LINEAR REGRESSION TO PREDICT CHANCE OF ADMISSION

In [50]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model  import Ridge,Lasso,RidgeCV, LassoCV, ElasticNet, ElasticNetCV, L
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

In [3]:

```
df=pd.read_csv("G:\\data\\Admission_Prediction.csv")
df.head()
```

Out[3]:

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

In [4]:

```
df1=df.copy()
```

In [5]:

```
df1.shape
```

Out[5]:

```
(500, 9)
```

In [6]:

```
df1.describe(include="all")
```

Out[6]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Re
count	500.000000	485.000000	490.000000	485.000000	500.000000	500.00000	500.000000	500
mean	250.500000	316.558763	107.187755	3.121649	3.374000	3.48400	8.576440	0
std	144.481833	11.274704	6.112899	1.146160	0.991004	0.92545	0.604813	0
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1
max	500.000000	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1

In [7]:

```
#Filling Up Missing Values

df1["GRE Score"]=df1["GRE Score"].fillna(df1["GRE Score"].mean())
df1["TOEFL Score"]=df1["TOEFL Score"].fillna(df1["TOEFL Score"].mean())
df1["University Rating"]=df1["University Rating"].fillna(df1["University Rating"].median())
```

In [8]:

```
df1.describe(include="all")
```

Out[8]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Re
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500
mean	250.500000	316.558763	107.187755	3.118000	3.374000	3.48400	8.576440	0
std	144.481833	11.103952	6.051338	1.128993	0.991004	0.92545	0.604813	0
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0
25%	125.750000	309.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0
50%	250.500000	316.558763	107.000000	3.000000	3.500000	3.50000	8.560000	1
75%	375.250000	324.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1
max	500.000000	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1

In [9]:

```
#Dropping the Serial Number collumn

df1=df1.drop(columns=["Serial No."],axis=1)
```

In [10]:

```
df1.head()
```

Out[10]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337.000000	118.0	4.0	4.5	4.5	9.65	1	0.92
1	324.000000	107.0	4.0	4.0	4.5	8.87	1	0.76
2	316.558763	104.0	3.0	3.0	3.5	8.00	1	0.72
3	322.000000	110.0	3.0	3.5	2.5	8.67	1	0.80
4	314.000000	103.0	2.0	2.0	3.0	8.21	0	0.65

In [11]:

```
df1.columns
```

Out[11]:

```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR', 'CGP
A',
       'Research', 'Chance of Admit'],
      dtype='object')
```

In [ ]:

In [ ]:

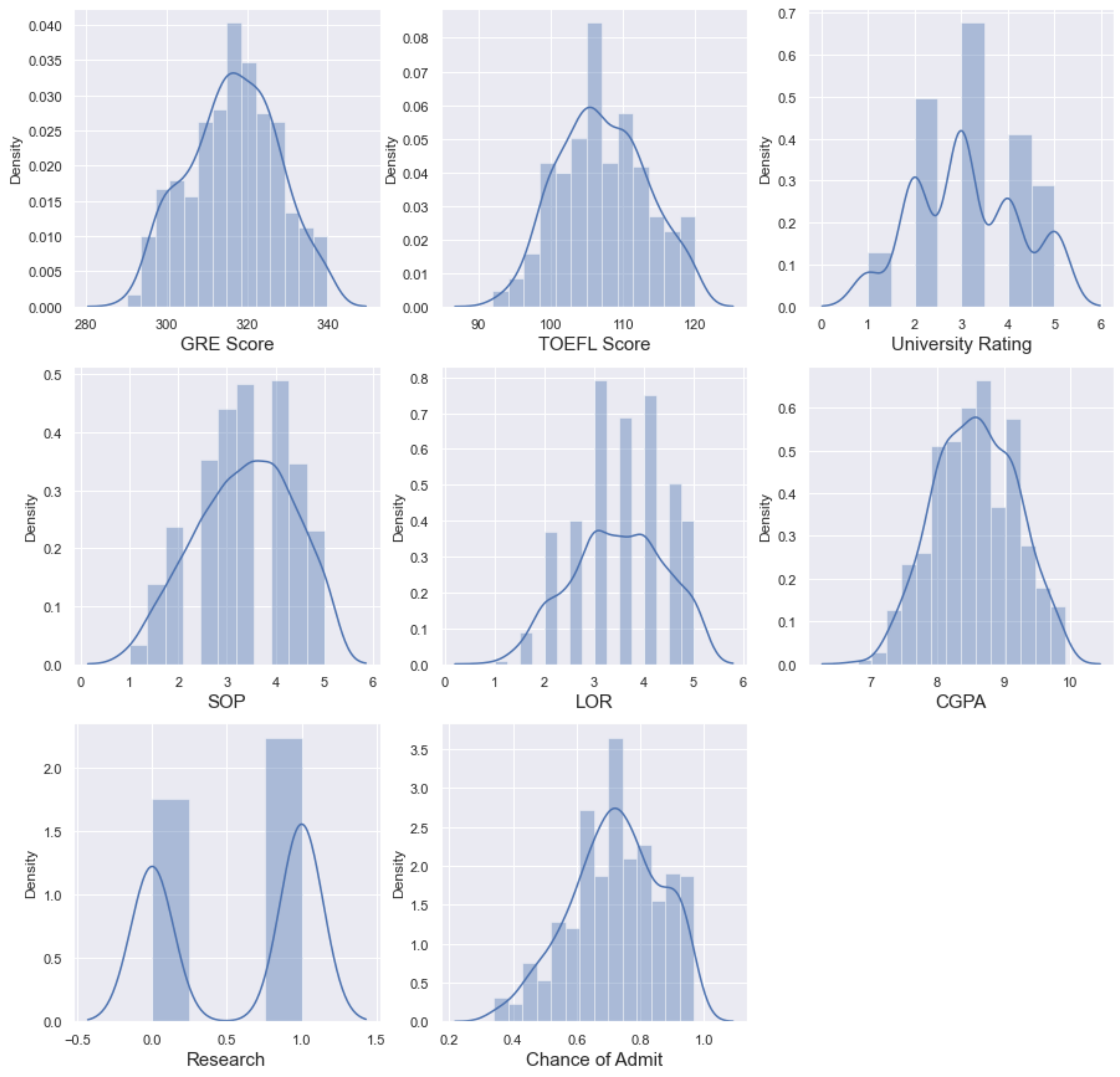
In [14]:

```
#Plotting the histogram of features to gain idea about the normality

plt.figure(figsize=(15,15))
plotnumber =1

for i in df1:
    if plotnumber<=15:
        ax=plt.subplot(3,3,plotnumber)
        sns.distplot(df1[i])
        plt.xlabel(i,fontsize=15)
    plotnumber+=1
```

```
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\Ranajay\anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-leve
l function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [41]:

```
df1.columns
```

Out[41]:

```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR', 'CGP
A',
       'Research', 'Chance of Admit'],
      dtype='object')
```

In [15]:

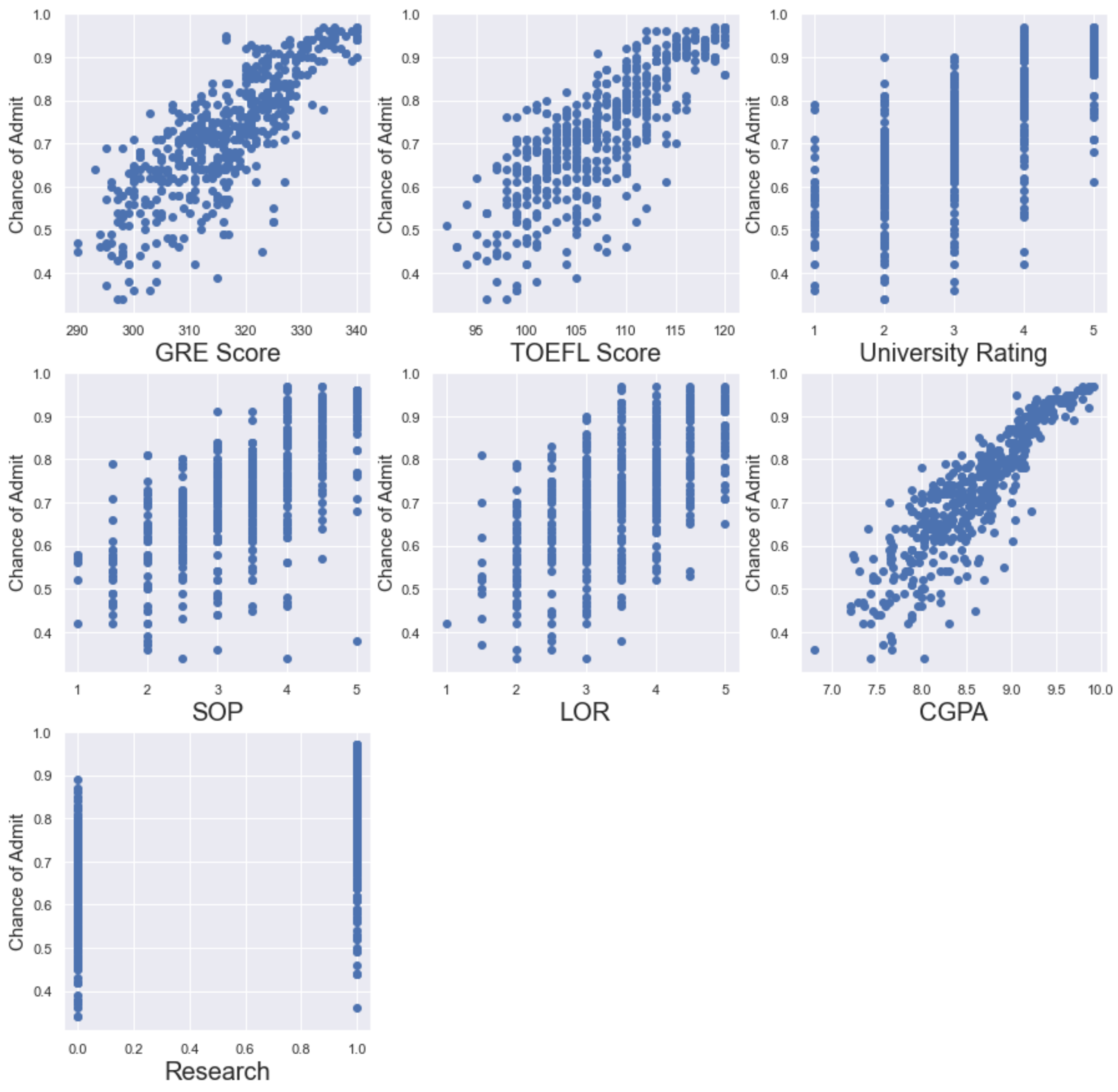
```
#Dividing the dataset into independent and dependant variables
y=df1["Chance of Admit"]
X=df1.drop(columns=["Chance of Admit"],axis=1)
```

In [16]:

```
#Scatterplots between X and y

plt.figure(figsize=(15,15))
plotnumber=1

for column in X:
    if plotnumber<=15:
        ax=plt.subplot(3,3,plotnumber)
        plt.scatter(X[column],y)
        plt.xlabel(column,fontsize=20)
        plt.ylabel("Chance of Admit",fontsize=15)
    plotnumber+=1
```



More or less linear.

In [64]:

```
#Standardizing the data.

scaler =StandardScaler()

X_scaled = scaler.fit_transform(X)
```

In [18]:

```
#Multicollinearity check

from statsmodels.stats.outliers_influence import variance_inflation_factor
variables = X_scaled

# we create a new data frame which will include all the VIFs
vif = pd.DataFrame()

# here we make use of the variance_inflation_factor, which will basically output the respec
vif["VIF"] = [variance_inflation_factor(variables, i) for i in range(variables.shape[1])]

# Finally, I would like to include names so it is easier to explore the result
vif["Features"] = X.columns
```

In [19]:

```
vif
```

Out[19]:

	VIF	Features
0	4.152735	GRE Score
1	3.793345	TOEFL Score
2	2.517272	University Rating
3	2.776393	SOP
4	2.037449	LOR
5	4.654369	CGPA
6	1.459411	Research

As a thumb rule, a VIF value greater than 10 means a very severe multicollinearity.We do not have any vif value>10 in this case

In [58]:

```
#Training and Testing

X_train, x_test, y_train, y_test= train_test_split(X_scaled,y,test_size=0.25,random_state=3
```

In [59]:

```
#Fitting the training set into a linear regression model

regression= LinearRegression()

regression.fit(X_train,y_train)
```

Out[59]:

```
LinearRegression()
```

In [22]:

```
#Let us make a function to find Adjusted R-square

def adj_R2(a,b):
    R2=regression.score(a,b)
    n= a.shape[0]
    k= a.shape[1]
    adj_R2= 1-(1-R2)*(n-1)/(n-k-1)
    return adj_R2
```

In [23]:

```
#Finding R-squared and #Adjusted R-squared for the training set

score=pd.DataFrame()

score["Method"]=["R2","Adj R2"]
score["Value"]=[regression.score(X_train,y_train),adj_R2(X_train,y_train)]

score
```

Out[23]:

	Method	Value
0	R2	0.841525
1	Adj R2	0.838502

We find that there is negligible difference between R2 and Adjusted R2.Thus we are not being penalized by use of any feature

In [24]:

```
#Finding the score for Test Data to look for overfitting:

score["Method"]=["R2","Adj R2"]
score["Value"]=[regression.score(x_test,y_test),adj_R2(x_test,y_test)]

score
```

Out[24]:

	Method	Value
0	R2	0.753490
1	Adj R2	0.738741

So it looks like our model R2 and Adjusted R2 score is less on the test data.

So we now check whether model is overfitting our training data

In [25]:

```
# Lasso Regularization
# LassoCV will return best alpha and coefficients after performing 10 cross validations

lassCV= LassoCV(alphas=None,cv=10,normalize=True,max_iter=100000)
lassCV.fit(X_train,y_train)
```

Out[25]:

```
LassoCV(cv=10, max_iter=100000, normalize=True)
```

In [26]:

```
#Best alpha parameter

alpha=lassCV.alpha_
alpha
```

Out[26]:

```
3.0341655445178153e-05
```

In [29]:

```
#now that we have best parameter, let's use Lasso regression and see how well our data has

lasso_reg= Lasso(alpha)
lasso_reg.fit(X_train,y_train)
```

Out[29]:

```
Lasso(alpha=3.0341655445178153e-05)
```

In [30]:

```
lasso_reg.score(x_test,y_test)
```

Out[30]:

```
0.7534654960492284
```

Our r2_score for test data (75.34%) comes same as before using regularization. So, it is fair to say our OLS model did not overfit the data.

In [39]:

```
#Ridge regression
alphas=np.random.uniform(low=0,high=10,size=(50,))
ridgecv= RidgeCV(alphas=alphas,cv=10,normalize=True)
ridgecv.fit(X_train,y_train)
```

Out[39]:

```
RidgeCV(alphas=array([5.44363402, 3.79446854, 2.74096334, 6.46760825, 0.6914
1592,
       2.80731163, 6.20415048, 9.47276382, 1.61579091, 2.62259262,
       4.57226322, 5.32637038, 4.25159156, 6.40290126, 5.26558927,
       2.93161182, 1.86439956, 9.97643113, 4.44478412, 5.9616184 ,
       5.8715213 , 8.36591981, 4.6817942 , 4.52595432, 4.28679354,
       3.68225933, 2.92358823, 2.72273647, 9.40646618, 7.33988227,
       9.70554947, 7.92125965, 5.87616028, 7.98891612, 5.38693007,
       7.54055143, 4.02228851, 3.26042382, 7.22453208, 0.15530369,
       2.14648996, 6.32663189, 6.83974256, 3.13569903, 3.02515556,
       7.39833411, 9.716825  , 7.51055367, 2.12402105, 9.82824446]),
        cv=10, normalize=True)
```

In [40]:

```
ridgecv.alpha_
```

Out[40]:

```
0.1553036886986936
```

In [41]:

```
ridge_model= Ridge(alpha=ridgecv.alpha_)
ridge_model.fit(X_train,y_train)
```

Out[41]:

```
Ridge(alpha=0.1553036886986936)
```

In [42]:

```
ridge_model.score(x_test,y_test)
```

Out[42]:

```
0.7535658379570921
```

We got the same R2 square using Ridge regression as well. So, it's safe to say there is no overfitting.

In [43]:

```
# Elastic net

elasticCV= ElasticNetCV(alphas=None,cv=10,normalize=True,max_iter=100000)
elasticCV.fit(X_train,y_train)
```

Out[43]:

```
ElasticNetCV(cv=10, max_iter=100000, normalize=True)
```

In [44]:

```
elasticCV.alpha_
```

Out[44]:

```
6.0683310890356314e-05
```

In [45]:

```
# l1_ration gives how close the model is to L1 regularization

elasticCV.l1_ratio
```

Out[45]:

```
0.5
```

Above value indicates we are giving equal preference to L1 and L2

In [46]:

```
elasticnet_reg=ElasticNet(alpha=elasticCV.alpha_, l1_ratio=elasticCV.l1_ratio)
elasticnet_reg.fit(X_train,y_train)
```

Out[46]:

```
ElasticNet(alpha=6.0683310890356314e-05)
```

In [47]:

```
elasticnet_reg.score(x_test,y_test)
```

Out[47]:

```
0.7534710950712854
```

So, we can see by using different type of regularization, we still are getting the same r2 score. That means our OLS model has been well trained over the training data and there is no overfitting.

Prediction

We want to predict the Admission chance for the array [300,110,5,5,5,10,1]

In [61]:

```
import pickle
```

In [62]:

```
# saving the model to the local file system
filename = 'finalized_model.pickle'
pickle.dump(regression, open(filename, 'wb'))
```

In [65]:

```
# prediction using the saved model
loaded_model = pickle.load(open(filename, 'rb'))
a=loaded_model.predict(scaler.transform([[300,110,5,5,5,10,1]]))
a
```

Out[65]:

```
array([0.92190162])
```

In [68]:

```
#We can also do it directly  without creating a pickle file

regression.predict(scaler.transform([[300,110,5,5,5,10,1]]))
```

Out[68]:

```
array([0.92190162])
```

So the person with GRE Score=300, TOEFL Score=110, University Rating=5, SOP=5, LOR=5,CGPA=10,Research=1 has a 92% chance of getting admission

In [ ]:

```

```

In [ ]:

```

```