In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

In [2]:
```
df = pd.read_csv("Jamboree_Admission.csv")
```

In [44]:
```
df
```

Out[44]:

	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
...	...	...	...	...	...	...	...	...	...
495	496	332	108	5	4.5	4.0	9.02	1	0.87
496	497	337	117	5	5.0	5.0	9.87	1	0.96
497	498	330	120	5	4.5	5.0	9.56	1	0.93
498	499	312	103	4	4.0	5.0	8.43	0	0.73
499	500	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 9 columns

In [3]:
```
# Dropping the serial column because pandas already has row numbers
df.drop(columns = ["Serial No."], inplace = True)
```

In [47]:
```
df
```

Out[47]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337	118	4	4.5	4.5	9.65	1	0.92
1	324	107	4	4.0	4.5	8.87	1	0.76
2	316	104	3	3.0	3.5	8.00	1	0.72
3	322	110	3	3.5	2.5	8.67	1	0.80
4	314	103	2	2.0	3.0	8.21	0	0.65
...	...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1	0.87
496	337	117	5	5.0	5.0	9.87	1	0.96
497	330	120	5	4.5	5.0	9.56	1	0.93
498	312	103	4	4.0	5.0	8.43	0	0.73
499	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 8 columns

Problem Statement:

Analyze the Jamboreee Dataset to understand the key factors determining the chances of getting admissions in top IVY league colleges. Also we will have to build ML model which will learn patterns in this dataset and make prediction of getting admission given other variables.

Shape and structure of data

In [4]:
```
df.shape
# There are 7 independant columns and 1 dependant column with 500 rows.
```

Out[4]:
```
(500, 8)
```

In [19]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   GRE Score          500 non-null    int64  
 1   TOEFL Score        500 non-null    int64  
 2   University Rating  500 non-null    int64  
 3   SOP                500 non-null    float64
 4   LOR                500 non-null    float64
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    int64  
 7   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(4)
memory usage: 31.4 KB
```

Checking for null values

In [22]:
```
df.isnull().sum().sum()
# There are no null values
```

Out[22]:
```
0
```

Statistical Summary

In [23]:
```
df.describe()
```

Out[23]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.00000
mean	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.72174
std	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0.14114
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.34000
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.63000
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.72000
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.82000
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.97000

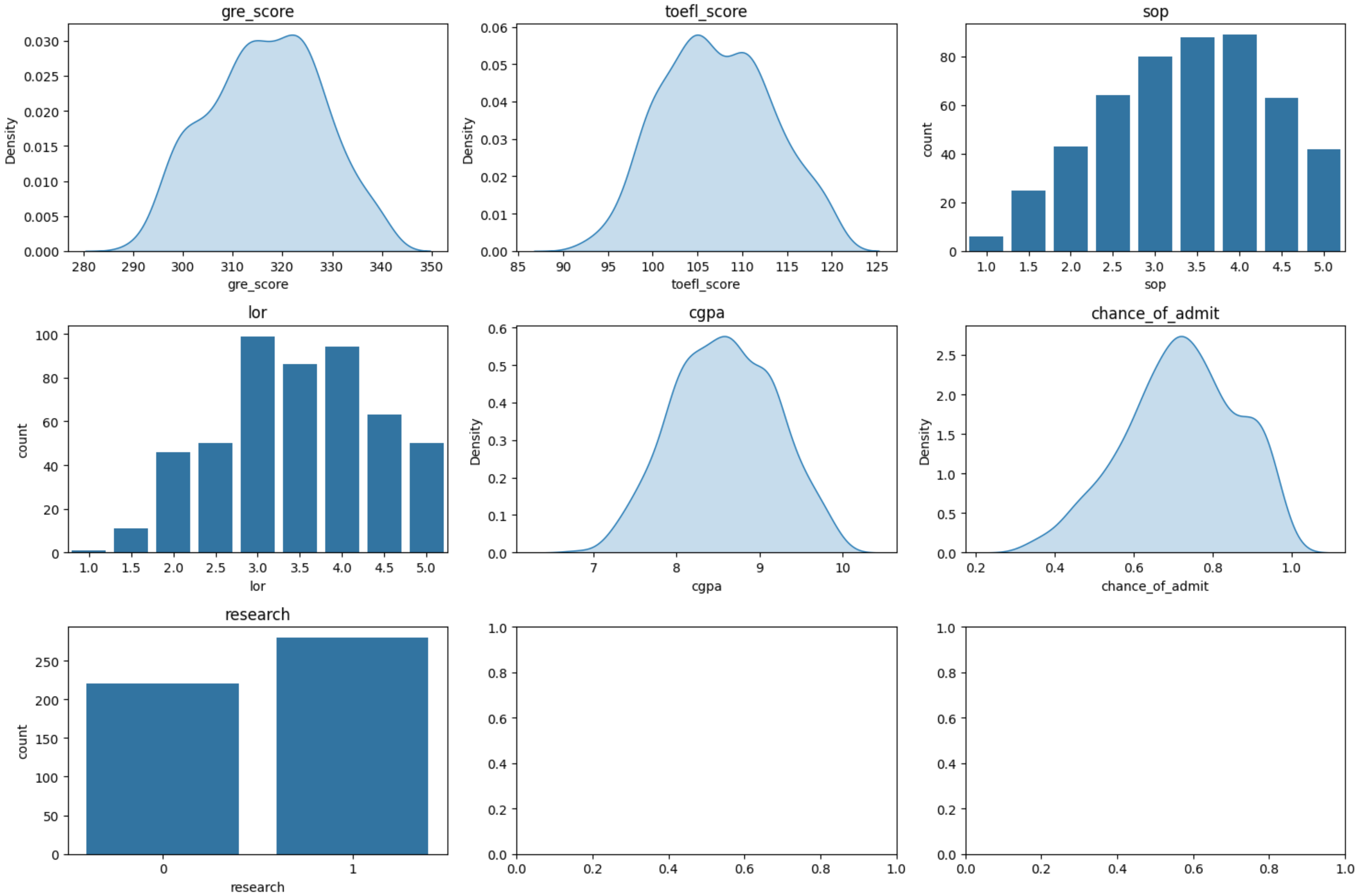
In [5]:
```
# Changing the names of the columns
df.columns = ["gre_score",'toefl_score','university_rating', 'sop', 'lor', 'cgpa', 'research', 'chance_of_admit']
```

Converting SOP, LOR and Research into categoric variables

In [10]:
```
df['sop'] = df['sop'].astype('category')
df['lor'] = df['lor'].astype('category')
df['research'] = df['research'].astype('category')
```

Univariate Data Analysis

In [7]:
```
# Set up the matplotlib figure (2x3 grid)
fig, axs = plt.subplots(3, 3, figsize=(15, 10))

# Plot each KDE plot
sns.kdeplot(data=df['gre_score'], ax=axs[0, 0], fill=True)
axs[0, 0].set_title('gre_score')

sns.kdeplot(data=df['toefl_score'], ax=axs[0, 1], fill=True)
axs[0, 1].set_title('toefl_score')

sns.countplot(x=df['sop'], ax=axs[0, 2], fill=True)
axs[0, 2].set_title('sop')

sns.countplot(x=df['lor'], ax=axs[1, 0], fill=True)
axs[1, 0].set_title('lor')

sns.kdeplot(data=df['cgpa'], ax=axs[1, 1], fill=True)
axs[1, 1].set_title('cgpa')

sns.kdeplot(data=df['chance_of_admit'], ax=axs[1, 2], fill=True)
axs[1, 2].set_title('chance_of_admit')

sns.countplot(x=df['research'], ax=axs[2, 0], fill=True)
axs[2, 0].set_title('research')

