

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

from sklearn.preprocessing import StandardScaler
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.model_selection import GridSearchCV

import warnings
warnings.simplefilter("ignore")
warnings.filterwarnings("ignore")
```

## Making Path for the Datasets

```
In [2]: WineDataPath = "https://raw.githubusercontent.com/aniruddhachoudhury/Red-Wine-Quality/master/winequality-red.csv"
AdmissionDataPath = "https://raw.githubusercontent.com/srinivasav22/Graduate-Admission-Prediction/master/AdmissionData.csv"
```

## Loading the Datasets

```
In [3]: WineData = pd.read_csv(WineDataPath)
WD = pd.read_csv(WineDataPath)
AdmitData = pd.read_csv(AdmissionDataPath)
```

## Wine Quality Dataset

```
In [4]: WineData.sample(6)
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
1417	7.3	0.34	0.33	2.5	0.064	21.0	37.0	0.99520	3.35	0.77	12.1	7
150	7.3	0.33	0.47	2.1	0.077	5.0	11.0	0.99580	3.33	0.53	10.3	6
1267	10.4	0.43	0.50	2.3	0.068	13.0	19.0	0.99600	3.10	0.87	11.4	6
1232	7.6	0.43	0.29	2.1	0.075	19.0	66.0	0.99718	3.40	0.64	9.5	5
152	7.5	0.60	0.03	1.8	0.095	25.0	99.0	0.99500	3.35	0.54	10.1	5
429	12.8	0.84	0.63	2.4	0.088	13.0	35.0	0.99970	3.10	0.60	10.4	6

## Admission Dataset

```
In [5]: AdmitData.sample(6)
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
299	300	305	112	3	3.0	3.5	8.65	0	0.71
6	7	321	109	3	3.0	4.0	8.20	1	0.75
172	173	322	110	4	4.0	5.0	9.13	1	0.86
388	389	296	97	2	1.5	2.0	7.80	0	0.49
21	22	325	114	4	3.0	2.0	8.40	0	0.70
183	184	314	110	3	4.0	4.0	8.80	0	0.75

## EDA (Exploratory Data Analysis)

### EDA for Wine Dataset

Stripping the Column Names If any

```
In [6]: WineData.columns
```

```
Out[6]: Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',  
            'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',  
            'pH', 'sulphates', 'alcohol', 'quality'],  
            dtype='object')
```

```
In [7]: [i.strip() for i in WineData.columns]
```

```
Out[7]: ['fixed acidity',  
        'volatile acidity',  
        'citric acid',  
        'residual sugar',  
        'chlorides',  
        'free sulfur dioxide',  
        'total sulfur dioxide',  
        'density',  
        'pH',  
        'sulphates',  
        'alcohol',  
        'quality']
```

## Checking the Numerical and Categorical Columns

```
In [8]: WineDataNumericalFeatures = [feature for feature in WineData.columns if WineData[feature].dtype != 'O']  
WineDataCategoricalFeatures = [feature for feature in WineData.columns if WineData[feature].dtype != 'O']  
  
print(f"We have {len(WineDataNumericalFeatures)} Numerical Feature: {WineDataNumericalFeatures}")  
print(f"We have {len(WineDataCategoricalFeatures)} Categorical Feature: {WineDataCategoricalFeatures}")
```

We have 12 Numerical Feature: ['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar', 'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol', 'quality']  
We have 12 Categorical Feature: ['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar', 'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol', 'quality']

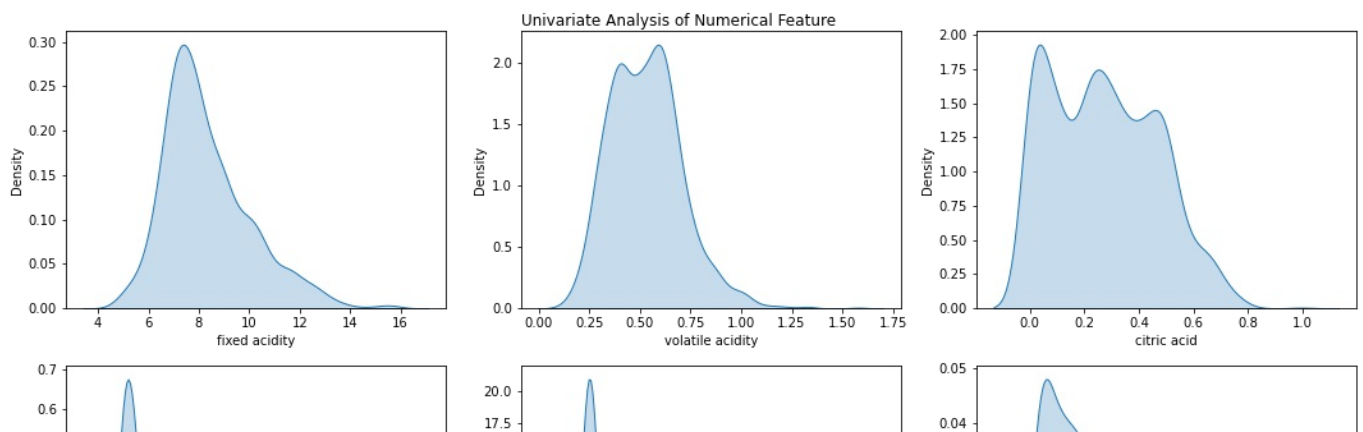
As above we can see that there are only Numerical Feature are present in this Wine Dataset

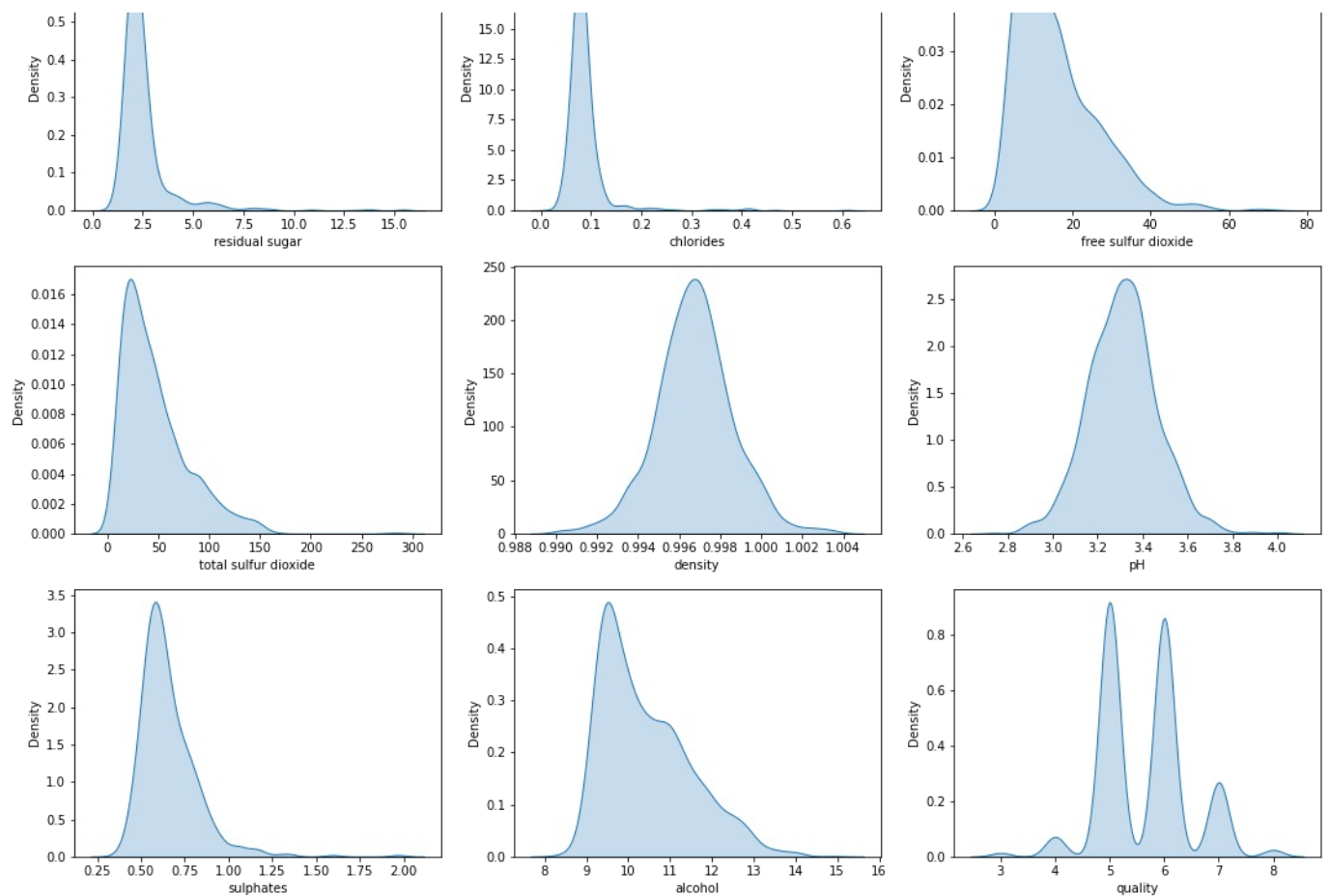
## Univariate Analysis

The term univariate analysis refers to the analysis of one variable prefix "uni" means "one". The purpose of univariate analysis is to understand the distribution of values for single variable.

### We have only Numerical Features

```
In [15]: plt.figure(figsize=(15, 15))  
plt.suptitle("Univariate Analysis of Numerical Feature")  
  
for i in range(0, len(WineDataNumericalFeatures)):  
    plt.subplot(4, 3, i+1)  
    sns.kdeplot(x=WineData[WineDataNumericalFeatures[i]], shade=True)  
    plt.xlabel(WineDataNumericalFeatures[i])  
    plt.ylabel("Density")  
    plt.tight_layout();
```





Wine Dataset is Skewed Dataset

## Multivariate Analysis

Multivariate analysis is the analysis of more than one variable.

Checking Multicollinearity in Numerical Features

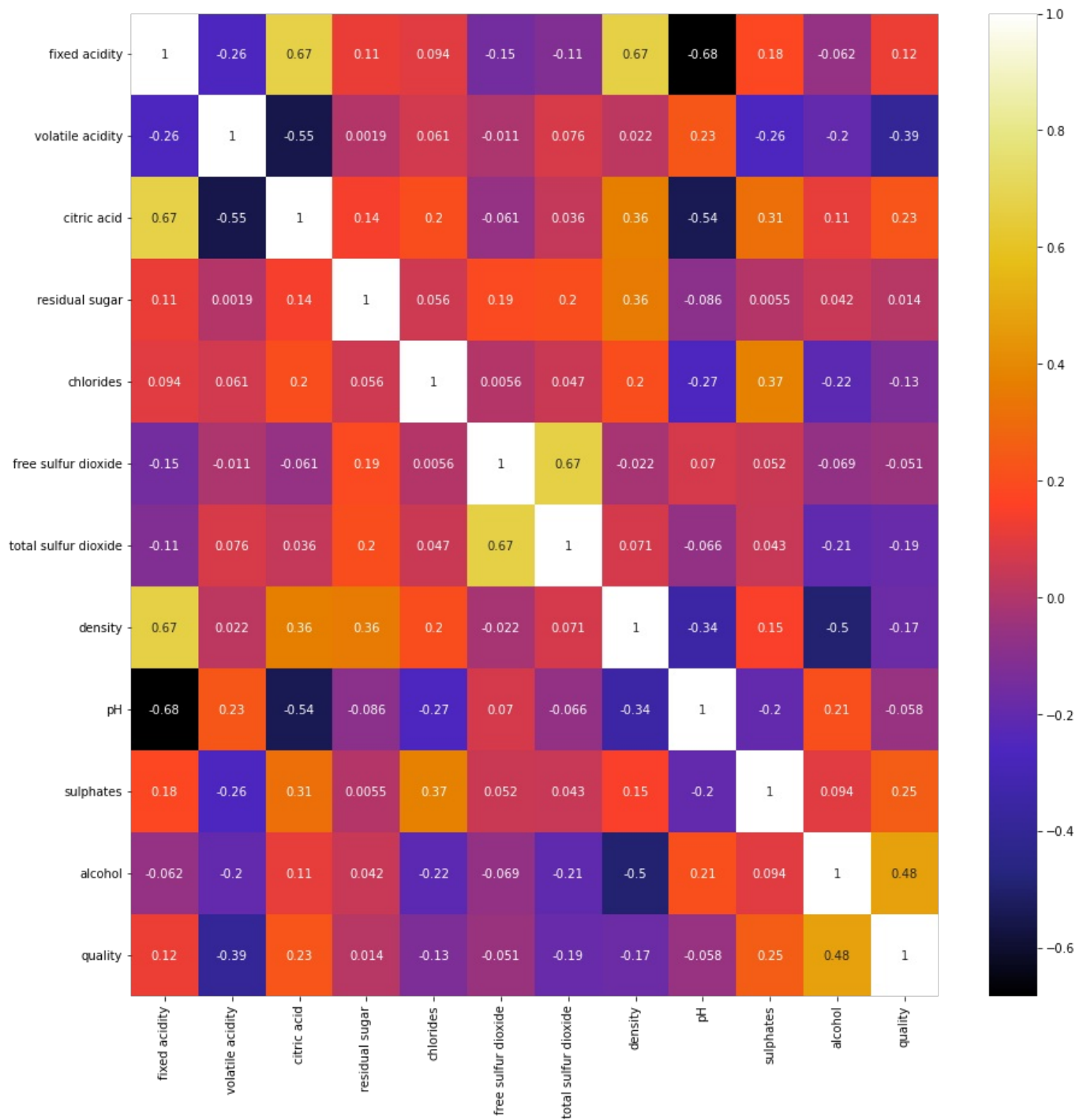
```
In [16]: WineData[WineData.columns].corr()
```

Out[16]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.682978	0.183006	-0.061668	0.124052
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	0.234937	-0.260987	-0.202288	-0.390558
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-0.541904	0.312770	0.109903	0.226373
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.085652	0.005527	0.042075	0.013732
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.265026	0.371260	-0.221141	-0.128907
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	0.070377	0.051658	-0.069408	-0.050656
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-0.066495	0.042947	-0.205654	-0.185100
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-0.341699	0.148506	-0.496180	-0.174919
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1.000000	-0.196648	0.205633	-0.057731
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506	-0.196648	1.000000	0.093595	0.251397
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180	0.205633	0.093595	1.000000	0.476166
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919	-0.057731	0.251397	0.476166	1.000000

```
In [17]: plt.figure(figsize=(15, 15))
sns.heatmap(WineData.corr(), cmap="CMRmap", annot=True)
```

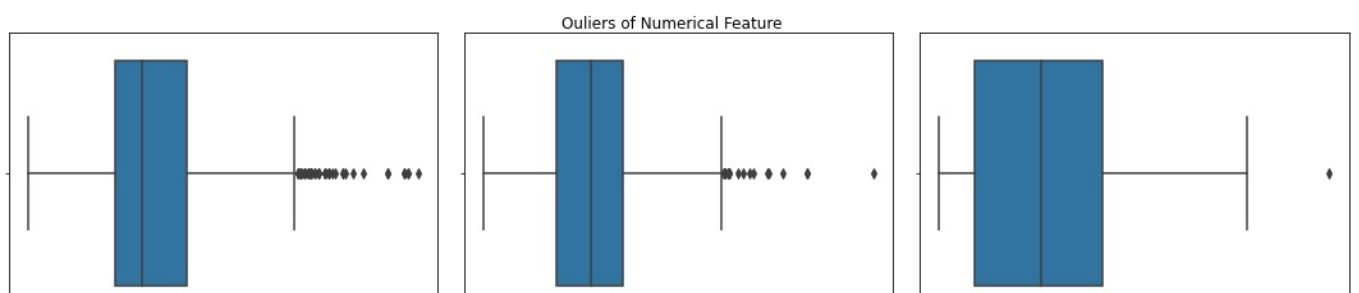
```
plt.show()
```

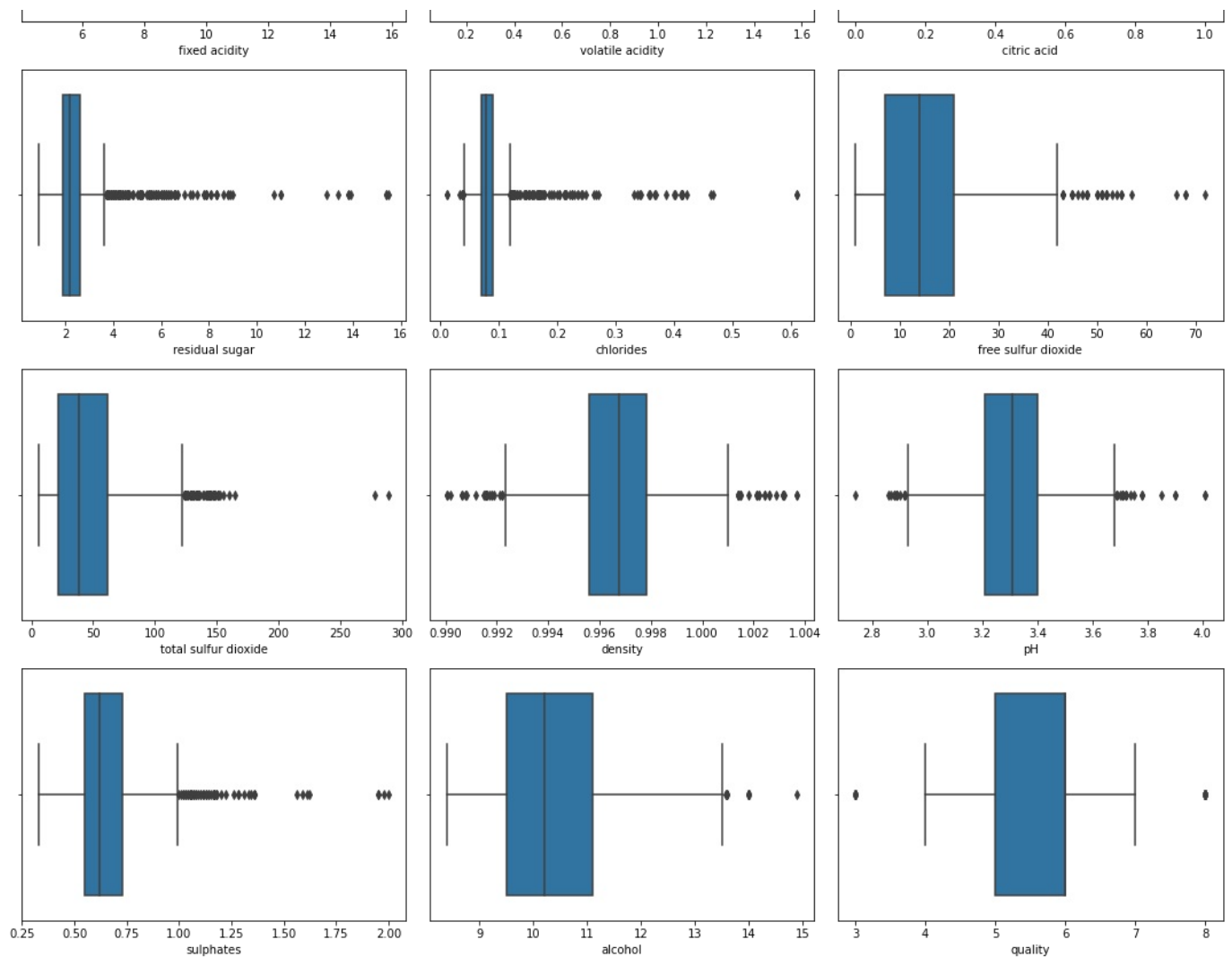


## Checking Outliers for Wine Dataset

```
In [18]: plt.figure(figsize=(15, 15))
plt.suptitle("Ouliers of Numerical Feature")

for i in range(0, len(WineDataNumericalFeatures)):
    plt.subplot(4, 3, i+1)
    sns.boxplot(x=WineData[WineDataNumericalFeatures[i]])
    plt.xlabel(WineDataNumericalFeatures[i])
    # plt.ylabel("Density")
    plt.tight_layout();
```





As we can see there are many outliers present in the Wine Data

## EDA for Admission Dataset

Stripping the Column Names If any

```
In [19]: AdmitData.columns
```

```
Out[19]: Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
              'LOR ', 'CGPA', 'Research', 'Chance of Admit'],
              dtype='object')
```

```
In [20]: AdmitData.columns = [i.strip() for i in AdmitData.columns]
          AdmitData.columns
```

```
Out[20]: Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
              'LOR', 'CGPA', 'Research', 'Chance of Admit'],
              dtype='object')
```

## Checking the Numerical and Categorical Columns

```
In [21]: AdmitDataNumericalFeatures = [feature for feature in AdmitData.columns if AdmitData[feature].dtype != 'O']
          AdmitDataCategoricalFeature = [feature for feature in AdmitData.columns if AdmitData[feature].dtype == 'O']

          print(f"We have {len(AdmitDataNumericalFeatures)} Numerical Feature: {AdmitDataNumericalFeatures}")
          print(f"We have {len(AdmitDataCategoricalFeature)} Categorical Feature: {AdmitDataCategoricalFeature}")
```

```
We have 9 Numerical Feature: ['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR', 'CGPA',
                             'Research', 'Chance of Admit']
We have 9 Categorical Feature: ['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR', 'CGP
A', 'Research', 'Chance of Admit']
```

As above we can see that there are only Numerical Features in Admission Dataset Also

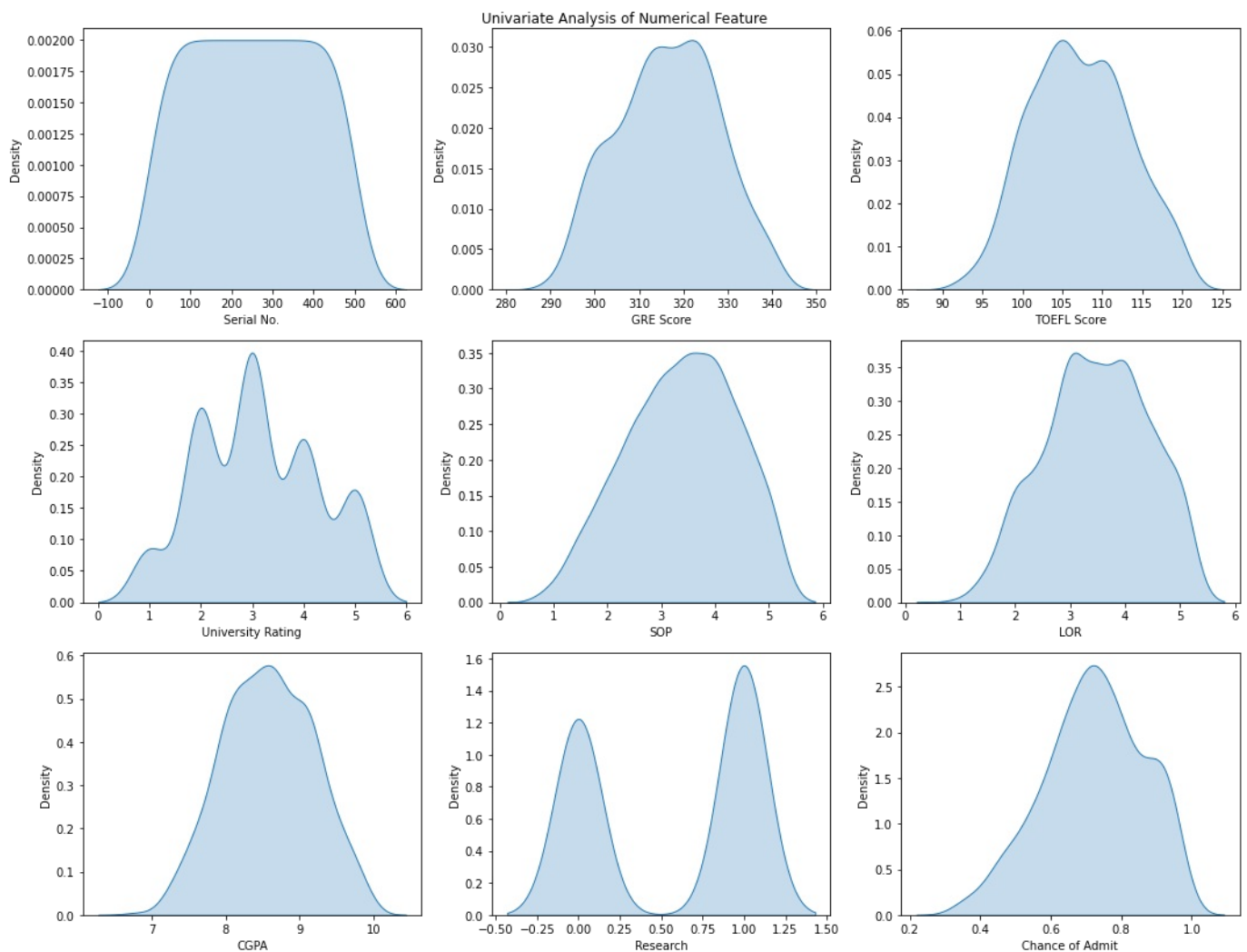
## Univariate Analysis

the term univariate analysis refers to the analysis of one variable prefix "uni" means "one". The purpose of univariate analysis is to understand the distribution of values for a single variable.

### We have only Numerical Features

```
In [22]: plt.figure(figsize=(15, 15))
plt.suptitle("Univariate Analysis of Numerical Feature")

for i in range(0, len(AdmitDataNumericalFeatures)):
    plt.subplot(4, 3, i+1)
    sns.kdeplot(x=AdmitData[AdmitDataNumericalFeatures[i]], shade=True)
    plt.xlabel(AdmitDataNumericalFeatures[i])
    plt.ylabel("Density")
    plt.tight_layout();
```



Admission Data seems like Normal Distribution

## Multivariate Analysis

Multivariate analysis is the analysis of more than one variable.

### Checking Multicollinearity in Numerical Features

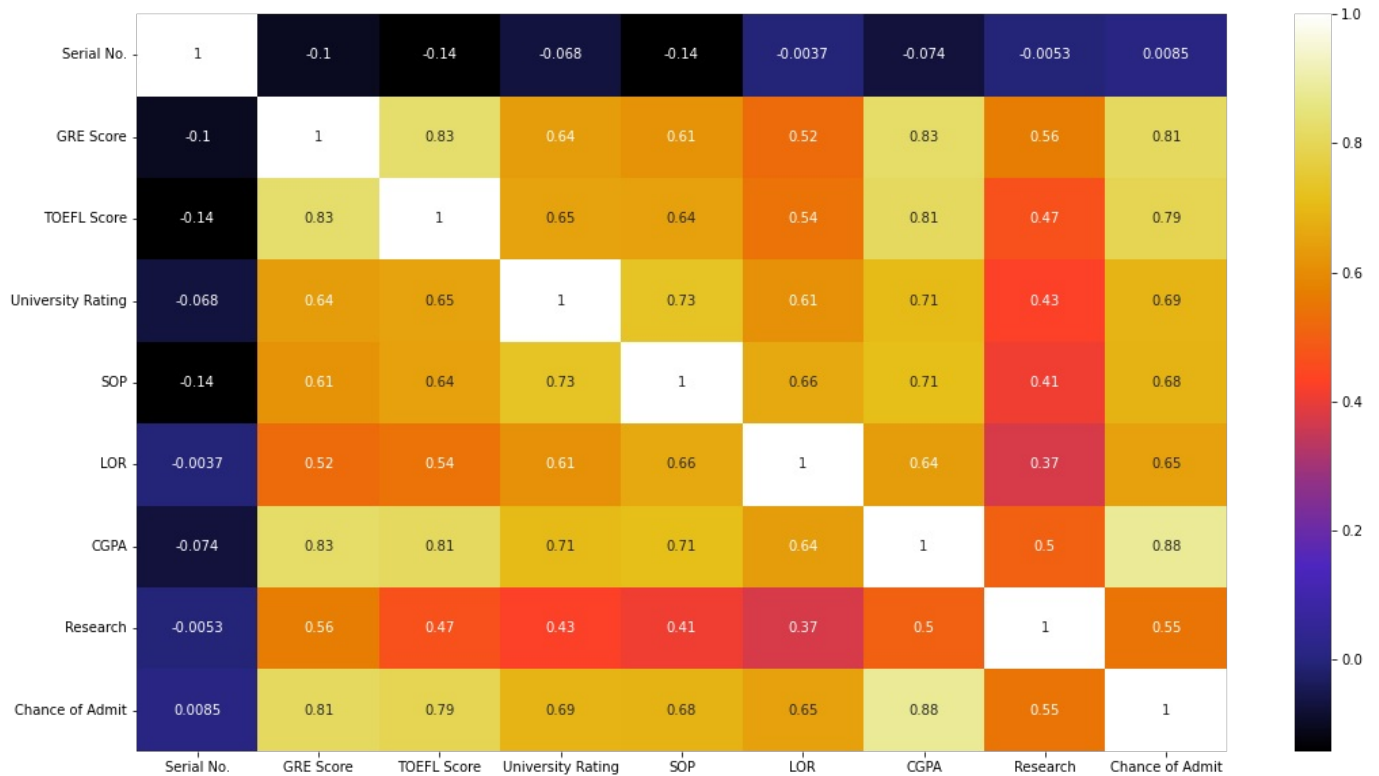
```
In [23]: AdmitData[(AdmitData.columns)].corr()
```

```
Out[23]:
```

Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
------------	-----------	-------------	-------------------	-----	-----	------	----------	-----------------

<b>Serial No.</b>	1.000000	-0.103839	-0.141696	-0.067641	-0.137352	-0.003694	-0.074289	-0.005332	0.008505
<b>GRE Score</b>	-0.103839	1.000000	0.827200	0.635376	0.613498	0.524679	0.825878	0.563398	0.810351
<b>TOEFL Score</b>	-0.141696	0.827200	1.000000	0.649799	0.644410	0.541563	0.810574	0.467012	0.792228
<b>University Rating</b>	-0.067641	0.635376	0.649799	1.000000	0.728024	0.608651	0.705254	0.427047	0.690132
<b>SOP</b>	-0.137352	0.613498	0.644410	0.728024	1.000000	0.663707	0.712154	0.408116	0.684137
<b>LOR</b>	-0.003694	0.524679	0.541563	0.608651	0.663707	1.000000	0.637469	0.372526	0.645365
<b>CGPA</b>	-0.074289	0.825878	0.810574	0.705254	0.712154	0.637469	1.000000	0.501311	0.882413
<b>Research</b>	-0.005332	0.563398	0.467012	0.427047	0.408116	0.372526	0.501311	1.000000	0.545871
<b>Chance of Admit</b>	0.008505	0.810351	0.792228	0.690132	0.684137	0.645365	0.882413	0.545871	1.000000

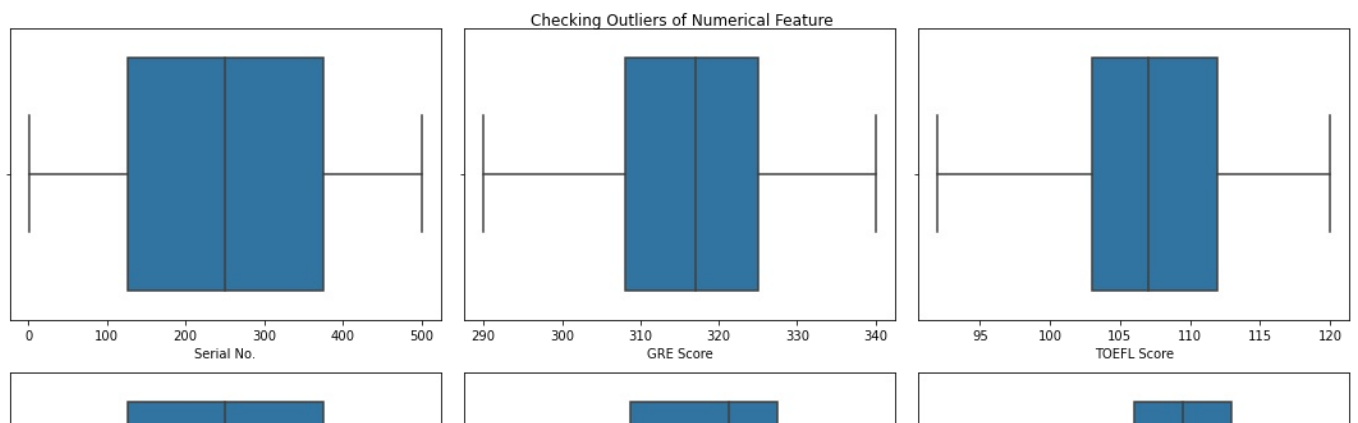
```
In [24]: plt.figure(figsize=(18, 10))
sns.heatmap(AdmitData.corr(), cmap="CMRmap", annot=True)
plt.show()
```

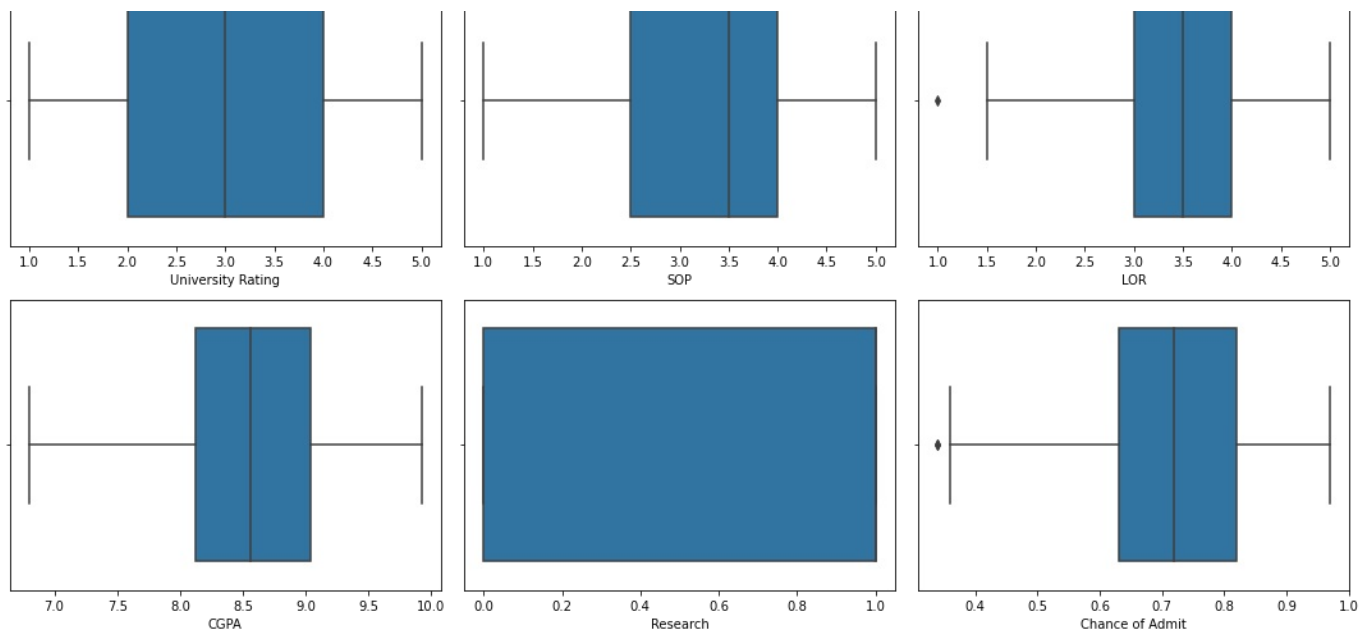


## Checking Outliers

```
In [25]: plt.figure(figsize=(15, 15))
plt.suptitle("Checking Outliers of Numerical Feature")

for i in range(0, len(AdmitDataNumericalFeatures)):
    plt.subplot(4, 3, i+1)
    sns.boxplot(x=AdmitData[AdmitDataNumericalFeatures[i]])
    plt.xlabel(AdmitDataNumericalFeatures[i])
    # plt.ylabel(Density)
    plt.tight_layout();
```





## Preprocesson the Data

### Preprocessing of Wine Dataset

#### Removing Outliers

```
In [39]: MaxFixedAcidity = int(WineData['fixed acidity'].quantile(0.96))
MinFixedAcidity = int(WineData['fixed acidity'].quantile(0.1))
print("Maximum Limit: ", MaxFixedAcidity)
print("Minimum Limit: ", MinFixedAcidity)

WineDataMeanFixedAcidity = int(WineData.loc[WineData['fixed acidity'] <= 12, 'fixed acidity'].mean())
print("\nMean: ", WineDataMeanFixedAcidity)

WineData['fixed acidity'] = np.where(WineData['fixed acidity'] >= MaxFixedAcidity, WineDataMeanFixedAcidity, WineData['fixed acidity'])
WineData['fixed acidity'] = np.where(WineData['fixed acidity'] < MinFixedAcidity, WineDataMeanFixedAcidity, WineData['fixed acidity'])

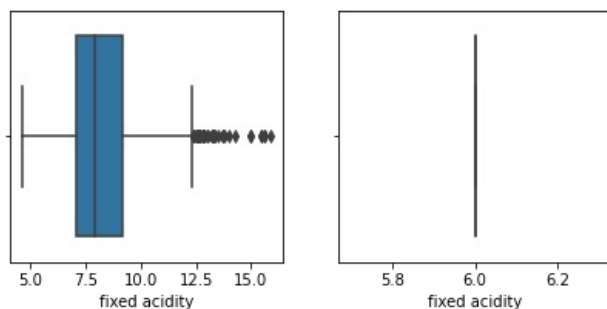
Maximum Limit: 6
Minimum Limit: 6

Mean: 6
```

```
In [40]: plt.figure(figsize=(7, 3))
plt.subplot(1, 2, 1)
sns.boxplot(WD['fixed acidity'])

plt.subplot(1, 2, 2)
sns.boxplot(WineData['fixed acidity'])
```

Out[40]: <AxesSubplot:xlabel='fixed acidity'>



### Preprocessing of Admition Dataset

In Admition Dataset Outliers are not present



# Model Training

## Training for Wine Dataset

### Creating X and y for Wine Data

```
In [42]: XWine = WineData.drop("quality", axis=1)
yWine = WineData["quality"]

print(f"Shape of XWine Data: {XWine.shape}")
print(f"Shape of yWine Data: {yWine.shape}")
```

Shape of XWine Data: (1599, 11)  
Shape of yWine Data: (1599,)

### Train Test Split the Wine Data

```
In [44]: Wine_X_train, Wine_X_test, Wine_y_train, Wine_y_test = train_test_split(XWine, yWine, test_size=0.30, random_state=42)
```

```
In [45]: print(f"Wine X Train Shape: {Wine_X_train.shape}")
print(f"Wine X Test Shape: {Wine_X_test.shape}")
print(f"Wine y Train Shape: {Wine_y_train.shape}")
print(f"Wine y Test Shape: {Wine_y_test.shape}")
```

Wine X Train Shape: (1119, 11)  
Wine X Test Shape: (480, 11)  
Wine y Train Shape: (1119,)  
Wine y Test Shape: (480,)

### Scaling Wine Data

```
In [46]: WineScaler = StandardScaler()
WineScaler.fit(Wine_X_train)
```

Out[46]: StandardScaler()

```
In [47]: Wine_X_train_tf = WineScaler.transform(Wine_X_train)
Wine_X_train_tf
```

```
Out[47]: array([[ 0.00000000e+00, -1.72107140e+00,  4.59303345e-01, ...,
        1.01180685e+00,  1.22661179e+00,  5.50057013e-01],
       [ 0.00000000e+00, -4.01957443e-01,  1.84105501e+00, ...,
       -2.10687612e+00,  1.22661179e+00, -2.05174641e-01],
       [ 0.00000000e+00,  3.77472102e-02, -1.28054303e-03, ...,
        4.92026353e-01,  2.97270776e-01,  5.50057013e-01],
       ...,
       [ 0.00000000e+00,  4.77451864e-01, -1.07597628e+00, ...,
        1.27169710e+00, -6.90154049e-01, -8.66002338e-01],
       [ 0.00000000e+00, -1.83099757e+00,  4.08127357e-01, ...,
        3.72184202e-02,  8.20025095e-01,  1.39969262e+00],
       [ 0.00000000e+00, -1.33632983e+00, -5.24565306e-02, ...,
        4.92026353e-01, -6.90154049e-01,  2.91015593e+00]])
```

```
In [48]: Wine_SVC_model = svm.SVC()
Wine_SVC_model.fit(Wine_X_train_tf, Wine_y_train)
```

Out[48]: SVC()

```
In [49]: print(f"Traning Accuracy of Wine Data: {Wine_SVC_model.score(Wine_X_train_tf, Wine_y_train)}")
```

Traning Accuracy of Wine Data: 0.6729222520107239

```
In [50]: Wine_y_pred = Wine_SVC_model.predict(WineScaler.transform(Wine_X_test))
```

```
In [51]: print(f"Testing Accuracy of Wine Data: {metrics.accuracy_score(Wine_y_test, Wine_y_pred)}")
```

Testing Accuracy of Wine Data: 0.5916666666666667

```
In [52]: print(f"Classification Report of Wine Data\n")
print(metrics.classification_report(Wine_y_test, Wine_y_pred))
```

Classification Report of Wine Data

	precision	recall	f1-score	support
3	0.00	0.00	0.00	1
4	0.00	0.00	0.00	17
5	0.63	0.78	0.70	195
6	0.56	0.57	0.56	200
7	0.52	0.28	0.36	61
8	0.00	0.00	0.00	6
accuracy			0.59	480
macro avg	0.28	0.27	0.27	480
weighted avg	0.55	0.59	0.56	480

## Training for Admission Dataset

### Creating X and y for Admission Data

```
In [53]: AdmitData.columns
```

```
Out[53]: Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
              'LOR', 'CGPA', 'Research', 'Chance of Admit'],
              dtype='object')
```

```
In [54]: XAdmit = AdmitData.drop("Chance of Admit", axis=1)
yAdmit = AdmitData["Chance of Admit"]

print(f"Shape of XAdmit Data: {XAdmit.shape}")
print(f"Shape of yAdmit Data: {yAdmit.shape}")
```

Shape of XAdmit Data: (500, 8)  
Shape of yAdmit Data: (500,)

## Train Test Split the Admission Data

```
In [55]: Admit_X_train, Admit_X_test, Admit_y_train, Admit_y_test = train_test_split(XAdmit, yAdmit, test_size=0.30, random_state=42)
```

```
In [56]: print(f"Admission X Train Shape: {Admit_X_train.shape}")
print(f"Admission X Test Shape: {Admit_X_test.shape}")
print(f"Admission y Train Shape: {Admit_y_train.shape}")
print(f"Admission y Test Shape: {Admit_y_test.shape}")
```

Admission X Train Shape: (350, 8)  
Admission X Test Shape: (150, 8)  
Admission y Train Shape: (350,)  
Admission y Test Shape: (150,)

## Scalling Admission Data

```
In [57]: AdmitScaler = StandardScaler()
```

```
AdmitScaler.fit(Admit_X_train)
```

```
Out[57]: StandardScaler()
```

```
In [58]: Admit_X_train_tf = AdmitScaler.transform(Admit_X_train)
Admit_X_train_tf
```

```
Out[58]: array([[ -1.75020856,  1.22318504,  1.27980924, ..., -0.5291228 ,
         1.28550609,  0.88127734],
        [-0.96385041, -1.61322396, -0.86815536, ...,  0.01556244,
         0.07349047, -1.13471657],
        [-1.46683625,  0.49120853,  0.45366901, ...,  0.56024767,
         0.88150088,  0.88127734],
        ...,
        [ 0.67970895, -1.33873276, -1.3638395 , ..., -1.61849327,
        -2.23270591, -1.13471657],
        [ 1.29604372, -0.69825331, -0.37247122, ...,  0.56024767,
        -1.50886325, -1.13471657],
        [-1.06303072, -0.24076799, -0.20724318, ...,  0.01556244,
        -0.54935089, -1.13471657]])
```

```
In [59]: Admit_SVR_model = svm.SVR()
Admit_SVR_model.fit(Admit_X_train_tf, Admit_y_train)
```

```
Out[59]: SVR()
```

```
In [60]: print(f"Traning Accuracy of Admition Data: {Admit_SVR_model.score(Admit_X_train_tf, Admit_y_train)}")
```

Traning Accuracy of Admition Data: 0.8056236255122253

```
In [61]: Admit_y_pred = Admit_SVR_model.predict(AdmitScaler.transform(Admit_X_test))
```

```
In [64]: print(f"Mean Absolute Error: {metrics.mean_absolute_error(Admit_y_test, Admit_y_pred)}")
print(f"Mean squared error: , {metrics.mean_squared_error(Admit_y_test, Admit_y_pred)}")
print(f"Median absolute error: {metrics.median_absolute_error(Admit_y_test, Admit_y_pred)}")
print(f"Explain variance score: , {metrics.explained_variance_score(Admit_y_test, Admit_y_pred)}")
print(f"R2 score: , {metrics.r2_score(Admit_y_test, Admit_y_pred)}")
```

Mean Absolute Error: 0.054483683833666634  
Mean squared error: , 0.004598432360858017  
Median absolute error: 0.04913018222582349  
Explain variance score: , 0.8078910066096596  
R2 score: , 0.779367688675496

## Hyperparameter Tunning

### GridSearchCV For Wine Data

```
In [65]: WineParameters = {'C': [0.1, 1, 10, 100, 1000],
                           'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                           'kernel': ['rbf']}
```

```
In [66]: WineHyperparameter = GridSearchCV(svm.SVC(), WineParameters, refit=True, verbose=3)
WineHyperparameter.fit(Wine_X_train_tf, Wine_y_train)
```

Fitting 5 folds for each of 25 candidates, totalling 125 fits

[CV 1/5] END	.....C=0.1, gamma=1, kernel=rbf; , score=0.433 total time=	0.0s
[CV 2/5] END	.....C=0.1, gamma=1, kernel=rbf; , score=0.433 total time=	0.0s
[CV 3/5] END	.....C=0.1, gamma=1, kernel=rbf; , score=0.433 total time=	0.0s
[CV 4/5] END	.....C=0.1, gamma=1, kernel=rbf; , score=0.438 total time=	0.1s
[CV 5/5] END	.....C=0.1, gamma=1, kernel=rbf; , score=0.435 total time=	0.1s
[CV 1/5] END	.....C=0.1, gamma=0.1, kernel=rbf; , score=0.558 total time=	0.0s
[CV 2/5] END	.....C=0.1, gamma=0.1, kernel=rbf; , score=0.540 total time=	0.0s
[CV 3/5] END	.....C=0.1, gamma=0.1, kernel=rbf; , score=0.589 total time=	0.0s
[CV 4/5] END	.....C=0.1, gamma=0.1, kernel=rbf; , score=0.607 total time=	0.0s

[CV 5/5]	END	.....C=0.1, gamma=0.1,	kernel=rbf;;	score=0.659	total time=	0.0s
[CV 1/5]	END	....C=0.1, gamma=0.01,	kernel=rbf;;	score=0.527	total time=	0.0s
[CV 2/5]	END	....C=0.1, gamma=0.01,	kernel=rbf;;	score=0.531	total time=	0.0s
[CV 3/5]	END	....C=0.1, gamma=0.01,	kernel=rbf;;	score=0.589	total time=	0.0s
[CV 4/5]	END	....C=0.1, gamma=0.01,	kernel=rbf;	score=0.589	total time=	0.0s
[CV 5/5]	END	....C=0.1, gamma=0.01,	kernel=rbf;;	score=0.619	total time=	0.0s
[CV 1/5]	END	...C=0.1, gamma=0.001,	kernel=rbf;;	score=0.433	total time=	0.0s
[CV 2/5]	END	...C=0.1, gamma=0.001,	kernel=rbf;;	score=0.433	total time=	0.0s
[CV 3/5]	END	...C=0.1, gamma=0.001,	kernel=rbf;	score=0.433	total time=	0.0s
[CV 4/5]	END	...C=0.1, gamma=0.001,	kernel=rbf;;	score=0.438	total time=	0.0s
[CV 5/5]	END	...C=0.1, gamma=0.001,	kernel=rbf;;	score=0.435	total time=	0.0s
[CV 1/5]	END	..C=0.1, gamma=0.0001,	kernel=rbf;;	score=0.433	total time=	0.0s
[CV 2/5]	END	..C=0.1, gamma=0.0001,	kernel=rbf;	score=0.433	total time=	0.0s
[CV 3/5]	END	..C=0.1, gamma=0.0001,	kernel=rbf;;	score=0.433	total time=	0.0s
[CV 4/5]	END	..C=0.1, gamma=0.0001,	kernel=rbf;;	score=0.438	total time=	0.0s
[CV 5/5]	END	..C=0.1, gamma=0.0001,	kernel=rbf;;	score=0.435	total time=	0.0s
[CV 1/5]	END	.....C=1, gamma=1,	kernel=rbf;	score=0.634	total time=	0.1s
[CV 2/5]	END	.....C=1, gamma=1,	kernel=rbf;	score=0.607	total time=	0.1s
[CV 3/5]	END	.....C=1, gamma=1,	kernel=rbf;;	score=0.607	total time=	0.1s
[CV 4/5]	END	.....C=1, gamma=1,	kernel=rbf;	score=0.701	total time=	0.1s
[CV 5/5]	END	.....C=1, gamma=1,	kernel=rbf;	score=0.704	total time=	0.1s
[CV 1/5]	END	.....C=1, gamma=0.1,	kernel=rbf;	score=0.576	total time=	0.0s
[CV 2/5]	END	.....C=1, gamma=0.1,	kernel=rbf;;	score=0.576	total time=	0.0s
[CV 3/5]	END	.....C=1, gamma=0.1,	kernel=rbf;	score=0.616	total time=	0.0s
[CV 4/5]	END	.....C=1, gamma=0.1,	kernel=rbf;;	score=0.647	total time=	0.0s
[CV 5/5]	END	.....C=1, gamma=0.1,	kernel=rbf;	score=0.686	total time=	0.0s
[CV 1/5]	END	.....C=1, gamma=0.01,	kernel=rbf;;	score=0.562	total time=	0.0s
[CV 2/5]	END	.....C=1, gamma=0.01,	kernel=rbf;	score=0.558	total time=	0.0s
[CV 3/5]	END	.....C=1, gamma=0.01,	kernel=rbf;;	score=0.580	total time=	0.0s
[CV 4/5]	END	.....C=1, gamma=0.01,	kernel=rbf;	score=0.603	total time=	0.0s
[CV 5/5]	END	.....C=1, gamma=0.01,	kernel=rbf;;	score=0.650	total time=	0.0s
[CV 1/5]	END	.....C=1, gamma=0.001,	kernel=rbf;	score=0.531	total time=	0.0s
[CV 2/5]	END	.....C=1, gamma=0.001,	kernel=rbf;;	score=0.531	total time=	0.0s
[CV 3/5]	END	.....C=1, gamma=0.001,	kernel=rbf;	score=0.589	total time=	0.0s
[CV 4/5]	END	.....C=1, gamma=0.001,	kernel=rbf;;	score=0.603	total time=	0.0s
[CV 5/5]	END	.....C=1, gamma=0.001,	kernel=rbf;	score=0.632	total time=	0.0s
[CV 1/5]	END	.....C=1, gamma=0.0001,	kernel=rbf;;	score=0.433	total time=	0.0s
[CV 2/5]	END	.....C=1, gamma=0.0001,	kernel=rbf;	score=0.433	total time=	0.0s
[CV 3/5]	END	.....C=1, gamma=0.0001,	kernel=rbf;;	score=0.433	total time=	0.0s
[CV 4/5]	END	.....C=1, gamma=0.0001,	kernel=rbf;;	score=0.438	total time=	0.0s
[CV 5/5]	END	.....C=1, gamma=0.0001,	kernel=rbf;;	score=0.435	total time=	0.0s
[CV 1/5]	END	.....C=10, gamma=1,	kernel=rbf;	score=0.643	total time=	0.1s
[CV 2/5]	END	.....C=10, gamma=1,	kernel=rbf;	score=0.634	total time=	0.1s
[CV 3/5]	END	.....C=10, gamma=1,	kernel=rbf;;	score=0.607	total time=	0.1s
[CV 4/5]	END	.....C=10, gamma=1,	kernel=rbf;	score=0.661	total time=	0.1s
[CV 5/5]	END	.....C=10, gamma=1,	kernel=rbf;;	score=0.686	total time=	0.1s
[CV 1/5]	END	.....C=10, gamma=0.1,	kernel=rbf;	score=0.585	total time=	0.0s
[CV 2/5]	END	.....C=10, gamma=0.1,	kernel=rbf;;	score=0.616	total time=	0.0s
[CV 3/5]	END	.....C=10, gamma=0.1,	kernel=rbf;	score=0.603	total time=	0.0s
[CV 4/5]	END	.....C=10, gamma=0.1,	kernel=rbf;;	score=0.643	total time=	0.0s
[CV 5/5]	END	.....C=10, gamma=0.1,	kernel=rbf;	score=0.695	total time=	0.0s
[CV 1/5]	END	.....C=10, gamma=0.01,	kernel=rbf;;	score=0.576	total time=	0.0s
[CV 2/5]	END	.....C=10, gamma=0.01,	kernel=rbf;	score=0.571	total time=	0.0s
[CV 3/5]	END	.....C=10, gamma=0.01,	kernel=rbf;;	score=0.585	total time=	0.0s
[CV 4/5]	END	.....C=10, gamma=0.01,	kernel=rbf;	score=0.616	total time=	0.0s
[CV 5/5]						

```
[CV 4/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.603 total time= 0.0s
[CV 5/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.659 total time= 0.0s
[CV 1/5] END .....C=1000, gamma=1, kernel=rbf;, score=0.643 total time= 0.0s
[CV 2/5] END .....C=1000, gamma=1, kernel=rbf;, score=0.634 total time= 0.1s
[CV 3/5] END .....C=1000, gamma=1, kernel=rbf;, score=0.612 total time= 0.1s
[CV 4/5] END .....C=1000, gamma=1, kernel=rbf;, score=0.656 total time= 0.1s
[CV 5/5] END .....C=1000, gamma=1, kernel=rbf;, score=0.682 total time= 0.1s
[CV 1/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.589 total time= 0.2s
[CV 2/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.594 total time= 0.2s
[CV 3/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.589 total time= 0.2s
[CV 4/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.625 total time= 0.2s
[CV 5/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.646 total time= 0.2s
[CV 1/5] END .....C=1000, gamma=0.01, kernel=rbf;, score=0.554 total time= 0.2s
[CV 2/5] END .....C=1000, gamma=0.01, kernel=rbf;, score=0.580 total time= 0.3s
[CV 3/5] END .....C=1000, gamma=0.01, kernel=rbf;, score=0.612 total time= 0.2s
[CV 4/5] END .....C=1000, gamma=0.01, kernel=rbf;, score=0.656 total time= 0.2s
[CV 5/5] END .....C=1000, gamma=0.01, kernel=rbf;, score=0.673 total time= 0.2s
[CV 1/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.580 total time= 0.1s
[CV 2/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.576 total time= 0.0s
[CV 3/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.612 total time= 0.1s
[CV 4/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.629 total time= 0.0s
[CV 5/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.668 total time= 0.1s
[CV 1/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.567 total time= 0.0s
[CV 2/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.545 total time= 0.0s
[CV 3/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.567 total time= 0.0s
[CV 4/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.612 total time= 0.0s
[CV 5/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.668 total time= 0.0s
```

```
Out[66]: GridSearchCV(estimator=SVC(),
                      param_grid={'C': [0.1, 1, 10, 100, 1000],
                                   'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                                   'kernel': ['rbf']},
                      verbose=3)
```

```
In [69]: print(f"Best Parameters: {WineHyperparameter.best_params_}")
         print(f"Best Estimators: {WineHyperparameter.best_estimator_}")
```

```
Best Parameters: {'C': 1, 'gamma': 1, 'kernel': 'rbf'}
Best Estimators: SVC(C=1, gamma=1)
```

```
In [72]: WineHyperPred = WineHyperparameter.predict(WineScaler.transform(Wine_X_test))
         print("Classification Report of Wine Hyperparameter Model\n")
         print(metrics.classification_report(Wine_y_test, WineHyperPred))
```

Classification Report of Wine Hyperparameter Model

	precision	recall	f1-score	support
3	0.00	0.00	0.00	1
4	0.00	0.00	0.00	17
5	0.69	0.76	0.72	195
6	0.60	0.69	0.65	200
7	0.60	0.34	0.44	61
8	0.00	0.00	0.00	6
accuracy			0.64	480
macro avg	0.32	0.30	0.30	480
weighted avg	0.61	0.64	0.62	480

Accuracy has been Increased by 2% after Hyperparameter in Wine Data

## GridSearchCV for Admission Data

```
In [74]: AdmitParameters = {'kernel': ('linear', 'rbf', 'poly'),
                           'C': [1.5, 10],
                           'gamma': [1e-7, 1e-4],
                           'epsilon': [0,1,0,2,0,5,0.3]}
```

```
In [75]: AdmitHyperparameter = GridSearchCV(svm.SVR(), AdmitParameters, refit=True, verbose=3)
         AdmitHyperparameter.fit(Admit_X_train_tf, Admit_y_train)
```

Fitting 5 folds for each of 84 candidates, totalling 420 fits

[illegible]

[illegible]

[CV 4/5]	END	C=1.5,	epsilon=5,	gamma=0.0001,	kernel=poly;;	score=-0.273	total time=	0.0s
[CV 5/5]	END	C=1.5,	epsilon=5,	gamma=0.0001,	kernel=poly;;	score=-0.303	total time=	0.0s
[CV 1/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=linear;;	score=-0.052	total time=	0.0s
[CV 2/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=linear;;	score=-0.141	total time=	0.0s
[CV 3/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=linear;;	score=-0.329	total time=	0.0s
[CV 4/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=linear;;	score=-0.181	total time=	0.0s
[CV 5/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=linear;;	score=-0.202	total time=	0.0s
[CV 1/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=rbf;	score=-0.081	total time=	0.0s
[CV 2/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=rbf;;	score=-0.147	total time=	0.0s
[CV 3/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=rbf;;	score=-0.369	total time=	0.0s
[CV 4/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=rbf;;	score=-0.237	total time=	0.0s
[CV 5/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=rbf;	score=-0.234	total time=	0.0s
[CV 1/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=poly;;	score=-0.082	total time=	0.0s
[CV 2/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=poly;;	score=-0.147	total time=	0.0s
[CV 3/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=poly;;	score=-0.369	total time=	0.0s
[CV 4/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=poly;;	score=-0.237	total time=	0.0s
[CV 5/5]	END	C=1.5,	epsilon=0.3,	gamma=1e-07,	kernel=poly;;	score=-0.234	total time=	0.0s
[CV 1/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=linear;;	score=-0.052	total time=	0.0s
[CV 2/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=linear;;	score=-0.141	total time=	0.0s
[CV 3/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=linear;;	score=-0.329	total time=	0.0s
[CV 4/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=linear;;	score=-0.181	total time=	0.0s
[CV 5/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=linear;;	score=-0.202	total time=	0.0s
[CV 1/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=rbf;	score=-0.051	total time=	0.0s
[CV 2/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=rbf;;	score=-0.141	total time=	0.0s
[CV 3/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=rbf;;	score=-0.330	total time=	0.0s
[CV 4/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=rbf;;	score=-0.185	total time=	0.0s
[CV 5/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=rbf;;	score=-0.208	total time=	0.0s
[CV 1/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=poly;;	score=-0.082	total time=	0.0s
[CV 2/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=poly;;	score=-0.147	total time=	0.0s
[CV 3/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=poly;;	score=-0.369	total time=	0.0s
[CV 4/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=poly;;	score=-0.237	total time=	0.0s
[CV 5/5]	END	C=1.5,	epsilon=0.3,	gamma=0.0001,	kernel=poly;;	score=-0.234	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.758	total time=	0.7s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.825	total time=	0.3s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.744	total time=	0.5s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.809	total time=	0.4s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.883	total time=	0.4s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;	score=-0.044	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.016	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.013	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.024	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.022	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.069	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.008	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.016	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.000	total time=	0.0s
[CV 5/5]	END							



[CV 3/5]	END	C=10,	epsilon=1,	gamma=0.0001,	kernel=poly;;	score=-0.419	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=1,	gamma=0.0001,	kernel=poly;;	score=-0.273	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=1,	gamma=0.0001,	kernel=poly;;	score=-0.303	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.758	total time=	0.5s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.825	total time=	0.4s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.744	total time=	0.6s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.809	total time=	0.3s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=linear;;	score=0.883	total time=	0.3s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=-0.044	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.016	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.013	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.024	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=rbf;;	score=0.022	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.069	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.008	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.016	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.000	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=1e-07,	kernel=poly;;	score=-0.003	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=linear;;	score=0.758	total time=	0.5s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=linear;;	score=0.825	total time=	0.4s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=linear;;	score=0.744	total time=	0.6s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=linear;;	score=0.809	total time=	0.4s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=linear;;	score=0.883	total time=	0.4s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=rbf;;	score=0.757	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=rbf;;	score=0.808	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=rbf;;	score=0.746	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=rbf;;	score=0.797	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=rbf;;	score=0.872	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=poly;;	score=-0.069	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=poly;;	score=-0.008	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=poly;;	score=-0.016	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=poly;;	score=-0.000	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=0,	gamma=0.0001,	kernel=poly;;	score=-0.003	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=linear;;	score=-0.133	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=linear;;	score=-0.203	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=linear;;	score=-0.419	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=linear;;	score=-0.273	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=linear;;	score=-0.303	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=rbf;;	score=-0.133	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=rbf;;	score=-0.203	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=rbf;;	score=-0.419	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=rbf;;	score=-0.273	total time=	0.0s
[CV 5/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=rbf;;	score=-0.303	total time=	0.0s
[CV 1/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=poly;;	score=-0.133	total time=	0.0s
[CV 2/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=poly;;	score=-0.203	total time=	0.0s
[CV 3/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=poly;;	score=-0.419	total time=	0.0s
[CV 4/5]	END	C=10,	epsilon=2,	gamma=1e-07,	kernel=poly;;	score=-0.273	total time=	0.0s
[CV 5/5]	END							

```

[CV 2/5] END C=10, epsilon=0, gamma=0.0001, kernel=poly;; score=-0.008 total time= 0.0s
[CV 3/5] END C=10, epsilon=0, gamma=0.0001, kernel=poly;; score=-0.016 total time= 0.0s
[CV 4/5] END C=10, epsilon=0, gamma=0.0001, kernel=poly;; score=-0.000 total time= 0.0s
[CV 5/5] END C=10, epsilon=0, gamma=0.0001, kernel=poly;; score=-0.003 total time= 0.0s
[CV 1/5] END C=10, epsilon=5, gamma=1e-07, kernel=linear;; score=-0.133 total time= 0.0s
[CV 2/5] END C=10, epsilon=5, gamma=1e-07, kernel=linear;; score=-0.203 total time= 0.0s
[CV 3/5] END C=10, epsilon=5, gamma=1e-07, kernel=linear;; score=-0.419 total time= 0.0s
[CV 4/5] END C=10, epsilon=5, gamma=1e-07, kernel=linear;; score=-0.273 total time= 0.0s
[CV 5/5] END C=10, epsilon=5, gamma=1e-07, kernel=linear;; score=-0.303 total time= 0.0s
[CV 1/5] END C=10, epsilon=5, gamma=1e-07, kernel=rbf;; score=-0.133 total time= 0.0s
[CV 2/5] END C=10, epsilon=5, gamma=1e-07, kernel=rbf;; score=-0.203 total time= 0.0s
[CV 3/5] END C=10, epsilon=5, gamma=1e-07, kernel=rbf;; score=-0.419 total time= 0.0s
[CV 4/5] END C=10, epsilon=5, gamma=1e-07, kernel=rbf;; score=-0.273 total time= 0.0s
[CV 5/5] END C=10, epsilon=5, gamma=1e-07, kernel=rbf;; score=-0.303 total time= 0.0s
[CV 1/5] END C=10, epsilon=5, gamma=1e-07, kernel=poly;; score=-0.133 total time= 0.0s
[CV 2/5] END C=10, epsilon=5, gamma=1e-07, kernel=poly;; score=-0.203 total time= 0.0s
[CV 3/5] END C=10, epsilon=5, gamma=1e-07, kernel=poly;; score=-0.419 total time= 0.0s
[CV 4/5] END C=10, epsilon=5, gamma=1e-07, kernel=poly;; score=-0.273 total time= 0.0s
[CV 5/5] END C=10, epsilon=5, gamma=1e-07, kernel=poly;; score=-0.303 total time= 0.0s
[CV 1/5] END C=10, epsilon=5, gamma=0.0001, kernel=linear;; score=-0.133 total time= 0.0s
[CV 2/5] END C=10, epsilon=5, gamma=0.0001, kernel=linear;; score=-0.203 total time= 0.0s
[CV 3/5] END C=10, epsilon=5, gamma=0.0001, kernel=linear;; score=-0.419 total time= 0.0s
[CV 4/5] END C=10, epsilon=5, gamma=0.0001, kernel=linear;; score=-0.273 total time= 0.0s
[CV 5/5] END C=10, epsilon=5, gamma=0.0001, kernel=linear;; score=-0.303 total time= 0.0s
[CV 1/5] END C=10, epsilon=5, gamma=0.0001, kernel=rbf;; score=-0.133 total time= 0.0s
[CV 2/5] END C=10, epsilon=5, gamma=0.0001, kernel=rbf;; score=-0.203 total time= 0.0s
[CV 3/5] END C=10, epsilon=5, gamma=0.0001, kernel=rbf;; score=-0.419 total time= 0.0s
[CV 4/5] END C=10, epsilon=5, gamma=0.0001, kernel=rbf;; score=-0.273 total time= 0.0s
[CV 5/5] END C=10, epsilon=5, gamma=0.0001, kernel=rbf;; score=-0.303 total time= 0.0s
[CV 1/5] END C=10, epsilon=5, gamma=0.0001, kernel=poly;; score=-0.133 total time= 0.0s
[CV 2/5] END C=10, epsilon=5, gamma=0.0001, kernel=poly;; score=-0.203 total time= 0.0s
[CV 3/5] END C=10, epsilon=5, gamma=0.0001, kernel=poly;; score=-0.419 total time= 0.0s
[CV 4/5] END C=10, epsilon=5, gamma=0.0001, kernel=poly;; score=-0.273 total time= 0.0s
[CV 5/5] END C=10, epsilon=5, gamma=0.0001, kernel=poly;; score=-0.303 total time= 0.0s
[CV 1/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=linear;; score=-0.052 total time= 0.0s
[CV 2/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=linear;; score=-0.141 total time= 0.0s
[CV 3/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=linear;; score=-0.329 total time= 0.0s
[CV 4/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=linear;; score=-0.181 total time= 0.0s
[CV 5/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=linear;; score=-0.202 total time= 0.0s
[CV 1/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=rbf;; score=-0.081 total time= 0.0s
[CV 2/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=rbf;; score=-0.147 total time= 0.0s
[CV 3/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=rbf;; score=-0.368 total time= 0.0s
[CV 4/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=rbf;; score=-0.237 total time= 0.0s
[CV 5/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=rbf;; score=-0.234 total time= 0.0s
[CV 1/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=poly;; score=-0.082 total time= 0.0s
[CV 2/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=poly;; score=-0.147 total time= 0.0s
[CV 3/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=poly;; score=-0.369 total time= 0.0s
[CV 4/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=poly;; score=-0.237 total time= 0.0s
[CV 5/5] END C=10, epsilon=0.3, gamma=1e-07, kernel=poly;; score=-0.234 total time= 0.0s
[CV 1/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=linear;; score=-0.052 total time= 0.0s
[CV 2/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=linear;; score=-0.141 total time= 0.0s
[CV 3/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=linear;; score=-0.329 total time= 0.0s
[CV 4/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=linear;; score=-0.181 total time= 0.0s
[CV 5/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=linear;; score=-0.202 total time= 0.0s
[CV 1/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=rbf;; score=-0.052 total time= 0.0s
[CV 2/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=rbf;; score=-0.141 total time= 0.0s
[CV 3/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=rbf;; score=-0.329 total time= 0.0s
[CV 4/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=rbf;; score=-0.181 total time= 0.0s
[CV 5/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=rbf;; score=-0.202 total time= 0.0s
[CV 1/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=poly;; score=-0.082 total time= 0.0s
[CV 2/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=poly;; score=-0.147 total time= 0.0s
[CV 3/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=poly;; score=-0.369 total time= 0.0s
[CV 4/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=poly;; score=-0.237 total time= 0.0s
[CV 5/5] END C=10, epsilon=0.3, gamma=0.0001, kernel=poly;; score=-0.234 total time= 0.0s
Out[75]: GridSearchCV(estimator=SVR(),
    param_grid={'C': [1.5, 10], 'epsilon': [0, 1, 0, 2, 0, 5, 0.3],
    'gamma': [1e-07, 0.0001],
    'kernel': ('linear', 'rbf', 'poly')},
    verbose=3)

```

In [76]:

```

print(f"Best Parameters: {AdmitHyperparameter.best_params}")
print(f"Best Estimators: {AdmitHyperparameter.best_estimator}")

```

```

Best Parameters: {'C': 1.5, 'epsilon': 0, 'gamma': 1e-07, 'kernel': 'linear'}
Best Estimators: SVR(C=1.5, epsilon=0, gamma=1e-07, kernel='linear')

```

In [77]:

```

AdmitHyperPred = AdmitHyperparameter.predict(AdmitScaler.transform(Admit_X_test))

print(f"Mean Absolute Error: {metrics.mean_absolute_error(Admit_y_test, AdmitHyperPred)}")
print(f"Mean squared error: , {metrics.mean_squared_error(Admit_y_test, AdmitHyperPred)}")

```

```
print(f"Median absolute error: {metrics.median_absolute_error(Admit_y_test, AdmitHyperPred)}")
print(f"Explain variance score: , {metrics.explained_variance_score(Admit_y_test, AdmitHyperPred)}")
print(f"R2 score: , {metrics.r2_score(Admit_y_test, AdmitHyperPred)}")
```

```
Mean Absolute Error: 0.042691468821372
Mean squared error: , 0.003684961104911344
Median absolute error: 0.03014154661587254
Explain variance score: , 0.8308028744214442
R2 score: , 0.8231959455057012
```

In [ ]: