## Gemini ✓ ••

## **Jamboore Admission case study**

Jamboree has helped thousands of students like you make it to top colleges abroad. Be it GMAT, GRE or SAT, their unique problem-solving methods ensure maximum scores with minimum effort.

They recently launched a feature where students/learners can come to their website and check their probability of getting into the IVY league college.

This feature estimates the chances of graduate admission from an Indian perspective.

### How can you help here?

Your analysis will help Jamboree in understanding what factors are important in graduate admissions and how these factors are interrelated among themselves. It will also help predict one's chances of admission given the rest of the variables.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv('/content/Jamboree_Admission.csv')

Double-click (or enter) to edit

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
₹	Д	399	110	3	3 5	25	ደ 67	1	0.80

Next steps:

Generate code with df

View recommended plots

New interactive sheet

df.describe()



		Serial No.	GRE Score	TOEFL Score	University Rating	SOP	l
CC	ount	500.000000	500.000000	500.000000	500.000000	500.000000	500.000
m	ean	250.500000	316.472000	107.192000	3.114000	3.374000	3.484
S	std	144.481833	11.295148	6.081868	1.143512	0.991004	0.925
n	nin	1.000000	290.000000	92.000000	1.000000	1.000000	1.000
2	5%	125.750000	308.000000	103.000000	2.000000	2.500000	3.000
5	0%	250.500000	317.000000	107.000000	3.000000	3.500000	3.500
7	5%	375.250000	325.000000	112.000000	4.000000	4.000000	4.000
m	nax	500.000000	340.000000	120.000000	5.000000	5.000000	5.000

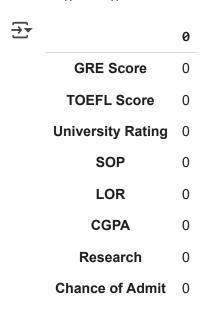
df.drop(['Serial No.'],axis=1,inplace=True)

df.shape

df.duplicated().sum()

**→** 0

df.isna().sum()



# Found out to be no null and no duplicates

```
df.columns.values
```

dtype: int64

df.dtypes

 $\overline{\mathbf{T}}$ 

0

GRE Score int64
TOEFL Score int64
University Rating int64
SOP float64

LOR float64

CGPA float64

Research int64

Chance of Admit float64

dtype: object

a=df['GRE Score'].sort\_values(ascending=True).head()
b=df['GRE Score'].sort\_values(ascending=False).head()
a

dtype: int64

b

<b>→</b> ▼		GRE Score
	429	340
	84	340
	81	340
	143	340
	202	340

dtype: int64

```
x=df['GRE Score'].sum()
y=df['GRE Score'].count()
```

avg=x/y avg

**316.472 316.472** 

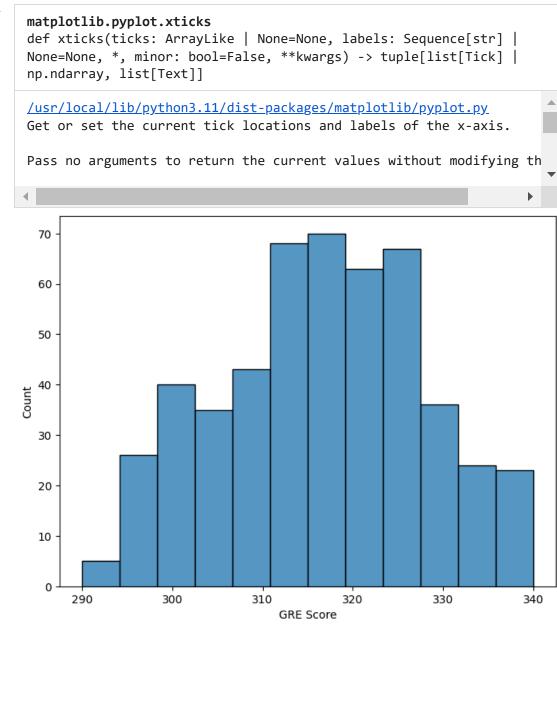
**AVG GRE SCORE**-316.472

Least GRE Score- 290

**Top GRE Score**-340

```
plt.figure(figsize=(8,6))
sns.histplot(x='GRE Score',data=df)
plt.xticks
```





```
df['TOEFL Score'].value_counts().head()
```

 $\overline{\mathbf{T}}$ 

count

**TOEFL Score** 

110	44
105	37
104	29
107	28
106	28

dtype: int64

```
c=df['TOEFL Score'].sum()
d=df['TOEFL Score'].count()
c/d
```

**→** 107.192

```
e=df['TOEFL Score'].sort_values(ascending=True).head()
f=df['TOEFL Score'].sort_values(ascending=True).tail()
e
```

<b>→</b>		TOEFL Score
	368	92
	28	93
	79	93
	411	94
	347	94

dtype: int64

f

<b>→</b>		TOEFL Score
	81	120
	97	120
	297	120
	143	120
	497	120

dtype: int64

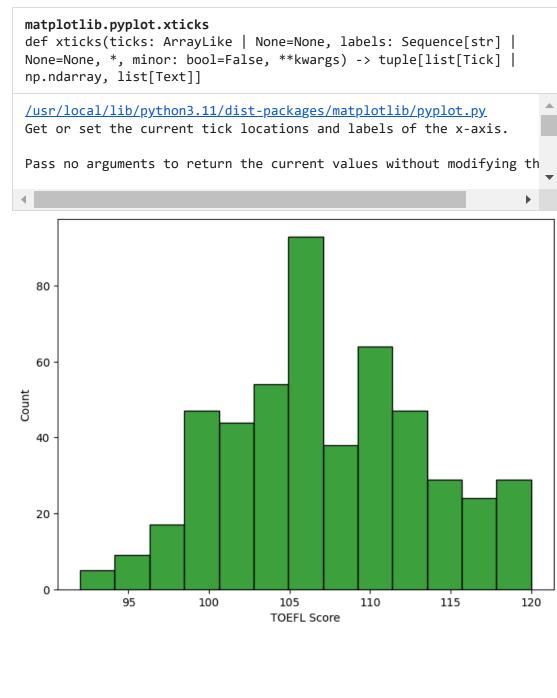
**Least Tofel Score**-92

**Top Tofel Score**-120

AVg tofel score- 107.192

plt.figure(figsize=(8,6))
sns.histplot(x='TOEFL Score',data=df,color='Green')
plt.xticks

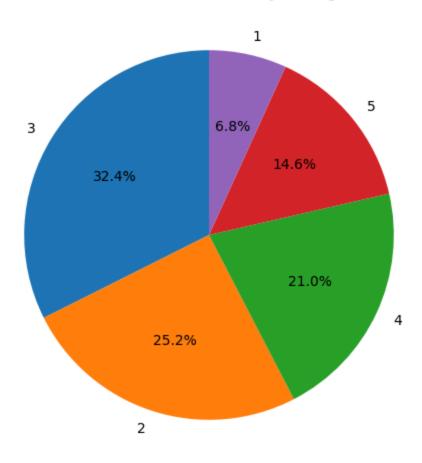




```
plt.figure(figsize=(8, 6))
rating_counts = df['University Rating'].value_counts()
plt.pie(rating_counts, labels=rating_counts.index, autopct='%1.1f%%', startaplt.title('Distribution of University Ratings')
plt.show()
```

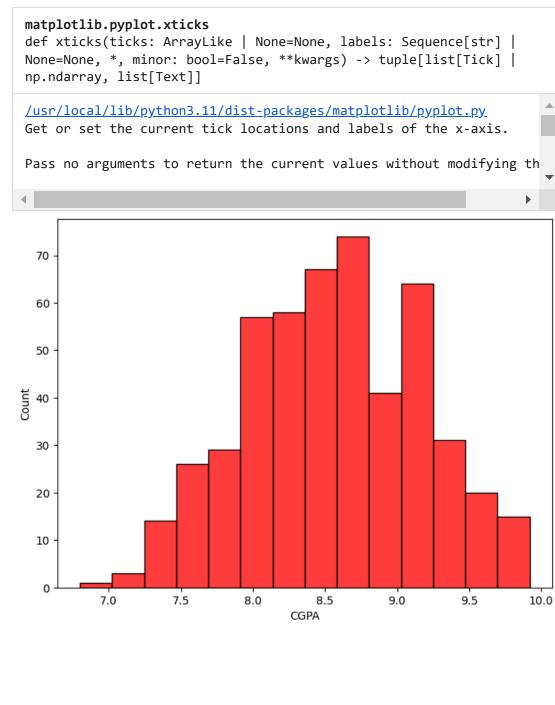


# Distribution of University Ratings

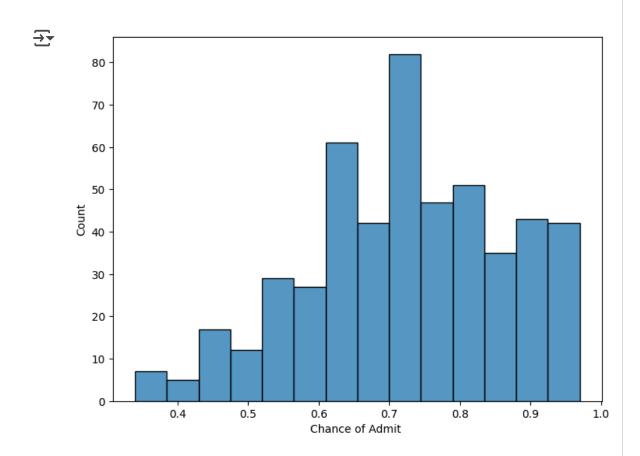


plt.figure(figsize=(8,6))
sns.histplot(x='CGPA',data=df,color='RED')
plt.xticks





```
plt.figure(figsize=(8,6))
sns.histplot(x='Chance of Admit ', data=df)
plt.show()
```



#### **INFERENCES FROM PLOTS**

. A huge number of graduates score between 310 - 330 in GRE.

- .The median of graduate score in TOEFL is around 107.
- .Many universities rank b/w 2.0 3.5.
- .Majority of the students have their cgpa between 8.0 9.3.

```
fig, axes = plt.subplots(2,2,figsize=(10,8))
fig.tight_layout(pad=5.0)
sns.scatterplot(data=df,x='GRE Score',y='CGPA',ax=axes[0,0])
sns.scatterplot(data=df,x='TOEFL Score',y='CGPA',ax=axes[0,1])
sns.scatterplot(data=df,x='GRE Score',y='Chance of Admit ',ax=axes[1,0])
sns.scatterplot(data=df,x='TOEFL Score',y='Chance of Admit ',ax=axes[1,1])
```



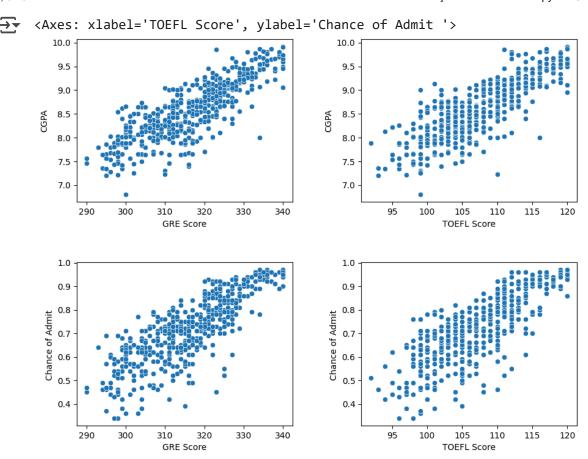
#### Gemini

Gemini is a powerful AI tool built by Google that helps you use Colab.

Not sure what to ask?

Try a suggested prompt below

How do I filter a Pandas DataFrame?



How can I create a plot in Colab?

Show me a list of publicly available datasets

```
cols=['GRE Score','TOEFL Score','University Rating','CGPA','Chance of Admit

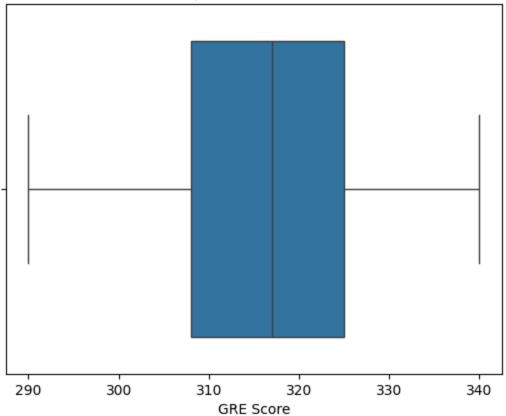
def visualize_boxplot(dataframe):
    for i in cols:

    plt.figure(figsize=(6,4))
        fig = plt.figure()
        fig.tight_layout(pad=5.0)
        plt.figure()
        sns.boxplot(data=dataframe, x = i)
        plt.title(f"Boxplot for {i}")
        plt.show()

visualize_boxplot(df)
```

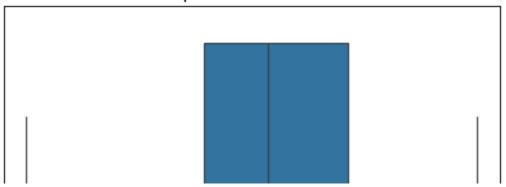
→ <Figure size 600x400 with 0 Axes> <Figure size 640x480 with 0 Axes>

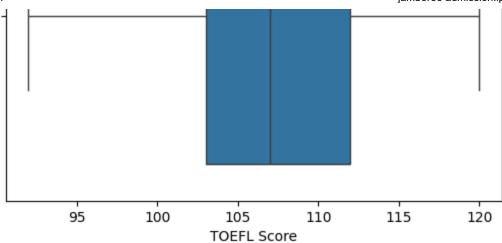
# Boxplot for GRE Score



<Figure size 600x400 with 0 Axes> <Figure size 640x480 with 0 Axes>

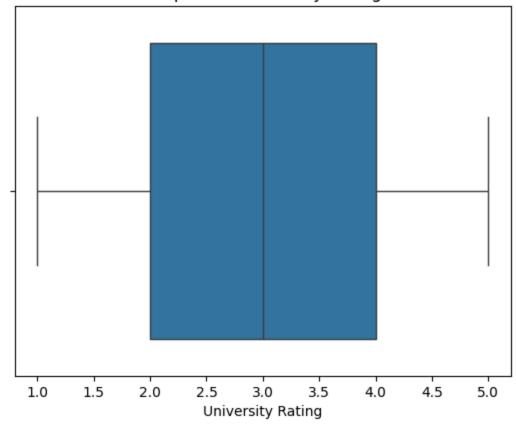
# Boxplot for TOEFL Score





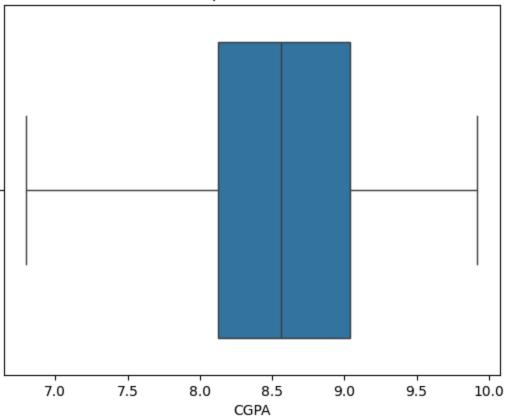
<Figure size 600x400 with 0 Axes>
<Figure size 640x480 with 0 Axes>

# **Boxplot for University Rating**



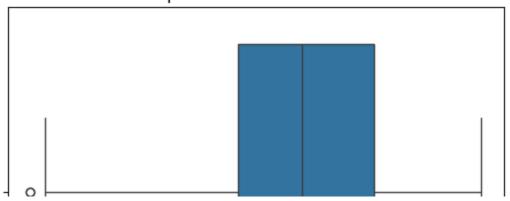
<Figure size 640x480 with 0 Axes>

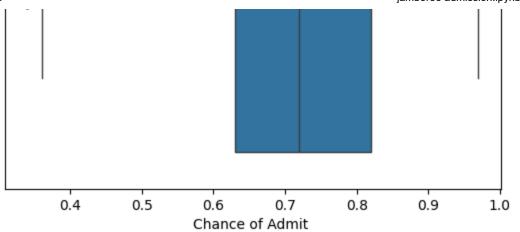
# Boxplot for CGPA



<Figure size 600x400 with 0 Axes>
<Figure size 640x480 with 0 Axes>

# Boxplot for Chance of Admit





# **Feature Engineering**

x=df.drop(columns=['Chance of Admit '])

x # prints all other columns except chance of admit

<b>→</b>		GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	
	0	337	118	4	4.5	4.5	9.65	1	1
	1	324	107	4	4.0	4.5	8.87	1	V
	2	316	104	3	3.0	3.5	8.00	1	
	3	322	110	3	3.5	2.5	8.67	1	
	4	314	103	2	2.0	3.0	8.21	0	
	495	332	108	5	4.5	4.0	9.02	1	
	496	337	117	5	5.0	5.0	9.87	1	
	497	330	120	5	4.5	5.0	9.56	1	
	498	312	103	4	4.0	5.0	8.43	0	
	499	327	113	4	4.5	4.5	9.04	0	

500 rows × 7 columns

Next steps: Generate code with x

View recommended plots

New interactive sheet

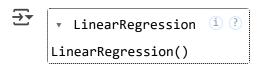
y=df['Chance of Admit ']

# **Data preparation for modelling**

```
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
```

from sklearn.preprocessing import StandardScaler # scaling the dataset scaler=StandardScaler() #The StandardScaler is used to standardize features b x\_train\_scaled=scaler.fit\_transform(x\_train) # Calculates the mean and standa #Applies the standardization using the calculated mean and standard deviation x\_test\_scaled=scaler.transform(x\_test) #We avoid using fit\_transform on x\_test #ensuring the model doesn't learn anything from the test set during training.

from sklearn.linear\_model import LinearRegression
model=LinearRegression()
model.fit(x\_train\_scaled,y\_train)

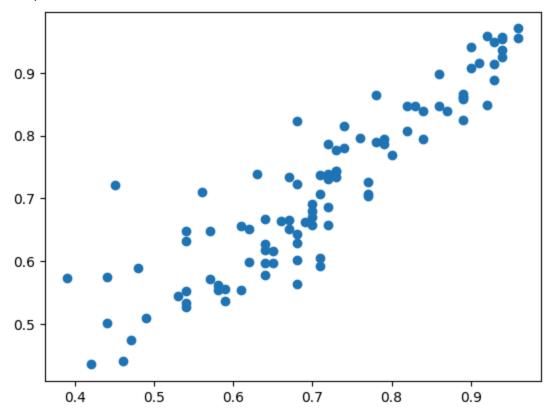


```
y_train_pred=model.predict(x_train_scaled)
y_pred = model.predict(x_test_scaled)
print(x_test.shape,y_test.shape)
```

plt.scatter(y\_test,y\_pred)



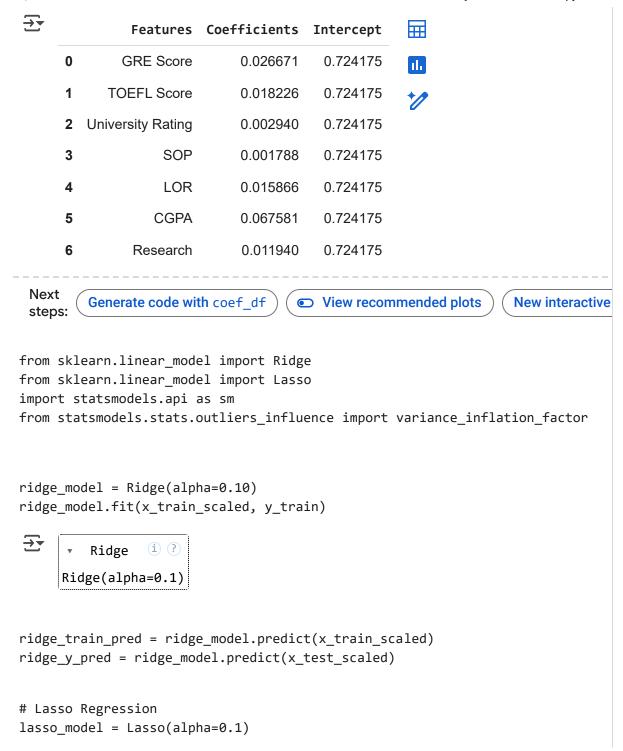
<matplotlib.collections.PathCollection at 0x790e5ebe3b50>



## **Model building**

- 1. Build the Linear Regression model and comment on the model statistics
- 2. Display model coefficients with column names
- 3. Try out Ridge and Lasso regression

```
coefficients = model.coef_
coef_df = pd.DataFrame({'Features':x_train.columns, 'Coefficients':coefficien
coef_df['Intercept'] = model.intercept_
coef_df
```



lasso\_model.fit(x\_train\_scaled,y\_train)



```
▼ Lasso ① ?
Lasso(alpha=0.1)
```

lasso\_train\_pred = lasso\_model.predict(x\_train\_scaled)
lasso\_y\_pred = lasso\_model.predict(x\_test\_scaled)

#### **OLS**

# Checking which features have a high impact on the target variable.

# constant term represents the expected value of the dependent variable wher
# all the independent variables are zero.

new\_x\_train = sm.add\_constant(x\_train)
ols\_model = sm.OLS(y\_train, new\_x\_train)
result = ols\_model.fit()

print(result.summary())



### OLS Regression Results

BIC:

Den Versiehler Charact Charact Description

Dep. Variable: Chance of Admit R-squared:
Model: OLS Adj. R-squared:
Method: Least Squares F-statistic:

Date: Fri, 14 Feb 2025 Prob (F-statistic): 3.<sup>2</sup> Time: 12:56:41 Log-Likelihood:

No. Observations: 400 AIC:

Df Residuals: 392
Df Model: 7

Covariance Type: nonrobust

=======================================		.=======			
	coef	std err	t	P> t	[0.02
const	-1.4214	0.123	-11.549	0.000	-1.66
GRE Score	0.0024	0.001	4.196	0.000	0.06
TOEFL Score	0.0030	0.001	3.174	0.002	0.00

University Rating	0.0026	0.004	0.611	0.541	-0.00
SOP	0.0018	0.005	0.357	0.721	-0.00
LOR	0.0172	0.005	3.761	0.000	0.00
CGPA	0.1125	0.011	10.444	0.000	0.09
Research	0.0240	0.007	3.231	0.001	0.00
============					
Omnibus:		86.232	Durbin-Watso	on:	
Prob(Omnibus):		0.000	Jarque-Bera	(JB):	1
Skew:		-1.107	Prob(JB):		5
Kurtosis:		5.551	Cond. No.		1
=======================================				.=======	

#### Notes:

[1] Standard Errors assume that the covariance matrix of the errors is ( [2] The condition number is large, 1.37e+04. This might indicate that the strong multicollinearity or other numerical problems.

From the above results it is clear that GRE Score, TOEFL Score, LOR, CGPA, and Research significantly impact the target variable whereas University Ranking and SOP don't.

### finding MSE, MAE, R2 SCORE, ADJ R2 SCORE

from sklearn.metrics import mean\_squared\_error, mean\_absolute\_error, r2\_scor import numpy as np

```
# TRAINING MODEL
n = len(y_train)
p = len(model.coef_) if len(model.coef_.shape) == 1 else len(model.coef_[0]);
mse = np.round(mean_squared_error(y_true=y_train, y_pred=y_train_pred), 2)
mae = np.round(mean_absolute_error(y_true=y_train, y_pred=y_train_pred), 2)
r2score = np.round(r2_score(y_true=y_train, y_pred=y_train_pred), 2)
adj_r = np.round(((1 - r2score) * (n - 1)) / (n - p - 1), 2)

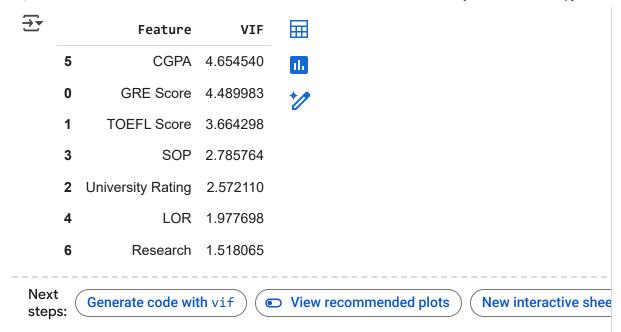
print(f"TRAINING MODEL\nMSE: {mse}\nMAE: {mae}\nr2 score: {r2score}\nadjust@print('-' * 30)
```

```
# TESTING MODEL
n = len(y test)
p = len(model.coef_) if len(model.coef_.shape) == 1 else len(model.coef_[0])
mse = np.round(mean_squared_error(y_true=y_test, y_pred=y_pred), 2)
mae = np.round(mean_absolute_error(y_true=y_test, y_pred=y_pred), 2)
r2score = np.round(r2_score(y_true=y_test, y_pred=y_pred), 2)
adj_r = np.round(((1 - r2score) * (n - 1)) / (n - p - 1), 2)
print(f"TESTING MODEL\nMSE: {mse}\nMAE: {mae}\nr2 score: {r2score}\nadjustec
→ TRAINING MODEL
     MSE: 0.0
     MAE: 0.04
     r2 score: 0.82
     adjusted r: 0.18
     TESTING MODEL
     MSE: 0.0
     MAE: 0.04
     r2 score: 0.82
     adjusted r: 0.19
```

As there is no difference between the results of the training and testing model, confusion can be drawn that there is no overfitting.

#### checking multicollinearity with VIF

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Feature'] = x_train.columns
vif['VIF'] = [variance_inflation_factor(x_train_scaled,i) for i in range(x_t
vif = vif.sort_values(by="VIF",ascending = False)
```



As there is no VIF>5 we can say that there is no multicollinearity b/w any two features.

## calculate mean of residuals

residuals = y\_test - y\_pred

residuals

```
\overline{\mathbf{T}}
           Chance of Admit
      361
                    0.015425
                    0.044819
       73
      374
                   -0.182660
      155
                    0.062630
      104
                   -0.075883
                   -0.015631
      347
       86
                    0.033357
print(residuals)
print('-'*55)
print(residuals.mean())
\rightarrow
     361
             0.015425
             0.044819
     73
      374
            -0.182660
     155
             0.062630
     104
            -0.075883
               . . .
      347
            -0.015631
     86
             0.033357
            -0.065988
     75
            -0.064694
     438
     15
            -0.108657
     Name: Chance of Admit , Length: 100, dtype: float64
      -0.005453623717661251
plt.figure(figsize=(12,5))
sns.histplot(residuals, kde=True)
     <Axes: xlabel='Chance of Admit ', ylabel='Count'>
```