# Adjust layout
plt.tight_layout()
plt.show()
```


gre_score
Density
gre_score
toefl_score
Density
toefl_score
sop
count
sop
lor
count
lor
cgpa
Density
cgpa
chance_of_admit
Density
chance_of_admit
research
count
research

Insights based on the univariate charts:

1. There are more students who have published research paper than those who have not

2. Visually speaking - GRE scores are on average around 320.

3. TOEFL score ranges from 90 to 125 and the mode is around 105.

4. The most common SOP score is 4, while score 1 and 5 is very less common.

5. Most common LOR score is 3 and 4, while score 1 is negligible.

6. CGPA mostly lies between 8 to 9, while no one got less than 6.8.

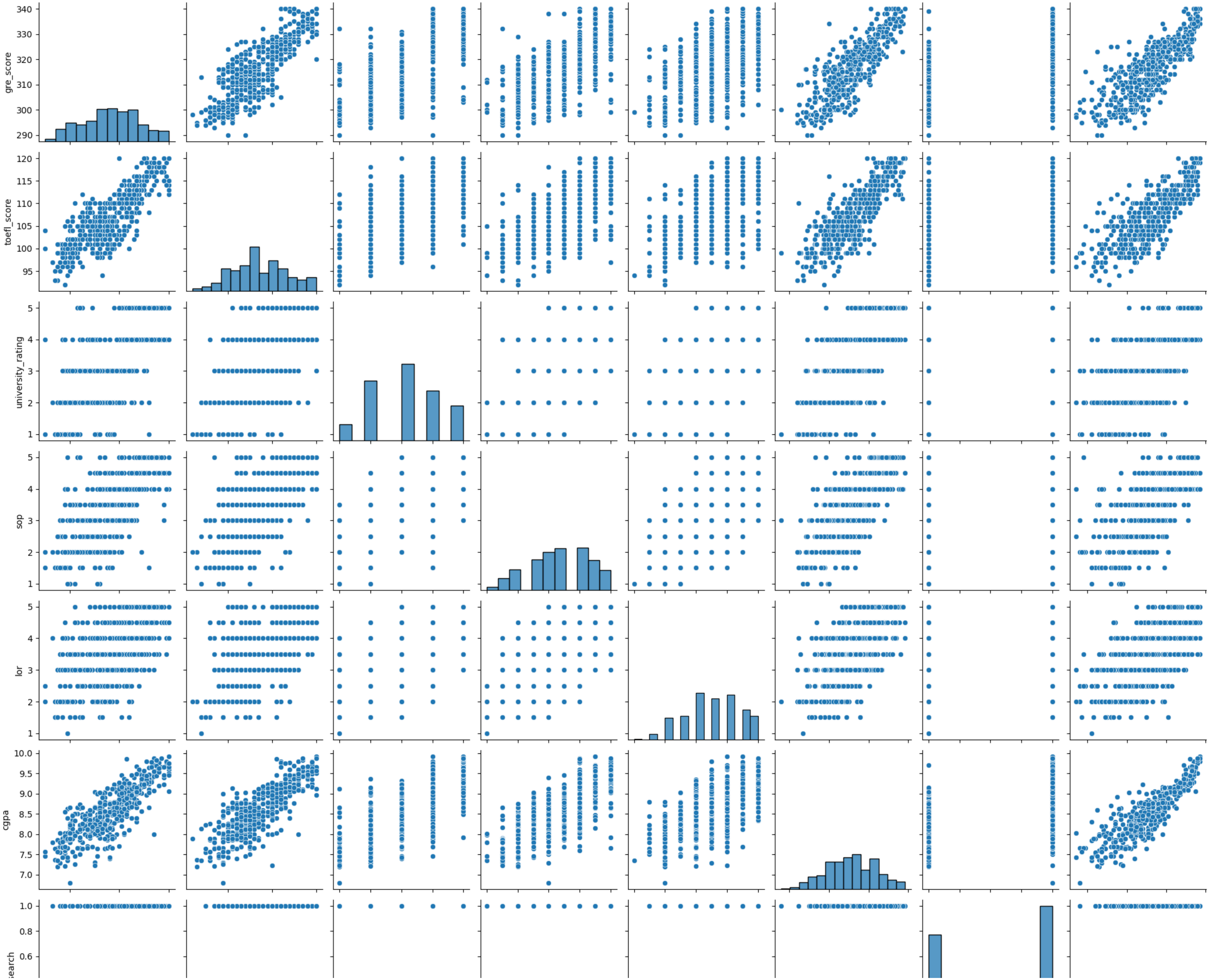
7. The median chance of admission is 0.72 which basically says most of the students who are present in Jamboree have high chances of getting through.

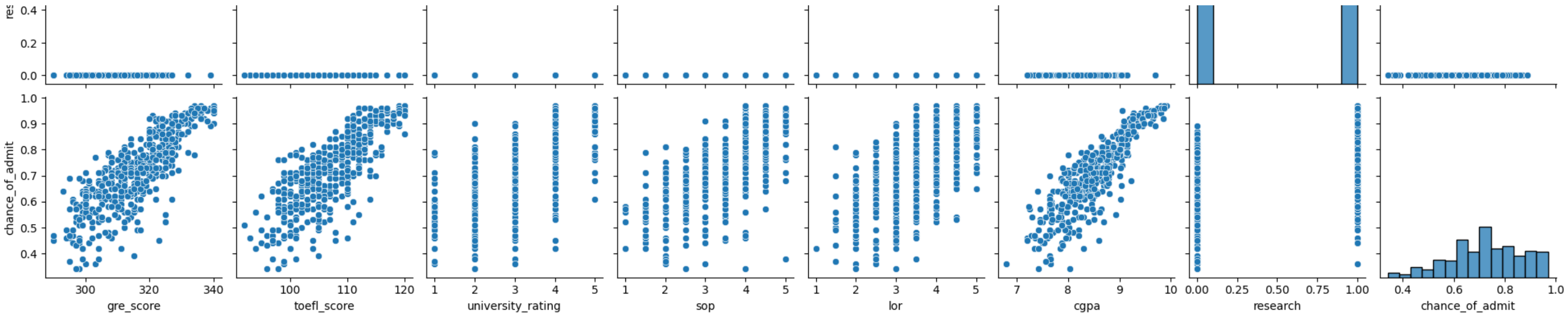
Bivariate Analysis

In [11]:
```
## let us convert back sop, lor, and research columns into numeric variables
df['sop'] = df['sop'].astype('float64')
df['lor'] = df['lor'].astype('float64')
df['research'] = df['research'].astype('float64')
```

In [55]:
```
sns.pairplot(df)
```

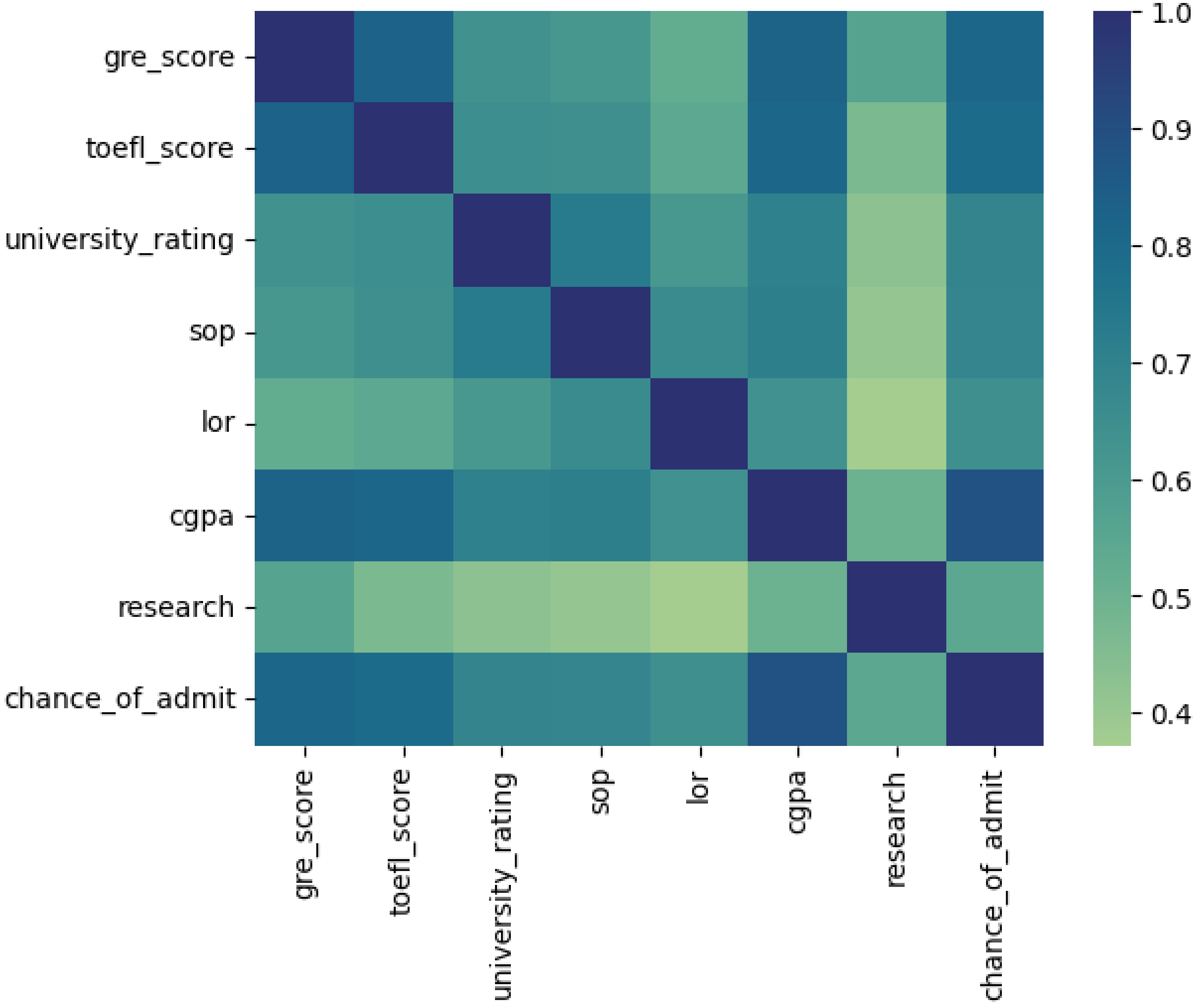
Out[55]:
```
<seaborn.axisgrid.PairGrid at 0x1347a5610>
```


gre_score
toefl_score
university_rating
sop
lor
cgpa
earch


chance_of_admit
gre_score
toefl_score
university_rating
sop
lor
cgpa
research
chance_of_admit

In [63]:
```
sns.heatmap(df.corr(), cmap = 'crest')
```

Out[63]: <Axes: >



Insights based on bivariate charts

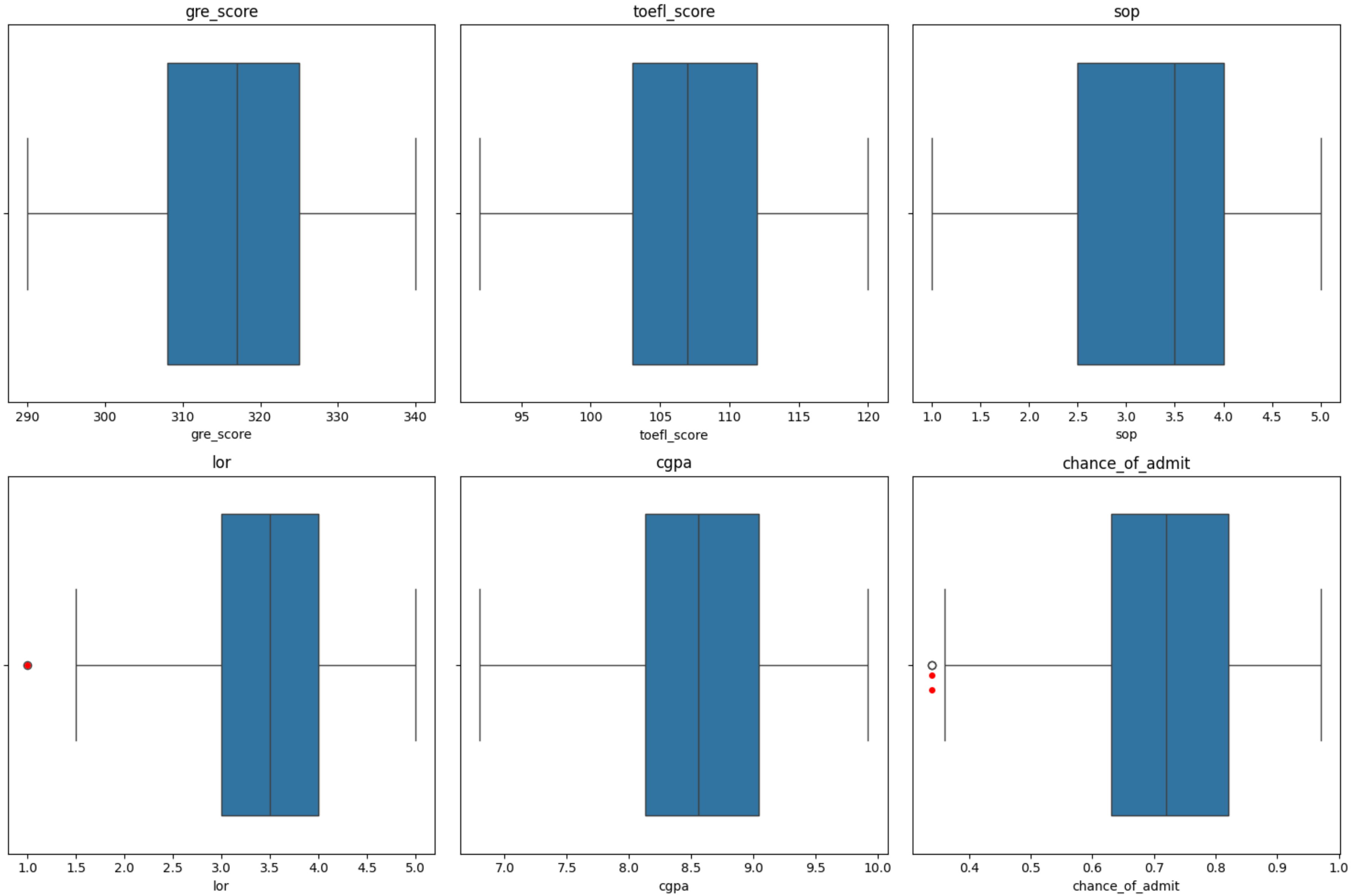
1. GRE score, TOEFL score and CGPA have high correlation with chances of admission.

2. LOR and Research have very low correlation with other variables.

Outlier Treatment

In [12]:
```
def outlier_func(arr):
    q1 = np.percentile(arr,25)
    q2 = np.percentile(arr,75)
    iqr = 1.5*(q2 - q1)
    low = max(q1 - iqr,0)
    high = q2 + iqr
    outliers = arr[(arr>high) | (arr<low)]
    return outliers
```

In [13]:
```
# Set up the matplotlib figure (2x3 grid)
fig, axs = plt.subplots(2, 3, figsize=(15, 10))

# Plot each KDE plot
sns.boxplot(x = df["gre_score"],ax=axs[0, 0], fill=True)
sns.stripplot(x = outlier_func(df["gre_score"]), color = "red", ax=axs[0, 0])
axs[0, 0].set_title('gre_score')

sns.boxplot(x = df["toefl_score"],ax=axs[0, 1], fill=True)
sns.stripplot(x = outlier_func(df["toefl_score"]), color = "red", ax=axs[0, 1])
axs[0, 1].set_title('toefl_score')

sns.boxplot(x = df["sop"],ax=axs[0, 2], fill=True)
sns.stripplot(x = outlier_func(df["sop"]), color = "red", ax=axs[0, 2])
axs[0, 2].set_title('sop')

sns.boxplot(x = df["lor"],ax=axs[1, 0], fill=True)
sns.stripplot(x = outlier_func(df["lor"]), color = "red", ax=axs[1, 0])
axs[1, 0].set_title('lor')

sns.boxplot(x = df["cgpa"],ax=axs[1, 1], fill=True)
sns.stripplot(x = outlier_func(df["cgpa"]), color = "red", ax=axs[1, 1])
axs[1, 1].set_title('cgpa')

sns.boxplot(x = df["chance_of_admit"],ax=axs[1, 2], fill=True)
sns.stripplot(x = outlier_func(df["chance_of_admit"]), color = "red", ax=axs[1, 2])
axs[1, 2].set_title('chance_of_admit')

# Adjust layout
plt.tight_layout()
plt.show()
```



In [14]:
```
outlier_func(df['lor'])
```

Out[14]:
```
347    1.0
Name: lor, dtype: float64
```

In [15]:
```
outlier_func(df['chance_of_admit'])
```

Out[15]:
```
92     0.34
376    0.34
Name: chance_of_admit, dtype: float64
```

In [16]:
```
df.iloc[[347,92,376]]
```

Out[16]:

	gre_score	toefl_score	university_rating	sop	lor	cgpa	research	chance_of_admit
347	299	94	1	1.0	1.0	7.34	0.0	0.42
92	298	98	2	4.0	3.0	8.03	0.0	0.34
376	297	96	2	2.5	2.0	7.43	0.0	0.34

We see that the outliers are not too extreme from the data and they give a valid representation of the reality rather than a mistake. So instead of imputing or removing them we will continue to use this for training as this will train the model to accurately understand reality.

Checking for Duplicate rows.

In [24]:
```
df.duplicated().sum()
# There are no duplicate rows in the dataframe.
```

Out[24]:
```
0
```

Data Preprocessing - Normalisation!

In [134]:
```
from sklearn.preprocessing import StandardScaler
```

In [135]:
```
scaler = StandardScaler()
data = pd.DataFrame(scaler.fit_transform(df), columns = df.columns)
```

In [136]:
```
data
```

Out[136]:

	gre_score	toefl_score	university_rating	sop	lor	cgpa	research	chance_of_admit
0	1.819238	1.778865	0.775582	1.137360	1.098944	1.776806	0.886405	1.406107
1	0.667148	-0.031601	0.775582	0.632315	1.098944	0.485859	0.886405	0.271349
2	-0.041830	-0.525364	-0.099793	-0.377773	0.017306	-0.954043	0.886405	-0.012340
3	0.489904	0.462163	-0.099793	0.127271	-1.064332	0.154847	0.886405	0.555039
4	-0.219074	-0.689952	-0.975168	-1.387862	-0.523513	-0.606480	-1.128152	-0.508797
...	...	...	...	...	...	...	...	...
495	1.376126	0.132987	1.650957	1.137360	0.558125	0.734118	0.886405	1.051495
496	1.819238	1.614278	1.650957	1.642404	1.639763	2.140919	0.886405	1.689797
497	1.198882	2.108041	1.650957	1.137360	1.639763	1.627851	0.886405	1.477030
498	-0.396319	-0.689952	0.775582	0.632315	1.639763	-0.242367	-1.128152	0.058582
499	0.933015	0.955926	0.775582	1.137360	1.098944	0.767220	-1.128152	0.838728

500 rows × 8 columns

Splitting train and test data

In [137]:
```
X = data.iloc[:,0:7]
Y = data.iloc[:, 7]
```

In [193]:
```
from sklearn.linear_model import Lasso, Ridge
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
```

Training the Model

In [175]:
```
lr = LinearRegression()
lr_ridge = Ridge(alpha = 1)
lr_lasso = Lasso(alpha = 0.1)
```

In [177]:
```
lr.fit(xtrain, ytrain)
lr_ridge.fit(xtrain, ytrain)
lr_lasso.fit(xtrain, ytrain)
```

Out[177]:
```
Lasso(alpha=0.1)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [180]:
```
y_pred_lr = lr.predict(xtest)
y_pred_ridge = lr_ridge.predict(xtest)
y_pred_lasso = lr_lasso.predict(xtest)
```

In [181]:
```
def adj_r2(xtest, ytest, model):
    y_pred = model.predict(xtest)
    r_squared = r2_score(ytest, y_pred)

    # Calculate Adjusted R^2
    n = xtest.shape[0]  # Number of observations
    p = xtest.shape[1]  # Number of predictors
    adjusted_r_squared = 1 - (1-r_squared) * (n-1) / (n-p-1)
    return adjusted_r_squared
```

Measuring the performance of the 3 models on both train and test data to see which performs the best.

In [191]:
```
y_pred_lr_train = lr.predict(xtrain)
y_pred_ridge_train = lr_ridge.predict(xtrain)
y_pred_lasso_train = lr_lasso.predict(xtrain)
```

In [192]:
```
print(f'for the ordinary linear regression model: R2 = {r2_score(ytrain, y_pred_lr_train)}, adj R2 = {adj_r2(xtrain, 
MAE = {mean_absolute_error(ytrain,y_pred_lr_train)}, RMSE = {mean_squared_error(ytrain,y_pred_lr_train, squared = Fal
print(f'for the Ridge linear regression model: R2 = {r2_score(ytrain, y_pred_ridge_train)}, adj R2 = {adj_r2(xtrain, 
MAE = {mean_absolute_error(ytrain,y_pred_ridge_train)}, RMSE = {mean_squared_error(ytrain,y_pred_ridge_train, squared
print(f'for the Lasso linear regression model: R2 = {r2_score(ytrain, y_pred_lasso_train)}, adj R2 = {adj_r2(xtrain, 
MAE = {mean_absolute_error(ytrain,y_pred_lasso_train)}, RMSE = {mean_squared_error(ytrain,y_pred_lasso_train, squared
```

```
for the ordinary linear regression model: R2 = 0.8207523447498908, adj R2 = 0.8175514937632817,MAE = 0.3061036544676
985, RMSE = 0.432000810069824
for the Ridge linear regression model: R2 = 0.8207470921804201, adj R2 = 0.8175461473979275,MAE = 0.3061309572611791
7, RMSE = 0.4320071395742188
for the Lasso linear regression model: R2 = 0.8047605761554439, adj R2 = 0.8012741578725054,MAE = 0.324301591457680
8, RMSE = 0.4508598666034221
```

On test data

In [190]:
```
print(f'for the ordinary linear regression model: R2 = {r2_score(ytest, y_pred_lr)}, adj R2 = {adj_r2(xtest, ytest, l
MAE = {mean_absolute_error(ytest,y_pred_lr)}, RMSE = {mean_squared_error(ytest,y_pred_lr, squared = False)}')
print(f'for the Ridge linear regression model: R2 = {r2_score(ytest, y_pred_ridge)}, adj R2 = {adj_r2(xtest, ytest, l
MAE = {mean_absolute_error(ytest,y_pred_ridge)}, RMSE = {mean_squared_error(ytest,y_pred_ridge, squared = False)}')
print(f'for the Lasso linear regression model: R2 = {r2_score(ytest, y_pred_lasso)}, adj R2 = {adj_r2(xtest, ytest, l
MAE = {mean_absolute_error(ytest,y_pred_lasso)}, RMSE = {mean_squared_error(ytest,y_pred_lasso, squared = False)}')
```

```
for the ordinary linear regression model: R2 = 0.8174673275904598, adj R2 = 0.8035789720810382,MAE = 0.3057443176799
5014, RMSE = 0.3865384454640839
for the Ridge linear regression model: R2 = 0.8177719029488089, adj R2 = 0.8039067216514356,MAE = 0.305531990053193
7, RMSE = 0.386215820379144
for the Lasso linear regression model: R2 = 0.8210010310873886, adj R2 = 0.8073815443222987,MAE = 0.3011203863970553
5, RMSE = 0.3827786040420496
```

From the test results it appears that Lasso regression model performs the best which also has the least MAE.

Another point to note is there is no big difference between the performance numbers in Test and Train data. This implies the data is not overfitting on the model.

Building a model using StatsModel and dropping features.

In [44]:
```
pip install statsmodels
```

```
Collecting statsmodels
  Downloading statsmodels-0.14.1-cp312-cp312-macosx_10_9_x86_64.whl.metadata (9.5 kB)
Requirement already satisfied: numpy<2,>=1.18 in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from statsmodels) (1.26.1)
Requirement already satisfied: scipy!=1.9.2,>=1.4 in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from statsmodels) (1.11.3)
Requirement already satisfied: pandas!=2.1.0,>=1.0 in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from statsmodels) (2.1.2)
Collecting patsy>=0.5.4 (from statsmodels)
  Downloading patsy-0.5.6-py2.py3-none-any.whl.metadata (3.5 kB)
Requirement already satisfied: packaging>=21.3 in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from statsmodels) (23.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from pandas!=2.1.0,>=1.0->statsmodels) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from pandas!=2.1.0,>=1.0->statsmodels) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from pandas!=2.1.0,>=1.0->statsmodels) (2023.3)
Requirement already satisfied: six in /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages (from patsy>=0.5.4->statsmodels) (1.16.0)
Downloading statsmodels-0.14.1-cp312-cp312-macosx_10_9_x86_64.whl (10.4 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10.4/10.4 MB 5.8 MB/s eta 0:00:0000:010:01m
Downloading patsy-0.5.6-py2.py3-none-any.whl (233 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 233.9/233.9 kB 4.1 MB/s eta 0:00:00a 0:00:01
Installing collected packages: patsy, statsmodels
Successfully installed patsy-0.5.6 statsmodels-0.14.1

[notice] A new release of pip is available: 23.3.2 -> 24.0
[notice] To update, run: pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

In [45]:
```
import statsmodels.api as sm
```

In [154]:
```
new_xtrain = sm.add_constant(xtrain)
```

In [155]:
```
model = sm.OLS(ytrain, new_xtrain)
```

In [156]:
```
results = model.fit()
```

In [157]:
```
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         chance_of_admit   R-squared:                       0.821
Model:                             OLS   Adj. R-squared:                  0.818
Method:                  Least Squares   F-statistic:                     256.4
Date:                 Thu, 22 Feb 2024   Prob (F-statistic):          4.81e-142
Time:                         13:08:51   Log-Likelihood:                -231.84
No. Observations:                  400   AIC:                             479.7
Df Residuals:                      392   BIC:                             511.6
Df Model:                            7
Covariance Type:             nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                -0.0131      0.022     -0.597      0.551      -0.056       0.030
gre_score             0.1533      0.046      3.343      0.001       0.063       0.243
toefl_score           0.0890      0.044      2.040      0.042       0.003       0.175
university_rating     0.0669      0.035      1.915      0.056      -0.002       0.136
sop                   0.0242      0.038      0.643      0.520      -0.050       0.098
lor                   0.1113      0.031      3.581      0.000       0.050       0.172
cgpa                  0.5266      0.049     10.824      0.000       0.431       0.622
research              0.0816      0.027      3.073      0.002       0.029       0.134
==============================================================================
Omnibus:                       90.591   Durbin-Watson:                   1.854
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              215.212
Skew:                          -1.128   Prob(JB):                     1.85e-47
Kurtosis:                       5.797   Cond. No.                         5.67
==============================================================================

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

The P value shown here is the probability where:

Null Hypothesis: A particular feature is insignificant.

Alternate Hypothesis: A particular feature is significant.

is p<0.05 then we reject null hypthesis and if p>0.05 then we accept the null hypothesis.

The R-square value comes out to be 0.821 whereas adjusted R-square is 0.818. Therefore we can confidently say that there exits some unnecessary features. The insignificant feature as shown by the P value seems to be const, university_rating and SOP. Let us try to remove them one by one and see how it affects R-square.

Since the P value of SOP is very high - which means that sop column might be insignificant. So let us drop the column and see how it affects the performance.

In [162]:
```
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
new_xtrain = sm.add_constant(xtrain)
new_xtrain = xtrain.drop('sop', axis = 1)
model = sm.OLS(ytrain, new_xtrain)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
=======================================================================================
Dep. Variable:         chance_of_admit   R-squared (uncentered):                   0.821
Model:                             OLS   Adj. R-squared (uncentered):              0.818
Method:                  Least Squares   F-statistic:                              300.3
Date:                 Thu, 22 Feb 2024   Prob (F-statistic):                   1.41e-143
Time:                         14:12:38   Log-Likelihood:                         -232.23
No. Observations:                  400   AIC:                                      476.5
Df Residuals:                      394   BIC:                                      500.4
Df Model:                            6
Covariance Type:             nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
gre_score             0.1536      0.046      3.356      0.001       0.064       0.244
toefl_score           0.0912      0.043      2.107      0.036       0.006       0.176
university_rating     0.0745      0.033      2.278      0.023       0.010       0.139
lor                   0.1181      0.030      3.990      0.000       0.060       0.176
cgpa                  0.5319      0.048     11.121      0.000       0.438       0.626
research              0.0825      0.026      3.117      0.002       0.030       0.135
==============================================================================
Omnibus:                       89.140   Durbin-Watson:                   1.854
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              209.597
Skew:                          -1.115   Prob(JB):                     3.07e-46
Kurtosis:                       5.758   Cond. No.                         5.23
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The R-square value hasn't changed a bit. Even the P values of every column is <0.05. Let us see how it performs on the test data.

In [159]:
```
ypred = results.predict(xtest.drop('sop', axis = 1))
r2_score(ytest, ypred)
```

Out[159]:
```
0.8204204090679413
```

It is performing well on test data aswell!

Checking VIF score to see if there is any multi-colinearity

In [74]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [160]:
```
vif = pd.DataFrame()
vif["Features"] = new_xtrain.columns
vif["VIF Scores"] = [variance_inflation_factor(new_xtrain.values, i) for i in range(new_xtrain.shape[1])]
```

In [161]:
```
print(vif)
```

```
            Features  VIF Scores
0          gre_score    4.508103
1        toefl_score    3.917250
2  university_rating    2.195041
3                lor    1.833988
4               cgpa    4.822205
5           research    1.486803
```

VIF score are not more than 5, so they look good.

Let us do the same for the column toefl_score because it had the highest P value even though p<0.05. This is because I observed adjusted R-square id < R-square.

In [163]:
```
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
#new_xtrain = sm.add_constant(xtrain)
new_xtrain = xtrain.drop(['sop', 'toefl_score'], axis = 1)
model = sm.OLS(ytrain, new_xtrain)
results = model.fit()
print(results.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:        chance_of_admit   R-squared (uncentered):                   0.819
Model:                            OLS   Adj. R-squared (uncentered):              0.816
Method:                 Least Squares   F-statistic:                              356.3
Date:                Thu, 22 Feb 2024   Prob (F-statistic):                   6.43e-144
Time:                        14:13:52   Log-Likelihood:                         -234.47
No. Observations:                 400   AIC:                                      478.9
Df Residuals:                     395   BIC:                                      498.9
Df Model:                           5
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
gre_score             0.1960      0.041      4.746      0.000       0.115       0.277
university_rating     0.0866      0.032      2.679      0.008       0.023       0.150
lor                   0.1174      0.030      3.953      0.000       0.059       0.176
cgpa                  0.5644      0.045     12.409      0.000       0.475       0.654
research              0.0789      0.027      2.974      0.003       0.027       0.131
==============================================================================
Omnibus:                       85.947   Durbin-Watson:                   1.861
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              202.069
Skew:                          -1.076   Prob(JB):                     1.32e-44
Kurtosis:                       5.738   Cond. No.                         4.73
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [164]:

```
ypred = results.predict(xtest.drop(['sop', 'toefl_score'], axis = 1))
r2_score(ytest, ypred)
```

Out[164]: 0.8087200845968682

In [165]:
```
vif = pd.DataFrame()
vif["Features"] = new_xtrain.columns
vif["VIF Scores"] = [variance_inflation_factor(new_xtrain.values, i) for i in range(new_xtrain.shape[1])]
print(vif)
```

```
            Features  VIF Scores
0          gre_score    3.638022
1  university_rating    2.127098
2                lor    1.833808
3               cgpa    4.322011
4           research    1.480607
```

We see that performance doesn't take a big hit when we remove toefl_score and even the vif scores comes within 5.

Next let us try removing University rating (because it had the highest P value) and see how it affects performance

In [167]:
```
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
#new_xtrain = sm.add_constant(xtrain)
new_xtrain = xtrain.drop(['sop', 'toefl_score', 'university_rating'], axis = 1)
model = sm.OLS(ytrain, new_xtrain)
results = model.fit()
print(results.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:         chance_of_admit   R-squared (uncentered):                   0.815
Model:                             OLS   Adj. R-squared (uncentered):              0.813
Method:                  Least Squares   F-statistic:                              436.8
Date:                 Thu, 22 Feb 2024   Prob (F-statistic):                   1.01e-143
Time:                         14:19:57   Log-Likelihood:                         -238.07
No. Observations:                  400   AIC:                                      484.1
Df Residuals:                      396   BIC:                                      500.1
Df Model:                            4
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
gre_score      0.2110      0.041      5.118      0.000       0.130       0.292
lor            0.1418      0.029      4.973      0.000       0.086       0.198
cgpa           0.5926      0.045     13.293      0.000       0.505       0.680
research       0.0834      0.027      3.124      0.002       0.031       0.136
==============================================================================
Omnibus:                       81.237   Durbin-Watson:                   1.855
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              184.413
Skew:                          -1.033   Prob(JB):                     9.02e-41
Kurtosis:                       5.607   Cond. No.                         4.29
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [168]:

```
ypred = results.predict(xtest.drop(['sop', 'toefl_score', 'university_rating'], axis = 1))
r2_score(ytest, ypred)
```

Out[168]: 0.8160542167053592

In [169]:
```
vif = pd.DataFrame()
vif["Features"] = new_xtrain.columns
vif["VIF Scores"] = [variance_inflation_factor(new_xtrain.values, i) for i in range(new_xtrain.shape[1])]
print(vif)
```

```
    Features  VIF Scores
0  gre_score    3.570785
1        lor    1.662386
2       cgpa    4.089269
3   research    1.474777
```

Performance on the test data has actually increased! Let us keep doing this for other columns - this time it is 'research'.

In [170]:
```
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
#new_xtrain = sm.add_constant(xtrain)
new_xtrain = xtrain.drop(['sop', 'toefl_score', 'university_rating','research'], axis = 1)
model = sm.OLS(ytrain, new_xtrain)
results = model.fit()
print(results.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:          chance_of_admit   R-squared (uncentered):                   0.811
Model:                              OLS   Adj. R-squared (uncentered):              0.809
Method:                   Least Squares   F-statistic:                              566.7
Date:                  Thu, 22 Feb 2024   Prob (F-statistic):                   4.79e-143
Time:                          14:24:34   Log-Likelihood:                         -242.94
No. Observations:                   400   AIC:                                      491.9
Df Residuals:                       397   BIC:                                      503.9
Df Model:                             3
Covariance Type:              nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
gre_score      0.2468      0.040      6.164      0.000       0.168       0.325
lor            0.1467      0.029      5.097      0.000       0.090       0.203
cgpa           0.6024      0.045     13.398      0.000       0.514       0.691
==============================================================================
Omnibus:                       86.990   Durbin-Watson:                   1.837
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              214.516
Skew:                          -1.069   Prob(JB):                     2.62e-47
Kurtosis:                       5.881   Cond. No.                         3.94
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [172]:
```
ypred = results.predict(xtest.drop(['sop', 'toefl_score', 'university_rating', 'research'], axis = 1))
r2_score(ytest, ypred)
```

Out[172]: 0.8090491577766505

In [173]:
```
vif = pd.DataFrame()
vif["Features"] = new_xtrain.columns
vif["VIF Scores"] = [variance_inflation_factor(new_xtrain.values, i) for i in range(new_xtrain.shape[1])]
print(vif)
```

```
    Features  VIF Scores
0  gre_score    3.294998
1        lor    1.657315
2       cgpa    4.069326
```

Performance on the test data has not decreased so this model should be the final one as it has only 3 features remaining. And removing columns further will adversely impact the performance.

Let us check our results with RFE and see what features sklearn selects

In [220]:
```
from sklearn.feature_selection import RFE
```

In [226]:
```
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
```

In [222]:
```
selector = RFE(lr, n_features_to_select=3, step=1)
selector = selector.fit(xtrain, ytrain)
```

In [224]:
```
print("Selected features:", selector.support_)
print("Feature ranking:", selector.ranking_)
```

```
Selected features: [ True False False False  True  True False]
Feature ranking: [1 2 4 5 1 1 3]
```

In [225]:
```
df
```

Out[225]:

	gre_score	toefl_score	university_rating	sop	lor	cgpa	research	chance_of_admit
0	337	118	4	4.5	4.5	9.65	1.0	0.92
1	324	107	4	4.0	4.5	8.87	1.0	0.76
2	316	104	3	3.0	3.5	8.00	1.0	0.72
3	322	110	3	3.5	2.5	8.67	1.0	0.80
4	314	103	2	2.0	3.0	8.21	0.0	0.65
...	...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1.0	0.87
496	337	117	5	5.0	5.0	9.87	1.0	0.96
497	330	120	5	4.5	5.0	9.56	1.0	0.93
498	312	103	4	4.0	5.0	8.43	0.0	0.73
499	327	113	4	4.5	4.5	9.04	0.0	0.84

500 rows × 8 columns

Therefore we see that only gre_score, lor and cgpa are being selected by the model just like what I did manually.

Now lets try building a model using only these three columns and measure their performance.

In [194]:
```
xtrain = xtrain.drop(['sop', 'toefl_score', 'university_rating','research'], axis = 1)
xtest = xtest.drop(['sop', 'toefl_score', 'university_rating', 'research'], axis = 1)
```

In [195]:
```
lr = LinearRegression()
lr_ridge = Ridge(alpha = 1)
lr_lasso = Lasso(alpha = 0.1)
```

In [196]:
```
lr.fit(xtrain, ytrain)
lr_ridge.fit(xtrain, ytrain)
lr_lasso.fit(xtrain, ytrain)
```

Out[196]:
```
Lasso(alpha=0.1)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [197]:
```
y_pred_lr = lr.predict(xtest)
y_pred_ridge = lr_ridge.predict(xtest)
y_pred_lasso = lr_lasso.predict(xtest)
```

In [198]:
```
y_pred_lr_train = lr.predict(xtrain)
y_pred_ridge_train = lr_ridge.predict(xtrain)
y_pred_lasso_train = lr_lasso.predict(xtrain)
```

In [199]:
```
print(f'for the ordinary linear regression model: R2 = {r2_score(ytrain, y_pred_lr_train)}, adj R2 = {adj_r2(xtrain, y
MAE = {mean_absolute_error(ytrain,y_pred_lr_train)}, RMSE = {mean_squared_error(ytrain,y_pred_lr_train, squared = Fal
print(f'for the Ridge linear regression model: R2 = {r2_score(ytrain, y_pred_ridge_train)}, adj R2 = {adj_r2(xtrain, y
MAE = {mean_absolute_error(ytrain,y_pred_ridge_train)}, RMSE = {mean_squared_error(ytrain,y_pred_ridge_train, squared
print(f'for the Lasso linear regression model: R2 = {r2_score(ytrain, y_pred_lasso_train)}, adj R2 = {adj_r2(xtrain, y
MAE = {mean_absolute_error(ytrain,y_pred_lasso_train)}, RMSE = {mean_squared_error(ytrain,y_pred_lasso_train, squared
```

```
for the ordinary linear regression model: R2 = 0.8106532112294966, adj R2 = 0.8092187658600232,MAE = 0.3165195580610
9433, RMSE = 0.4440039068662178
for the Ridge linear regression model: R2 = 0.8106491851047297, adj R2 = 0.809214709234311,MAE = 0.3165238098108890
7, RMSE = 0.444008627320246
for the Lasso linear regression model: R2 = 0.7979199785905783, adj R2 = 0.7963890693374767,MAE = 0.332334630054078
8, RMSE = 0.45869025035415245
```

On test data

In [200]:
```
print(f'for the ordinary linear regression model: R2 = {r2_score(ytest, y_pred_lr)}, adj R2 = {adj_r2(xtest, ytest, l
MAE = {mean_absolute_error(ytest,y_pred_lr)}, RMSE = {mean_squared_error(ytest,y_pred_lr, squared = False)}')
print(f'for the Ridge linear regression model: R2 = {r2_score(ytest, y_pred_ridge)}, adj R2 = {adj_r2(xtest, ytest, l
MAE = {mean_absolute_error(ytest,y_pred_ridge)}, RMSE = {mean_squared_error(ytest,y_pred_ridge, squared = False)}')
print(f'for the Lasso linear regression model: R2 = {r2_score(ytest, y_pred_lasso)}, adj R2 = {adj_r2(xtest, ytest, l
MAE = {mean_absolute_error(ytest,y_pred_lasso)}, RMSE = {mean_squared_error(ytest,y_pred_lasso, squared = False)}')
```

```
for the ordinary linear regression model: R2 = 0.8076404299320017, adj R2 = 0.8016291933673767,MAE = 0.3055641506358
432, RMSE = 0.3968069667594844
for the Ridge linear regression model: R2 = 0.8080039930757872, adj R2 = 0.8020041178594055,MAE = 0.3052806495362892
5, RMSE = 0.39643180315742493
for the Lasso linear regression model: R2 = 0.8115794612437004, adj R2 = 0.805691319407566,MAE = 0.3061434771657499,
RMSE = 0.3927231569540251
```

Let us use sklearn's LassoCV and RidgeCV to do cross validation and pick the best alpha for the best performance.

Lasso

In [227]:
```
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
from sklearn.linear_model import LassoCV
lr_lasso = LassoCV(n_alphas=100, cv=5, random_state=42)
lr_lasso.fit(xtrain, ytrain)
y_pred_lasso = lr_lasso.predict(xtest)
y_pred_lasso_train = lr_lasso.predict(xtrain)
```

In [229]:
```
print("Best alpha:", lr_lasso.alpha_)

# Evaluate on test data
test_score = lr_lasso.score(xtest, ytest)
print("Test score (R-squared):", test_score)
```

```
Best alpha: 0.005935979513186637
Test score (R-squared): 0.8189572341070348
```

Ridge

In [234]:
```
xtrain,xtest, ytrain, ytest = train_test_split(X, Y, test_size = 0.2, random_state = 24)
from sklearn.linear_model import RidgeCV
lr_ridge = RidgeCV(alphas=np.logspace(-10, 2, 100), cv=5)
lr_ridge.fit(xtrain, ytrain)
y_pred_ridge = lr_ridge.predict(xtest)
y_pred_ridge_train = lr_ridge.predict(xtrain)
```

In [235]:
```
print("Best alpha:", lr_ridge.alpha_)

# Evaluate on test data
test_score = lr_ridge.score(xtest, ytest)
print("Test score (R-squared):", test_score)
```

```
Best alpha: 6.135907273413185
Test score (R-squared): 0.8190136790559127
```

From all the models we tested the best one we got so far is this - Ridge model with alpha as 6.13, which gave a score of 0.819 with only three columns - gre_score, lor and cgpa.

1. Mean of residuals

In [243]:
```
y_pred_ridge = lr_ridge.predict(X)
```

In [244]:
```
residuals = y_pred_ridge - Y
np.mean(residuals)
```

Out[244]:
```
-0.013150102918659094
```

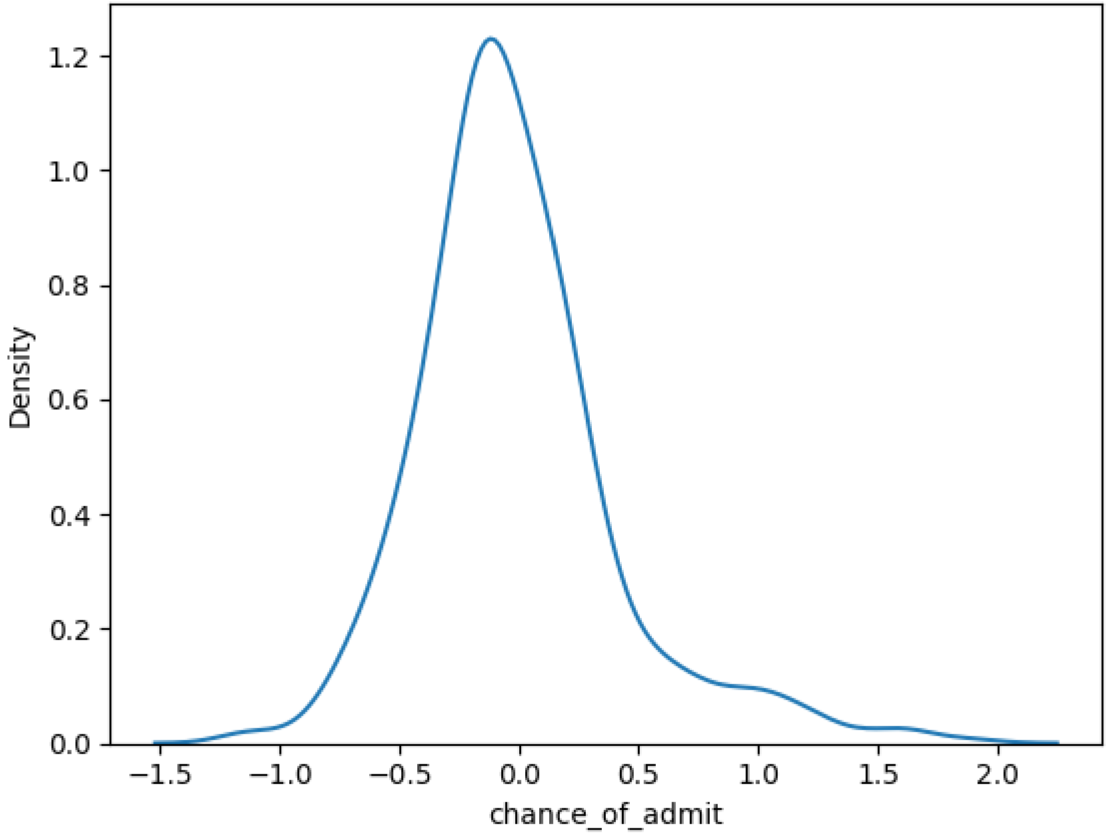
In [245]:
```
residuals
```

Out[245]:
```
0      0.218038
1      0.332502
2     -0.477034
3     -0.417957
4     -0.171539
         ...   
495   -0.179814
496    0.236767
497    0.127279
498   -0.157395
499   -0.106427
Name: chance_of_admit, Length: 500, dtype: float64
```

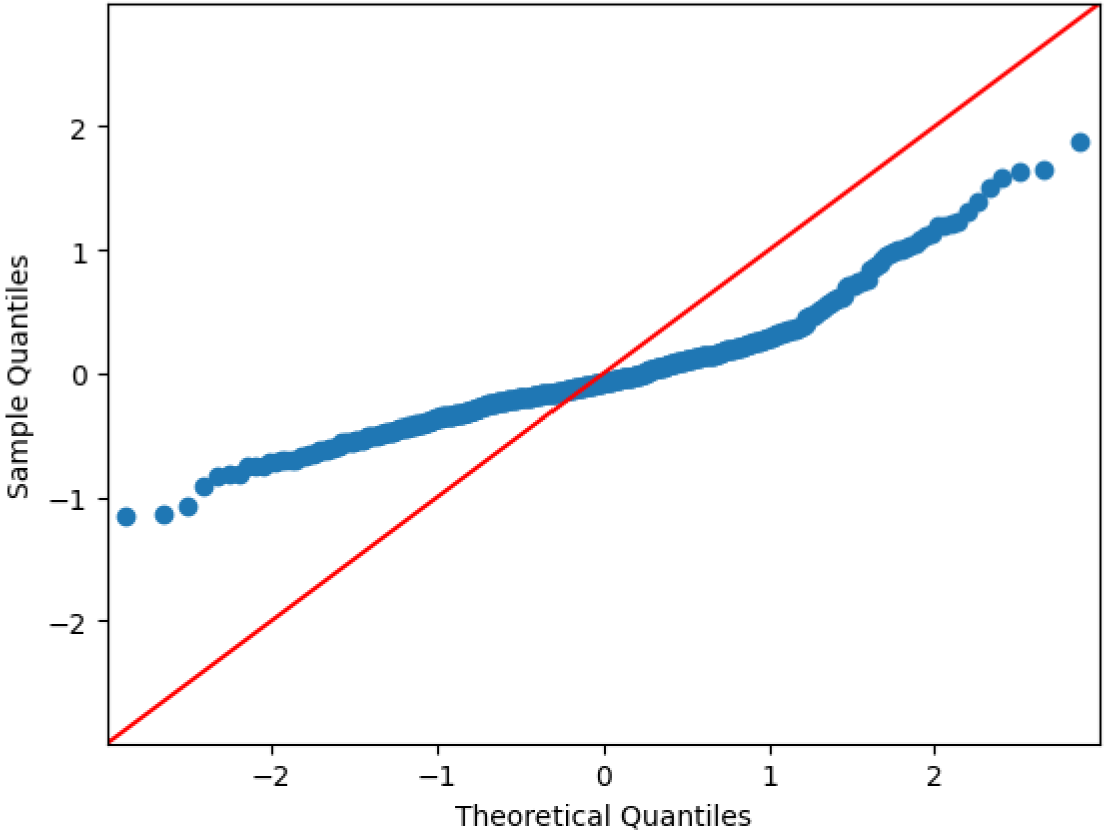
2. Normality of residuals

In [246]:
```
sns.kdeplot(residuals)
```

Out[246]:
```
<Axes: xlabel='chance_of_admit', ylabel='Density'>
```



In [247]:
```
fig = sm.qqplot(residuals, line ='45')
plt.show()
```

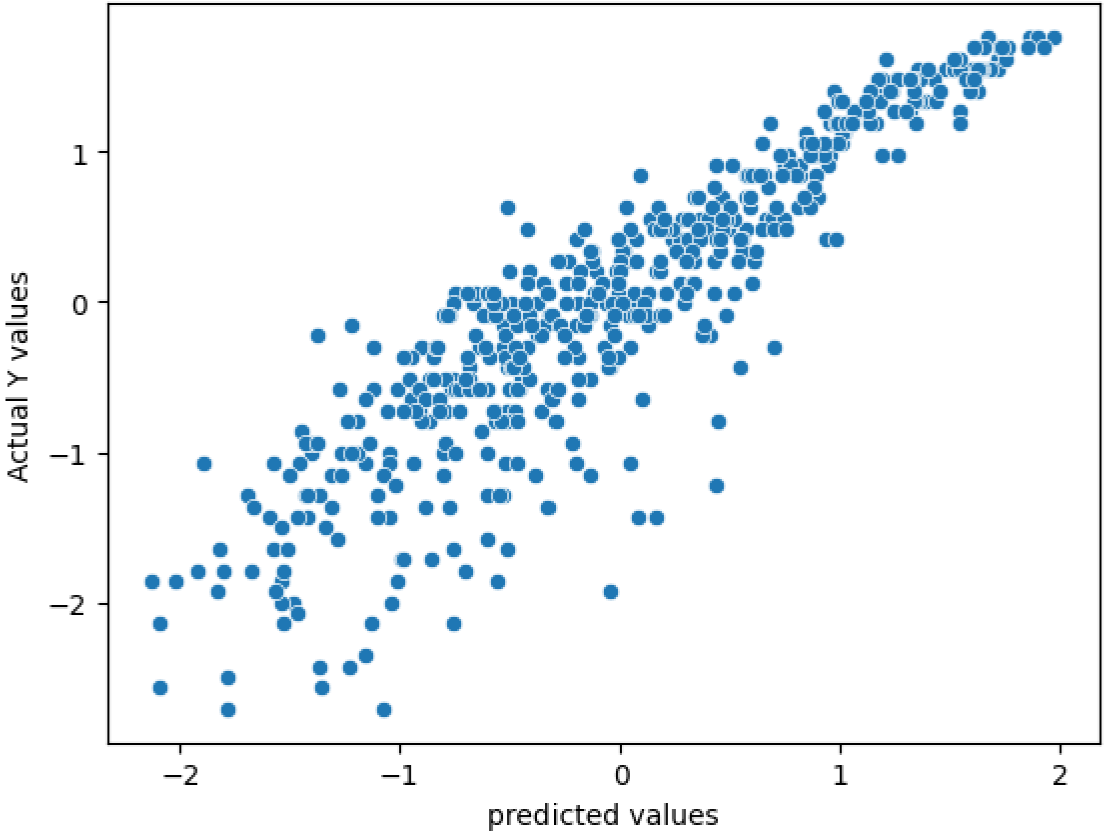


The QQ plot doesn't seem to confidently tell that residual distribution follow normal graph, however from kde plot above it is visually clear that residuals follow normality.

3. Linearity of variables

In [250]:
```
sns.scatterplot(x = y_pred_ridge, y = Y)
plt.xlabel('predicted values')
plt.ylabel('Actual Y values')
```

Out[250]: Text(0, 0.5, 'Actual Y values')

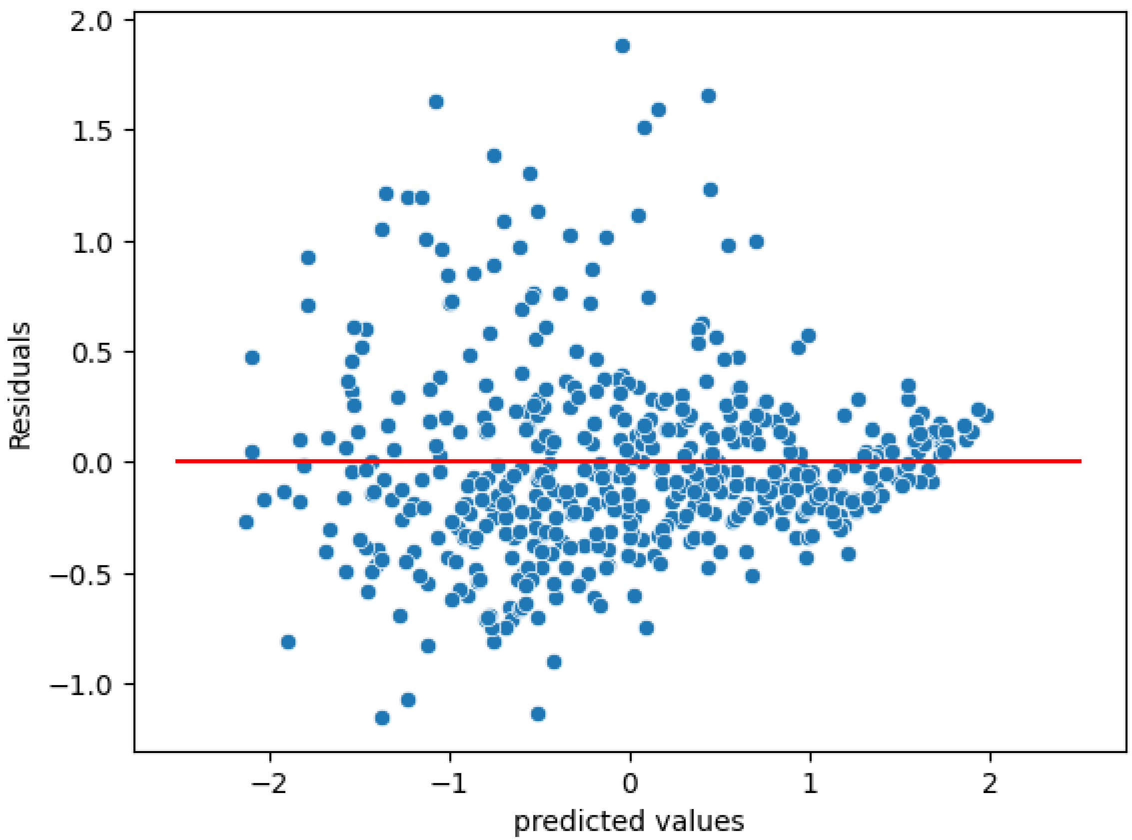


We observe that predicted values and actual values follow a straight line. Which basically means the data follows a linear pattern and Linear Regression is the right model to fit.

4. Test for Homoskedasticity

In [256]:
```
sns.scatterplot(x = y_pred_ridge, y = residuals)
plt.xlabel('predicted values')
plt.ylabel('Residuals')
sns.lineplot(x=[-2.5,2.5], y=[0,0], color='red')
```

Out[256]:
```
<Axes: xlabel='predicted values', ylabel='Residuals'>
```



We observe there is no Homoskedasticity since the residuals don't appear to diverge or converge.

Business insights and recommendation.

1. From our evaluation using RFE and VIF scores we found out that the most important parameters to determine the chances of admission is GRE score, LOR and CGPA. We can suggest our customers/students to focus on this more.

2. The other 4 parameters like SOP, university rating, TOEFL score and Research is not too important. We can suggest student to give less priority, but not outright removing it since TOEFL, SOP etc is mandatory to apply.

3. I would suggest Jamboree to collect more data, since we only had data for 500 students. Having more data is going to help us train our model better and make better predictions without having to worry about overfitting.

4. In one of the models we got R2 on train data as 0.97 whereas on test data it was 0.81. This was significant difference due to overfitting. We further modified the model to prevent overfitting like using Lasso or Ridge Regression.

5. Speaking about overfitting, the best Linear regression model comes out to be the Ridge regression model with a small alpha.

6. GRE score, TOEFL score and cgpa had a strong correlation with each other since they all measure the aptitude/skills of the candidate. So if a candidate is good at academics, he/she will be definitely good at all these parameters.

7. TOEFL, SOP directly measure the communication skills of a candidate in english language, so we saw a strong multicollinearity between such parameters.

8. Research and the least correlation with chances of admission. So we can ask the student to neglect this part as anyways it takes a lot of time and effort to publish a

paper. He would be better off utilizing this time to prepare for gre or TOEFI.

9. Using our ML model we can predict the chances of admission at 80% to 82% accuracy. If we had more data, we could utilize the rest of the columns (because model won't overfit on large dataset) and increase the accuracy even more so our prediction will be reliable.

10. Even with a more data if we find out that some of the columns do not contribute much, then we can just ask the candidate to input 3-4 parameters and give our prediction rather than taking all of the information from candidate. This is going to improve the user experience.

11. If we can collect data regarding the candidate's real admission status for e.g like a survey then we can train our model with more precise data. And we can actually build a classification model since the candidate is going to be either admitted (1) or not admitted (0), rather than our predicted probabilities. ¶

12. If it is possible, we can have objective metrics rather than subjective metrics like SOP score, LOR score. Because the score is given by a human and nobody is perfect, the score will depend on person to person. Therefore if we had like a metric that objectively measures the score (let's say we can ask ChatGPT to give the score)

13. I would also suggest Jamboree to give objective metric to Research column. If we have a continuous variable rather than 0 or 1 then the model may utilize this better and this could be a significant paramter just like cgpa, gre score etc. Since we have only 0 and 1 there is no strong correlation with chances of admission.

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