REPORT ON PREDICTION OF ADMISSION IN ENGINEERING

MACHINE LEARING

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Question No.:5

Problem Statement :

"Due to the changing technology and its requirement for getting employed in India and abroad, there has to be improvements suggested by experts for predicting the Prediction of **Admission** in Engineering & Technology with respect to his/her strength, age, location and similar important factors. This is not a one time process and needs to be done frequently as trends in the industry keep changing. Addressing this problem will introduce the required changes that would bring the current youth and upcoming generations in parallel with the students of other countries in terms of knowledge and skills in that domain."

Dataset:
https://www.kaggle.com/code/suneelpatel/graduate-admission-analysis-and-prediction/data

Predict using **Lasso** Regression

Description :

To build a machine learning model which predicts Admissions in engineering based upon various parameters present in dataset. This problem statement comes under regression.

Steps involved in building my model:

1. Importing the data set.
2. Handling the null values.
3. Visualizing the dataset for better understanding.
4. Splitting the dataset into training and testing data.
5. Importing all the regression model.
6. Fitting the training and testing data into different regression models.
7. Building models
    a. Linear regression
    b. Lasso regression
    c. Ridge regression
    d. Elastic net
8. Predicting the habitability score using all the above models.

CODE :

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

data=pd.read_csv('Admission_Predict.csv')

df=pd.DataFrame(data)

df.head()

categorical = [var for var in df.columns if df[var].dtype=='O']

print('There are {} categorical variables\n'.format(len(categorical)))

print('The categorical variables are :\n\n', categorical)

df.isnull().sum()

import matplotlib.pyplot as plt

import seaborn as sns

col=df.columns

fig,ax=plt.subplots(figsize=(10,5))

corr=df[col].corr()

sns.heatmap(corr,annot=True,mask=np.triu(np.ones_like(corr,dtype=bool)))

x=df.iloc[:,0:8]

y=df.iloc[:,8]

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)

all_metrics=['Regression','MSE','RMSE','R2']

summary=[]

name='Lasso'
```

```
from sklearn import linear_model
lasso_reg=linear_model.Lasso(alpha=50,max_iter=100,tol=0.1)
lasso_reg.fit(x_train,y_train)
y_pred_lasso = lasso_reg.predict(x_test)
from sklearn.metrics import mean_squared_error,r2_score
mse=mean_squared_error(y_test,y_pred_lasso)
print("MSE :",mse)
rmse=np.sqrt(mse)
print("RMSE :",rmse)
r2=r2_score(y_test,y_pred_lasso)
print("R2 :",r2)
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
reg = LinearRegression()
reg.fit(x_train, y_train)
y_pred= reg.predict(x_test)
print("Cofficient :",reg.coef_)
print("Intercept :",reg.intercept_)
print("Test Score",reg.score(x_test,y_test))
print("Train Score :",reg.score(x_train,y_train))
mean_squared_error = np.mean((y_pred - y_test)**2)
print(mean_squared_error)
name1='Linear'
from sklearn.metrics import mean_squared_error,r2_score
```

```
mse=mean_squared_error(y_test,y_pred)
print("MSE :",mse)
rmse=np.sqrt(mse)
print("RMSE :",rmse)
r2=r2_score(y_test,y_pred)
print("R2 :",r2)
summary.append([name1,mse,rmse,r2])
name2='Elastic Net'
from sklearn.linear_model import ElasticNet
e_net = ElasticNet(alpha = 1)
e_net.fit(x_train, y_train)
y_pred_elastic = e_net.predict(x_test)
from sklearn.metrics import mean_squared_error,r2_score
mse=mean_squared_error(y_test,y_pred_elastic)
print("MSE :",mse)
rmse=np.sqrt(mse)
print("RMSE :",rmse)
r2=r2_score(y_test,y_pred_elastic)
print("R2 :",r2)
summary.append([name2,mse,rmse,r2])
name3='Ridge'
from sklearn.linear_model import Ridge
ridge_reg=Ridge(alpha=50,max_iter=100,tol=0.1)
ridge_reg.fit(x_train,y_train)
```

