Support Vector Regression on Admission Dataset

Problem Statement

- Predict the chances of admission based on the given attributes

Task we have performed:

1. Data ingestion
2. EDA
3. Graphical Analysis (DATA Visualization)
4. check correlation between features
5. Perform Train Test Split
6. SVR Model Training
7. Check Performance Metrics
    - mean_sqaured_error
    - mean_absolute_error
8. R Sqaure
9. Adjusted R Square
10. Hypter-Parameter Tuning
11. Again check performance metrics after hyper-parameter tunning
    - mean_sqaured_error
    - mean_absolute_error
    - R Sqaure
    - Adjusted R Square

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

import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.pyplot as plt
```

```python
%matplotlib inline

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix

import warnings
warnings.filterwarnings('ignore')
```

Data ingestion

In [2]:
```python
df = pd.read_csv(r"G:\Udemy\DATA SCIENCE ineuron\Resources\Admision prediction.csv")
df.head()
```

Out[2]:

	Unnamed: 0	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	0	1	337.0	118.0	4.0	4.5	4.5	9.65	1	0.92
1	1	2	324.0	107.0	4.0	4.0	4.5	8.87	1	0.76
2	2	3	NaN	104.0	3.0	3.0	3.5	8.00	1	0.72
3	3	4	322.0	110.0	3.0	3.5	2.5	8.67	1	0.80
4	4	5	314.0	103.0	2.0	2.0	3.0	8.21	0	0.65

In [3]:
```python
df.columns
```

Out[3]:
```
Index(['Unnamed: 0', 'Serial No.', 'GRE Score', 'TOEFL Score',
       'University Rating', 'SOP', 'LOR', 'CGPA', 'Research',
       'Chance of Admit'],
      dtype='object')
```

In [4]:
```python
df.drop(['Unnamed: 0','Serial No.'],axis = 1,inplace= True)
```

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

Out[5]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337.0	118.0	4.0	4.5	4.5	9.65	1	0.92
1	324.0	107.0	4.0	4.0	4.5	8.87	1	0.76
2	NaN	104.0	3.0	3.0	3.5	8.00	1	0.72
3	322.0	110.0	3.0	3.5	2.5	8.67	1	0.80
4	314.0	103.0	2.0	2.0	3.0	8.21	0	0.65

Rename the columns

In [6]:
```python
df.rename(columns = {"GRE Score":"GRE_Score", "TOEFL Score":"TOEFL_Score","University Rating"
```

In [7]:
```python
df.columns
```

Out[7]:
```
Index(['GRE_Score', 'TOEFL_Score', 'University_Rating', 'SOP', 'LOR', 'CGPA',
       'Research', 'Chance of Admit'],
      dtype='object')
```

In [8]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   GRE_Score          485 non-null    float64
 1   TOEFL_Score        490 non-null    float64
 2   University_Rating  485 non-null    float64
 3   SOP                500 non-null    float64
 4   LOR                500 non-null    float64
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    int64
 7   Chance of Admit    500 non-null    float64
dtypes: float64(7), int64(1)
memory usage: 31.4 KB
```

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

Out[9]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	485.000000	490.000000	485.000000	500.000000	500.00000	500.000000	500.000000	500.00000
mean	316.558763	107.187755	3.121649	3.374000	3.48400	8.576440	0.560000	0.72174
std	11.274704	6.112899	1.146160	0.991004	0.92545	0.604813	0.496884	0.14114
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.34000
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.63000
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.72000
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.82000
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.97000

In [10]:
```
df.shape
```

Out[10]:
```
(500, 8)
```

Check the duplcate values

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

Out[11]:

GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Chance of Admit

Checking For Null Values

In [12]:
```
df.isna().sum()
```

Out[12]:
```
GRE_Score            15
TOEFL_Score          10
University_Rating    15
SOP                   0
LOR                   0
CGPA                  0
Research              0
Chance of Admit       0
dtype: int64
```

Fill the null values with the mean

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

```
Out[13]: Index(['GRE_Score', 'TOEFL_Score', 'University_Rating', 'SOP', 'LOR', 'CGPA',
                'Research', 'Chance of Admit'],
               dtype='object')
```

```
In [14]: df['GRE_Score'] = df['GRE_Score'].fillna(round(df['GRE_Score'].mean()))
         df['TOEFL_Score'] = df['TOEFL_Score'].fillna(round(df['TOEFL_Score'].mean()))
         df['University_Rating'] = df['University_Rating'].fillna(round(df['University_Rating'].mean()
```

```
In [15]: df.isna().sum()
```

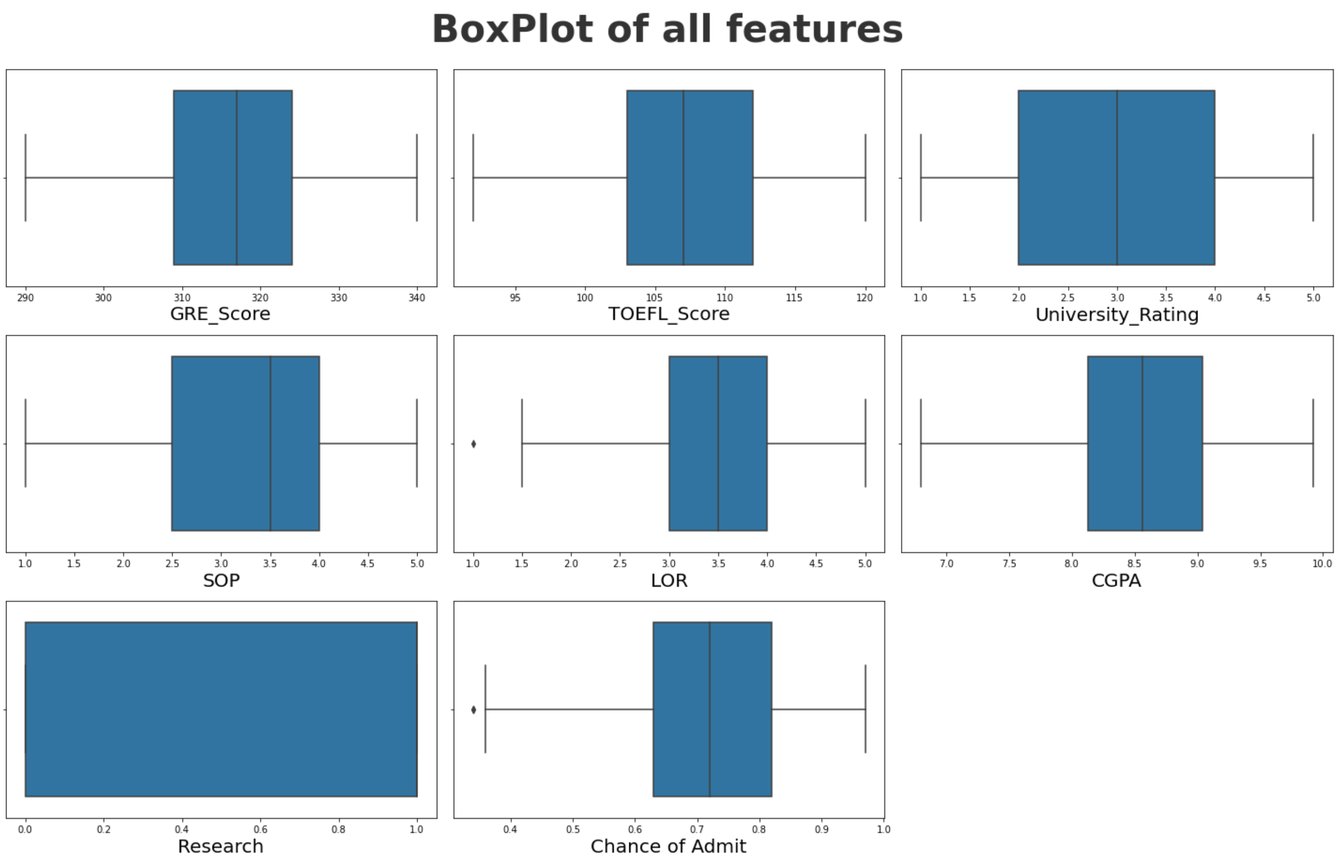
```
Out[15]: GRE_Score            0
         TOEFL_Score          0
         University_Rating    0
         SOP                  0
         LOR                  0
         CGPA                 0
         Research             0
         Chance of Admit      0
         dtype: int64
```

Check the outliers

Box plot

```
In [16]: plt.figure(figsize = (20,20))
         plt.suptitle('BoxPlot of all features', fontsize = 40, fontweight = "bold", alpha = 0.8, y =

         for i in range(0, len(df.columns)):
             plt.subplot(5,3,i+1)
             sns.boxplot(x= df[df.columns[i]], data = df)
             plt.xlabel(df.columns[i],fontsize = 20)
             #plt.ylabel("Classes")
             #plt.title("{} .format(data.columns[i]))
             plt.tight_layout()
```



Obeservation

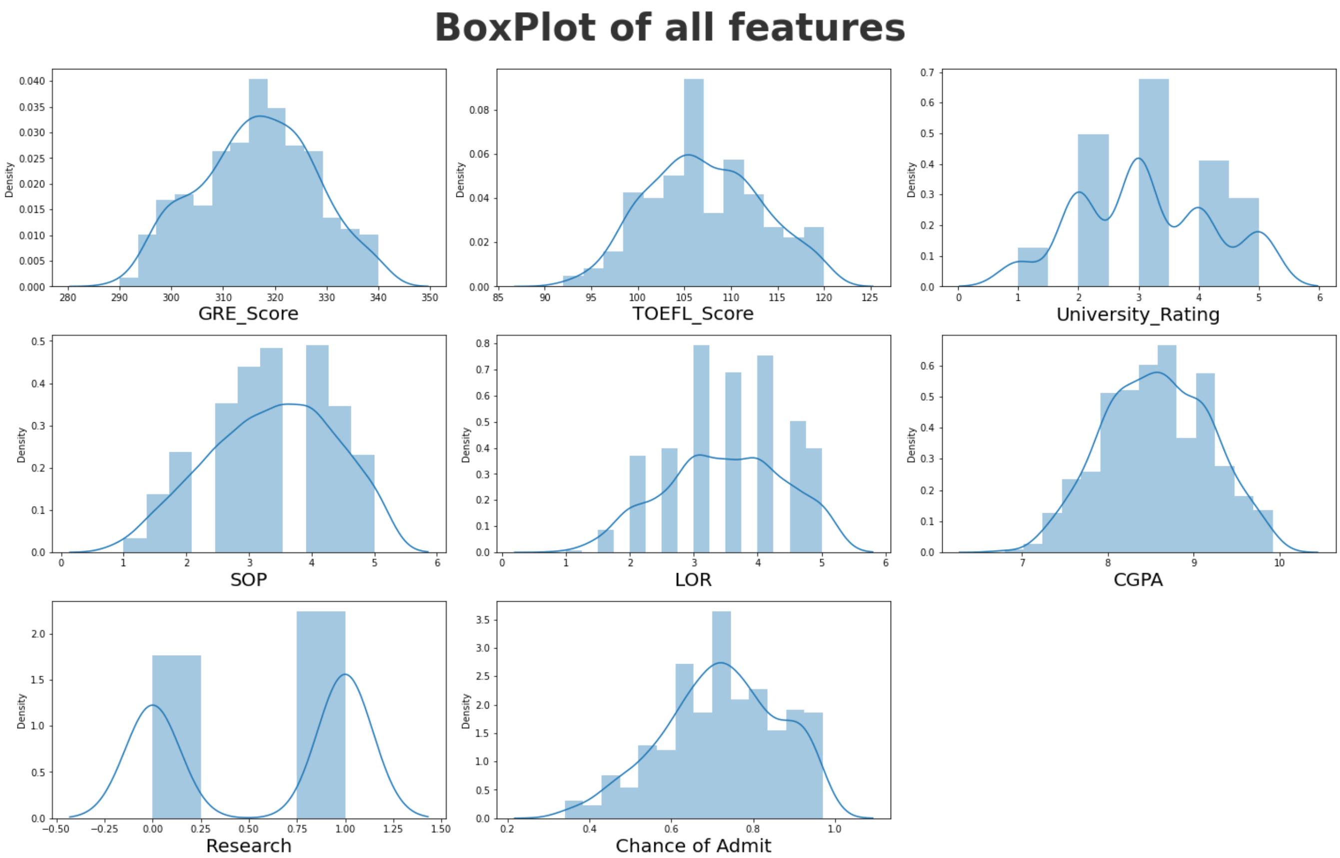
Very Few outliers are present in the dataset, this will not affect our model so we do not handle it

Graphical Analysis (DATA Visualization)

In [17]:

```
plt.figure(figsize = (20,20))
plt.suptitle('BoxPlot of all features', fontsize = 40, fontweight = "bold", alpha = 0.8, y =

for i in range(0, len(df.columns)):
    plt.subplot(5,3,i+1)
    sns.distplot(x= df[df.columns[i]])
    plt.xlabel(df.columns[i],fontsize = 20)
    #plt.ylabel("Classes")
    #plt.title("{} .format(data.columns[i]))
    plt.tight_layout()
```



Correlation

In [18]:

```
df.corr()
```

Out[18]:

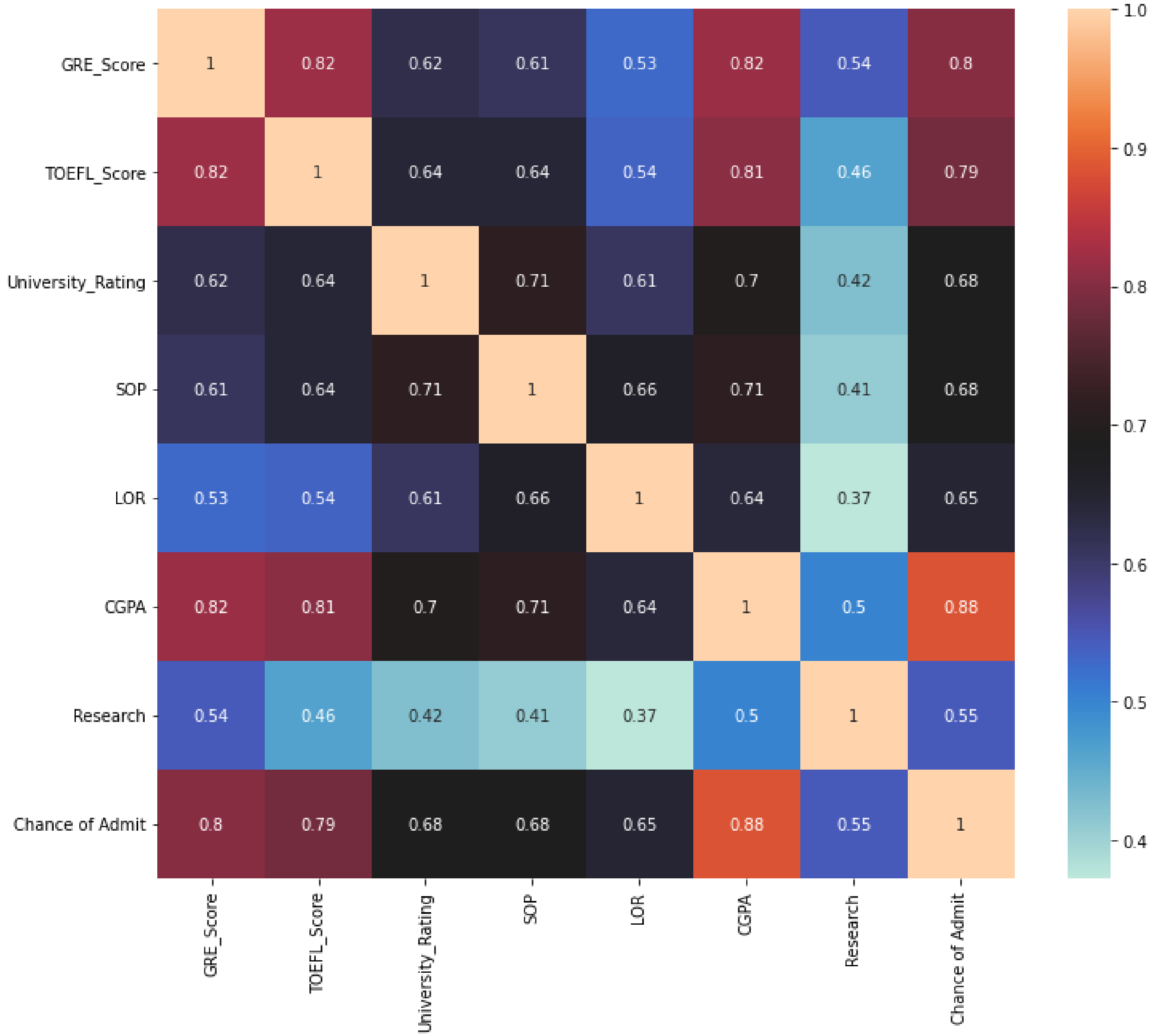
	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Chance of Admit
GRE_Score	1.000000	0.819885	0.623467	0.608349	0.528105	0.818344	0.544756	0.802321
TOEFL_Score	0.819885	1.000000	0.644189	0.642976	0.535500	0.805547	0.464858	0.786543
University_Rating	0.623467	0.644189	1.000000	0.713657	0.606949	0.697704	0.424966	0.681482
SOP	0.608349	0.642976	0.713657	1.000000	0.663707	0.712154	0.408116	0.684137
LOR	0.528105	0.535500	0.606949	0.663707	1.000000	0.637469	0.372526	0.645365
CGPA	0.818344	0.805547	0.697704	0.712154	0.637469	1.000000	0.501311	0.882413
Research	0.544756	0.464858	0.424966	0.408116	0.372526	0.501311	1.000000	0.545871
Chance of Admit	0.802321	0.786543	0.681482	0.684137	0.645365	0.882413	0.545871	1.000000

