Data Exploration GRE Scores Case Study

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
#reading the data
df= pd.read_csv("/content/Admission_Predict.csv")
#how the data looks
df.head()
```

	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

df.shape

(400, 8)

print("DATA INFORMATION AND DATA TYPES") df.info()

DATA INFORMATION AND DATA TYPES <class 'pandas.core.frame.DataFrame'> RangeIndex: 400 entries, 0 to 399 Data columns (total 8 columns):

#	Column	Non-Null Count	Dtype
0	GRE Score	400 non-null	int64
1	TOEFL Score	400 non-null	int64
2	University Rating	400 non-null	int64
3	SOP	400 non-null	float64
4	LOR	400 non-null	float64
5	CGPA	400 non-null	float64
6	Research	400 non-null	int64
7	Chance of Admit	400 non-null	float64

dtypes: float64(4), int64(4)
memory usage: 25.1 KB

df.drop("SOP",axis=1,inplace=True)

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 8 columns):

#	Column	Non-Null Count	Dtype
0	GRE Score	400 non-null	int64
1	TOEFL Score	400 non-null	int64
2	University Rating	400 non-null	int64
3	SOP	400 non-null	float64
4	LOR	400 non-null	float64
5	CGPA	400 non-null	float64
6	Research	400 non-null	int64

7 Chance of Admit 400 non-null float64

dtypes: float64(4), int64(4)
memory usage: 25.1 KB

print('MISSING DATA (IF ANY)') df.isnull().sum()

MISSING DATA (IF ANY) Serial No. GRE Score 0 TOEFL Score 0 University Rating 0 SOP LOR 0 CGPA 0 Research 0 Chance of Admit 0 dtype: int64

df.describe()

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	CI
count	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	40
mean	200.500000	316.807500	107.410000	3.087500	3.400000	3.452500	8.598925	0.547500	
std	115.614301	11.473646	6.069514	1.143728	1.006869	0.898478	0.596317	0.498362	
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.000000	6.800000	0.000000	
25%	100.750000	308.000000	103.000000	2.000000	2.500000	3.000000	8.170000	0.000000	
50%	200.500000	317.000000	107.000000	3.000000	3.500000	3.500000	8.610000	1.000000	
75%	300.250000	325.000000	112.000000	4.000000	4.000000	4.000000	9.062500	1.000000	
max	400.000000	340.000000	120.000000	5.000000	5.000000	5.000000	9.920000	1.000000	

df.corr()

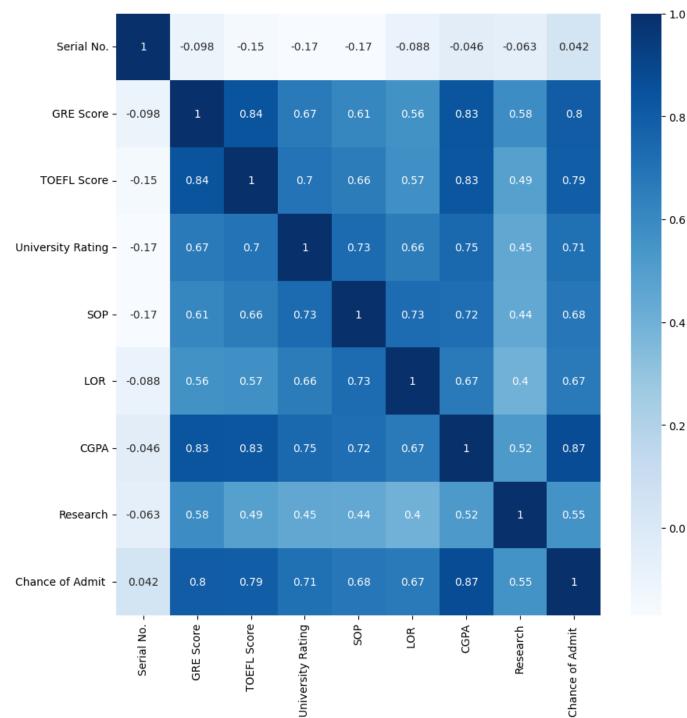
	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	CI
Serial No.	1.000000	-0.097526	-0.147932	-0.169948	-0.166932	-0.088221	-0.045608	-0.063138	
GRE Score	-0.097526	1.000000	0.835977	0.668976	0.612831	0.557555	0.833060	0.580391	
TOEFL Score	-0.147932	0.835977	1.000000	0.695590	0.657981	0.567721	0.828417	0.489858	
University Rating	-0.169948	0.668976	0.695590	1.000000	0.734523	0.660123	0.746479	0.447783	
SOP	-0.166932	0.612831	0.657981	0.734523	1.000000	0.729593	0.718144	0.444029	
LOR	-0.088221	0.557555	0.567721	0.660123	0.729593	1.000000	0.670211	0.396859	
CGPA	-0.045608	0.833060	0.828417	0.746479	0.718144	0.670211	1.000000	0.521654	
Research	-0.063138	0.580391	0.489858	0.447783	0.444029	0.396859	0.521654	1.000000	
Chance of Admit	0.042336	0.802610	0.791594	0.711250	0.675732	0.669889	0.873289	0.553202	

There is a 0.802 correlation between the GRE score and the chance of admission. So there might be a big chance that these variables (data) are highly related. In fact, the correlation is the second-highest, after the CGPA. So, we can determine that CGPA

and GRE scores are most important in determining the chances of admission.

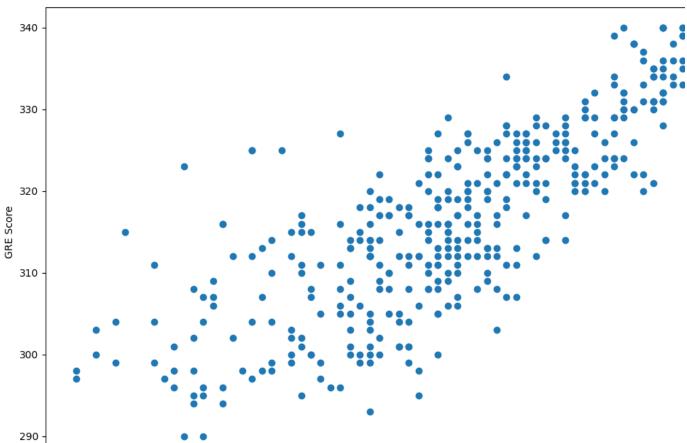
```
plt.figure(figsize = (10,10))
sns.heatmap(df.corr(),annot=True, cmap='Blues')
```

<Axes: >



