Salary Prediction using SVM Regression

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

1. Data Pre-processing :

In [2]:
```
df = pd.read_csv('Salary_dataset.csv')
```

In [3]:
```
df.drop('Unnamed: 0', axis=1, inplace=True)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     float64
dtypes: float64(2)
memory usage: 612.0 bytes
```

In [5]:
```
X = df.drop('Salary', axis=1)
Y = df['Salary']
```

In [6]:
```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(X, Y, test_size=0.20, random_state=42)
```

2. Create and Train SVM Regression Model :

In [7]:
```
from sklearn.svm import SVR
```

In [8]:
```
svr = SVR(kernel='linear')
svr.fit(x_train, y_train)
```

Out[8]:
```
▾ SVR
SVR(kernel='linear')
```
(https://scikit-learn.org/1.4/modules/generated/sklearn.svm.SVR.html)

3. Predict Test Set Results :

In [9]:
```
y_pred = svr.predict(x_test)
```

In [10]:
```
pd.DataFrame({'Actual':y_test, 'Predicted':y_pred})
```

Out[10]:

	Actual	Predicted
27	112636.0	62472.76
15	67939.0	62205.33
23	113813.0	62393.10
17	83089.0	62228.09
8	64446.0	62108.60
9	57190.0	62137.05

4. Evaluate Model Performance :

In [11]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [12]:
```
mae = mean_absolute_error(y_test, y_pred)
mae
```

Out[12]: 22577.028333225255

In [13]:
```
mse = mean_squared_error(y_test, y_pred)
mse
```

Out[13]: 943057673.9043975

In [14]:
```
rmse = np.sqrt(mse)
rmse
```

Out[14]: 30709.244111576525

In [15]:
```
r2 = r2_score(y_test, y_pred)
r2
```

Out[15]: -0.846251298098931

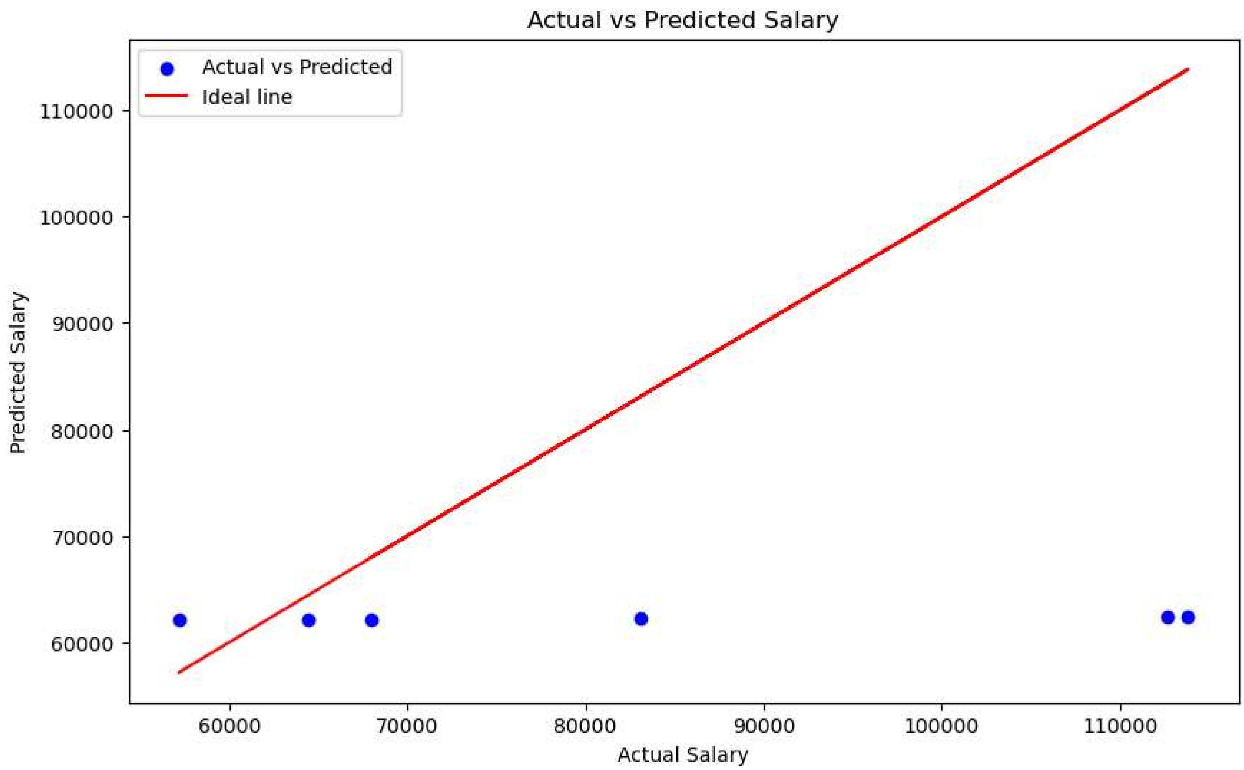
5. Visualization of Evaluate Model Performance

In [16]:
```python
# Plotting actual vs predicted
plt.figure(figsize=(10, 6))

# Plotting the actual values
plt.scatter(y_test, y_pred, color='blue', label='Actual vs Predicted')

# Plotting the line of best fit
plt.plot(y_test, y_test, color='red', label='Ideal line')

plt.title('Actual vs Predicted Salary')
plt.xlabel('Actual Salary')
plt.ylabel('Predicted Salary')
plt.legend()
plt.show()
```



Universal bank Prediction

To build and train a model using Universal Bank records,and classify the customer is eligible to take Credit Card or not

In [17]:
```
df = pd.read_csv('UniversalBank.csv')
df.head()
```

Out[17]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Account	CD Account	Or
0	1	25	1	49	91107	4	1.6	1	0	0	1	0	
1	2	45	19	34	90089	3	1.5	1	0	0	1	0	
2	3	39	15	11	94720	1	1.0	1	0	0	0	0	
3	4	35	9	100	94112	1	2.7	2	0	0	0	0	
4	5	35	8	45	91330	4	1.0	2	0	0	0	0	

In [18]:
```
df.isnull().sum()
```

Out[18]:
```
ID                    0
Age                   0
Experience            0
Income                0
ZIP Code              0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Personal Loan         0
Securities Account    0
CD Account            0
Online                0
CreditCard            0
dtype: int64
```

In [19]:
```
df.shape
```

Out[19]:
```
(5000, 14)
```

In [20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   ID                  5000 non-null   int64
 1   Age                 5000 non-null   int64
 2   Experience          5000 non-null   int64
 3   Income              5000 non-null   int64
 4   ZIP Code            5000 non-null   int64
 5   Family              5000 non-null   int64
 6   CCAvg               5000 non-null   float64
 7   Education           5000 non-null   int64
 8   Mortgage            5000 non-null   int64
 9   Personal Loan       5000 non-null   int64
 10  Securities Account  5000 non-null   int64
 11  CD Account          5000 non-null   int64
 12  Online              5000 non-null   int64
 13  CreditCard          5000 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

In [21]:
```
df.describe()
```

Out[21]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	2500.500000	45.338400	20.104600	73.774200	93152.503000	2.396400	1.937913	1.881000
std	1443.520003	11.463166	11.467954	46.033729	2121.852197	1.147663	1.747666	0.839869
min	1.000000	23.000000	-3.000000	8.000000	9307.000000	1.000000	0.000000	1.000000
25%	1250.750000	35.000000	10.000000	39.000000	91911.000000	1.000000	0.700000	1.000000
50%	2500.500000	45.000000	20.000000	64.000000	93437.000000	2.000000	1.500000	2.000000
75%	3750.250000	55.000000	30.000000	98.000000	94608.000000	3.000000	2.500000	3.000000
max	5000.000000	67.000000	43.000000	224.000000	96651.000000	4.000000	10.000000	3.000000

In [22]:
```
df.columns
```

Out[22]:
```
Index(['ID', 'Age', 'Experience', 'Income', 'ZIP Code', 'Family', 'CCAvg',
       'Education', 'Mortgage', 'Personal Loan', 'Securities Account',
       'CD Account', 'Online', 'CreditCard'],
      dtype='object')
```

In [23]:
```
df1 = df.drop(["ID","ZIP Code"], axis = 1)
```

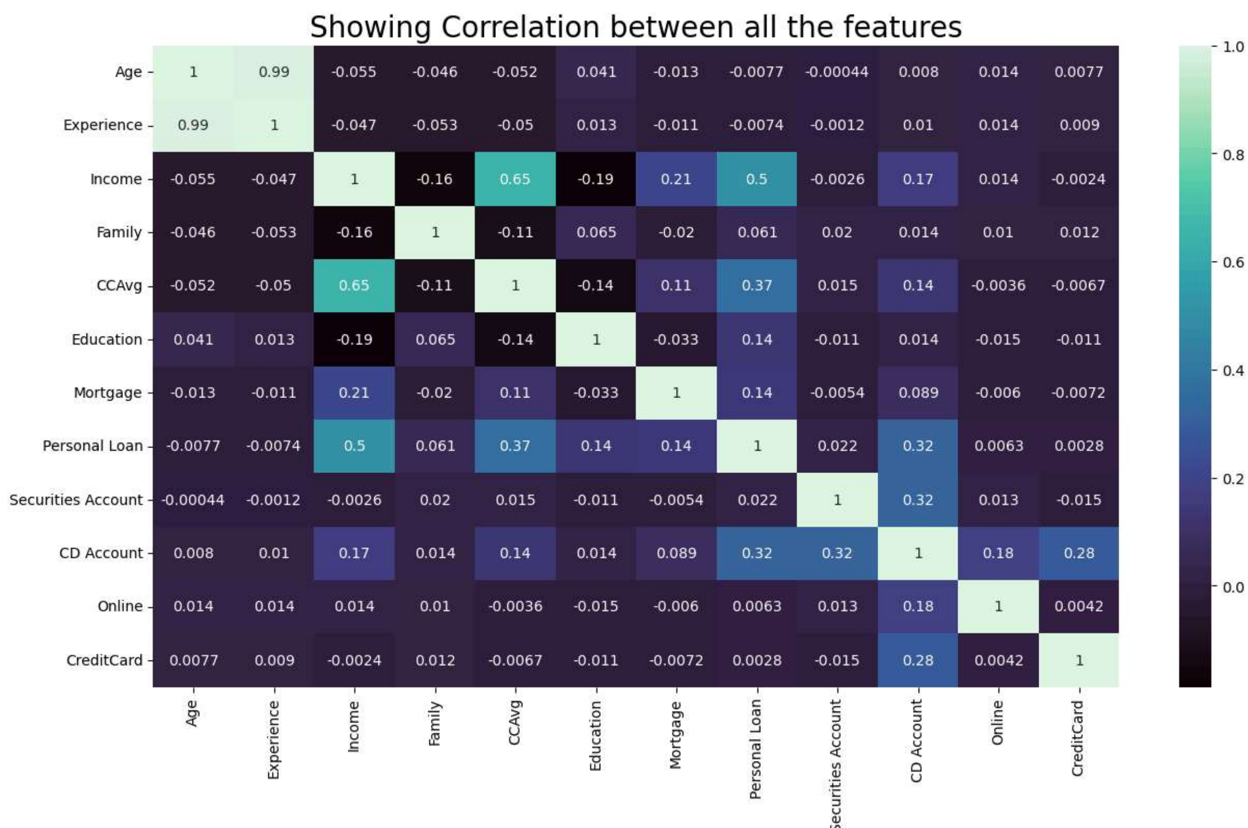
In [24]:
```python
df.head()
```

Out[24]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Account	CD Account	Or
0	1	25	1	49	91107	4	1.6	1	0	0	1	0	
1	2	45	19	34	90089	3	1.5	1	0	0	1	0	
2	3	39	15	11	94720	1	1.0	1	0	0	0	0	
3	4	35	9	100	94112	1	2.7	2	0	0	0	0	
4	5	35	8	45	91330	4	1.0	2	0	0	0	0	

In [25]:
```python
plt.figure(figsize=(15,8))
plt.title("Showing Correlation between all the features", fontsize=20)
sns.heatmap(df1.corr(),annot = True, cmap='mako')
```

Out[25]: <Axes: title={'center': 'Showing Correlation between all the features'}>



In [26]:
```python
class_0 = df1[df1.CreditCard==0]
class_0.shape
```

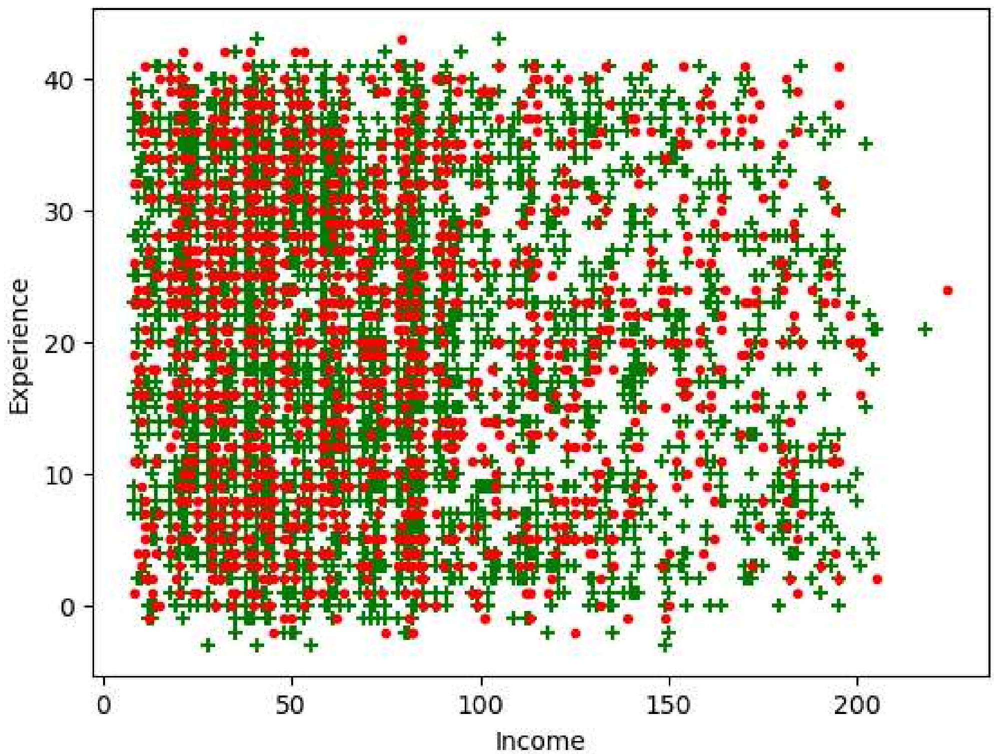
Out[26]: (3530, 12)

In [27]:
```python
class_1 = df1[df1.CreditCard==1]
class_1.shape
```

Out[27]: (1470, 12)

In [28]:
```python
# Income vs Experience scatter plot
plt.xlabel('Income')
plt.ylabel('Experience')
plt.scatter(class_0['Income'],class_0['Experience'], color = 'green',marker='+')
plt.scatter(class_1['Income'], class_1['Experience'], color = 'red', marker='.')
```

Out[28]: <matplotlib.collections.PathCollection at 0x15f23ea2190>



In [29]:
```python
 # Scaling the data using Standard Scaler
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled = scaler.fit(df1.drop('CreditCard',axis=1)).transform(df1.drop('CreditCard',axis=1))
df_scaled = pd.DataFrame(scaled, columns=df1.columns[:-1])
df_scaled.head()
```

Out[29]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Account	CD Account	
0	-1.774417	-1.666078	-0.538229	1.397414	-0.193371	-1.049078	-0.555524	-0.325875	2.928915	-0.25354	-
1	-0.029524	-0.096330	-0.864109	0.525991	-0.250595	-1.049078	-0.555524	-0.325875	2.928915	-0.25354	-
2	-0.552992	-0.445163	-1.363793	-1.216855	-0.536720	-1.049078	-0.555524	-0.325875	-0.341423	-0.25354	-
3	-0.901970	-0.968413	0.569765	-1.216855	0.436103	0.141703	-0.555524	-0.325875	-0.341423	-0.25354	-
4	-0.901970	-1.055621	-0.625130	1.397414	-0.536720	0.141703	-0.555524	-0.325875	-0.341423	-0.25354	-

In [30]:
```
# Splitting the columns in to dependent variable (x) and independent variable(y).
x = df_scaled
y = df1['CreditCard']
```

In [31]:
```
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,random_state=0)
```

In [32]:
```
# Apply SVM Model
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

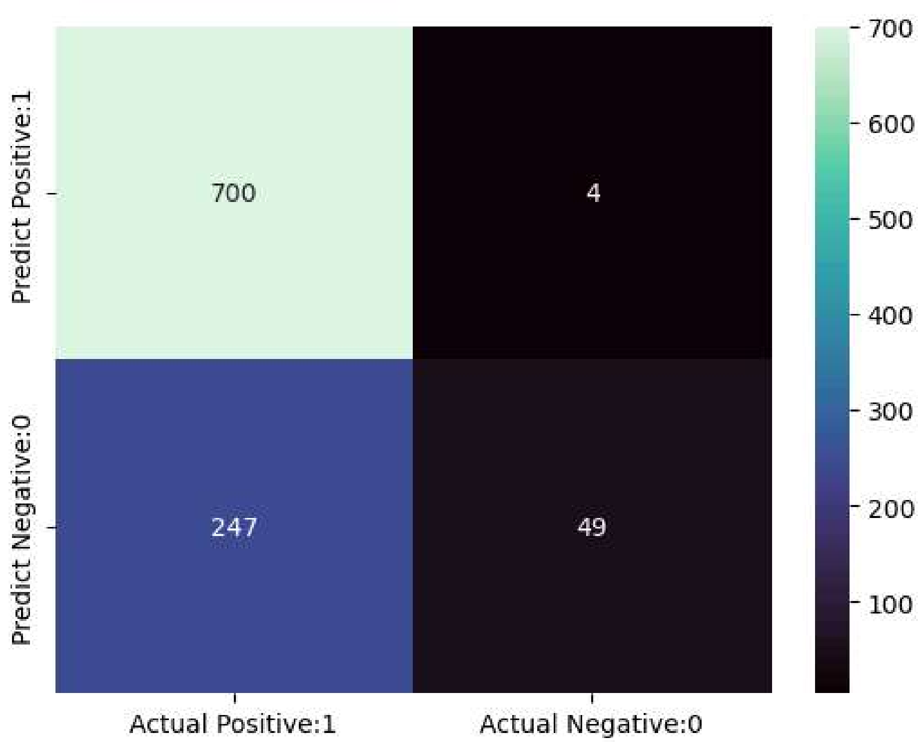
In [33]:
```
svc=SVC()
svc.fit(x_train, y_train)
y_pred=svc.predict(x_test)
```

In [34]:
```
print('Model accuracy : {0:0.3f}'. format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy : 0.749
```

In [35]:
```
# Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
cm_matrix = pd.DataFrame(data=cm, columns=['Actual Positive:1', 'Actual Negative:0'],
index=['Predict Positive:1', 'Predict Negative:0'])
sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='mako')
```

Out[35]: <Axes: >



In [36]:
```
# Classification Report
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.74      0.99      0.85       704
           1       0.92      0.17      0.28       296

    accuracy                           0.75      1000
   macro avg       0.83      0.58      0.56      1000
weighted avg       0.79      0.75      0.68      1000
```

SVM Kernel Functions

Sigmoid Kernel

In [37]:
```
# Apply SVM model using Sigmoid Kernel function
Poly_svc=SVC(kernel='sigmoid', C=1).fit(x_train,y_train)
y_pred = Poly_svc.predict(x_test)
print('Model accuracy with rbf kernel : {0:0.3f}'.format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy with rbf kernel : 0.629
```

Linear Kernel

In [38]:
```
# Apply SVM model using Linear Kernel function
linear_classifier=SVC(kernel='linear').fit(x_train,y_train)
y_pred = linear_classifier.predict(x_test)
print('Model accuracy with linear kernel : {0:0.3f}'.format(accuracy_score(y_test, y_pred))
```

```
Model accuracy with linear kernel : 0.747
```

Polynomial Kernel

In [39]:
```
# Apply SVM model using Polynomial Kernel function
Poly_svc=SVC(kernel='poly', C=1).fit(x_train,y_train)
y_pred = Poly_svc.predict(x_test)
print('Model accuracy with rbf kernel : {0:0.3f}'.format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy with rbf kernel : 0.749
```

Gaussian RBF kernel

In [40]:
```
# Apply SVM model using Gaussian RBF kernel function
rbf_svc=SVC(kernel='rbf').fit(x_train,y_train)
y_pred = rbf_svc.predict(x_test)
print('Model accuracy with rbf kernel : {0:0.3f}'.format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy with rbf kernel : 0.749
```

House Price Prediction

In [41]:
```
df=pd.read_csv("boston.csv")
```

In [42]:
```
df.head()
```

Out[42]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	36.2

In [43]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    int64  
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64  
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

In [44]:
```
X = df.drop('MEDV', axis=1)
Y = df['MEDV']
```

In [45]:
```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(X, Y, test_size=0.20, random_state=42)
```

In [46]:
```
from sklearn.svm import SVR
```

In [47]:
```
svr = SVR(kernel='linear')
svr.fit(x_train, y_train)
```

Out[47]:
```
SVR
(https://scikit-learn.org/1.4/modules/generated/sklearn.svm.SVR.html)
SVR(kernel='linear')
```

In [48]:
```
y_pred = svr.predict(x_test)
```

In [49]:
```
pd.DataFrame({'Actual':y_test, 'Predicted':y_pred})
```

Out[49]:

	Actual	Predicted
173	23.6	26.112730
274	32.4	32.551996
491	13.6	15.522970
72	22.8	24.140992
452	16.1	18.499756
...	...	...
412	17.9	-3.169195
436	9.6	13.189656
411	17.2	13.865112
86	22.5	21.442180
75	21.4	23.146530

102 rows × 2 columns

In [50]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [51]:
```
mae = mean_absolute_error(y_test, y_pred)
mae
```

Out[51]: 3.1404227783347185

In [52]:
```
mse = mean_squared_error(y_test, y_pred)
mse
```

Out[52]: 29.435701924289845

In [53]:
```
rmse = np.sqrt(mse)
rmse
```

Out[53]: 5.4254678991115455

In [54]:
```
r2 = r2_score(y_test, y_pred)
r2
```

Out[54]:
```
0.5986065268181071
```

In [ ]: