JAMBROE_EDA

August 23, 2023

[165]:
```
# import sys
# !{sys.executable} -m pip install pandas
# !{sys.executable} -m pip install sklearn

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

[166]:
```
df=pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/839/original/Jamboree_Admission.csv',encoding='latin-1')
df.head()
```

[166]:

	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

[167]:
```
df.columns=df.columns.str.strip()

def changes_names(column_name):
    if '' in column_name:
        return column_name.replace(' ','_')
    return column_name

df.columns=df.columns.map(changes_names)
```

[168]:
```
df.describe()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Serial_No.         500 non-null    int64  
 1   GRE_Score          500 non-null    int64  
 2   TOEFL_Score        500 non-null    int64  
 3   University_Rating  500 non-null    int64  
 4   SOP                500 non-null    float64
 5   LOR                500 non-null    float64
 6   CGPA               500 non-null    float64
 7   Research           500 non-null    int64  
 8   Chance_of_Admit    500 non-null    float64
dtypes: float64(4), int64(5)
memory usage: 35.3 KB
```

[127]:
```
print(f'Origina Dataframe Shape {df.shape}')
```

```
Origina Dataframe Shape (500, 9)
```

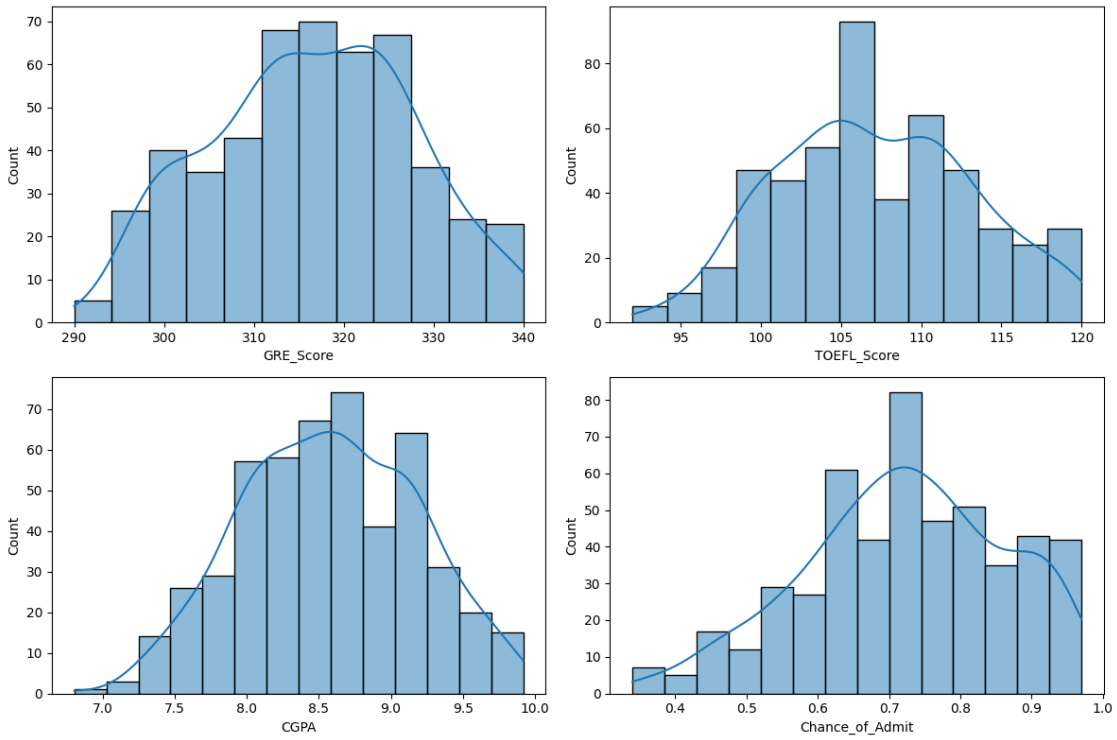
[169]:
```
features_with_na=[features for features in df.columns if df[features].isnull().
 ↪sum()>1]
features_with_na


for features in features_with_na:
    print(features,np.round(df[features].isnull().mean() *100 ,4),f'% Missing␣
 ↪Values {name}')
```

[170]:
```
df.dropna(inplace=True)
df.drop(columns='Serial_No.',inplace=True)
```

[130]:
```
category_cols = ['University_Rating', 'SOP', 'LOR', 'Research'] # Values are␣
 ↪fixed in the column
num_cols = ['GRE_Score', 'TOEFL_Score', 'CGPA'] # Continous variable
target = 'Chance_of_Admit'  # Actual Prediction
```

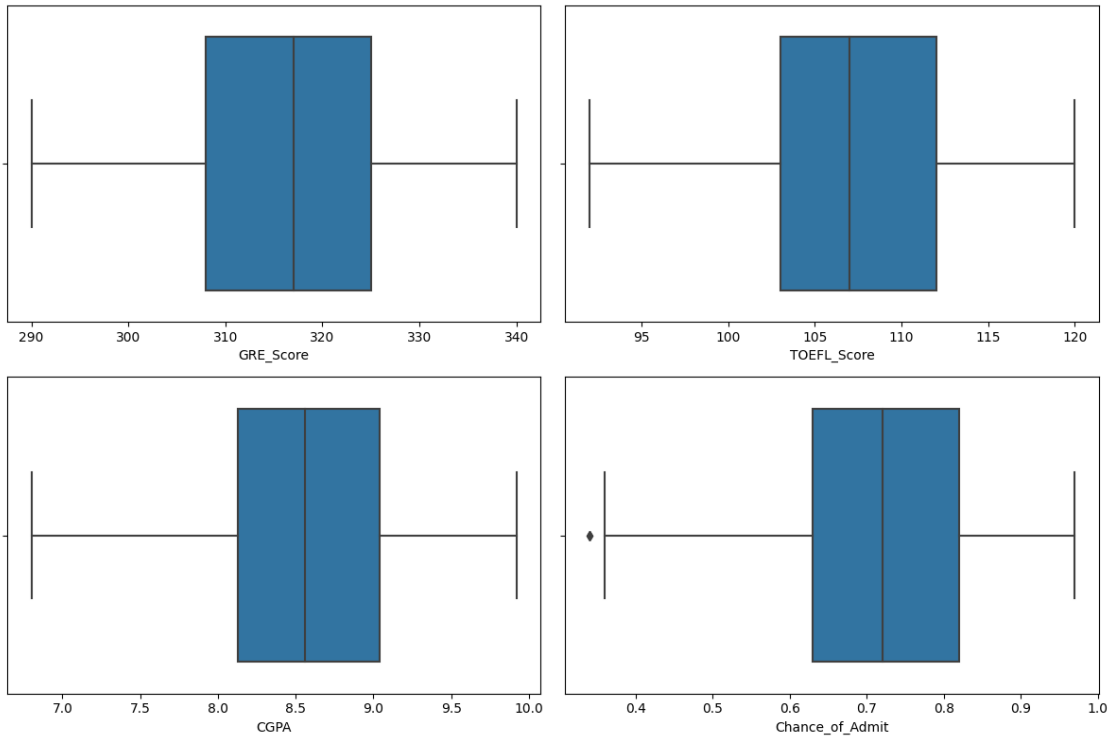
1 Univariate Analysis

[90]:
```
#Numerical values

rows, cols = 2, 2
fig, axs = plt.subplots(rows, cols, figsize=(12, 8))


for i, ax in enumerate(axs.flat):
    if i < len(num_cols):
        sns.histplot(df[num_cols[i]], kde=True, ax=ax)

sns.histplot(df[target], kde=True, ax=axs[1,1])
plt.tight_layout()
plt.show()
```



[91]:
```
#Outliers in numerical variables

rows, cols = 2, 2
fig, axs = plt.subplots(rows, cols, figsize=(12, 8))


for i, ax in enumerate(axs.flat):
```

```
    if i<len(num_cols):
        sns.boxplot(x=df[num_cols[i]], data=df, ax=ax)

sns.boxplot(x=df[target], data=df, ax=axs[1,1])

plt.tight_layout()
plt.show()
```



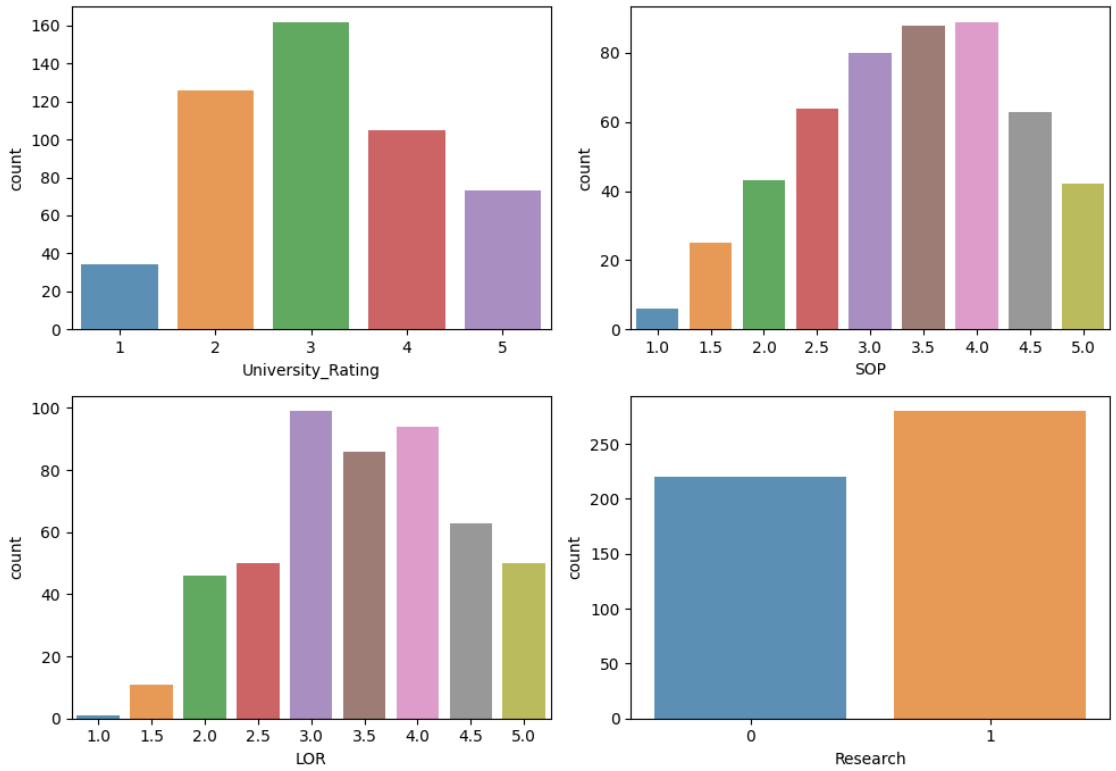
No outliers

[92]:
```
# unique values in categorical variables
for col in category_cols:
    print(f" {col}   {df[col].nunique()} ")
```

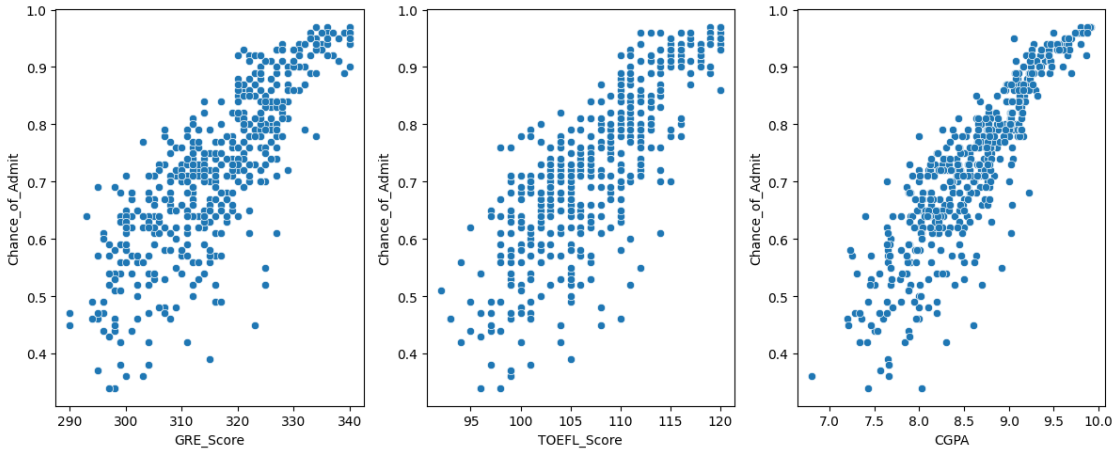
```
University_Rating   5
SOP   9
LOR   9
Research   2
```

[93]:
```
rows, cols = 2, 2
fig, axs = plt.subplots(rows, cols, figsize=(10, 7))

for i, ax in enumerate(axs.flat):
    sns.countplot(x=category_cols[i], data=df, ax=ax, alpha=0.8)
```

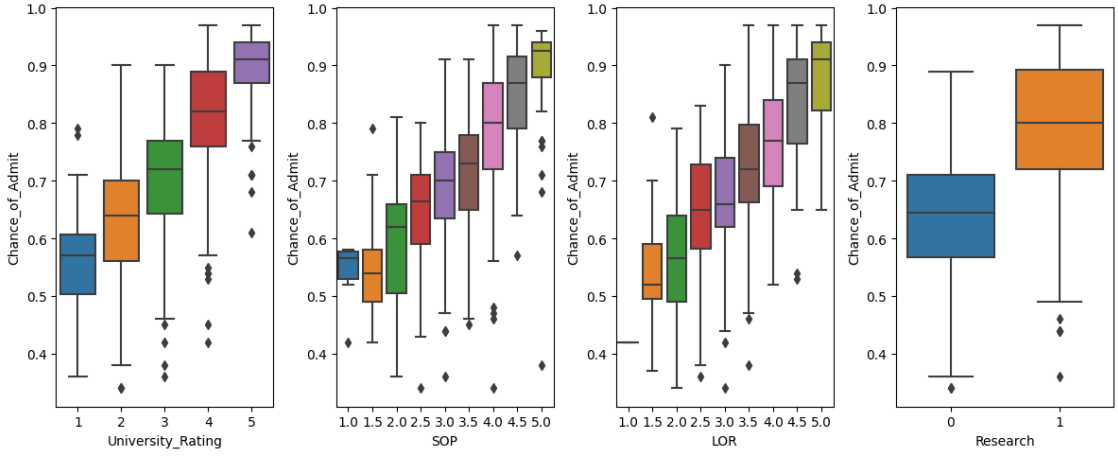
```
plt.tight_layout()
plt.show()
```



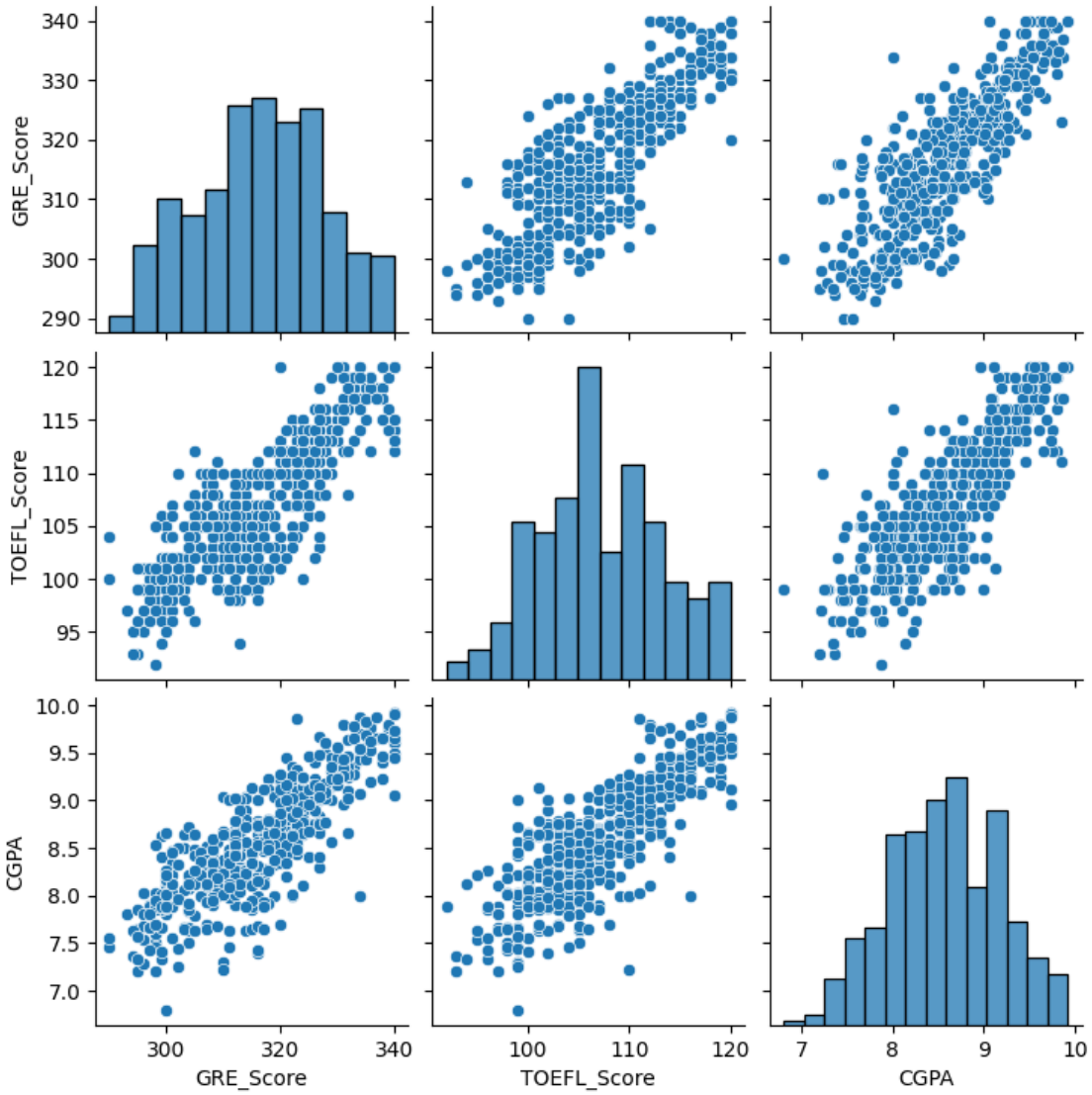
[94]:
```
####Bivariate analysis



# check relation bw continuous variables & target variable
fig, axs = plt.subplots(1, len(num_cols), figsize=(12, 5))

for i, col in enumerate(num_cols):
    sns.scatterplot(x=col, y=target, data=df, ax=axs[i])

plt.tight_layout()
plt.show()
```



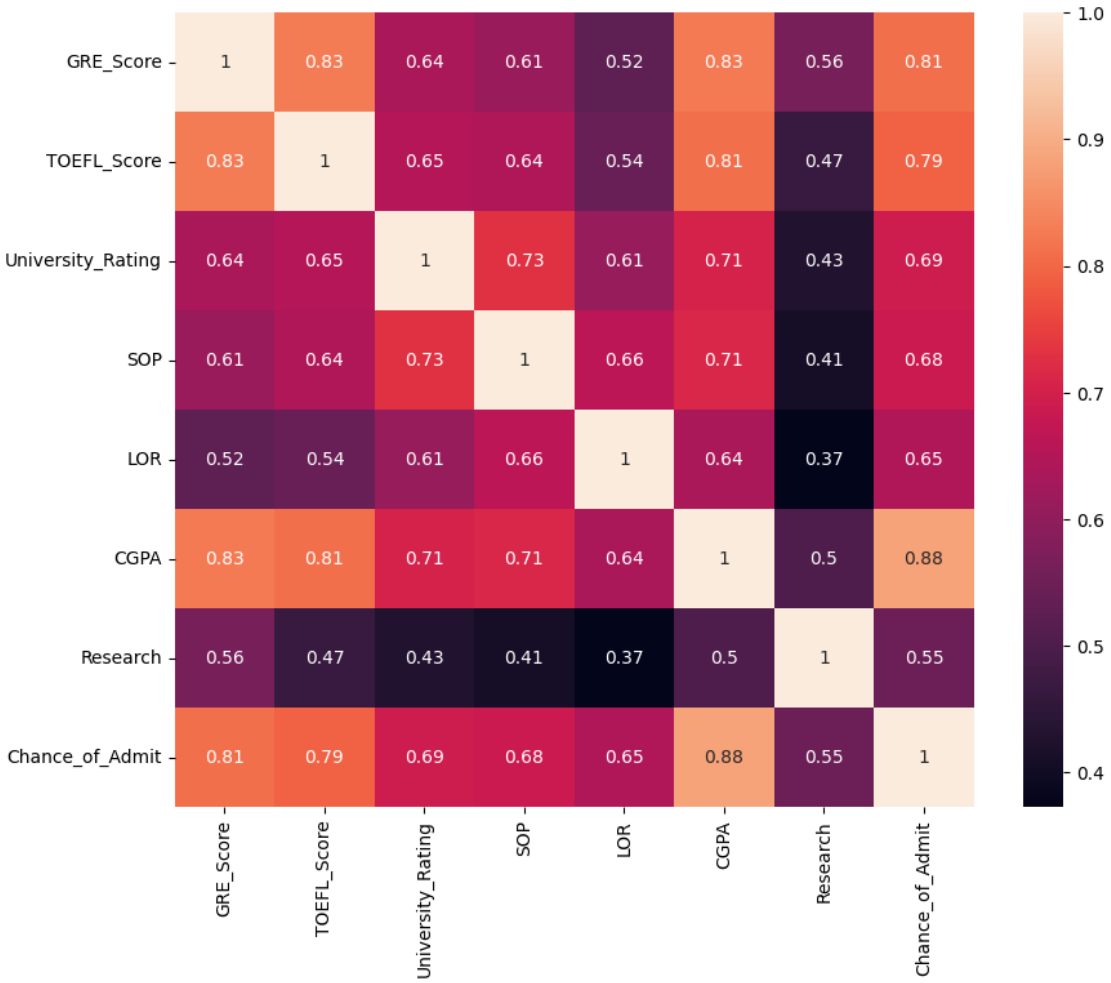
[95]:
```
# check relation bw categorical variables & target variable
fig, axs = plt.subplots(1, len(category_cols), figsize=(12, 5))

for i, col in enumerate(category_cols):
    sns.boxplot(x=col, y=target, data=df, ax=axs[i])

plt.tight_layout()
plt.show()
```



[96]:
```
####Multivariate Analysis

sns.pairplot(df[num_cols])
plt.show()
```



[97]:
```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



[171]:
```
# check for duplicates
df.duplicated().sum()
```

[171]: 0

[172]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import r2_score
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy import stats
```

[173]:
```
y = df[target]
X=df.drop(columns=[target])
X
```

[173]:
```
     GRE_Score  TOEFL_Score  University_Rating  SOP  LOR  CGPA  Research
0          337          118                  4  4.5  4.5  9.65         1
1          324          107                  4  4.0  4.5  8.87         1
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 x 7 columns]
```

[174]:
```
scaling = StandardScaler()
X = scaling.fit_transform(X)
X
```

[174]:
```
array([[ 1.81923762,  1.77886545,  0.77558214, …,  1.09894429,
         1.77680627,  0.88640526],
       [ 0.66714832, -0.03160087,  0.77558214, …,  1.09894429,
         0.48585943,  0.88640526],
       [-0.0418297 , -0.52536441, -0.09979274, …,  0.01730621,
        -0.95404281,  0.88640526],
       …,
       [ 1.19888185,  2.10804114,  1.65095702, …,  1.63976333,
         1.62785086,  0.88640526],
       [-0.39631872, -0.68995225,  0.77558214, …,  1.63976333,
        -0.24236699, -1.12815215],
       [ 0.93301508,  0.95592621,  0.77558214, …,  1.09894429,
         0.76721964, -1.12815215]])
```

[175]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=1)

print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(350, 7) (350,)
(150, 7) (150,)
```

[176]:
```
# Add a constant to the independent variables
check_train = sm.add_constant(X_train)
check_test = sm.add_constant(X_test)

# Fit the linear regression model using OLS
```

```
model123 = sm.OLS(y_train, check_train).fit()

# Print the summary of the model
print(model123.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance_of_Admit   R-squared:                       0.821
Model:                            OLS   Adj. R-squared:                  0.817
Method:                 Least Squares   F-statistic:                     224.1
Date:                Wed, 23 Aug 2023   Prob (F-statistic):          1.27e-123
Time:                        17:29:21   Log-Likelihood:                 500.20
No. Observations:                 350   AIC:                            -984.4
Df Residuals:                     342   BIC:                            -953.5
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.7250      0.003    230.864      0.000       0.719       0.731
x1             0.0187      0.007      2.798      0.005       0.006       0.032
x2             0.0232      0.006      3.653      0.000       0.011       0.036
x3             0.0116      0.005      2.116      0.035       0.001       0.022
x4            -0.0010      0.005     -0.189      0.850      -0.011       0.009
x5             0.0125      0.004      2.849      0.005       0.004       0.021
x6             0.0647      0.007      9.356      0.000       0.051       0.078
x7             0.0140      0.004      3.613      0.000       0.006       0.022
==============================================================================
Omnibus:                       77.752   Durbin-Watson:                   1.981
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              179.766
Skew:                          -1.100   Prob(JB):                     9.21e-40
Kurtosis:                       5.736   Cond. No.                         5.69
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[177]:
```
def adjusted_r2(r2, p, n):
    """
    n: no of samples
    p: no of predictors
    r2: r2 score
    """
    adj_r2 = 1 - ((1-r2)*(n-1) / (n-p-1))
    return adj_r2
```

```
def get_metrics(y_true, y_pred, p=None):
    n = y_true.shape[0]
    mse = np.sum((y_true - y_pred)**2) / n
    rmse = np.sqrt(mse)
    mae = np.mean(np.abs(y_true - y_pred))
    score = r2_score(y_true, y_pred)
    adj_r2 = None
    if p is not None:
        adj_r2 = adjusted_r2(score, p, n)

    res = {
        "mean_absolute_error": round(mae, 2),
        "rmse": round(rmse, 2),
        "r2_score": round(score, 2),
        "adj_r2": round(adj_r2, 2)
    }
    return res
```

[179]:
```
def train_models(X_train, y_train, X_test, y_test, cols, models):
    results = []
    for model_info in models:
        model_name = model_info[0]
        model_class = model_info[1]
        alpha = None
        if len(model_info) > 2:
            alpha = model_info[2]

        model = model_class(alpha=alpha) if alpha is not None else model_class()
        model.fit(X_train, y_train)

        y_pred_train = model.predict(X_train)
        y_pred_test = model.predict(X_test)
        p = X_train.shape[1]
        train_res = get_metrics(y_train, y_pred_train, p)
        test_res = get_metrics(y_test, y_pred_test, p)

        coef_df = pd.DataFrame({"Column": cols, "Coef": model.coef_})

        results.append({
            "model_name": model_name,
            "train_metrics": train_res,
            "test_metrics": test_res,
            "intercept": model.intercept_,
            "coefficients": coef_df
        })

    return results
```

```
models = [
    ("linear", LinearRegression),
    ("ridge", Ridge, 1.0),
    ("lasso", Lasso, 0.001)
]

results = train_models(X_train, y_train, X_test, y_test, df.columns[:-1],␣
 ↪models)

for result in results:
    print("\n" + "-"*50)
    print(f" {result['model_name'].title()} Regression Model ")
    print("-"*50)
    print(f"Train Metrics: {result['train_metrics']}")
    print(f"Test Metrics: {result['test_metrics']}")
    print(f"Intercept: {result['intercept']}")
    print(result['coefficients'])
```

```
--------------------------------------------------
 Linear Regression Model
--------------------------------------------------
Train Metrics: {'mean_absolute_error': 0.04, 'rmse': 0.06, 'r2_score': 0.82,
'adj_r2': 0.82}
Test Metrics: {'mean_absolute_error': 0.04, 'rmse': 0.06, 'r2_score': 0.82,
'adj_r2': 0.81}
Intercept: 0.724978121476996
              Column      Coef
0          GRE_Score  0.018657
1        TOEFL_Score  0.023176
2  University_Rating  0.011565
3                SOP -0.000999
4                LOR  0.012497
5               CGPA  0.064671
6           Research  0.013968

--------------------------------------------------
 Ridge Regression Model
--------------------------------------------------
Train Metrics: {'mean_absolute_error': 0.04, 'rmse': 0.06, 'r2_score': 0.82,
'adj_r2': 0.82}
Test Metrics: {'mean_absolute_error': 0.04, 'rmse': 0.06, 'r2_score': 0.82,
'adj_r2': 0.81}
Intercept: 0.7249823645841696
              Column      Coef
0          GRE_Score  0.018902
```

```
1        TOEFL_Score  0.023252
2  University_Rating  0.011594
3                SOP -0.000798
4                LOR  0.012539
5               CGPA  0.064004
6           Research  0.013990

--------------------------------------------------
 Lasso Regression Model
--------------------------------------------------
Train Metrics: {'mean_absolute_error': 0.04, 'rmse': 0.06, 'r2_score': 0.82,
'adj_r2': 0.82}
Test Metrics: {'mean_absolute_error': 0.04, 'rmse': 0.06, 'r2_score': 0.82,
'adj_r2': 0.81}
Intercept: 0.7249659139557142
              Column      Coef
0          GRE_Score  0.018671
1        TOEFL_Score  0.022770
2  University_Rating  0.010909
3                SOP  0.000000
4                LOR  0.011752
5               CGPA  0.064483
6           Research  0.013401
```

[186]:
```
def vif(newdf):
    # VIF dataframe
    vif_data = pd.DataFrame()
    vif_data["feature"] = newdf.columns

    # calculating VIF for each feature
    vif_data["VIF"] = [variance_inflation_factor(newdf.values, i)
                              for i in range(len(newdf.columns))]
    return vif_data
```

[187]:
```
res = vif(df.iloc[:,:-1])
res
```

[187]:
```
              feature          VIF
0          GRE_Score  1308.061089
1        TOEFL_Score  1215.951898
2  University_Rating    20.933361
3                SOP    35.265006
4                LOR    30.911476
5               CGPA   950.817985
6           Research     2.869493
```

[188]:
```
res = vif(df.iloc[:, 1:-1])
res
```

[188]:

	feature	VIF
0	TOEFL_Score	639.741892
1	University_Rating	19.884298
2	SOP	33.733613
3	LOR	30.631503
4	CGPA	728.778312
5	Research	2.863301

[189]:
```
# # drop TOEFL Score and again calculate the VIF
res = vif(df.iloc[:,2:-1])
res
```

[189]:

	feature	VIF
0	University_Rating	19.777410
1	SOP	33.625178
2	LOR	30.356252
3	CGPA	25.101796
4	Research	2.842227

[190]:
```
# Now lets drop the SOP and again calculate VIF
res = vif(df.iloc[:,2:-1].drop(columns=['SOP']))
res
```

[190]:

	feature	VIF
0	University_Rating	15.140770
1	LOR	26.918495
2	CGPA	22.369655
3	Research	2.819171

[191]:
```
# lets drop the LOR as well
newdf = df.iloc[:,2:-1].drop(columns=['SOP'])
newdf = newdf.drop(columns=['LOR'], axis=1)
res = vif(newdf)
res
```

[191]:

	feature	VIF
0	University_Rating	12.498400
1	CGPA	11.040746
2	Research	2.783179

[192]:
```
# drop the University Rating
newdf = newdf.drop(columns=['University_Rating'])
res = vif(newdf)
res
```

[192]:
```
     feature       VIF
0       CGPA  2.455008
1   Research  2.455008
```

[193]:
```
# now again train the model with these only two features
X = df[['CGPA', 'Research']]
sc = StandardScaler()
X = sc.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=1)
```

[194]:
```
models = [
    ("linear", LinearRegression),
    ("ridge", Ridge, 1.0),
    ("lasso", Lasso, 0.001)
]

results = train_models(X_train, y_train, X_test, y_test, ['CGPA', 'Research'],␣
 ↪models)

for result in results:
    print("\n" + "-"*50)
    print(f" {result['model_name'].title()} Regression Model ")
    print("-"*50)
    print(f"Train Metrics: {result['train_metrics']}")
    print(f"Test Metrics: {result['test_metrics']}")
    print(f"Intercept: {result['intercept']}")
    print(result['coefficients'])
```

```
--------------------------------------------------
 Linear Regression Model
--------------------------------------------------
Train Metrics: {'mean_absolute_error': 0.05, 'rmse': 0.06, 'r2_score': 0.78,
'adj_r2': 0.78}
Test Metrics: {'mean_absolute_error': 0.05, 'rmse': 0.07, 'r2_score': 0.81,
'adj_r2': 0.81}
Intercept: 0.7247774222727991
     Column      Coef
0      CGPA  0.112050
1  Research  0.020205

--------------------------------------------------
 Ridge Regression Model
--------------------------------------------------
Train Metrics: {'mean_absolute_error': 0.05, 'rmse': 0.06, 'r2_score': 0.78,
```

```
'adj_r2': 0.78}
Test Metrics: {'mean_absolute_error': 0.05, 'rmse': 0.07, 'r2_score': 0.81,
'adj_r2': 0.81}
Intercept: 0.7247830300095277
     Column      Coef
0      CGPA  0.111630
1  Research  0.020362

--------------------------------------------------
 Lasso Regression Model
--------------------------------------------------
Train Metrics: {'mean_absolute_error': 0.05, 'rmse': 0.06, 'r2_score': 0.78,
'adj_r2': 0.78}
Test Metrics: {'mean_absolute_error': 0.05, 'rmse': 0.07, 'r2_score': 0.81,
'adj_r2': 0.81}
Intercept: 0.7247713356661623
     Column      Coef
0      CGPA  0.111344
1  Research  0.019571
```

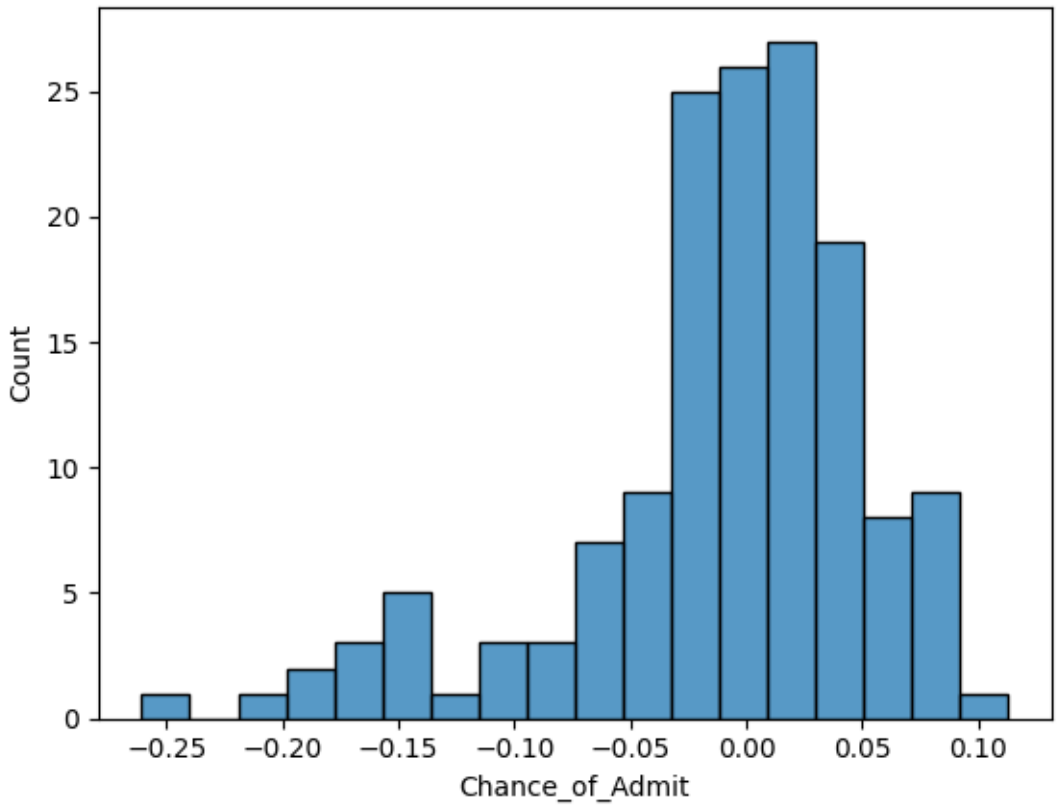
After removing multicollinear features only 2 are enough to gave the accurate results

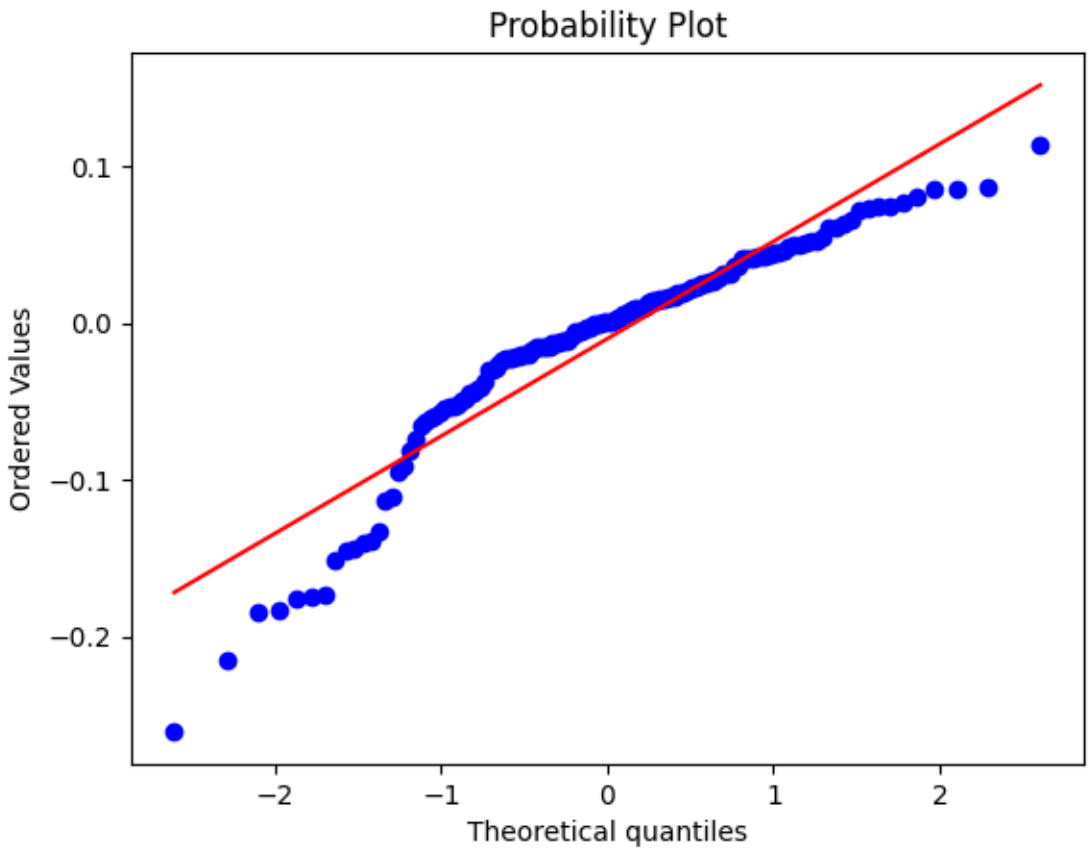
RMSE is almost zero

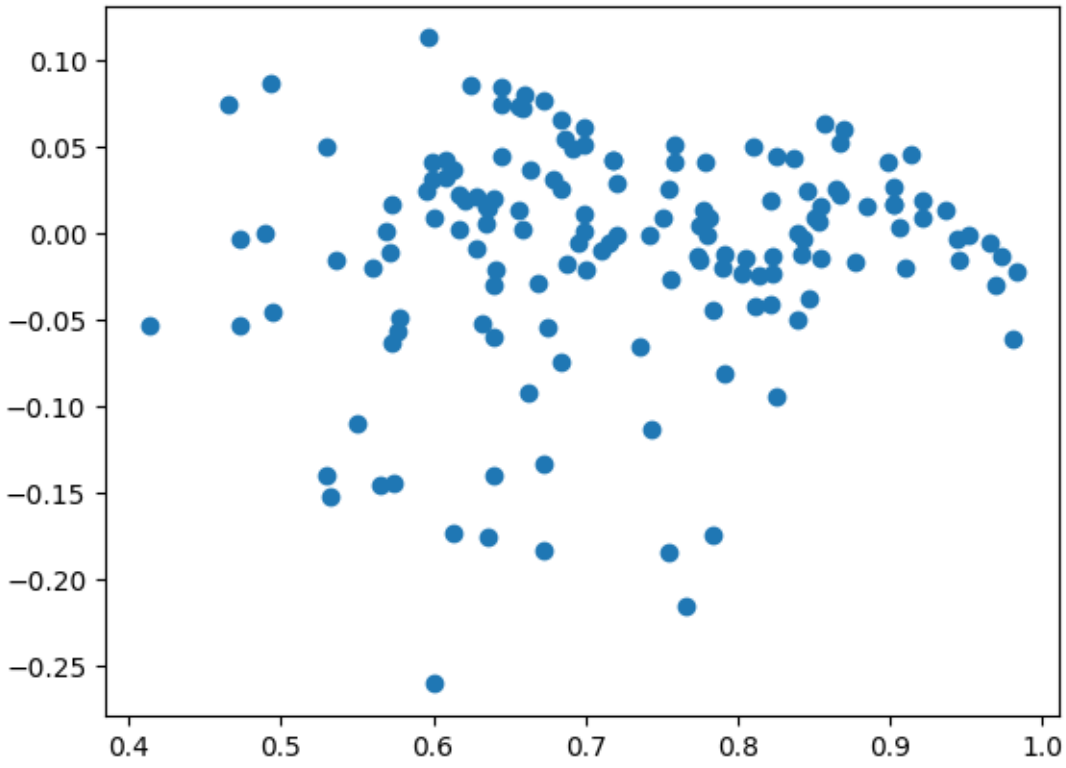
Independent feature is linearly dependent on the target variables

[199]:
```python
def train_models(X_train, y_train, X_test, y_test, cols, models):
    results = []
    for model_info in models:
        model_name = model_info[0]
        model_class = model_info[1]
        alpha = None
        if len(model_info) > 2:
            alpha = model_info[2]

        model = model_class(alpha=alpha) if alpha is not None else model_class()
        model.fit(X_train, y_train)

        y_pred_train = model.predict(X_train)
        y_pred_test = model.predict(X_test)
        p = X_train.shape[1]
        train_res = get_metrics(y_train, y_pred_train, p)
        test_res = get_metrics(y_test, y_pred_test, p)

        return model

models = [
    ("linear", LinearRegression),
    ("ridge", Ridge, 1.0),
```

```
    ("lasso", Lasso, 0.001)
]

results = train_models(X_train, y_train, X_test, y_test, ['CGPA', 'Research'],␣
 ↪models)
y_pred = results.predict(X_test)
residuals = (y_test - y_pred)
sns.histplot(residuals)
plt.show()

stats.probplot(residuals, plot=plt)
plt.show()


#### Test for Homoscedasticity
plt.scatter(y_pred, residuals)
plt.show()
```




Probability Plot
Ordered Values
Theoretical quantiles
0.1
0.0
−0.1
−0.2
−2
−1
0
1
2



No Homoscedasticity

Only two features that is CGPA and Research is enough to prredict the Chances of admit

[ ]: