FYMCA-B
Roll No.:87

Practical-1

AIM: Program on Prolog

```
precious(gold).

precious(silver).

female(mary).

father(surya,ramesh).

likes(surya,food).

likes(surya,car).

likes(surya,bike).

likes(surya,book).

likes(shreya,chocolate).

likes(sudha,food).

likes(surya,coffee).

likes(samudra,chocolate).

likes(samanta,X) :- likes(X,chocolate).
```

SWI-Prolog (AMD64, Multi-threaded, version 9.0.4)

File Edit Settings Run Debug Help

```
Welcome to SWI-Prolog (threaded, 64 bits, version 9.0.4)
SWI-Prolog comes with ABSOLUTELY NO WARRANTY. This is free software.
Please run ?- license. for legal details.

For online help and background, visit https://www.swi-prolog.org
For built-in help, use ?- help(Topic). or ?- apropos(Word).

?-
% c:/users/lab2_51/documents/pract1 compiled 0.00 sec, -2 clauses
?- precious(gold)
|
ERROR: Stream user_input:9:15 Syntax error: Unexpected end of file
?- precious(gold).
true.

?- precious(silver).
true.

?- precious(platinium).
false.

?- likes(surya,food).
true
Unknown action: ( (h for help)
Action?
ERROR: Type error: `character_code' expected, found `-1' (an integer)
ERROR: In:
ERROR:   [11] char_code(_14626,-1)
ERROR:   [10] '$in_reply'(-1,'?h') at c:/program files/swipl/boot/init.pl:1037
?- likes(shreya,book).
false.

?- likes(samanta,X)
|
|
ERROR: Stream user_input:33:0 Syntax error: Unexpected end of file
?- likes(samanta,X).
X = shreya ,

?- likes(samanta,X).
X = shreya
```

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Practical-2

AIM: Implementation of water jug problem using prolog

```
water_jug(X,Y):- X>4,Y<3,write('4L jug overflow.'),nl.
water_jug(X,Y):- X<4,Y>3,write('3L jug overflow.'),nl.
water_jug(X,Y):- X>4,Y>3,write('Both jugs overflow.'),nl.

water_jug(0, 0) :- write('4L:0 & 3L:0'), nl, water_jug(4, 0).

water_jug(4, 0) :- write('4L:4 & 3L:0 (Action: Fill 4L jug.)'), nl,
water_jug(1, 3).

water_jug(1, 3) :- write('4L:1 & 3L:3 (Action: Pour water from 4L to
3L jug.)'), nl, water_jug(1, 0).

water_jug(1, 0) :- write('4L:1 & 3L:0 (Action: Empty 3L jug.)'), nl,
water_jug(0, 1).

water_jug(0, 1) :- write('4L:0 & 3L:1 (Action: Pour water from 4L jug
to 3L jug.)'), nl, water_jug(4, 1).

water_jug(4, 1) :- write('4L:4 & 3L:1 (Action: Fill 4L jug.)'), nl,
water_jug(2, 3).

water_jug(2, 3) :- write('4L:2 & 3L:3 (Action: Pour water from 4L to
3L jug untill 3L jug is full.)'), nl, water_jug(2, 0).

water_jug(2, 0) :- write('4L:2 & 3L:0 (Action: Empty 3L jug. Goal
State reached..)'), nl.
```

```
Welcome to SWI-Prolog (threaded, 64 bits, version 9.3.3-21-g1fbd70c21)
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Please run ?- license. for legal details.

For online help and background, visit https://www.swi-prolog.org
For built-in help, use ?- help(Topic). or ?- apropos(Word).

?-
% c:/Users/USER/Downloads/demoBhushan.pl compiled 0.00 sec, 11 clauses
?- waterjug(9,0).
Correct to: "water_jug(9,0)"? yes
4L jug overflow.
true .

?- waterjug(0,6).
Correct to: "water_jug(0,6)"? yes
3L jug overflow.
true .

?- waterjug(6,6).
Correct to: "water_jug(6,6)"? yes
Both jugs overflow.
true.

?-
|    waterjug(0,0).
Correct to: "water_jug(0,0)"? yes
4L:0 & 3L:0
4L:4 & 3L:0 (Action: Fill 4L jug.)
4L:1 & 3L:3 (Action: Pour water from 4L to 3L jug.)
4L:1 & 3L:0 (Action: Empty 3L jug.)
4L:0 & 3L:1 (Action: Pour water from 4L jug to 3L jug.)
4L:4 & 3L:1 (Action: Fill 4L jug.)
4L:2 & 3L:3 (Action: Pour water from 4L to 3L jug untill 3L jug is full.)
4L:2 & 3L:0 (Action: Empty 3L jug. Goal State reached..)
true .

?-
```

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Practical 3

AIM: Introduction to Python Programming

jupyter Untitled33 Last Checkpoint: 3 minutes ago (unsaved changes)

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)

In [7]:
```python
# Assigning value to a string variable
myString = "Hello World!"

# Setting working directory
import os
print(os.getcwd())
```
```
C:\Users\Lab2_51
```

In [8]:
```python
# Assigning value to x
x = 1
print(type(x))

# Checking if x is an integer
print(isinstance(x, int))
```
```
<class 'int'>
True
```

In [9]:
```python
# Rounding x and assigning it to y
y = round(x)
print(y)

# Assigning value to z and converting it to integer
z = 3.14
z = int(z)
print(z)

# Creating a vector using list
x1 = [34, 52.5, 45.2]
print(x1)
```
```
1
3
[34, 52.5, 45.2]
```


In [10]:
```python
# Arithmetic operations
r1 = 21
r2 = 20
add = r1 + r2
print(add)
```
```
41
```

In [11]:
```python
s1 = 22
s2 = 12
sub = s2 - s1
print(sub)
```
```
-10
```

In [12]:
```python
m1 = 2
m2 = 5
mul = m1 * m2
print(mul)
```
```
10
```

In [13]:
```python
d1 = 20
d2 = 10
div = d1 / d2
print(div)
```
```
2.0
```

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Practical-4

AIM: Introduction to Python Libraries

```
In [1]: import numpy as np
        import pandas as pd
```

```
In [2]: df = pd.read_csv('C:\\Users\\USER\\Desktop\\eda\\mtcars.csv')
```

```
In [3]: print(df)
```

```
                  model   mpg  cyl   disp   hp  drat     wt   qsec  vs  am  \
0             Mazda RX4  21.0    6  160.0  110  3.90  2.620  16.46   0   1
1         Mazda RX4 Wag  21.0    6  160.0  110  3.90  2.875  17.02   0   1
2            Datsun 710  22.8    4  108.0   93  3.85  2.320  18.61   1   1
3        Hornet 4 Drive  21.4    6  258.0  110  3.08  3.215  19.44   1   0
4     Hornet Sportabout  18.7    8  360.0  175  3.15  3.440  17.02   0   0
5               Valiant  18.1    6  225.0  105  2.76  3.460  20.22   1   0
6            Duster 360  14.3    8  360.0  245  3.21  3.570  15.84   0   0
7             Merc 240D  24.4    4  146.7   62  3.69  3.190  20.00   1   0
8              Merc 230  22.8    4  140.8   95  3.92  3.150  22.90   1   0
9              Merc 280  19.2    6  167.6  123  3.92  3.440  18.30   1   0
10            Merc 280C  17.8    6  167.6  123  3.92  3.440  18.90   1   0
11           Merc 450SE  16.4    8  275.8  180  3.07  4.070  17.40   0   0
12           Merc 450SL  17.3    8  275.8  180  3.07  3.730  17.60   0   0
13          Merc 450SLC  15.2    8  275.8  180  3.07  3.780  18.00   0   0
14   Cadillac Fleetwood  10.4    8  472.0  205  2.93  5.250  17.98   0   0
15  Lincoln Continental  10.4    8  460.0  215  3.00  5.424  17.82   0   0
16    Chrysler Imperial  14.7    8  440.0  230  3.23  5.345  17.42   0   0
17             Fiat 128  32.4    4   78.7   66  4.08  2.200  19.47   1   1
18          Honda Civic  30.4    4   75.7   52  4.93  1.615  18.52   1   1
19       Toyota Corolla  33.9    4   71.1   65  4.22  1.835  19.90   1   1
20        Toyota Corona  21.5    4  120.1   97  3.70  2.465  20.01   1   0
21     Dodge Challenger  15.5    8  318.0  150  2.76  3.520  16.87   0   0
22          AMC Javelin  15.2    8  304.0  150  3.15  3.435  17.30   0   0
23           Camaro Z28  13.3    8  350.0  245  3.73  3.840  15.41   0   0
24     Pontiac Firebird  19.2    8  400.0  175  3.08  3.845  17.05   0   0
25            Fiat X1-9  27.3    4   79.0   66  4.08  1.935  18.90   1   1
26        Porsche 914-2  26.0    4  120.3   91  4.43  2.140  16.70   0   1
27         Lotus Europa  30.4    4   95.1  113  3.77  1.513  16.90   1   1
28       Ford Pantera L  15.8    8  351.0  264  4.22  3.170  14.50   0   1
29         Ferrari Dino  19.7    6  145.0  175  3.62  2.770  15.50   0   1
30        Maserati Bora  15.0    8  301.0  335  3.54  3.570  14.60   0   1
31           Volvo 142E  21.4    4  121.0  109  4.11  2.780  18.60   1   1

    gear  carb
0      4     4
1      4     4
2      4     1
3      3     1
4      3     2
5      3     1
6      3     4
7      4     2
8      4     2
9      4     4
10     4     4
11     3     3
12     3     3
```

```
In [5]: df.head()
```

Out[5]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
1	Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
2	Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
3	Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
4	Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
5	Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1

```
In [ ]: df.head(10)
```

```
In [6]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   model   32 non-null     object
 1   mpg     32 non-null     float64
 2   cyl     32 non-null     int64
 3   disp    32 non-null     float64
 4   hp      32 non-null     int64
 5   drat    32 non-null     float64
 6   wt      32 non-null     float64
 7   qsec    32 non-null     float64
 8   vs      32 non-null     int64
 9   am      32 non-null     int64
 10  gear    32 non-null     int64
 11  carb    32 non-null     int64
dtypes: float64(5), int64(6), object(1)
memory usage: 3.1+ KB
```

```
In [9]: df.isnull()
```

Out[9]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False
5	False	False	False	False	False	False	False	False	False	False	False	False
6	False	False	False	False	False	False	False	False	False	False	False	False
7	False	False	False	False	False	False	False	False	False	False	False	False
8	False	False	False	False	False	False	False	False	False	False	False	False
9	False	False	False	False	False	False	False	False	False	False	False	False
10	False	False	False	False	False	False	False	False	False	False	False	False

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
model    0
mpg      0
cyl      0
disp     0
hp       0
drat     0
wt       0
qsec     0
vs       0
am       0
gear     0
carb     0
dtype: int64
```

In [11]:
```
df.tail()
```

Out[11]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
27	Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.9	1	1	5	2
28	Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.5	0	1	5	4
29	Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.5	0	1	5	6
30	Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.6	0	1	5	8
31	Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.6	1	1	4	2

In [12]:
```
df.describe()
```

Out[12]:

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carl
count	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000
mean	20.090625	6.187500	230.721875	146.687500	3.596563	3.217250	17.848750	0.437500	0.406250	3.687500	2.812
std	6.026948	1.785922	123.938694	68.562868	0.534679	0.978457	1.786943	0.504016	0.498991	0.737804	1.615
min	10.400000	4.000000	71.100000	52.000000	2.760000	1.513000	14.500000	0.000000	0.000000	3.000000	1.000
25%	15.425000	4.000000	120.825000	96.500000	3.080000	2.581250	16.892500	0.000000	0.000000	3.000000	2.000
50%	19.200000	6.000000	196.300000	123.000000	3.695000	3.325000	17.710000	0.000000	0.000000	4.000000	2.000
75%	22.800000	8.000000	326.000000	180.000000	3.920000	3.610000	18.900000	1.000000	1.000000	4.000000	4.000
max	33.900000	8.000000	472.000000	335.000000	4.930000	5.424000	22.900000	1.000000	1.000000	5.000000	8.000

In [13]:
```
df.size
```

Out[13]: 384

In [14]:
```
df.shape
```

Out[14]: (32, 12)

In [15]:
```
df.ndim
```

Out[15]: 2

In [16]:
```
df.at[4,'model']
```

Out[16]: 'Hornet Sportabout'

In [17]:
```
df.at[4,'disp']
```

Out[17]: 360.0

In [18]:
```
df.iat[3,4]
```

Out[18]: 110

In [20]:
```
df.loc[:,'model']
```

Out[20]:
```
0               Mazda RX4
1           Mazda RX4 Wag
2              Datsun 710
3          Hornet 4 Drive
4       Hornet Sportabout
5                 Valiant
6              Duster 360
7               Merc 240D
8                Merc 230
9                Merc 280
10              Merc 280C
11             Merc 450SE
12             Merc 450SL
13            Merc 450SLC
14     Cadillac Fleetwood
15    Lincoln Continental
16      Chrysler Imperial
17               Fiat 128
18            Honda Civic
19         Toyota Corolla
20          Toyota Corona
21       Dodge Challenger
22            AMC Javelin
23             Camaro Z28
24       Pontiac Firebird
25              Fiat X1-9
26          Porsche 914-2
27           Lotus Europa
28         Ford Pantera L
29           Ferrari Dino
30          Maserati Bora
31             Volvo 142E
Name: model, dtype: object
```

In [23]:
```
df.iloc[0:5,0:2]
```

Out[23]:

	model	mpg
0	Mazda RX4	21.0
1	Mazda RX4 Wag	21.0
2	Datsun 710	22.8
3	Hornet 4 Drive	21.4
4	Hornet Sportabout	18.7

In [26]:
```
df.iloc[22:32,:]
```

Out[26]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
22	AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
23	Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
24	Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
25	Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
26	Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
27	Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
28	Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
29	Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
30	Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
31	Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

In [27]:
```
df.dtypes
```

Out[27]:
```
model     object
mpg      float64
cyl        int64
disp     float64
hp         int64
drat     float64
wt       float64
qsec     float64
vs         int64
am         int64
gear       int64
carb       int64
dtype: object
```

```
In [28]: df['model'].dtype
Out[28]: dtype('O')

In [29]: df.axes
Out[29]: [RangeIndex(start=0, stop=32, step=1),
          Index(['model', 'mpg', 'cyl', 'disp', 'hp', 'drat', 'wt', 'qsec', 'vs', 'am',
                 'gear', 'carb'],
                dtype='object')]

In [30]: df.columns
Out[30]: Index(['model', 'mpg', 'cyl', 'disp', 'hp', 'drat', 'wt', 'qsec', 'vs', 'am',
                'gear', 'carb'],
               dtype='object')

In [31]: df['hp'].std()
Out[31]: 68.56286848932059

In [32]: df['mpg'].mean()
Out[32]: 20.090625000000003

In [33]: df['mpg'].median()
Out[33]: 19.2

In [34]: df['hp'].describe()
Out[34]: count     32.000000
         mean     146.687500
         std       68.562868
         min       52.000000
         25%       96.500000
         50%      123.000000
         75%      180.000000
         max      335.000000
         Name: hp, dtype: float64
```

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Practical-5

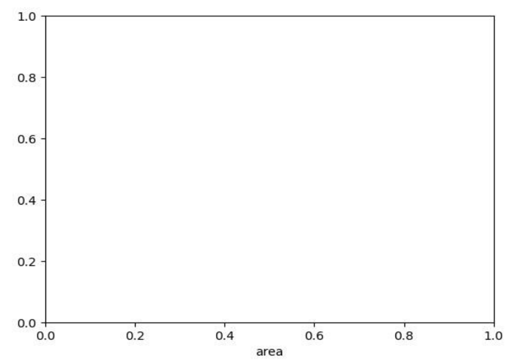
AIM: Program to implement Linear Regression

jupyter linear regression Last Checkpoint: 24 minutes ago (unsaved changes)

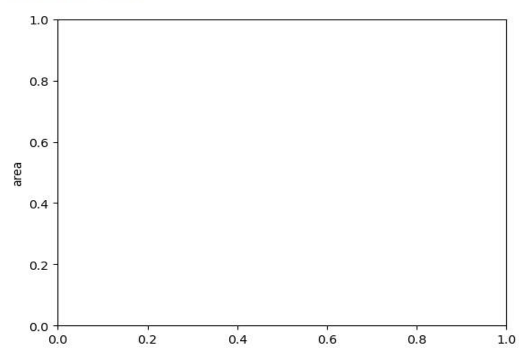
```
In [1]: import pandas as pd

In [2]: import numpy as np

In [3]: from sklearn import linear_model

In [4]: import matplotlib.pyplot as plt

In [5]: df = pd.read_csv(r'C:\Users\Lab2_51\Music\area - area.csv')

In [6]: df
Out[6]:
```

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

```
In [7]: plt.xlabel('area')
Out[7]: Text(0.5, 0, 'area')
```




```
In [8]: plt.ylabel('area')
Out[8]: Text(0, 0.5, 'area')
```



```
In [12]: price = df.price

In [13]: price

Out[13]: 0    550000
         1    565000
         2    610000
         3    680000
         4    725000
         Name: price, dtype: int64

In [14]: reg = linear_model.LinearRegression()

In [15]: reg.fit(new_df,price)

Out[15]: ▾ LinearRegression
         LinearRegression()

In [16]: reg.predict([[3300]])

         C:\Users\Lab2_51\anaconda3\lib\site-packages\sklearn\base.py:420: UserWarning: X does not have valid feature names, but LinearR
         egression was fitted with feature names
           warnings.warn(

Out[16]: array([628715.75342466])

In [17]: reg.coef_

Out[17]: array([135.78767123])

In [18]: reg.intercept_

Out[18]: 180616.43835616432

In [19]: reg.predict([[5000]])

         C:\Users\Lab2_51\anaconda3\lib\site-packages\sklearn\base.py:420: UserWarning: X does not have valid feature names, but LinearR
         egression was fitted with feature names
           warnings.warn(

Out[19]: array([859554.79452055])
```

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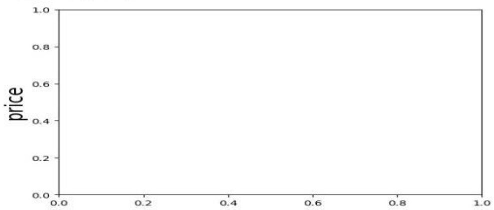
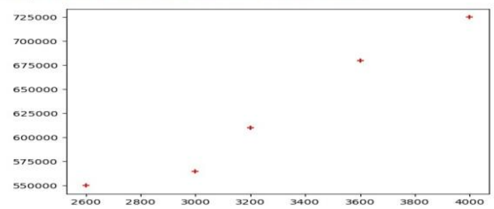
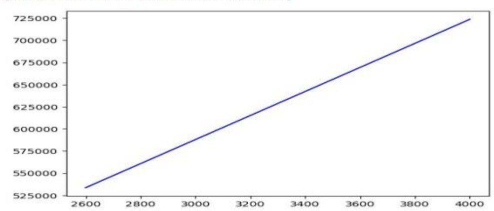
In [21]:
```
plt.ylabel('price',fontsize = 20)
```
Out[21]: Text(0, 0.5, 'price')



In [22]:
```
plt.scatter(df.area,df.price,color='red', marker = '+')
```
Out[22]: <matplotlib.collections.PathCollection at 0x1e30a01f430>



In [23]:
```
plt.plot(df.area,reg.predict(df[['area']]),color = 'blue')
```
Out[23]: [<matplotlib.lines.Line2D at 0x1e30a09aa70>]



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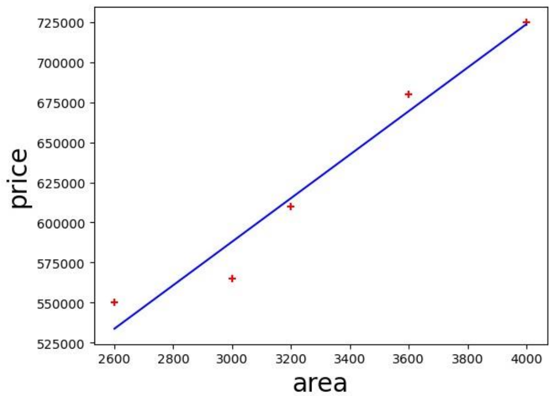
```
In [25]: plt.xlabel('area',fontsize = 20)
         plt.ylabel('price',fontsize = 20)
         plt.scatter(df.area,df.price,color='red', marker = '+')
         plt.plot(df.area,reg.predict(df[['area']]),color = 'blue')
Out[25]: [<matplotlib.lines.Line2D at 0x1e309672b30>]
```




```
In [ ]:
```

Practical-6

AIM: Program to Implement Logistic Regression

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
credit_df = pd.read_csv('D:/Rukhsar_AIMLPracts/CreditRisk.csv')
```

In [3]:
```
credit_df.shape
```

Out[3]: (614, 13)

In [4]:
```
credit_df.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Pr
0	LP001002	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	

In [5]:
```
credit_df.tail()
```

Out[5]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71	360.0	1.0
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40	180.0	1.0
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253	360.0	1.0
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187	360.0	1.0
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133	360.0	0.0

In [6]:
```
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         614 non-null    int64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    int64
dtypes: float64(3), int64(3), object(7)
memory usage: 62.5+ KB
```

In [7]:
```
credit_df.describe()
```

Out[7]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status
count	614.000000	614.000000	614.000000	600.00000	564.000000	614.000000
mean	5403.459283	1621.245798	141.166124	342.00000	0.842199	0.687296
std	6109.041673	2926.248369	88.340630	65.12041	0.364878	0.463973
min	150.000000	0.000000	0.000000	12.00000	0.000000	0.000000
25%	2877.500000	0.000000	98.000000	360.00000	1.000000	0.000000
50%	3812.500000	1188.500000	125.000000	360.00000	1.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.00000	1.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000	1.000000

In [8]:
```
credit_df.Loan_Status.value_counts()
```

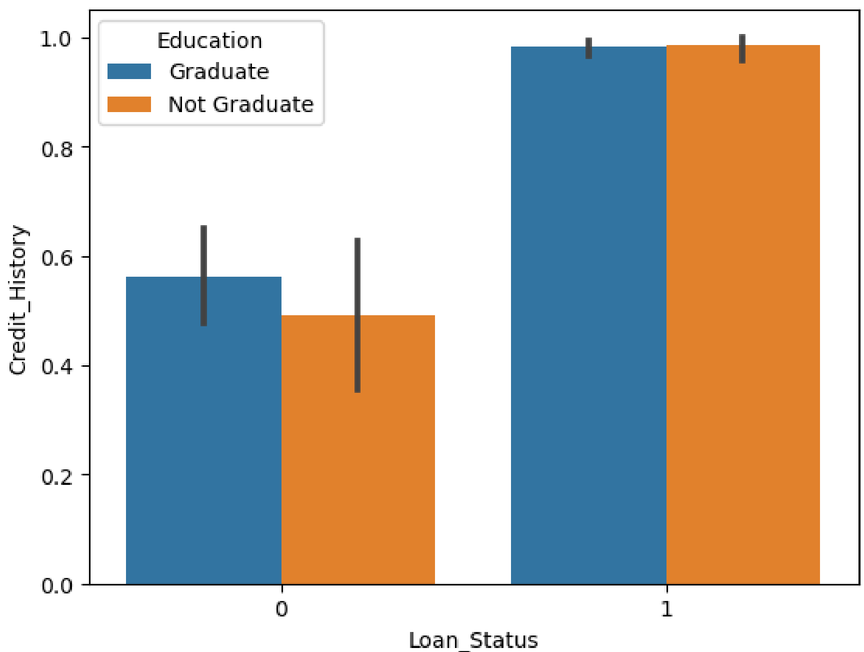
Out[8]:
```
1    422
0    192
Name: Loan_Status, dtype: int64
```

In [9]:
```
credit_df.groupby(['Education', 'Loan_Status']).Education.count()
```

Out[9]:
```
Education     Loan_Status
Graduate      0              140
              1              340
Not Graduate  0               52
              1               82
Name: Education, dtype: int64
```

In [10]:
```
sns.barplot(y = 'Credit_History' , x='Loan_Status', hue='Education', data=credit_df)
```

Out[10]:
```
<Axes: xlabel='Loan_Status', ylabel='Credit_History'>
```



In [11]:
```
100 * credit_df.isnull().sum() / credit_df.shape[0]
```

Out[11]:
```
Loan_ID              0.000000
Gender               2.117264
Married              0.488599
Dependents           2.442997
Education            0.000000
Self_Employed        5.211726
ApplicantIncome      0.000000
CoapplicantIncome    0.000000
LoanAmount           0.000000
Loan_Amount_Term     2.280130
Credit_History       8.143322
Property_Area        0.000000
Loan_Status          0.000000
dtype: float64
```

In [12]:
```
DF=credit_df.drop(credit_df.columns[0],axis=1)
```

In [13]:
```
DF.head()
```

Out[13]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	Urban
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	Rura
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	Urban
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	Urban
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	Urban

In [14]:
```
object_columns = DF.select_dtypes(include=['object']).columns
numeric_columns = DF.select_dtypes(exclude=['object']).columns
```

In [15]:
```
for column in object_columns:
    majority = DF[column].value_counts().iloc[0]
    DF[column].fillna(majority, inplace=True)
```

In [17]:
```
for column in numeric_columns:
    mean = DF[column].mean()
    DF[column].fillna(mean, inplace=True)
```

In [18]:
```
DF.head()
```

Out[18]:

arried	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
No	0	Graduate	No	5849	0.0	0	360.0	1.0	Urban	1
Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	Rural	0
Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	Urban	1
Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	Urban	1
No	0	Graduate	No	6000	0.0	141	360.0	1.0	Urban	1

In [20]:
```
DF[object_columns].Property_Area #Categorical Columns
```

Out[20]:
```
0          Urban
1          Rural
2          Urban
3          Urban
4          Urban
         ...
609        Rural
610        Rural
611        Urban
612        Urban
613    Semiurban
Name: Property_Area, Length: 614, dtype: object
```

In [21]:
```
DF[object_columns].Property_Area.head()
```

Out[21]:
```
0    Urban
1    Rural
2    Urban
3    Urban
4    Urban
Name: Property_Area, dtype: object
```

In [22]:
```
Df_dummy = pd.get_dummies(DF, columns=object_columns)
```

In [23]:
```
Df_dummy.head()
```

Out[23]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Gender_489	Gender_Female	Gender_Male	Married_398
0	5849	0.0	0	360.0	1.0	1	0	0	1	0
1	4583	1508.0	128	360.0	1.0	0	0	0	1	0
2	3000	0.0	66	360.0	1.0	1	0	0	1	0
3	2583	2358.0	120	360.0	1.0	1	0	0	1	0
4	6000	0.0	141	360.0	1.0	1	0	0	1	0

5 rows × 25 columns

```
In [24]: Df_dummy.shape
```

```
Out[24]: (614, 25)
```

```
In [25]: from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

```
In [29]: x = Df_dummy.drop('Loan_Status', axis=1)
         y = Df_dummy.Loan_Status
         train_x, test_x, train_y, test_y = train_test_split(x, y, test_size=0.3, random_state=42)
```

```
In [30]: train_x.shape, test_x.shape
```

```
Out[30]: ((429, 24), (185, 24))
```

```
model = LogisticRegression() #LogisticRegression_Model
```

```
model.fit(train_x, train_y)
```

```
train_y_hat = model.predict(train_x)
test_y_hat = model.predict(test_x)
```

```
print('train_accuracy', accuracy_score(train_y, train_y_hat))
print('test accuracy', accuracy_score(test_y, test_y_hat))
```

```
train_accuracy 0.8205128205128205
test accuracy 0.7837837837837838
```

In [35]:
```
print(confusion_matrix(train_y, train_y_hat))
```
```
[[ 57  70]
 [  7 295]]
```

In [36]:
```
print(confusion_matrix(test_y, test_y_hat))
```
```
[[ 27  38]
 [  2 118]]
```

In [37]:
```
test_y.value_counts()
```
Out[37]:
```
1    120
0     65
Name: Loan_Status, dtype: int64
```

In [38]:
```
pd.Series(test_y_hat).value_counts()
```
Out[38]:
```
1    156
0     29
dtype: int64
```

In [39]:
```
(57 + 295) / train_y.shape[0]
```
Out[39]:
```
0.8205128205128205
```

In [40]:
```
print(classification_report(test_y, test_y_hat))
```
```
              precision    recall  f1-score   support

           0       0.93      0.42      0.57        65
           1       0.76      0.98      0.86       120

    accuracy                           0.78       185
   macro avg       0.84      0.70      0.71       185
weighted avg       0.82      0.78      0.76       185
```

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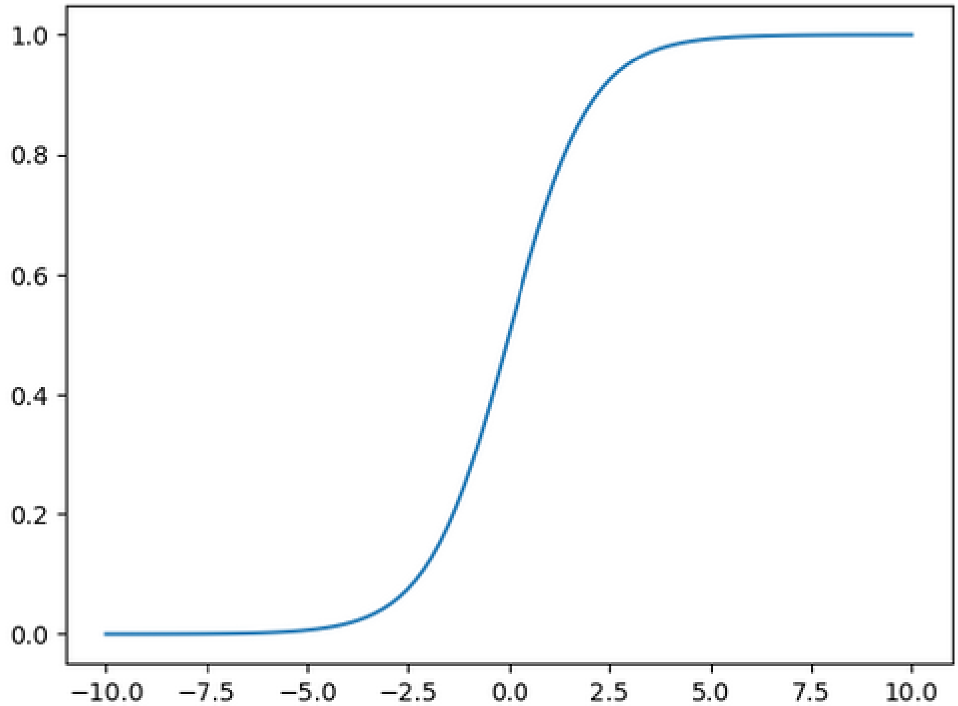
In [41]:
```
x = np.linspace(-10, 10, 100)
y = 1 / (1 + np.exp(-x)) #Sigmoid
plt.plot(x, y)
```

Out[41]: [<matplotlib.lines.Line2D at 0x1d457f4c460>]



Practical-7

AIM: Program to Implement KNN Classification

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
credit_df = pd.read_csv('D:/Rukhsar_AIMLPracts/CreditRisk.csv')
```

In [3]:
```
credit_df.shape
```

Out[3]: (614, 13)

In [4]:
```
credit_df.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Pr
0	LP001002	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	

In [5]:
```
credit_df.tail()
```

Out[5]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71	360.0	1.0
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40	180.0	1.0
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253	360.0	1.0
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187	360.0	1.0
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133	360.0	0.0

In [6]:
```
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         614 non-null    int64  
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    int64  
dtypes: float64(3), int64(3), object(7)
memory usage: 62.5+ KB
```

In [7]:
```
credit_df.describe()
```

Out[7]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status
count	614.000000	614.000000	614.000000	600.00000	564.000000	614.000000
mean	5403.459283	1621.245798	141.166124	342.00000	0.842199	0.687296
std	6109.041673	2926.248369	88.340630	65.12041	0.364878	0.463973
min	150.000000	0.000000	0.000000	12.00000	0.000000	0.000000
25%	2877.500000	0.000000	98.000000	360.00000	1.000000	0.000000
50%	3812.500000	1188.500000	125.000000	360.00000	1.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.00000	1.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000	1.000000

In [8]:
```
credit_df.Loan_Status.value_counts()
```

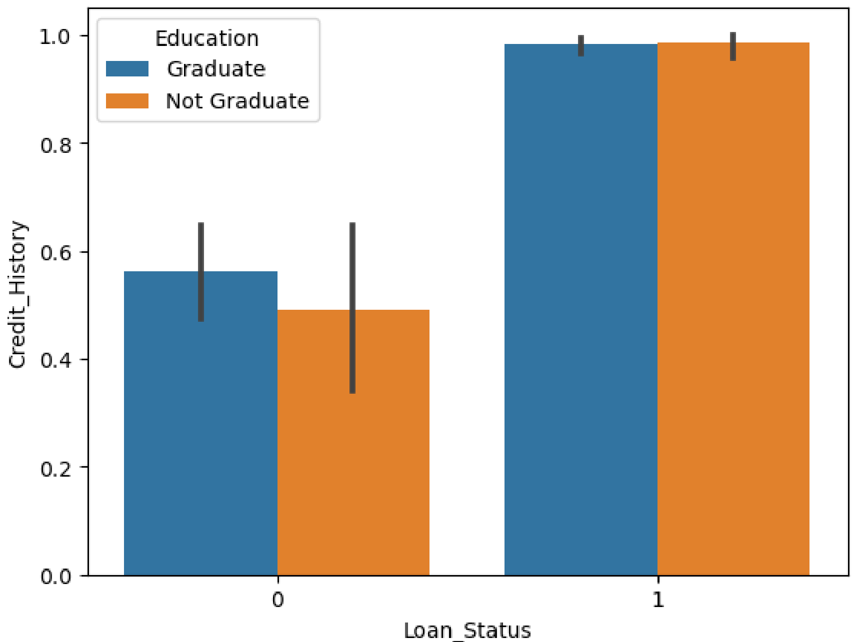
Out[8]:
```
1    422
0    192
Name: Loan_Status, dtype: int64
```

In [9]:
```
credit_df.groupby(['Education', 'Loan_Status']).Education.count()
```

Out[9]:
```
Education     Loan_Status
Graduate      0              140
              1              340
Not Graduate  0               52
              1               82
Name: Education, dtype: int64
```

In [10]:
```
sns.barplot(y = 'Credit_History' , x='Loan_Status', hue='Education', data=credit_df)
```

Out[10]: <Axes: xlabel='Loan_Status', ylabel='Credit_History'>



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In [11]:
```
credit_df.isnull().sum()
```

Out[11]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [12]:
```
DF=credit_df.drop(credit_df.columns[0],axis=1)
```

In [13]:
```
DF.head()
```

Out[13]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	Urbar
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	Rura
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	Urbar
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	Urbar
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	Urbar

In [14]:
```
object_columns = DF.select_dtypes(include=['object']).columns
numeric_columns = DF.select_dtypes(exclude=['object']).columns
```

In [15]:
```
for column in object_columns:
    majority = DF[column].value_counts().iloc[0]
    DF[column].fillna(majority, inplace=True)
```

In [16]:
```
for column in numeric_columns:
    mean = DF[column].mean()
    DF[column].fillna(mean, inplace=True)
```

In [17]:
```
DF.head()
```

Out[17]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	Urbar
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	Rura
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	Urbar
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	Urbar
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	Urbar

In [18]:
```
DF[object_columns].Property_Area
```

Out[18]:
```
0          Urban
1          Rural
2          Urban
3          Urban
4          Urban
         ...
609        Rural
610        Rural
611        Urban
612        Urban
613    Semiurban
Name: Property_Area, Length: 614, dtype: object
```


In [19]:
```
DF[object_columns].Property_Area.head()
```

Out[19]:
```
0    Urban
1    Rural
2    Urban
3    Urban
4    Urban
Name: Property_Area, dtype: object
```

In [20]:
```
Df_dummy = pd.get_dummies(DF, columns=object_columns)
```

In [21]:
```
Df_dummy.head()
```

Out[21]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Gender_489	Gender_Female	Gender_Male	Married_398
0	5849	0.0	0	360.0	1.0	1	0	0	1	0
1	4583	1508.0	128	360.0	1.0	0	0	0	1	0
2	3000	0.0	66	360.0	1.0	1	0	0	1	0
3	2583	2358.0	120	360.0	1.0	1	0	0	1	0
4	6000	0.0	141	360.0	1.0	1	0	0	1	0

5 rows × 25 columns

In [22]:
```
Df_dummy.shape
```
Out[22]:
```
(614, 25)
```

In [31]:
```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report
```

In [24]:
```
x = Df_dummy.drop('Loan_Status', axis=1)
y = Df_dummy.Loan_Status
train_x, test_x, train_y, test_y = train_test_split(x, y, test_size=0.3, random_state=42)
```

In [25]:
```
train_x.shape, test_x.shape
```
Out[25]:
```
((429, 24), (185, 24))
```

In [26]:
```
knn_model = KNeighborsClassifier(n_neighbors=7)#KNN_Model
```

In [27]:
```
knn_model.fit(train_x, train_y)
```
Out[27]:
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=7)
```

In [32]:
```
train_y_hat = knn_model.predict(train_x)
test_y_hat = knn_model.predict(test_x)

print('-' *20, 'Train', '-'*20)
print(classification_report(train_y, train_y_hat))
print('-'*20, 'Test', '-'*20)
print(classification_report(test_y, test_y_hat))
```

```
-------------------- Train --------------------
              precision    recall  f1-score   support

           0       0.70      0.24      0.35       127
           1       0.75      0.96      0.84       302

    accuracy                           0.74       429
   macro avg       0.72      0.60      0.60       429
weighted avg       0.73      0.74      0.70       429

-------------------- Test --------------------
              precision    recall  f1-score   support

           0       0.36      0.12      0.18        65
           1       0.65      0.88      0.75       120

    accuracy                           0.62       185
   macro avg       0.51      0.50      0.47       185
weighted avg       0.55      0.62      0.55       185
```

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Practical-8

AIM: Program to Implement Principal Component Analysis

Principal Component Analysis

In [1]:
```
from sklearn.datasets import load_digits
import pandas as pd
dataset=load_digits()
dataset.keys()
```

Out[1]:
```
dict_keys(['data', 'target', 'frame', 'feature_names', 'target_names', 'images', 'DESCR'])
```

In [2]:
```
dataset.data.shape
```

Out[2]:
```
(1797, 64)
```

In [3]:
```
dataset.data[0]
```

Out[3]:
```
array([ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.,  0.,  0., 13., 15., 10.,
       15.,  5.,  0.,  0.,  3., 15.,  2.,  0., 11.,  8.,  0.,  0.,  4.,
       12.,  0.,  0.,  8.,  8.,  0.,  0.,  5.,  8.,  0.,  0.,  9.,  8.,
        0.,  0.,  4., 11.,  0.,  1., 12.,  7.,  0.,  0.,  2., 14.,  5.,
       10., 12.,  0.,  0.,  0.,  0.,  6., 13., 10.,  0.,  0.,  0.])
```

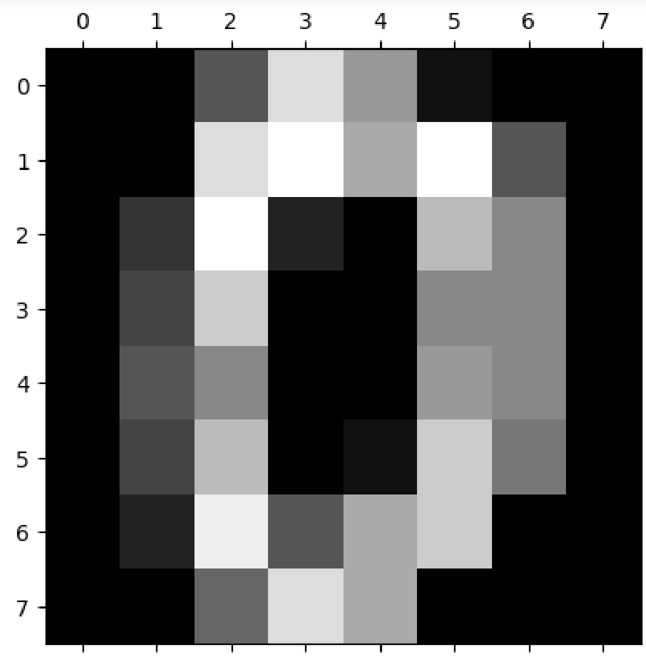
In [4]:
```
dataset.data[0].reshape(8,8)
```

Out[4]:
```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]])
```

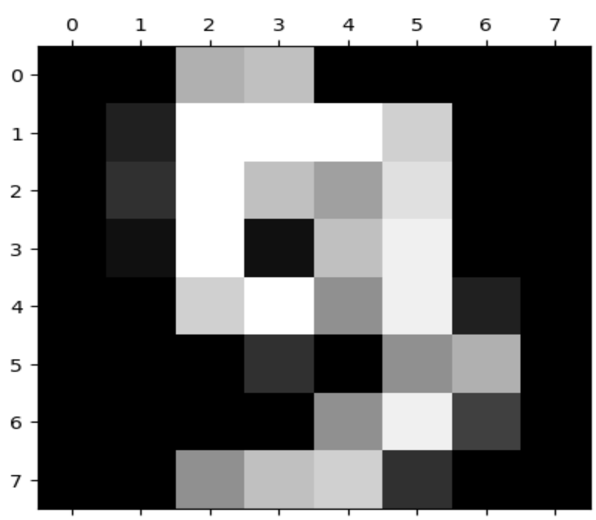
In [5]:
```
from matplotlib import pyplot as plt
%matplotlib inline
plt.gray()
plt.matshow(dataset.data[0].reshape(8,8))
```

Out[5]:
```
<matplotlib.image.AxesImage at 0x1c9c48eeda0>

<Figure size 640x480 with 0 Axes>
```



```
In [6]: plt.matshow(dataset.data[9].reshape(8,8))
Out[6]: <matplotlib.image.AxesImage at 0x1c9c4a21900>
```



```
In [7]: dataset.target[:5]
Out[7]: array([0, 1, 2, 3, 4])
```

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In [8]:
```
df=pd.DataFrame(dataset.data,columns=dataset.feature_names)
df.head()
```

Out[8]:

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	pixel_0_6	pixel_0_7	pixel_1_0	pixel_1_1	...	pixel_6_6	pixel_6_7	pixel_7_0	pixel_7_1	pix
0	0.0	0.0	5.0	13.0	9.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	12.0	13.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	4.0	15.0	12.0	0.0	0.0	0.0	0.0	...	5.0	0.0	0.0	0.0	
3	0.0	0.0	7.0	15.0	13.0	1.0	0.0	0.0	0.0	8.0	...	9.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	1.0	11.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	

5 rows × 64 columns

In [9]:
```
dataset.target
```

Out[9]:
```
array([0, 1, 2, ..., 8, 9, 8])
```

In [10]:
```
df.describe()
```

Out[10]:

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	pixel_0_6	pixel_0_7	pixel_1_0	pixel_1_1	...	pixel_6_6	pix
count	1797.0	1797.000000	1797.000000	1797.000000	1797.000000	1797.000000	1797.000000	1797.000000	1797.000000	1797.000000	...	1797.000000	1797.
mean	0.0	0.303840	5.204786	11.835838	11.848080	5.781859	1.362270	0.129661	0.005565	1.993879	...	3.725097	0.
std	0.0	0.907192	4.754826	4.248842	4.287388	5.666418	3.325775	1.037383	0.094222	3.196160	...	4.919406	0.
min	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.
25%	0.0	0.000000	1.000000	10.000000	10.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.
50%	0.0	0.000000	4.000000	13.000000	13.000000	4.000000	0.000000	0.000000	0.000000	0.000000	...	1.000000	0.
75%	0.0	0.000000	9.000000	15.000000	15.000000	11.000000	0.000000	0.000000	0.000000	3.000000	...	7.000000	0.
max	0.0	8.000000	16.000000	16.000000	16.000000	16.000000	16.000000	15.000000	2.000000	16.000000	...	16.000000	13.

8 rows × 64 columns

In [11]:
```
x=df
y=dataset.target
```

In [12]:
```
from sklearn.preprocessing import StandardScaler
```

In [13]:
```
scaler=StandardScaler()
x_scaled=scaler.fit_transform(x)
x_scaled
```

Out[13]:
```
array([[ 0.        , -0.33501649, -0.04308102, ..., -1.14664746,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649, -1.09493684, ...,  0.54856067,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649, -1.09493684, ...,  1.56568555,
         1.6951369 , -0.19600752],
       ...,
       [ 0.        , -0.33501649, -0.88456568, ..., -0.12952258,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649, -0.67419451, ...,  0.8876023 ,
        -0.5056698 , -0.19600752],
       [ 0.        , -0.33501649,  1.00877481, ...,  0.8876023 ,
        -0.26113572, -0.19600752]])
```

In [14]:
```
from sklearn.model_selection import train_test_split
```

In [16]:
```
x_train,x_test,y_train,y_test=train_test_split(x_scaled,y,test_size=0.2, random_state=30)
```

In [17]:
```
from sklearn.linear_model import LogisticRegression
```

In [19]:
```
model = LogisticRegression()
model.fit(x_train, y_train)
model.score(x_test, y_test)
```

```
Out[19]: 0.9722222222222222

In [20]: from sklearn.decomposition import PCA

In [21]: pca = PCA(0.95)
         x_pca = pca.fit_transform(x)
         x_pca.shape

Out[21]: (1797, 29)

In [22]: pca.explained_variance_ratio_

Out[22]: array([0.14890594, 0.13618771, 0.11794594, 0.08409979, 0.05782415,
                0.0491691 , 0.04315987, 0.03661373, 0.03353248, 0.03078806,
                0.02372341, 0.02272697, 0.01821863, 0.01773855, 0.01467101,
                0.01409716, 0.01318589, 0.01248138, 0.01017718, 0.00905617,
                0.00889538, 0.00797123, 0.00767493, 0.00722904, 0.00695889,
                0.00596081, 0.00575615, 0.00515158, 0.0048954 ])

In [23]: pca.n_components_

Out[23]: 29

In [24]: x_train_pca, x_test_pca, y_train, y_test = train_test_split(x_pca, y, test_size=0.2, random_state=30)

In [25]: from sklearn.linear_model import LogisticRegression
```

```
In [26]: model = LogisticRegression(max_iter=1000)
         model.fit(x_train_pca, y_train)
         model.score(x_test_pca, y_test)

C:\ProgramData\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(

Out[26]: 0.9694444444444444

In [28]: pca = PCA(n_components=2)
         x_pca = pca.fit_transform(x)
         x_pca.shape

Out[28]: (1797, 2)

In [29]: pca.explained_variance_ratio_

Out[29]: array([0.14890594, 0.13618771])

In [30]: x_train_pca, x_test_pca, y_train, y_test = train_test_split(x_pca, y, test_size=0.2, random_state=30)
```

```
In [31]: model = LogisticRegression(max_iter=1000)
         model.fit(x_train_pca, y_train)
         model.score(x_test_pca, y_test)

Out[31]: 0.6083333333333333
```

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Practical-9

AIM: Program to Implement K means Algorithm

In [1]:
```
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
```

In [3]:
```
df = pd.read_csv('D:/Rukhsar_AIMLPracts/dataset2.csv')
df.head()
```

Out[3]:

	id	mean_dist_day	mean_over_speed_perc
0	3423311935	71.24	28
1	3423313212	52.53	25
2	3423313724	64.54	27
3	3423311373	55.69	22
4	3423310999	54.58	25

In [4]:
```
df.describe()
```

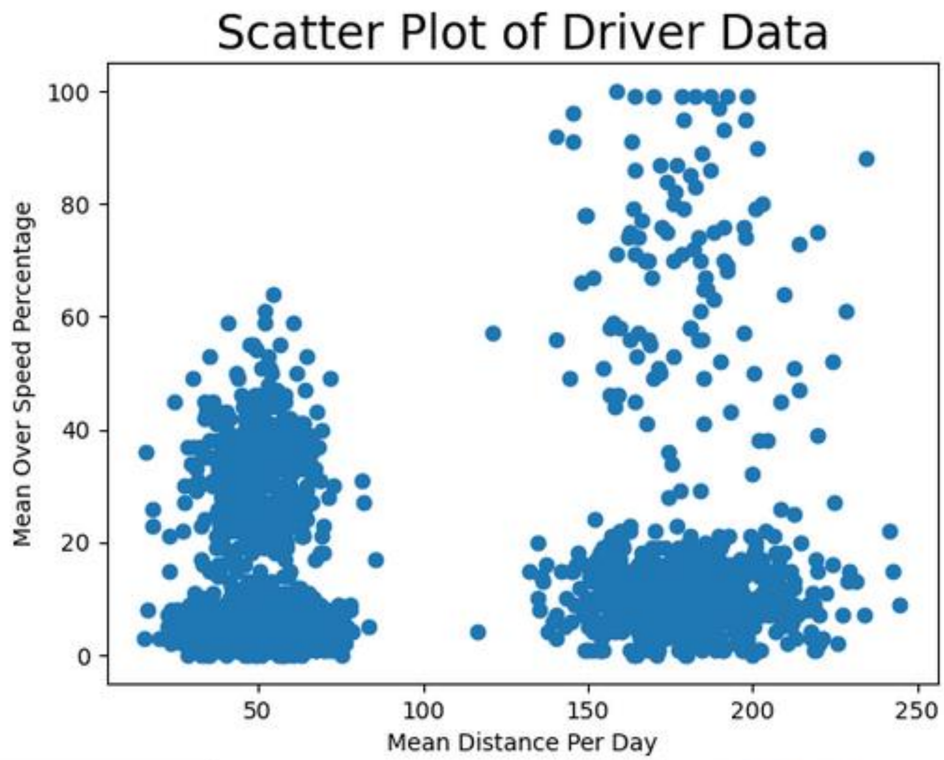
Out[4]:

	id	mean_dist_day	mean_over_speed_perc
count	4.000000e+03	4000.000000	4000.000000
mean	3.423312e+09	76.041522	10.721000
std	1.154845e+03	53.469563	13.708543
min	3.423310e+09	15.520000	0.000000
25%	3.423311e+09	45.247500	4.000000
50%	3.423312e+09	53.330000	6.000000
75%	3.423313e+09	65.632500	9.000000
max	3.423314e+09	244.790000	100.000000

In [5]:
```
df.shape
```

Out[5]: (4000, 3)

In [6]:
```
plt.plot(df.mean_dist_day, df.mean_over_speed_perc, 'o')
plt.xlabel('Mean Distance Per Day')
plt.ylabel('Mean Over Speed Percentage')
plt.title('Scatter Plot of Driver Data', fontsize=20)
plt.show()
```



In [7]:
```
df.head()
```

Out[7]:

	id	mean_dist_day	mean_over_speed_perc
0	3423311935	71.24	28
1	3423313212	52.53	25
2	3423313724	64.54	27
3	3423311373	55.69	22
4	3423310999	54.58	25

In [8]:
```
data = df.drop(['id'], axis=1)
cluster_model = KMeans(n_clusters=2)
cluster_model.fit(data)
```

Out[8]:
```
KMeans
KMeans(n_clusters=2)
```

In [9]:
```
df['labels'] = cluster_model.labels_
```

In [10]:
```
df.head()
```

Out[10]:

	id	mean_dist_day	mean_over_speed_perc	labels
0	3423311935	71.24	28	1
1	3423313212	52.53	25	1
2	3423313724	64.54	27	1
3	3423311373	55.69	22	1
4	3423310999	54.58	25	1

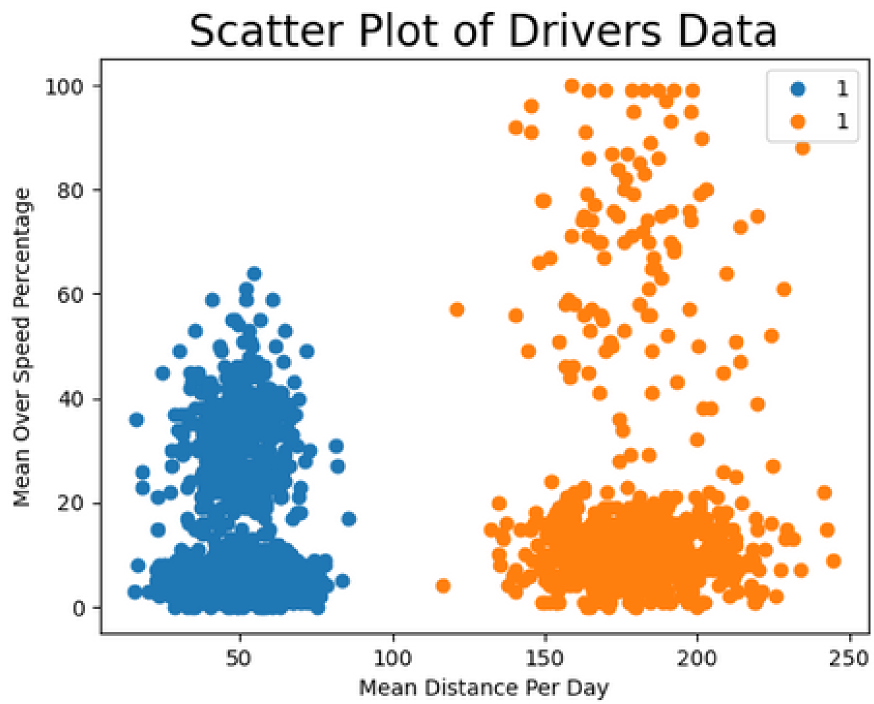
In [11]:
```
df.labels.unique()
```

Out[11]:
```
array([1, 0])
```

In [12]:
```
df['labels'].value_counts()
```

Out[12]:
```
1    3200
0     800
Name: labels, dtype: int64
```

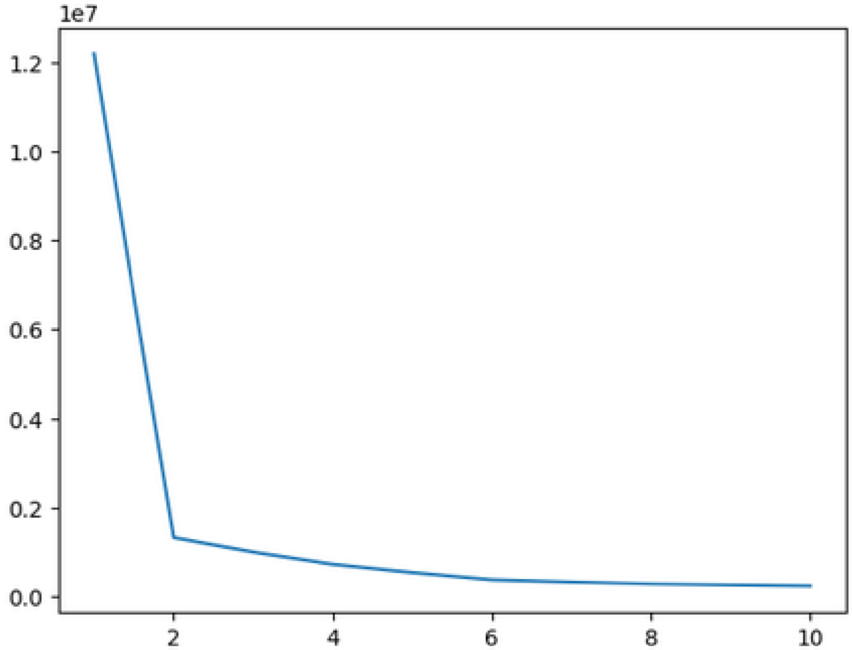
In [18]:
```
for label in df.labels.unique():
    plt.plot(df.loc[df.labels == label, 'mean_dist_day'],
             df.loc[df.labels == label, 'mean_over_speed_perc'], 'o', label=1)
plt.xlabel('Mean Distance Per Day')
plt.ylabel('Mean Over Speed Percentage')
plt.title('Scatter Plot of Drivers Data', fontsize=20)
plt.legend()
plt.show()
```



In [19]:
```
cluster_model.cluster_centers_
```

Out[19]:
```
array([[180.017075  ,  18.29      ],
       [ 50.04763438,   8.82875   ]])
```

In [20]:
```
error = []
for k in range(1,11):
    cluster_model = KMeans(k)
    cluster_model.fit(data)
    error.append(cluster_model.inertia_)
plt.plot(range(1,11), error)
plt.show()
```



Practical-10

AIM: Program to implement Support Vector Machine (SVM)

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
credit_df = pd.read_csv('D:/Rukhsar_AIMLPracts/CreditRisk.csv')
```

In [3]:
```
credit_df.shape
```

Out[3]: (614, 13)

In [4]:
```
credit_df.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_I
0	LP001002	Male	No	0	Graduate	No	5849	0.0	0	360.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141	360.0	

In [5]:
```
credit_df.tail()
```

Out[5]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credi
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71	360.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40	180.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253	360.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187	360.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133	360.0	

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In [6]:
```
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         614 non-null    int64  
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    int64  
dtypes: float64(3), int64(3), object(7)
memory usage: 62.5+ KB
```

In [7]:
```
credit_df.describe()
```

Out[7]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status
count	614.000000	614.000000	614.000000	600.00000	564.000000	614.000000
mean	5403.459283	1621.245798	141.166124	342.00000	0.842199	0.687296
std	6109.041673	2926.248369	88.340630	65.12041	0.364878	0.463973
min	150.000000	0.000000	0.000000	12.00000	0.000000	0.000000
25%	2877.500000	0.000000	98.000000	360.00000	1.000000	0.000000
50%	3812.500000	1188.500000	125.000000	360.00000	1.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.00000	1.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000	1.000000

In [8]:
```
credit_df.Loan_Status.value_counts()
```

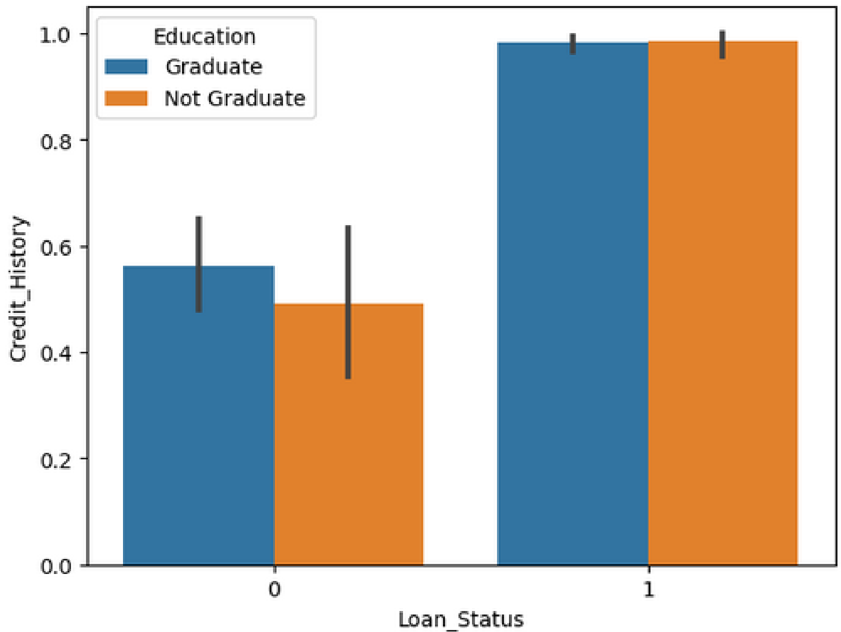
Out[8]:
```
1    422
0    192
Name: Loan_Status, dtype: int64
```

```
In [9]: credit_df.groupby(['Education', 'Loan_Status']).Education.count()

Out[9]: Education     Loan_Status
        Graduate      0              140
                      1              340
        Not Graduate  0               52
                      1               82
        Name: Education, dtype: int64
```

```
In [10]: sns.barplot(y = 'Credit_History' , x='Loan_Status', hue='Education', data=credit_df)

Out[10]: <Axes: xlabel='Loan_Status', ylabel='Credit_History'>
```



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In [11]:
```
credit_df.isnull().sum()
```

Out[11]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [13]:
```
DF.head()
```

Out[13]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Pr
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	

In [14]:
```
object_columns = DF.select_dtypes(include=['object']).columns
numeric_columns = DF.select_dtypes(exclude=['object']).columns
```

In [15]:
```
for column in object_columns:
    majority = DF[column].value_counts().iloc[0]
    DF[column].fillna(majority, inplace=True)
```

In [16]:
```
for column in numeric_columns:
    mean = DF[column].mean()
    DF[column].fillna(mean, inplace=True)
```

In [17]:
```
DF.head()
```

Out[17]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Pr
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	

In [18]:
```
credit_df.drop('Loan_ID', axis=1, inplace=True)
```

object_columns=credit_df.select_dtypes(include=['object']).columns

In [19]:
```
object_columns=credit_df.select_dtypes(include=['object']).columns
```

In [20]:
```
credit_df.head()
```

Out[20]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Pr
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	

In [21]:
```
DF[object_columns].Property_Area
```

Out[21]:
```
0          Urban
1          Rural
2          Urban
3          Urban
4          Urban
         ...
609        Rural
610        Rural
611        Urban
612        Urban
613    Semiurban
Name: Property_Area, Length: 614, dtype: object
```

In [22]:
```
DF[object_columns].Property_Area.head()
```

Out[22]:
```
0    Urban
1    Rural
2    Urban
3    Urban
4    Urban
Name: Property_Area, dtype: object
```

In [23]:
```
Df_dummy = pd.get_dummies(DF, columns=object_columns)
```

In [24]:
```
Df_dummy.head()
```

Out[24]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Gender_489	Gender_Female	Gender_Male	Ma
0	5849	0.0	0	360.0	1.0	1	0	0	1	
1	4583	1508.0	128	360.0	1.0	0	0	0	1	
2	3000	0.0	66	360.0	1.0	1	0	0	1	
3	2583	2358.0	120	360.0	1.0	1	0	0	1	
4	6000	0.0	141	360.0	1.0	1	0	0	1	

5 rows × 25 columns

In [25]:
```
Df_dummy.shape
```

Out[25]: (614, 25)

In [27]:
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report
```

In [30]:
```
x = Df_dummy.drop('Loan_Status', axis=1)
y = Df_dummy.Loan_Status
train_x, test_x,train_y, test_y = train_test_split(x,y, test_size=0.3, random_state=42)
```


In [31]:
```
train_x.shape, test_x.shape
```

Out[31]: ((429, 24), (185, 24))

In [27]:
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report
```

In [30]:
```
x = Df_dummy.drop('Loan_Status', axis=1)
y = Df_dummy.Loan_Status
train_x, test_x,train_y, test_y = train_test_split(x,y, test_size=0.3, random_state=42)
```

In [31]:
```
train_x.shape, test_x.shape
```

Out[31]: ((429, 24), (185, 24))

In [32]:
```
svm_model = SVC(kernel='rbf', gamma=0.00001, C=1000)
```

In [33]:
```
svm_model.fit(train_x, train_y)
```

In [34]:
```
train_y_hat = svm_model.predict(train_x)
test_y_hat = svm_model.predict(test_x)
```

In [35]:
```
print('-'*20, 'Train', '-'*20)
print(classification_report(train_y, train_y_hat))
print('-'*20, 'Test', '-'*20)
print(classification_report(test_y, test_y_hat))
```

```
-------------------- Train --------------------
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       127
           1       0.98      0.98      0.98       302

    accuracy                           0.97       429
   macro avg       0.96      0.96      0.96       429
weighted avg       0.97      0.97      0.97       429

-------------------- Test --------------------
              precision    recall  f1-score   support

           0       0.36      0.18      0.24        65
           1       0.65      0.82      0.73       120

    accuracy                           0.60       185
   macro avg       0.51      0.50      0.49       185
weighted avg       0.55      0.60      0.56       185
```

In [36]:
```
confusion_matrix(test_y, test_y_hat)
```

Out[36]:
```
array([[12, 53],
       [21, 99]], dtype=int64)
```

Practical 11

AIM: Program to Implement Decision Tree Algorithm

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
credit_df = pd.read_csv('D:/Rukhsar_AIMLPracts/CreditRisk.csv')
```

In [3]:
```
credit_df.shape
```

Out[3]: (614, 13)

In [4]:
```
credit_df.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_I
0	LP001002	Male	No	0	Graduate	No	5849	0.0	0	360.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141	360.0	

In [5]:
```
credit_df.tail()
```

Out[5]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credi
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71	360.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40	180.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253	360.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187	360.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133	360.0	

In [6]:
```
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         614 non-null    int64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    int64
dtypes: float64(3), int64(3), object(7)
memory usage: 62.5+ KB
```

In [7]:
```
credit_df.describe()
```

Out[7]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status
count	614.000000	614.000000	614.000000	600.00000	564.000000	614.000000
mean	5403.459283	1621.245798	141.166124	342.00000	0.842199	0.687296
std	6109.041673	2926.248369	88.340630	65.12041	0.364878	0.463973
min	150.000000	0.000000	0.000000	12.00000	0.000000	0.000000
25%	2877.500000	0.000000	98.000000	360.00000	1.000000	0.000000
50%	3812.500000	1188.500000	125.000000	360.00000	1.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.00000	1.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000	1.000000

In [8]:
```
credit_df.Loan_Status.value_counts()
```

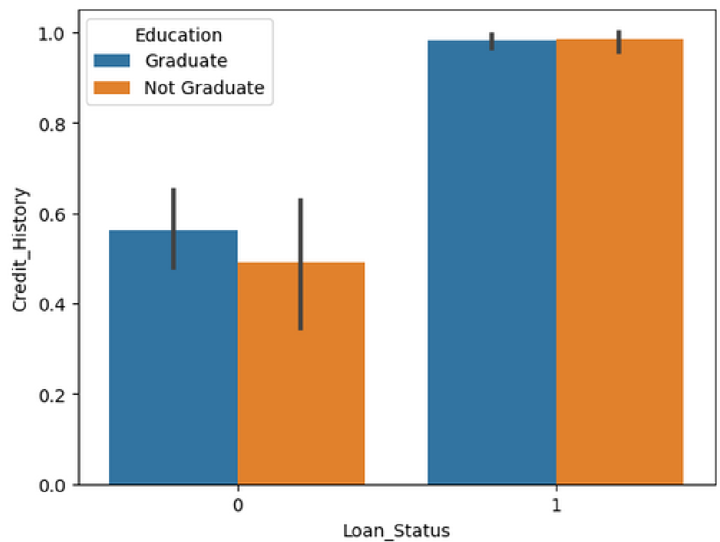
Out[8]:
```
1    422
0    192
Name: Loan_Status, dtype: int64
```

In [9]:
```
credit_df.groupby(['Education', 'Loan_Status']).Education.count()
```

Out[9]:
```
Education     Loan_Status
Graduate      0              140
              1              340
Not Graduate  0               52
              1               82
Name: Education, dtype: int64
```

In [10]:
```
sns.barplot(y = 'Credit_History' , x='Loan_Status', hue='Education', data=credit_df)
```

Out[10]: `<Axes: xlabel='Loan_Status', ylabel='Credit_History'>`



In [11]:
```
credit_df.isnull().sum()
```

Out[11]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [12]:
```
DF=credit_df.drop(credit_df.columns[0],axis=1)
```

In [13]:
```
DF.head()
```

Out[13]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Pr
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	

In [14]:
```
object_columns = DF.select_dtypes(include=['object']).columns
numeric_columns = DF.select_dtypes(exclude=['object']).columns
```

In [15]:
```
for column in object_columns:
    majority = DF[column].value_counts().iloc[0]
    DF[column].fillna(majority, inplace=True)
```

In [16]:
```
for column in numeric_columns:
    mean = DF[column].mean()
    DF[column].fillna(mean, inplace=True)
```

In [17]:
```
DF.head()
```

Out[17]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Pr
0	Male	No	0	Graduate	No	5849	0.0	0	360.0	1.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128	360.0	1.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66	360.0	1.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120	360.0	1.0	
4	Male	No	0	Graduate	No	6000	0.0	141	360.0	1.0	

In [18]:
```
DF[object_columns].Property_Area
```

Out[18]:
```
0          Urban
1          Rural
2          Urban
3          Urban
4          Urban
         ...
609        Rural
610        Rural
611        Urban
612        Urban
613    Semiurban
Name: Property_Area, Length: 614, dtype: object
```


In [19]:
```
DF[object_columns].Property_Area.head()
```

Out[19]:
```
0    Urban
1    Rural
2    Urban
3    Urban
4    Urban
Name: Property_Area, dtype: object
```

In [20]:
```
Df_dummy = pd.get_dummies(DF, columns=object_columns)
```

In [21]:
```
Df_dummy.head()
```

Out[21]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Gender_489	Gender_Female	Gender_Male	Ma
0	5849	0.0	0	360.0	1.0	1	0	0	1	
1	4583	1508.0	128	360.0	1.0	0	0	0	1	
2	3000	0.0	66	360.0	1.0	1	0	0	1	
3	2583	2358.0	120	360.0	1.0	1	0	0	1	
4	6000	0.0	141	360.0	1.0	1	0	0	1	

5 rows × 25 columns

In [16]:
```
from sklearn.model_selection import train_test_split as TTS
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [17]:
```
X = DF_dummy.drop('Loan_Status', axis=1)
Y = DF_dummy.Loan_Status
train_x, test_x, train_y, test_y = TTS(X, Y, test_size = 0.3, random_state=42)
```

In [18]:
```
train_x.shape, test_x.shape
```

Out[18]:
```
((429, 24), (185, 24))
```

In [19]:
```
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier(max_depth=14)
```

In [20]:
```
dt_model.fit(train_x, train_y)
```

Out[20]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=14)
```

In [21]:
```
train_y_hat = dt_model.predict(train_x)
test_y_hat = dt_model.predict(test_x)
```

In [22]:
```
print('-'*20, 'Train', '-'*20)
print(classification_report(train_y, train_y_hat))
print('-'*20, 'Test', '-'*20)
print(classification_report(test_y, test_y_hat))
```

```
-------------------- Train --------------------
              precision    recall  f1-score   support

           0       0.99      1.00      1.00       127
           1       1.00      1.00      1.00       302

    accuracy                           1.00       429
   macro avg       1.00      1.00      1.00       429
weighted avg       1.00      1.00      1.00       429

-------------------- Test --------------------
              precision    recall  f1-score   support

           0       0.57      0.54      0.56        65
           1       0.76      0.78      0.77       120

    accuracy                           0.70       185
   macro avg       0.67      0.66      0.66       185
weighted avg       0.69      0.70      0.69       185
```

In [23]:
```
confusion_matrix(train_y, train_y_hat)
```

Out[23]:
```
array([[127,   0],
       [  1, 301]], dtype=int64)
```

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Practical 12

AIM: Program to Implement Random Forest

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
```

In [2]:
```
train = pd.read_csv(r"F:\FYMCA\Sem2\AIML\titanic.csv")
print(train.shape)
```

```
(891, 12)
```

In [3]:
```
#checking for missing data
NAs = pd.concat([train.isnull().sum()], axis=1, keys=["Train"])
NAs[NAs.sum(axis=1) > 0]
```

Out[3]:

	Train
Age	177
Cabin	687
Embarked	2

In [4]:
```
train.pop("Cabin")
train.pop("Name")
train.pop("Ticket")
```

Out[4]:
```
0             A/5 21171
1              PC 17599
2      STON/O2. 3101282
3                113803
4                373450
             ...       
886              211536
887              112053
888          W./C. 6607
889              111369
890              370376
Name: Ticket, Length: 891, dtype: object
```

In [5]:
```
# Filling missing Age values with mean
train["Age"] = train["Age"].fillna(train["Age"].mean())
```

In [6]:
```
# Filling missing Embarked values with most common value
train["Embarked"] = train["Embarked"].fillna(train["Embarked"].mode()[0])
```

In [7]:
```
train["Pclass"] = train["Pclass"].apply(str)
```

In [8]:
```
# Getting Dummies from all other categorical vars
for col in train.dtypes[train.dtypes == "object"].index:
    for_dummy = train.pop(col)
    train = pd.concat([train, pd.get_dummies(for_dummy, prefix=col)], axis=1)
train.head()
```

Out[8]:

	PassengerId	Survived	Age	SibSp	Parch	Fare	Pclass_1	Pclass_2	Pclass_3	Sex_female	Sex_male	Embarked_C	Embarked_Q	Embarked_S
0	1	0	22.0	1	0	7.2500	0	0	1	0	1	0	0	1
1	2	1	38.0	1	0	71.2833	1	0	0	1	0	1	0	0
2	3	1	26.0	0	0	7.9250	0	0	1	1	0	0	0	1
3	4	1	35.0	1	0	53.1000	1	0	0	1	0	0	0	1
4	5	0	35.0	0	0	8.0500	0	0	1	0	1	0	0	1

In [9]:
```
labels = train.pop("Survived")
```

In [10]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(train, labels, test_size=0.25)
```

In [11]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=100)
rf.fit(x_train, y_train)
```

Out[11]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [12]:
```
y_pred = rf.predict(x_test)
```

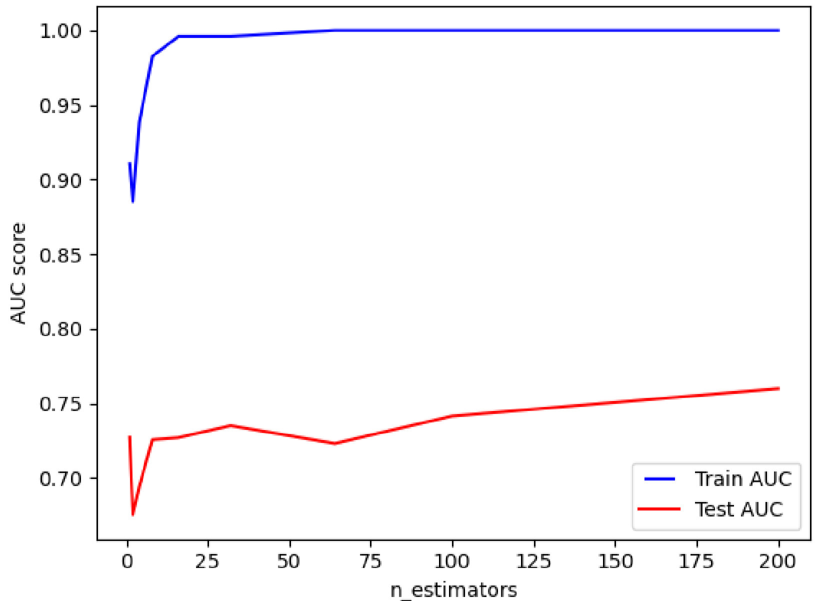
In [14]:
```
from sklearn.metrics import roc_curve, auc
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

Out[14]: 0.7425986842105263

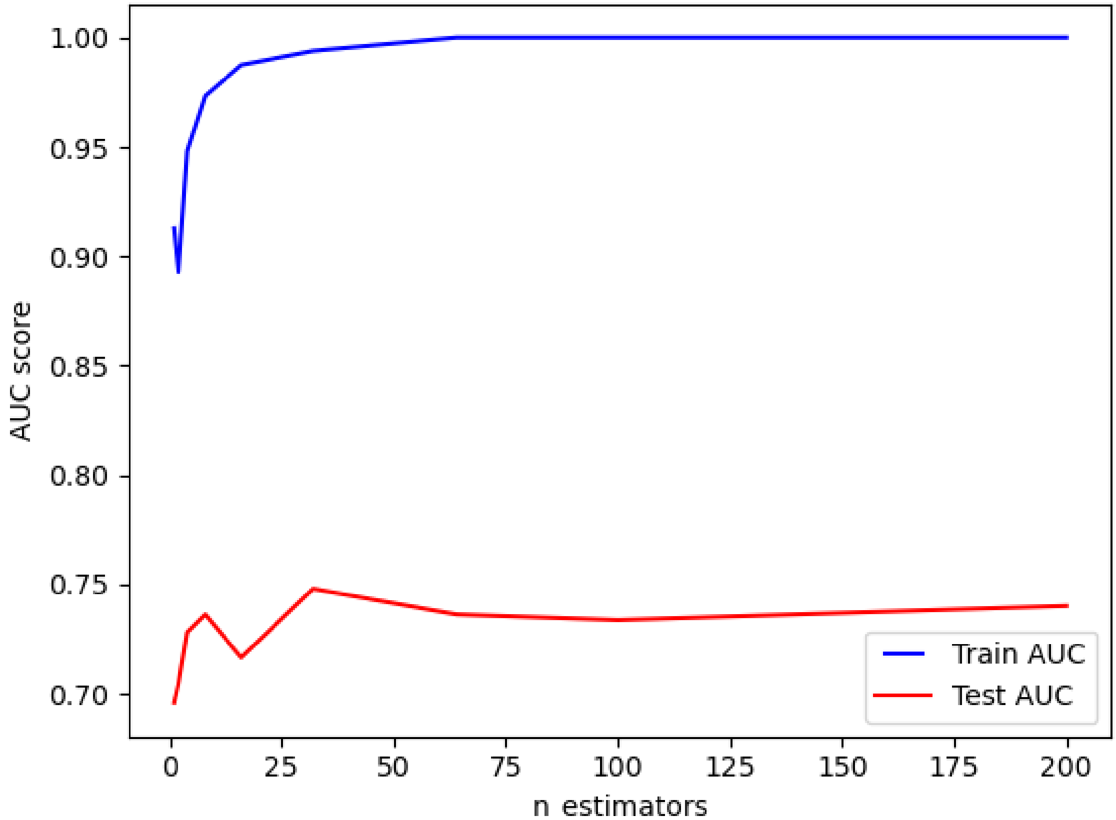
In [15]:
```
n_estimators = [1, 2, 4, 8, 16, 32, 64, 100, 200]
train_results = []
test_results = []
```

In [16]:
```
for estimator in n_estimators:
    rf = RandomForestClassifier(n_estimators=estimator, n_jobs=-1)
    rf.fit(x_train, y_train)
    train_pred = rf.predict(x_train)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,train_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    train_results.append(roc_auc)
    y_pred = rf.predict(x_test)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    test_results.append(roc_auc)
```

In [17]:
```
from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(n_estimators, train_results, "b", label="Train AUC")
line2, = plt.plot(n_estimators, test_results, "r", label="Test AUC")
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel("AUC score")
plt.xlabel("n_estimators")
plt.show()
```




```
In [18]: from sklearn.ensemble import RandomForestClassifier
         rf = RandomForestClassifier(n_estimators=200)
         rf.fit(x_train, y_train)

Out[18]: RandomForestClassifier
         RandomForestClassifier(n_estimators=200)

In [19]: y_pred = rf.predict(x_test)
         from sklearn.metrics import roc_curve, auc
         false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
         roc_auc = auc(false_positive_rate, true_positive_rate)
         roc_auc

Out[19]: 0.7400493421052632

In [20]: n_estimators = [1, 2, 4, 8, 16, 32, 64, 100, 200]
         train_results = []
         test_results = []

In [21]: for estimator in n_estimators:
             rf = RandomForestClassifier(n_estimators=estimator, n_jobs=-1)
             rf.fit(x_train, y_train)
             train_pred = rf.predict(x_train)
             false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train,train_pred)
             roc_auc = auc(false_positive_rate, true_positive_rate)
             train_results.append(roc_auc)
             y_pred = rf.predict(x_test)
             false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
             roc_auc = auc(false_positive_rate, true_positive_rate)
             test_results.append(roc_auc)

In [22]: from matplotlib.legend_handler import HandlerLine2D
         line1, = plt.plot(n_estimators, train_results, "b", label="Train AUC")
         line2, = plt.plot(n_estimators, test_results, "r", label="Test AUC")
         plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
         plt.ylabel("AUC score")
         plt.xlabel("n_estimators")
         plt.show()
```


1.00
0.95
0.90
0.85
0.80
0.75
0.70
AUC score
0
25
50
75
100
125
150
175
200
n_estimators
Train AUC
Test AUC

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Practical 13

AIM: Program to Implement AdaBoost

```
[1]: from sklearn.ensemble import AdaBoostClassifier
[2]: from sklearn import datasets
[3]: from sklearn.model_selection import train_test_split
[4]: from sklearn import metrics
[5]: iris=datasets.load_iris()
     X=iris.data
     y=iris.target
[6]: X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2)
[7]: AdaModel=AdaBoostClassifier(n_estimators=100,learning_rate=1)
     model=AdaModel.fit(X_train,y_train)
     y_pred=model.predict(X_test)
[11]: print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
     Accuracy: 0.9333333333333333
```


```
[11]: print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
     Accuracy: 0.9333333333333333
```


```
[25]: from sklearn.svm import SVC
      from sklearn import metrics
      svc=SVC(probability=True,kernel='linear')
      abc=AdaBoostClassifier(n_estimators=70,base_estimator=svc,learning_rate=1)
[26]: model=abc.fit(X_train,y_train)
      y_pred=model.predict(X_test)
      C:\Users\USER\anaconda3\Lib\site-packages\sklearn\ensemble\_base.py:166: FutureWarning: `base_estimator` was renamed to `estimator` in version 1.2 and wi
      ll be removed in 1.4.
        warnings.warn(
[27]: print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
      Accuracy: 0.9
```

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Practical 14

AIM: Program to Implement Gradient Boosting

In [2]:
```
# Importing necessary packages
from sklearn.ensemble import GradientBoostingRegressor
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
import warnings

# Suppressing warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
# Fetching the California housing dataset
from sklearn.datasets import fetch_california_housing
housing = fetch_california_housing()

# Splitting the data into features and target variable
X = pd.DataFrame(housing.data, columns=housing.feature_names)
y = pd.DataFrame(housing.target, columns=['target'])
```

In [5]:
```
#Viewing Data - predictors
X.head()
```

Out[5]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23

In [5]:
```
#Viewing Data - predictors
X.head()
```


Out[5]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25

In [ ]:
```
y[1:10] #response
```

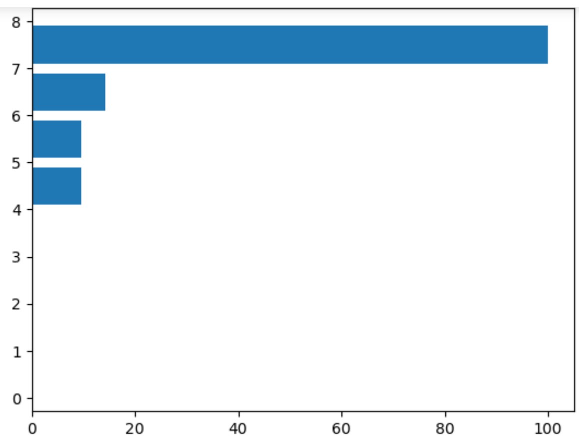
In [7]:
```
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2) # 80% training and 20% test
```

In [8]:
```
# Create gradientboost REGRESSOR object
gradientregressor = GradientBoostingRegressor(max_depth=2,n_estimators=3,learning_rate=1.0)
```

In [9]:
```
# Train gradientboost REGRESSOR
model = gradientregressor.fit(X_train, y_train)

#Predict the response for test dataset
y_pred = model.predict(X_test)
```

```
In [ ]: r2_score(y_pred,y_test)
```

```
In [14]: import matplotlib.pyplot as plt
%matplotlib inline

# Plot feature importance
feature_importance = model.feature_importances_

# make importances relative to max importance
feature_importance = 100.0 * (feature_importance / feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, boston.feature_names[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```




```
In [*]: from sklearn.model_selection import GridSearchCV
LR = {'learning_rate':[0.15,0.1,0.10,0.05], 'n_estimators':[100,150,200,250]}

tuning = GridSearchCV(estimator =GradientBoostingRegressor(),
            param_grid = LR, scoring='r2')
tuning.fit(X_train,y_train)
```

```
from sklearn.model_selection import GridSearchCV
LR = {'learning_rate':[0.15,0.1,0.10,0.05], 'n_estimators':[100,150,200,250]}

tuning = GridSearchCV(estimator =GradientBoostingRegressor(),
            param_grid = LR, scoring='r2')
tuning.fit(X_train,y_train)
tuning.best_params_, tuning.best_score_
```

Python

```
({'learning_rate': 0.15, 'n_estimators': 200}, 0.8413790739479519)
```