```
print("Test Score :",ridge_reg.score(x_test,y_test))

print("Train Score :",ridge_reg.score(x_train,y_train))

y_predict_ridge_reg = ridge_reg.predict(x_test)

from sklearn.metrics import mean_squared_error,r2_score

mse=mean_squared_error(y_test,y_predict_ridge_reg)

print("MSE :",mse)

rmse=np.sqrt(mse)

print("RMSE :",rmse)

r2=r2_score(y_test,y_predict_ridge_reg)

print("R2 :",r2)

summary.append([name3,mse,rmse,r2])

summary=pd.DataFrame(summary,columns=all_metrics)

summary

plt.barh(summary.iloc[:,0],summary.iloc[:,1])

plt.title('MSE Comparison')

for i,value in enumerate(summary.iloc[:,1]):

   plt.text(value,i,str(value))

plt.show()

plt.barh(summary.iloc[:,0],summary.iloc[:,2])

plt.title('RMSE Comparison')

for i,value in enumerate(summary.iloc[:,2]):

   plt.text(value,i,str(value))

plt.show()

plt.barh(summary.iloc[:,0],summary.iloc[:,3])
```

plt.title('R2 Comparison')

for i,value in enumerate(summary.iloc[:,3]):

    plt.text(value,i,str(value))

plt.show()

Importing Libraries

In [84]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

Data Preprocessing

In [3]:
```
data=pd.read_csv('Admission_Predict.csv')
df=pd.DataFrame(data)
df.head()
```

Out[3]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65

In [4]:
```
df.shape
```

Out[4]:
```
(400, 9)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Serial No.         400 non-null    int64
 1   GRE Score          400 non-null    int64
 2   TOEFL Score        400 non-null    int64
 3   University Rating  400 non-null    int64
 4   SOP                400 non-null    float64
 5   LOR                400 non-null    float64
 6   CGPA               400 non-null    float64
 7   Research           400 non-null    int64
 8   Chance of Admit    400 non-null    float64
dtypes: float64(4), int64(5)
memory usage: 28.2 KB
```

In [86]:
```
df.describe()
```

Out[86]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000
mean	200.500000	316.807500	107.410000	3.087500	3.400000	3.452500	8.598925	0.547500	0.724350
std	115.614301	11.473646	6.069514	1.143728	1.006869	0.898478	0.596317	0.498362	0.142609
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.000000	6.800000	0.000000	0.340000
25%	100.750000	308.000000	103.000000	2.000000	2.500000	3.000000	8.170000	0.000000	0.640000
50%	200.500000	317.000000	107.000000	3.000000	3.500000	3.500000	8.610000	1.000000	0.730000

Check for Categorical Data

In [6]:
```
categorical = [var for var in df.columns if df[var].dtype=='O']
print('There are {} categorical variables\n'.format(len(categorical)))
print('The categorical variables are :\n\n', categorical)
```

```
There are 0 categorical variables

The categorical variables are :

 []
```

Check for Missing Values

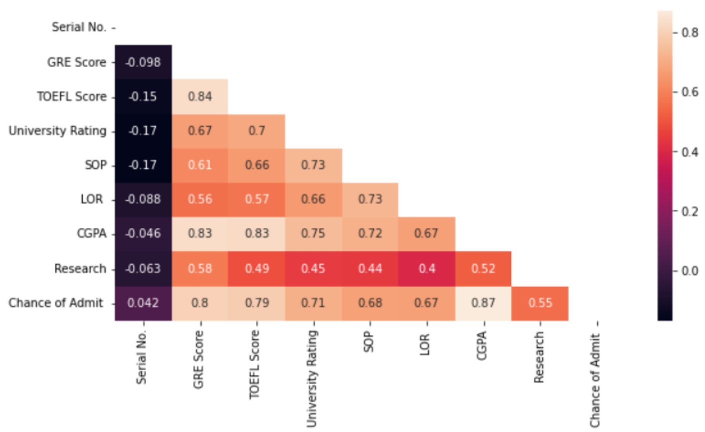
In [7]:
```
df.isnull().sum()
```

Out[7]:
```
Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

Correlation

In [8]:
```
import matplotlib.pyplot as plt
import seaborn as sns
col=df.columns
fig,ax=plt.subplots(figsize=(10,5))
corr=df[col].corr()
sns.heatmap(corr,annot=True,mask=np.triu(np.ones_like(corr,dtype=bool)))
```

Out[8]: <AxesSubplot:>



In [10]:
```
x=df.iloc[:,0:8]
y=df.iloc[:,8]
```

Out[10]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
0	1	337	118	4	4.5	4.5	9.65	1
1	2	324	107	4	4.0	4.5	8.87	1
2	3	316	104	3	3.0	3.5	8.00	1
3	4	322	110	3	3.5	2.5	8.67	1
4	5	314	103	2	2.0	3.0	8.21	0
...	...	...	...	...	...	...	...	...
395	396	324	110	3	3.5	3.5	9.04	1
396	397	325	107	3	3.0	3.5	9.11	1
397	398	330	116	4	5.0	4.5	9.45	1
398	399	312	103	3	3.5	4.0	8.78	0
399	400	333	117	4	5.0	4.0	9.66	1

