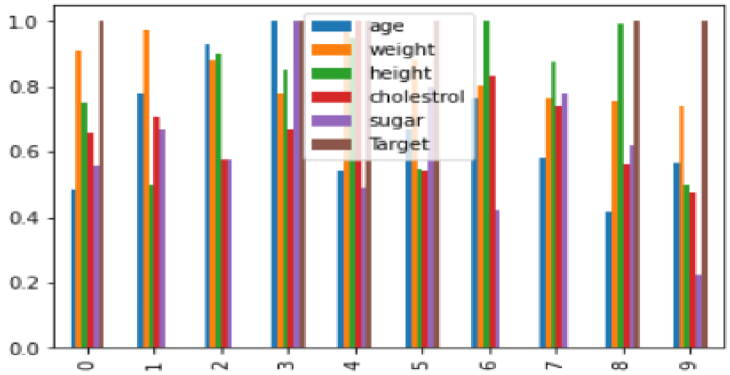
 # Simple feature scaling

```
for column in ds.columns:
    ds[column]=ds[column]/ds[column].abs().max()
ds.head()
```

	age	weight	height	cholestrol	sugar	Target
0	0.486111	0.909091	0.75	0.658192	0.555556	1.0
1	0.777778	0.974026	0.50	0.706215	0.666667	0.0
2	0.930556	0.883117	0.90	0.576271	0.577778	0.0
3	1.000000	0.779221	0.85	0.666667	1.000000	1.0
4	0.541667	1.000000	0.95	1.000000	0.488889	1.0

```
import matplotlib.pyplot as pl
ds.plot(kind='bar')
```

```
<AxesSubplot:>
```



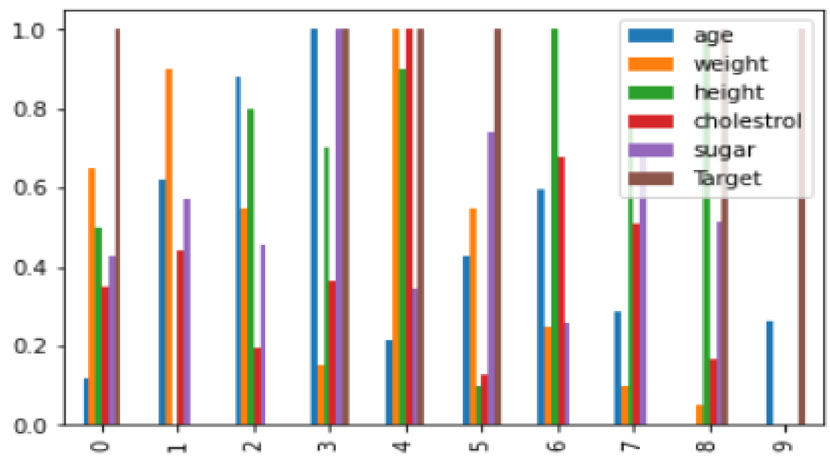
 # Min Max method xold=(xold-xmin)/(xmax-xmin)

```
ds1= ds.copy()
for column in ds1.columns:
   ds1[column]= (ds1[column] - ds1[column].min()) / (ds1[column].max() -
ds1[column].min())
ds1.head()
```

	age	weight	height	cholestrol	sugar	Target
0	0.119048	0.65	0.5	0.349462	0.428571	1.0
1	0.619048	0.90	0.0	0.440860	0.571429	0.0
2	0.880952	0.55	0.8	0.193548	0.457143	0.0
3	1.000000	0.15	0.7	0.365591	1.000000	1.0
4	0.214286	1.00	0.9	1.000000	0.342857	1.0

```
ds1.plot(kind='bar')
```

<AxesSubplot:>



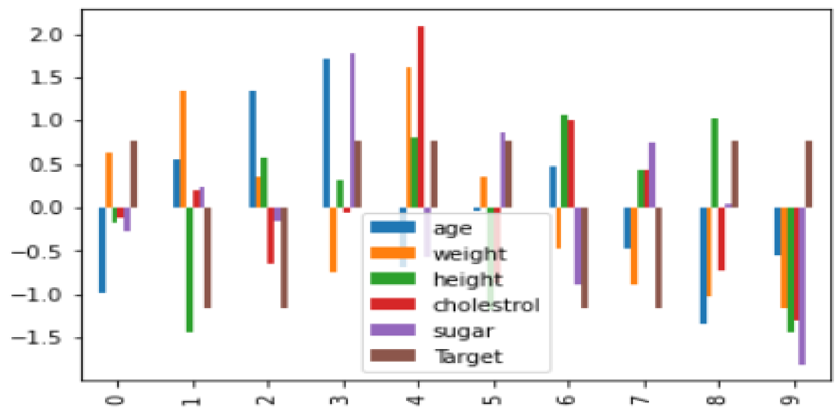
Standardization (Z score method or 0 mean)

```
ds2=ds.copy()
for column in ds2.columns:
    ds2[column]=(ds2[column] - ds2[column].mean()) / ds2[column].std()
ds2.head()
```

	age	weight	height	cholestrol	sugar	Target
0	-0.980397	0.637633	-0.182525	-0.114881	-0.266226	0.774597
1	0.544665	1.330712	-1.432694	0.195116	0.245747	-1.161895
2	1.343507	0.360401	0.567577	-0.643699	-0.163831	-1.161895
3	1.706617	-0.748525	0.317543	-0.060176	1.781663	0.774597
4	-0.689909	1.607944	0.817611	2.091567	-0.573409	0.774597

```
ds2.plot(kind='bar')
```

<AxesSubplot:>



2) Principal Components Analysis

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as pl
ds = pd.read_csv("wine.csv")
ds.head()
```

	Alcohol	Malic.acid	Ash	Acl	Mg	Phenols	Flavanoids	Nonflavanoid.phenols	Proanth	Color.int	Hue	OD	Proline	Wine
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64	1.04	3.92	1065	1
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.40	1050	1
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68	1.03	3.17	1185	1
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80	0.86	3.45	1480	1
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32	1.04	2.93	735	1

```
X = ds.iloc[:,0:13]
X.head()
```

	Alcohol	Malic.acid	Ash	Acl	Mg	Phenols	Flavanoids	Nonflavanoid.phenols	Proanth	Color.int	Hue	OD	Proline
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64	1.04	3.92	1065
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.40	1050
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68	1.03	3.17	1185
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80	0.86	3.45	1480
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32	1.04	2.93	735

```
y = ds.iloc[:,-1]
y.head()
```

```
0    1
1    1
2    1
3    1
4    1
Name: Wine, dtype: int64
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2)
from sklearn.preprocessing import StandardScaler
st = StandardScaler()
```

 # fit and transform

```
X_train = st.fit_transform(X_train)
X_train
```

```
array([[ 0.86085012, -0.83342199,  0.47848374, ..., -0.21754034,
         0.38175836,  1.84584136],
       [-0.73835419,  1.70964634,  1.29881334, ..., -0.08954008,
         0.73014966, -1.20811907],
       [-0.22168818,  0.46354285,  0.87081528, ..., -0.21754034,
        -0.62160859, -0.46122657],
       ...,
       [-1.47644849, -0.58759206, -1.73283953, ..., -0.00420658,
        -0.21747468, -1.04214296],
       [-1.15660763, -1.08772883,  0.51415024, ...,  1.57446322,
         0.17272357, -0.32844568],
       [ 1.27910356, -0.66388411, -0.30617936, ...,  0.63579469,
         1.55235313,  0.16948265]])
```

```
X_test = st.transform(X_test)
```

 # Applying PCA

```
from sklearn.decomposition import PCA
```

 # Check Eigenvalue of components

```
pca = PCA(n_components = 2)
X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)
pca.explained_variance_ratio_
```

array([0.36138769, 0.1937306])

 # Sorted ......Descending order

 # Now classification

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
LogisticRegression()
y_test
```

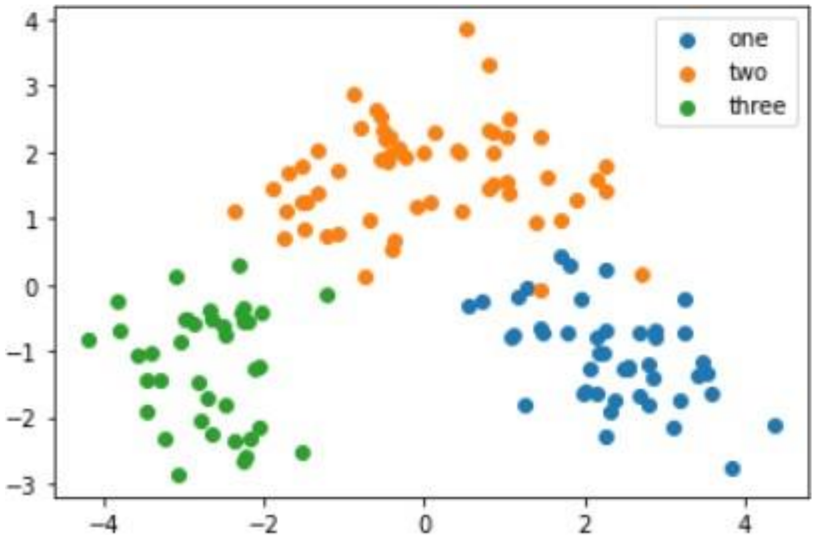
```
29     1
149    3
63     2
158    3
22     1
Name: Wine, dtype: int64
```

```
y_predict = logreg.predict(X_test)
y_predict
array([1, 3, 2, 3, 1, 1, 2, 2, 2, 1, 1, 3, 2, 3, 2, 1, 3, 3, 1, 1, 3, 2,
       1, 1, 2, 1, 1, 2, 2, 3, 3, 1, 2, 3, 1, 2], dtype=int64)
```

```
# check with Confusion Metrix for Actual vs Predict
from sklearn.metrics import confusion_matrix
c = confusion_matrix(y_test, y_predict)
c
array([[13,  1,  0],
       [ 1, 11, 1],
       [ 0,  0,  9]], dtype=int64)
```

 # 3 category
 # Visualize 2 components (0th and 1st)

```
X_disp, y_disp = X_train, y_train
pl.scatter(X_disp[ y_disp == 1,0], X_disp[ y_disp == 1,1], label = 'one')
pl.scatter(X_disp[ y_disp == 2,0], X_disp[ y_disp == 2,1], label = 'two')
pl.scatter(X_disp[ y_disp == 3,0], X_disp[ y_disp == 3,1], label = 'three')
pl.legend()
pl.show()
```



Practical No : 7

Aim : Study of Support Vector Machines (SVMs).

```
import pandas as pd
from sklearn.datasets import load_iris
iris = load_iris()
iris.feature_names
```

```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

```
ds = pd.DataFrame(iris.data, columns=iris.feature_names)
ds.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

 # Appending one column as target column

```
ds['target'] = iris.target
ds.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

 # 0 ----> Setosa 1-->Versicolor 2---> Virginica

```
iris.target_names
```

array(['setosa', 'versicolor', 'virginica'], dtype='<U10')

#Want to see the number of rows for each flower type

```
ds[ds.target==2]
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
100	6.3	3.3	6.0	2.5	2
101	5.8	2.7	5.1	1.9	2
102	7.1	3.0	5.9	2.1	2
103	6.3	2.9	5.6	1.8	2
104	6.5	3.0	5.8	2.2	2
105	7.6	3.0	6.6	2.1	2
106	4.9	2.5	4.5	1.7	2

...

146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

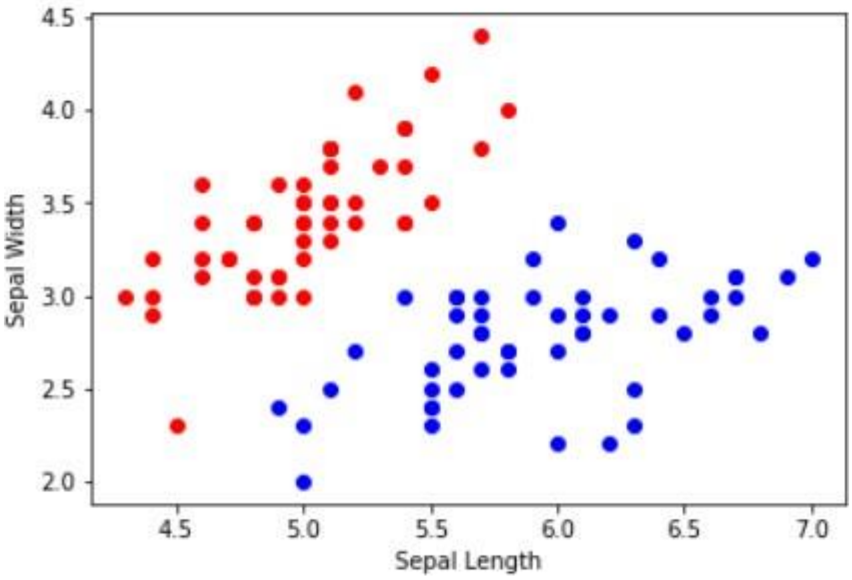
 # Want to append flower name column ---> based on index (0, 1, 2) i.e Setosa and all
ds['fname'] = ds.target.apply(lambda x: iris.target_names[x])
ds.head()

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	fname
0	5.1	3.5	1.4	0.2	0	setosa
1	4.9	3.0	1.4	0.2	0	setosa
2	4.7	3.2	1.3	0.2	0	setosa
3	4.6	3.1	1.5	0.2	0	setosa
4	5.0	3.6	1.4	0.2	0	setosa

from matplotlib import pyplot as pl
 # Create 3 DF for three flowers
ds1 = ds[ds.target==0]
ds2 = ds[ds.target==1]
ds3 = ds[ds.target==2]

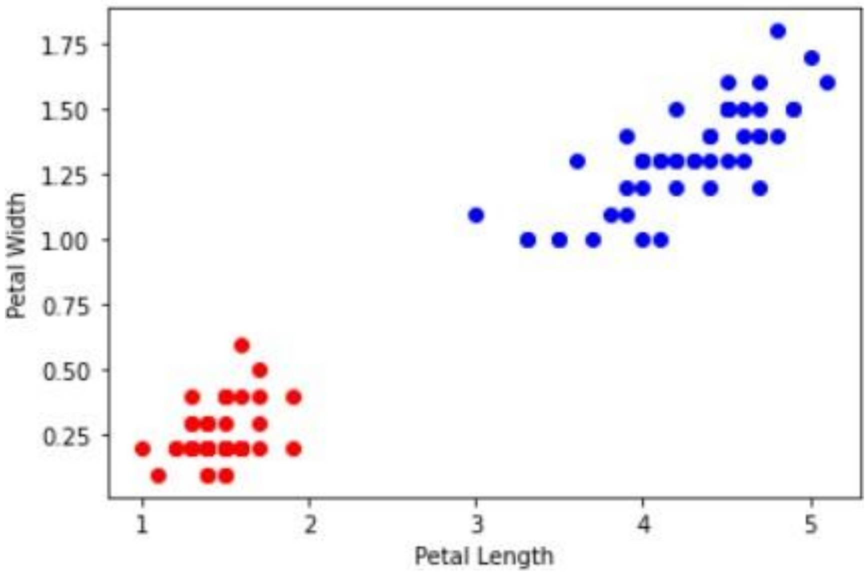
pl.scatter(ds1['sepal length (cm)'], ds1['sepal width (cm)'], color = 'red', marker = 'o')
pl.scatter(ds2['sepal length (cm)'], ds2['sepal width (cm)'], color = 'blue', marker = 'o')
pl.xlabel('Sepal Length')
pl.ylabel('Sepal Width')

```
Text(0, 0.5, 'Sepal Width')
```



pl.scatter(ds1['petal length (cm)'], ds1['petal width (cm)'], color = 'red', marker = 'o')
pl.scatter(ds2['petal length (cm)'], ds2['petal width (cm)'], color = 'blue', marker = 'o')
pl.xlabel('Petal Length')
pl.ylabel('Petal Width')

```
Text(0, 0.5, 'Petal Width')
```




```
from sklearn.model_selection import train_test_split
# Remove fname column
X = ds.drop(['target','fname'], axis = 'columns')
X.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

```
y = ds['target']
y.head()
```

```
0    0
1    0
2    0
3    0
4    0
Name: target, dtype: int32
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)
from sklearn.svm import SVC
svmodel = SVC(kernel='linear')
svmodel.fit(X_train, y_train)
```

SVC(kernel='linear')

 # Accuracy of model

```
svmodel.score(X_train, y_train)
```

0.9916666666666667