```
plt.subplots(figsize=(12,8))
plt.scatter(df["Chance of Admit "],df["GRE Score"])
plt.xlabel("Chance of Admit")
plt.ylabel("GRE Score")
```

Text(0, 0.5, 'GRE Score')



#There does appear to be a connection between the two variables. Some exploration needs to be done.

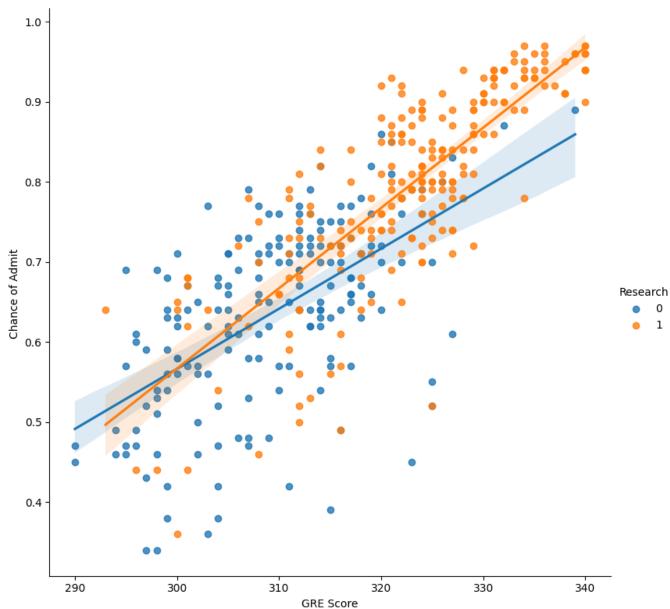
plt.subplots(figsize=(12,8))
sns.regplot(x="GRE Score", y="Chance of Admit ", data=df)

<Axes: xlabel='GRE Score', ylabel='Chance of Admit '>

Research experience of a candidate helps in getting admits
sns.lmplot(x="GRE Score", y="Chance of Admit ", data=df, hue="Research",height= 8)

#The data does show that candidates having research experience (orange in the figure), usually have more chance of admit #Having research experience is very important.

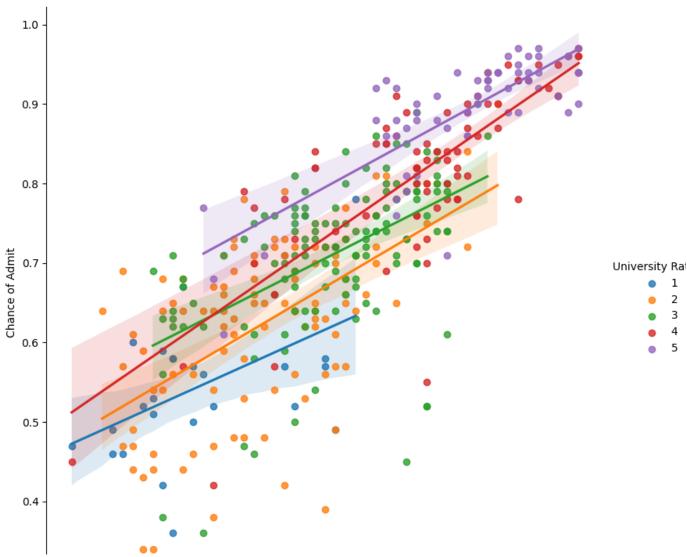




#university ratings

sns.lmplot(x="GRE Score", y="Chance of Admit ", data=df, hue="University Rating",height=8)





Observations:

Students having higher GRE scores (>320) usually have a high chance of admission into the university with higher ratings (4/5). A lower GRE score has a lower chance of admission, that too for universities of low ratings. Students having a higher chance of admission, all have good GRE scores and University ratings of 4 or 5. Now we take some data where we take chances of admit to being 0.8 or higher and check how important are GRE scores.

admit_high_chance= df[df["Chance of Admit "]>=0.8] admit_high_chance.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 128 entries, 0 to 399
Data columns (total 9 columns):
    Column
                       Non-Null Count Dtype
    -----
                       -----
    Serial No.
0
                       128 non-null
                                       int64
    GRE Score
                       128 non-null
                                       int64
1
    TOEFL Score
                       128 non-null
                                       int64
    University Rating 128 non-null
                                       int64
    SOP
                        128 non-null
                                       float64
5
    LOR
                                       float64
                       128 non-null
    CGPA
                       128 non-null
                                       float64
6
                       128 non-null
                                       int64
    Research
    Chance of Admit
                       128 non-null
                                       float64
dtypes: float64(4), int64(5)
memory usage: 10.0 KB
```

admit_high_chance.corr()

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	CI
Serial No.	1.000000	-0.140435	-0.223184	-0.211793	-0.088391	-0.141164	-0.220561	-0.031246	-
GRE Score	-0.140435	1.000000	0.722463	0.358013	0.320138	0.246629	0.754434	0.167532	
TOEFL Score	-0.223184	0.722463	1.000000	0.274811	0.337175	0.302047	0.648308	0.083921	
University Rating	-0.211793	0.358013	0.274811	1.000000	0.584860	0.531448	0.479284	0.190083	
SOP	-0.088391	0.320138	0.337175	0.584860	1.000000	0.601405	0.519791	0.148911	
LOR	-0.141164	0.246629	0.302047	0.531448	0.601405	1.000000	0.441634	0.050772	
CGPA	-0.220561	0.754434	0.648308	0.479284	0.519791	0.441634	1.000000	0.158186	
Research	-0.031246	0.167532	0.083921	0.190083	0.148911	0.050772	0.158186	1.000000	
Chance of Admit	-0.227214	0.716187	0.673774	0.584556	0.565463	0.488480	0.871533	0.226028	

Now let us look at the distribution of Chance of Admit and GRE score.

plt.subplots(figsize=(12,8))
sns.set_theme(style="darkgrid")
sns.distplot(admit_high_chance["GRE Score"])

<ipython-input-12-02911b31d2ab>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

```
sns.distplot( admit_high_chance["GRE Score"])
<Axes: xlahel='GRE Score'. vlahel='Densitv'>
```

plt.subplots(figsize=(12,8))
sns.set_theme(style="darkgrid")

sns.distplot(admit_high_chance["Chance of Admit "])

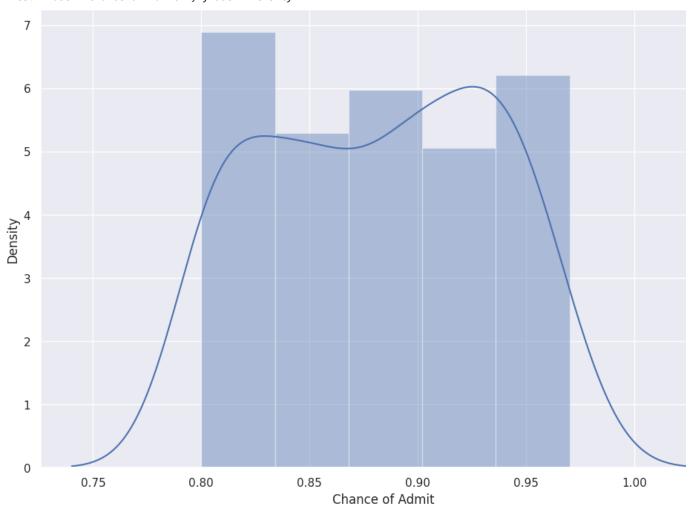
<ipython-input-13-ab381f61a609>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(admit_high_chance["Chance of Admit "])
<Axes: xlabel='Chance of Admit ', ylabel='Density'>



Observations:

For a higher chance of admission, the GRE score is also high. Maximum GRE scores are in the range of 320-340.

```
#Linear Regression between GRE Scores and the chance of admit:
X= df["GRE Score"].values
#bringing GRE score in a range of 0-1
X=X/340
y= df["Chance of Admit "].values
#sk learn train test split data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25)
#sk learn linear regression
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
#training the model on training data
lr.fit(X_train.reshape(-1,1), y_train)
y_pred = lr.predict(X_test.reshape(-1,1))
#model score
lr.score(X_test.reshape(-1,1),y_test.reshape(-1,1))
     0.6334295343566941
plt.subplots(figsize=(12,8))
plt.scatter(X_train, y_train, color = "red")
plt.plot(X_train, lr.predict(X_train.reshape(-1,1)), color = "green")
plt.title("GRE Score vs Chance of Admit")
plt.xlabel("GRE Score")
plt.ylabel("Chance Of Admit")
plt.show()
```

GRE Score vs Chance of Admit

1.0

The model is not performing that well, but we do understand that there is a correlation between GRE scores and the chance of admit.

```
#test input
test= 320
val= test/340
val_out=lr.predict(np.array([[val]]))
print("Chance of admission :", val_out[0])
     Chance of admission: 0.754513490079177
                               • - -
#Creating a Model on the entire data:
x = df.drop(['Chance of Admit ','Serial No.'],axis=1)
y = df['Chance of Admit ']
X_train, X_test, y_train, y_test = train_test_split(x,y,test_size=0.25, random_state = 7)
#random forest regression
from sklearn.ensemble import RandomForestRegressor
regr = RandomForestRegressor(max_depth=2, random_state=0, n_estimators=5)
regr.fit(X_train,y_train)
regr.score(X_test, y_test)
     0.6901443456671795
#Let us work with a sample input.
val=regr.predict([[325, 100, 3, 4.1, 3.7, 7.67, 1]])
print("Your chances are (in %):")
print(val[0]*100)
     Your chances are (in %):
     54.47694678499888
     /usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but
       warnings.warn(
    4
```

Conclusion: GRE Score is important for admission. Students having good GRE score, seem to have good overall profiles. There are obviously exceptions, which comprise the outliers.

A machine learning model classifier using Decision tree to predict

df.head()

df['Chance of Admit'] = [1 if each > 0.75 else 0 for each in df['Chance of Admit']]
df.head()

```
Serial No. GRE Score TOEFL Score University Rating SOP
                                                                     LOR CGPA Research Chance of Admit
      0
                  1
                           337
                                                                 4.5
                                                                      4.5
                                                                           9.65
                                                                                                          1
                                         118
                  2
                           324
                                                                           8.87
      1
                                         107
                                                                 4.0
                                                                      4.5
                                                                                        1
                                                                                                          1
                  3
                           316
                                         104
                                                                 3.0
                                                                      3.5
                                                                           8.00
      3
                  4
                           322
                                         110
                                                                 3.5
                                                                      2.5
                                                                           8.67
                                                                                                          1
                  5
                           314
                                         103
                                                                 2.0
                                                                      3.0
                                                                           8.21
                                                                                                          0
x = df[['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR', 'CGPA',
y = df['Chance of Admit ']
from sklearn.model_selection import train_test_split
```

x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.25,random_state=1)
print(f"Size of splitted data")
print(f"x_train {x_train.shape}")
print(f"y_train {y_train.shape}")
print(f"y_train {x_test.shape}")
print(f"y_test {y_test.shape}")

Size of splitted data
 x_train (300, 7)
 y_train (300,)
 y_train (100, 7)
 y_test (100,)

from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LogisticRegression
model_dt = DecisionTreeRegressor(random_state=1)
model_rf = RandomForestRegressor(random_state=1)
model_lr = LogisticRegression(random_state=1,solver='lbfgs',max_iter=1000)

model_dt.fit(x_train,y_train)

```
DecisionTreeRegressorDecisionTreeRegressor(random_state=1)
```

model_rf.fit(x_train,y_train)

```
r RandomForestRegressor
RandomForestRegressor(random_state=1)
```

model_lr.fit(x_train,y_train)

```
LogisticRegression
LogisticRegression(max_iter=1000, random_state=1)
```

```
y_pred_dt = model_dt.predict(x_test) #int
https://colab.research.google.com/drive/1lc0FryFiOal-bhWis9KFSxJfw808t2Rv#scrollTo=npz0fhRNbvrT
```

```
y_pred_rf = model_rf.predict(x_test) #float
y_pred_lr = model_lr.predict(x_test) #

result = pd.DataFrame({
    "Actual": y_test,
    "predicted" : y_pred_dt })
result
```

	Actual	predicted
398	0	1.0
125	0	0.0
328	1	1.0
339	1	0.0
172	1	1.0
300	0	0.0
277	0	0.0
289	1	0.0
260	1	1.0
173	1	1.0

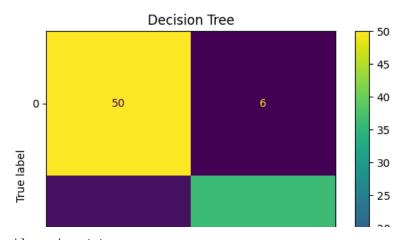
100 rows × 2 columns

```
y_pred_rf = [1 if each > 0.75 else 0 for each in y_pred_rf]
```

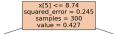
from sklearn.metrics import ConfusionMatrixDisplay, accuracy_score
from sklearn.metrics import classification_report

Decision Tree

```
ConfusionMatrixDisplay.from_predictions(y_test,y_pred_dt)
plt.title('Decision Tree')
plt.show()
print(f" Accuracy is {accuracy_score(y_test,y_pred_dt)}")
print(classification_report(y_test,y_pred_dt))
```



from sklearn import tree
import matplotlib.pyplot as plt
plt.figure(figsize=(30,30))
tree.plot_tree(model_dt, filled=True, fontsize=16)
plt.show()

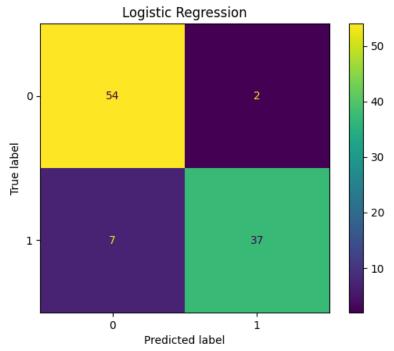


samples = 124

Logistic Regression

ConfusionMatrixDisplay.from_predictions(y_test,y_pred_lr) plt.title('Logistic Regression') plt.show()

print(f" Accuracy is {accuracy_score(y_test,y_pred_lr)}") print(classification_report(y_test,y_pred_lr))

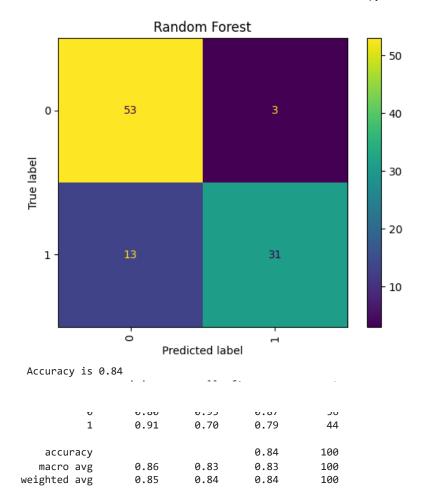


samples = 1/6

0.91			
precision	recall	f1-score	support
0.89	0.96	0.92	56
0.95	0.84	0.89	44
		0.91	100
0.02	0.00		
			100
0.91	0.91	0.91	100
	precision 0.89	precision recall 0.89 0.96 0.95 0.84 0.92 0.90	precision recall f1-score 0.89 0.96 0.92 0.95 0.84 0.89 0.91 0.92 0.90 0.91

Random Forest

ConfusionMatrixDisplay.from_predictions(y_test,y_pred_rf,xticks_rotation='vertical') plt.title('Random Forest') plt.show() print(f" Accuracy is {accuracy_score(y_test,y_pred_rf)}") print(classification_report(y_test,y_pred_rf))



×