In [19]:

```
plt.figure(figsize = (12,10))
```

```
sns.heatmap(df.corr(),annot = True, cmap='icefire')
```

Out[19]: <AxesSubplot:>



Splitting data into independet and dependent features

In [20]:
```
X = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

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

Out[21]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research
0	337.0	118.0	4.0	4.5	4.5	9.65	1
1	324.0	107.0	4.0	4.0	4.5	8.87	1
2	317.0	104.0	3.0	3.0	3.5	8.00	1
3	322.0	110.0	3.0	3.5	2.5	8.67	1
4	314.0	103.0	2.0	2.0	3.0	8.21	0

In [22]:
```
y.head()
```

Out[22]:
```
0    0.92
1    0.76
2    0.72
3    0.80
4    0.65
Name: Chance of Admit, dtype: float64
```

Train Test split

In [24]:
```
## random state train test split ....
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.33, random_state=42)
```

In [25]:
```
X_train.head()
```

Out[25]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research
471	311.0	103.0	3.0	2.0	4.0	8.09	0
26	322.0	109.0	5.0	4.5	3.5	8.80	0
7	308.0	101.0	2.0	3.0	4.0	7.90	0
453	319.0	103.0	3.0	2.5	4.0	8.76	1
108	331.0	116.0	5.0	5.0	5.0	9.38	1

In [26]:
```
X_train.shape,y_train.shape
```

Out[26]:
```
((335, 7), (335,))
```

In [27]:
```
X_test.shape,y_test.shape
```

Out[27]:
```
((165, 7), (165,))
```

StandardScaler

In [28]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler
```

Out[28]:
```
▾ StandardScaler
StandardScaler()
```

In [29]:
```
X_train =scaler.fit_transform(X_train)
X_train
```

Out[29]:
```
array([[-5.45279323e-01, -7.01035861e-01, -8.61745113e-02, ...,
         5.38819022e-01, -8.35765678e-01, -1.14470294e+00],
       [ 4.69546084e-01,  2.85025777e-01,  1.66342920e+00, ...,
        -1.61323061e-03,  3.63045482e-01, -1.14470294e+00],
       [-8.22049889e-01, -1.02972307e+00, -9.60976368e-01, ...,
         5.38819022e-01, -1.15657430e+00, -1.14470294e+00],
       ...,
       [-1.37559102e+00, -1.35841029e+00, -1.83577823e+00, ...,
        -1.62290999e+00, -2.25407747e+00, -1.14470294e+00],
       [-7.29793033e-01, -3.72348648e-01, -9.60976368e-01, ...,
         5.38819022e-01, -1.52803691e+00, -1.14470294e+00],
       [-2.68508758e-01, -2.08005042e-01, -9.60976368e-01, ...,
        -1.61323061e-03, -5.65611050e-01, -1.14470294e+00]])
```

In [30]:
```
X_test=scaler.transform(X_test)
X_test
```

Out[30]:
```
array([[ 1.57662835e+00,  1.43543102e+00,  7.88627346e-01, ...,
        -1.61323061e-03,  1.61251063e+00,  8.73589088e-01],
       [-2.68508758e-01,  1.20682171e-01,  7.88627346e-01, ...,
         5.38819022e-01,  7.68277423e-01,  8.73589088e-01],
       [-1.76251902e-01, -3.72348648e-01, -9.60976368e-01, ...,
        -1.08247774e+00, -1.57869090e+00, -1.14470294e+00],
       ...,
       [-8.39950473e-02, -7.01035861e-01, -9.60976368e-01, ...,
         1.07925128e+00,  2.61737496e-01, -1.14470294e+00],
       [-6.37536178e-01, -1.35841029e+00, -9.60976368e-01, ...,
        -1.62290999e+00, -2.16965415e+00, -1.14470294e+00],
       [ 8.26180793e-03, -2.08005042e-01, -1.83577823e+00, ...,
        -1.61323061e-03, -1.57869090e+00,  8.73589088e-01]])
```

SVR Model

In [31]:
```
from sklearn.svm import SVR
regression = SVR(kernel='rbf')
regression.fit(X_train,y_train)
```

Out[31]:
```
▾ SVR
SVR()
```

In [32]:
```
y_pred = regression.predict(X_test)
y_pred
```

Out[32]:
```
array([0.86817586, 0.78381503, 0.57919574, 0.68776952, 0.79439379,
       0.84743105, 0.50171033, 0.6328119 , 0.78957916, 0.75818072,
       0.65436264, 0.70519786, 0.65328173, 0.87229071, 0.81272357,
       0.46396312, 0.78826018, 0.59247838, 0.49116878, 0.60358816,
       0.65586878, 0.61633488, 0.69401787, 0.70125121, 0.7306518 ,
       0.5865494 , 0.87402932, 0.83488954, 0.62479868, 0.72564384,
       0.5550858 , 0.71302285, 0.57115598, 0.84909071, 0.62762574,
       0.68927902, 0.50776722, 0.81791217, 0.63304541, 0.6809731 ,
       0.86318472, 0.56233921, 0.64817504, 0.85738211, 0.84872702,
       0.55864135, 0.89758476, 0.81012598, 0.74054261, 0.87390643,
       0.82908825, 0.58610923, 0.71086135, 0.5011529 , 0.88303906,
       0.59799981, 0.85593607, 0.70669597, 0.68232427, 0.48531637,
       0.63384423, 0.65854597, 0.57107234, 0.60456737, 0.45790852,
       0.57292054, 0.86601987, 0.85203547, 0.6347303 , 0.65992005,
       0.61291378, 0.72230055, 0.66038355, 0.56688316, 0.50314065,
       0.69042144, 0.80075229, 0.86708173, 0.47854057, 0.68123108,
       0.63887457, 0.81365599, 0.64441117, 0.79420446, 0.66324822,
       0.62715684, 0.61540247, 0.6959036 , 0.76488711, 0.65508961,
       0.69498782, 0.88387867, 0.86332134, 0.65499083, 0.71332777,
       0.46769764, 0.64999881, 0.67814391, 0.69048495, 0.65097042,
       0.74425955, 0.72834786, 0.65438121, 0.64871712, 0.6427819 ,
       0.54722967, 0.70363131, 0.78590853, 0.59293695, 0.67086153,
       0.55539812, 0.8820174 , 0.82444881, 0.87746818, 0.48749459,
       0.78884566, 0.66249366, 0.86003862, 0.59996085, 0.64841941,
       0.70963509, 0.88043536, 0.69676286, 0.6400109 , 0.68707835,
       0.69461809, 0.59979697, 0.86041258, 0.8428662 , 0.48602802,
       0.63371219, 0.67048444, 0.80975464, 0.45350734, 0.74676375,
       0.56995655, 0.80823255, 0.84923933, 0.65321481, 0.68766358,
       0.6624655 , 0.63095662, 0.80911766, 0.49080934, 0.89593473,
       0.65310692, 0.81932024, 0.72755498, 0.63260553, 0.70911831,
       0.83278346, 0.6422509 , 0.80228742, 0.69007864, 0.61275747,
       0.58985811, 0.75276095, 0.77376976, 0.50914472, 0.56440524,
       0.65396734, 0.75382677, 0.67478053, 0.45899005, 0.59553593])
```

Peformance Matrics

In [33]:
```
# Performance matrics
from sklearn.metrics import mean_squared_error
```

```
from sklearn.metrics import mean_absolute_error
```

In [34]:
```
print(mean_squared_error(y_test,y_pred))
print(mean_absolute_error(y_test,y_pred))
```

```
0.005073575747495135
0.05874253823892985
```

R-Square & Adjusted R-Square

In [37]:
```
from sklearn.metrics import r2_score
score = r2_score(y_test , y_pred)
print("R-Square:",score)
```

```
R-Square: 0.753750387888641
```

In [42]:
```
## Adjuste r2
adjusted_r_2 = 1-(1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
print("Adjusted R_2:",adjusted_r_2)
```

```
Adjusted R_2: 0.7427711058199817
```

In [48]:
```
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
```

Hyper-parameter Tuning

In [46]:
```
# Hyper-parameter tuning the SVM model
param_grid = {'kernel':['rbf','linear','poly']}

grid = GridSearchCV(estimator = SVR(),
                    param_grid=param_grid,
                            cv=5,
                            n_jobs= -1)

grid.fit(X_train,y_train)
```

Out[46]:

▸ GridSearchCV

▸ estimator: SVR

▸ SVR

▾ GridSearchCV

```
GridSearchCV(cv=5, estimator=SVR(), n_jobs=-1,
             param_grid={'kernel': ['rbf', 'linear', 'poly']})
```

▾ estimator: SVR

```
SVR()
```

▾ SVR

```
SVR()
```

In [49]:
```
#prdicting data
svr_pred = grid.predict(X_test)

## r2 score
svr_r2Score = metrics.r2_score(y_test,svr_pred)
print("SVR R2 score:",svr_r2Score)
```

```
## Adjusted r2 score
Adjusted_r2 = 1 - (1-svr_r2Score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
print("SVR Adjusted R2:",Adjusted_r2)
```

```
SVR R2 score: 0.8018295745415123
SVR Adjusted R2: 0.7929939504764841
```

In [53]:
```
print("After Hyper-parameter Tuning")
print(mean_squared_error(y_test,svr_pred))
print(mean_absolute_error(y_test,svr_pred))
```

```
After Hyper-parameter Tuning
0.004082984798655958
0.049113186798944365
```

Before and After Hyperparameter Tuning

In [51]:
```
print(f"Before Hyper-parameter Tuning\n R-Square: {score} \n Adjusted R_2: {adjusted_r_2}\n")
print(f"After Hyper-parameter Tuning\n R-Square: {svr_r2Score} \n Adjusted R_2: {Adjusted_r2}
```

```
Before Hyper-parameter Tuning
 R-Square: 0.753750387888641
 Adjusted R_2: 0.7427711058199817

After Hyper-parameter Tuning
 R-Square: 0.8018295745415123
 Adjusted R_2: 0.7929939504764841
```