400 rows × 8 columns

Target Variable

In [93]:
```
y
```

Out[93]:
```
0      0.92
1      0.76
2      0.72
```

Splitting Data

In [11]:
```
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)
```

Lasso Regression

In [69]:
```
name='Lasso'
from sklearn import linear_model
lasso_reg=linear_model.Lasso(alpha=50,max_iter=100,tol=0.1)
lasso_reg.fit(x_train,y_train)
y_pred_lasso = lasso_reg.predict(x_test)
from sklearn.metrics import mean_squared_error,r2_score
mse=mean_squared_error(y_test,y_pred_lasso)
print("MSE :",mse)
rmse=np.sqrt(mse)
print("RMSE :",rmse)
r2=r2_score(y_test,y_pred_lasso)
print("R2 :",r2)
```

```
MSE : 0.018300454101562502
RMSE : 0.13527917098194572
R2 : -0.0073191050460172935
```

Grid Search

In [70]:
```
from sklearn.model_selection import GridSearchCV
alpha=[1,0.1,0.01,0.001,0.0001]
param_grid=dict(alpha=alpha)
cv=GridSearchCV(estimator=lasso_reg,param_grid=param_grid,scoring='r2',verbose=1)
cv_result=cv.fit(x_train,y_train)
print("Best Score :",cv_result.best_score_)
print("Optimal Learning Rate :",cv_result.best_params_)
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
Best Score : 0.8174698463132634
Optimal Learning Rate : {'alpha': 0.0001}
```

In [71]:
```
lasso_reg1=linear_model.Lasso(alpha=0.0001)
lasso_reg1.fit(x_train,y_train)
y_pred_lasso1 = lasso_reg1.predict(x_test)
from sklearn.metrics import mean_squared_error,r2_score
mse=mean_squared_error(y_test,y_pred_lasso1)
print("MSE :",mse)
rmse=np.sqrt(mse)
print("RMSE :",rmse)
r2=r2_score(y_test,y_pred_lasso)
print("R2 :",r2)
summary.append([name,mse,rmse,r2])
```

```
MSE : 0.004363534605680688
RMSE : 0.06605705568431497
R2 : -0.0073191050460172935
```

In [95]:
```
y_pred_lasso1
```

Out[95]:
```
array([0.69248863, 0.71641068, 0.79961683, 0.61414503, 0.72396198,
       0.57757922, 0.69854768, 0.65376503, 0.86013677, 0.92188296,
       0.5069094 , 0.8774854 , 0.69679481, 0.48109587, 0.82558075,
       0.59549636, 0.63648914, 0.79871241, 0.58629372, 0.73092045,
       0.87879199, 0.8564732 , 0.64810932, 0.47754236, 0.78628006,
       0.60297593, 0.48126932, 0.61698352, 0.91080019, 0.63720429,
       0.62987227, 0.75595068, 0.76843385, 0.5558714 , 0.76484414,
       0.75232102, 0.63996787, 0.85721455, 0.62591153, 0.96165105,
       0.71264697, 0.68593653, 0.6825164 , 0.77626193, 0.84300863,
       0.63948264, 0.59246734, 0.70957984, 0.59783902, 0.60030165,
       0.67353732, 0.78529419, 0.65917558, 0.88265858, 0.73340739,
       0.77009479, 0.70374123, 0.7053033 , 0.74065772, 0.81263768,
       0.74418599, 0.47550956, 0.59992646, 0.54473879, 0.84339826,
       0.84150049, 0.7229683 , 0.84410946, 0.75655041, 0.7637281 ,
       0.56733111, 0.84415455, 0.79916165, 0.58829877, 0.91474455,
       0.61031907, 0.65522188, 0.65723103, 0.93217513, 0.53065993])
```

In [72]:
```
labels=['Model','MSE','RMSE','R2']
pd.DataFrame([['Lasso Regression',mse,rmse,r2]],columns=labels)
```

Out[72]:

	Model	MSE	RMSE	R2
0	Lasso Regression	0.004364	0.066057	-0.007319

Comparison

Linear Regression

In [73]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
reg = LinearRegression()
reg.fit(x_train, y_train)
y_pred= reg.predict(x_test)
print("Cofficient :",reg.coef_)
print("Intercept :",reg.intercept_)
print("Test Score",reg.score(x_test,y_test))
print("Train Score :",reg.score(x_train,y_train))
mean_squared_error = np.mean((y_pred - y_test)**2)
print(mean_squared_error)
```

```
Cofficient : [ 0.0001531   0.00202242  0.00273325  0.0098671  -0.00075995  0.01967423
  0.11250958  0.02385384]
Intercept : -1.3181528289408715
Test Score 0.7594824470194687
Train Score : 0.8308145815615404
0.004369598885687038
```

In [74]:
```
name1='Linear'
from sklearn.metrics import mean_squared_error,r2_score
mse=mean_squared_error(y_test,y_pred)
print("MSE :",mse)
rmse=np.sqrt(mse)
print("RMSE :",rmse)
r2=r2_score(y_test,y_pred)
print("R2 :",r2)
summary.append([name1,mse,rmse,r2])
```

```
MSE : 0.004369598885687038
RMSE : 0.0661030415811063
```

Elastic Net

In [76]:
```
name2='Elastic Net'
from sklearn.linear_model import ElasticNet
e_net = ElasticNet(alpha = 1)
e_net.fit(x_train, y_train)
y_pred_elastic = e_net.predict(x_test)
from sklearn.metrics import mean_squared_error,r2_score
mse=mean_squared_error(y_test,y_pred_elastic)
print("MSE :",mse)
rmse=np.sqrt(mse)
print("RMSE :",rmse)
r2=r2_score(y_test,y_pred_elastic)
print("R2 :",r2)
summary.append([name2,mse,rmse,r2])
```

```
MSE : 0.008874715462533312
RMSE : 0.09420570822690795
R2 : 0.511505540373786
```

Ridge Regression

In [77]:
```
name3='Ridge'
from sklearn.linear_model import Ridge
ridge_reg=Ridge(alpha=50,max_iter=100,tol=0.1)
ridge_reg.fit(x_train,y_train)
print("Test Score :",ridge_reg.score(x_test,y_test))
print("Train Score :",ridge_reg.score(x_train,y_train))
y_predict_ridge_reg = ridge_reg.predict(x_test)
from sklearn.metrics import mean_squared_error,r2_score
mse=mean_squared_error(y_test,y_predict_ridge_reg)
```

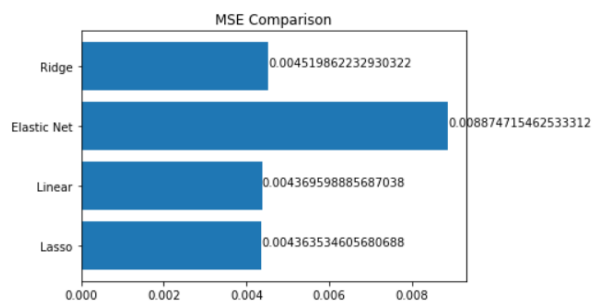
Summary

In [78]:
```
summary=pd.DataFrame(summary,columns=all_metrics)
summary
```

Out[78]:

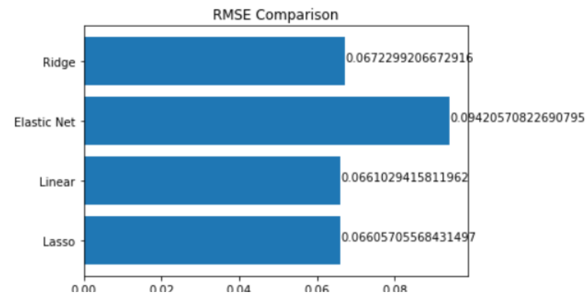
	Regression	MSE	RMSE	R2
0	Lasso	0.004364	0.066057	-0.007319
1	Linear	0.004370	0.066103	0.759482
2	Elastic Net	0.008875	0.094206	0.511506
3	Ridge	0.004520	0.067230	0.751211

In [80]:
```
plt.barh(summary.iloc[:,0],summary.iloc[:,1])
plt.title('MSE Comparison')
for i,value in enumerate(summary.iloc[:,1]):
    plt.text(value,i,str(value))
plt.show()
```



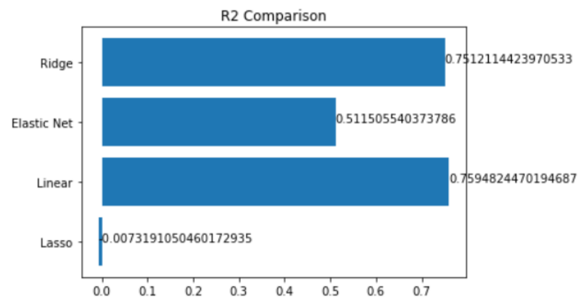
In [82]:

```
plt.barh(summary.iloc[:,0],summary.iloc[:,2])
plt.title('RMSE Comparison')
for i,value in enumerate(summary.iloc[:,2]):
    plt.text(value,i,str(value))
plt.show()
```



In [83]:

```
plt.barh(summary.iloc[:,0],summary.iloc[:,3])
plt.title('R2 Comparison')
for i,value in enumerate(summary.iloc[:,3]):
    plt.text(value,i,str(value))
plt.show()
```



Analysis :

Dataset is taken and it is analysed through some pre processing steps and feature selection.

Then different models were built like Linear Regression, Ridge Regression, Lasso Regression and Elastic Net Regression. Their Admission prediction scores are compared with each other. So for this particular dataset Lasso regression model is best Suitable

Github

url: https://github.com/shoebking/ML_Case_Study