导入所需模块

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn import linear_model
```

```python
data = pd.read_csv('Admission_Predict.csv')
# 查看 data 中的数据
data.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

```python
# 生成描述性统计数据
data.describe()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000
mean	200.500000	316.807500	107.410000	3.087500	3.400000	3.452500	8.598925	0.547500	0.724350
std	115.614301	11.473646	6.069514	1.143728	1.006869	0.898478	0.596317	0.498362	0.142609
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.000000	6.800000	0.000000	0.340000
25%	100.750000	308.000000	103.000000	2.000000	2.500000	3.000000	8.170000	0.000000	0.640000
50%	200.500000	317.000000	107.000000	3.000000	3.500000	3.500000	8.610000	1.000000	0.730000
75%	300.250000	325.000000	112.000000	4.000000	4.000000	4.000000	9.062500	1.000000	0.830000
max	400.000000	340.000000	120.000000	5.000000	5.000000	5.000000	9.920000	1.000000	0.970000

```python
# 查看 data 数据中是否有缺失数据
data.info()
```

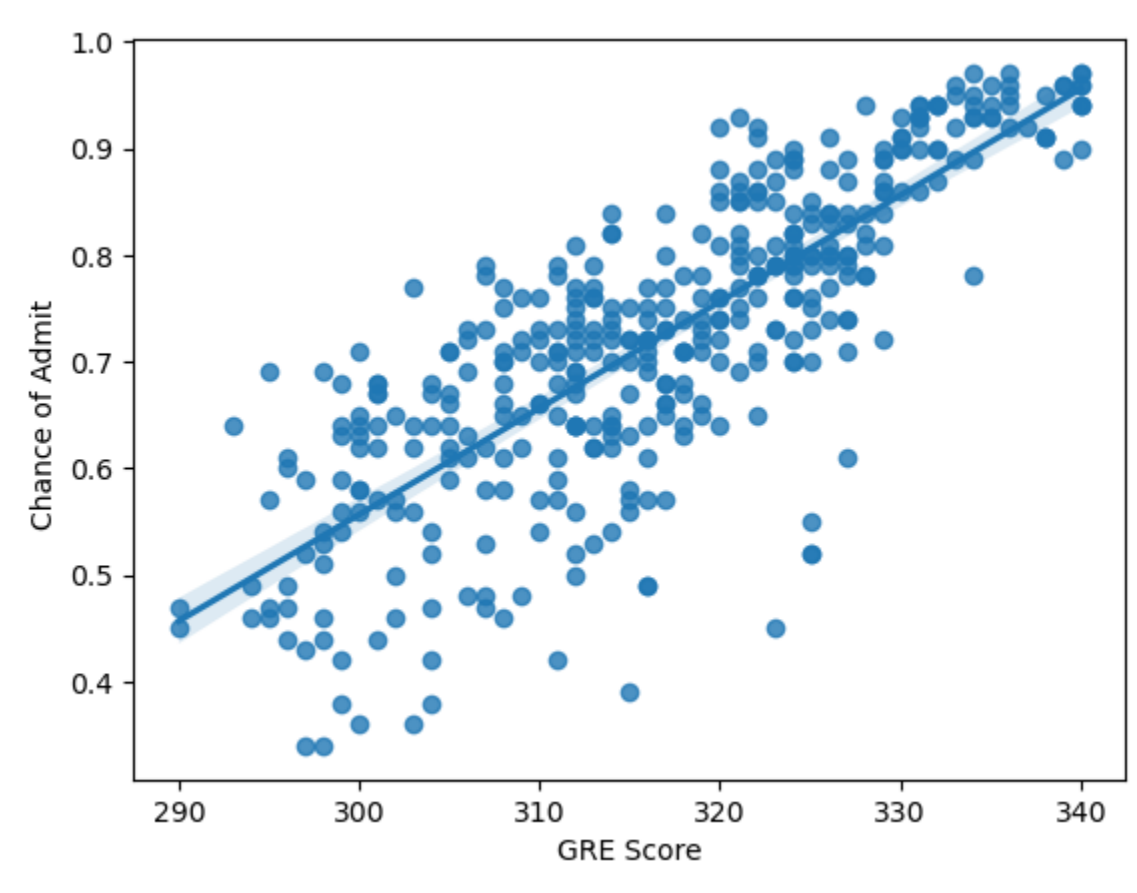
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Serial No.         400 non-null    int64
 1   GRE Score          400 non-null    int64
 2   TOEFL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

```python
# 取出相关字段，并生成相关性的可视化图
field = ['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA', 'Research', 'Chance of Admit ']
sns.heatmap(data[field].corr(), annot=True, vmin=-1, vmax=1)
```

```
<AxesSubplot:>
```

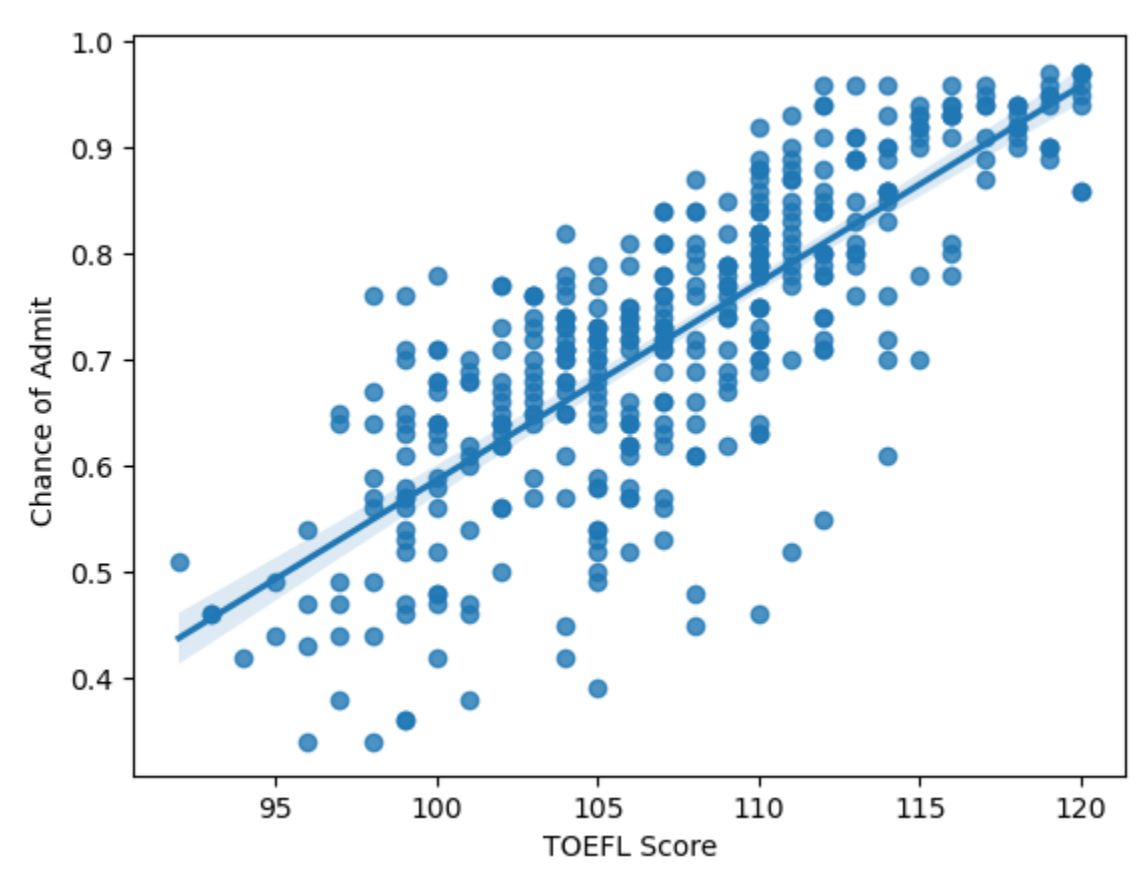
```python
# GRE成绩与入学承认率的关系
sns.regplot(x='GRE Score', y='Chance of Admit ', data=data)
```

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



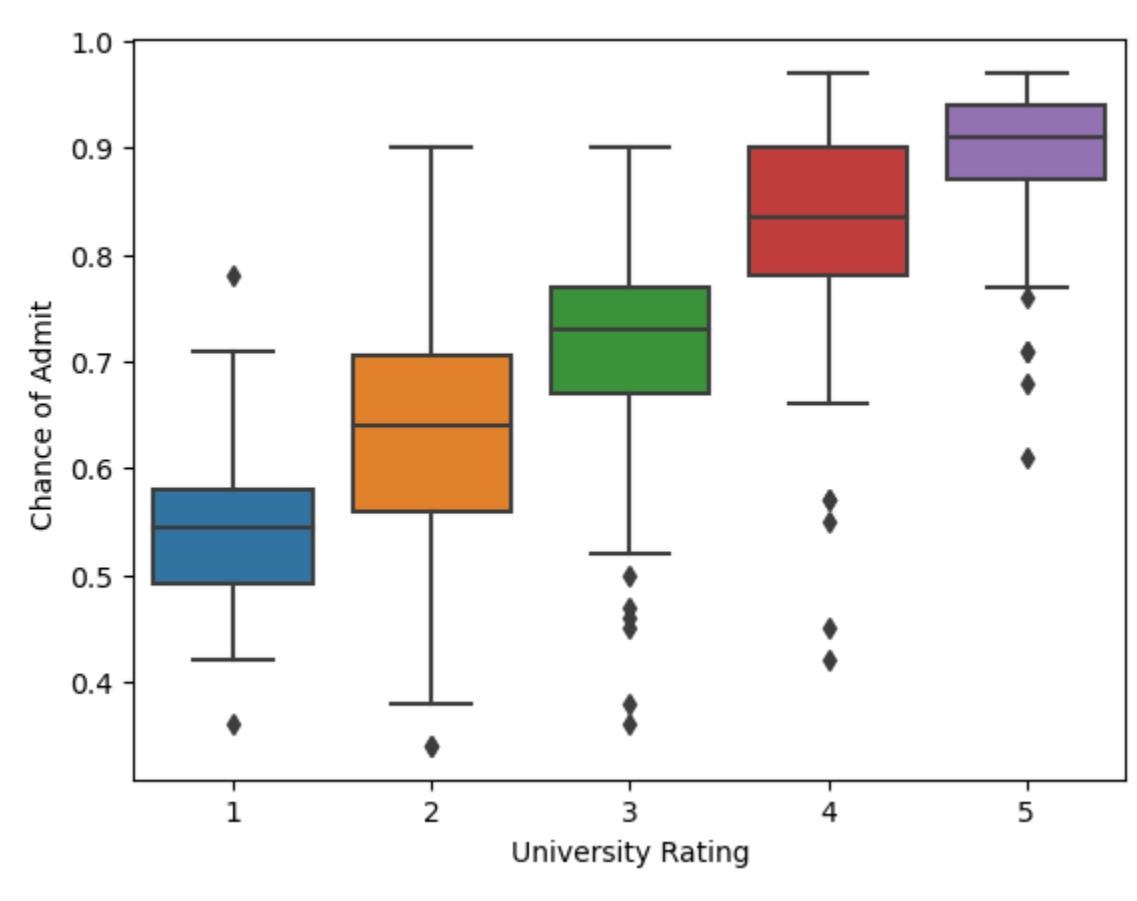
```python
# 托福分数与入学承认率的关系
sns.regplot(x='TOEFL Score', y='Chance of Admit ', data=data)
```

```
<AxesSubplot:xlabel='TOEFL Score', ylabel='Chance of Admit '>
```



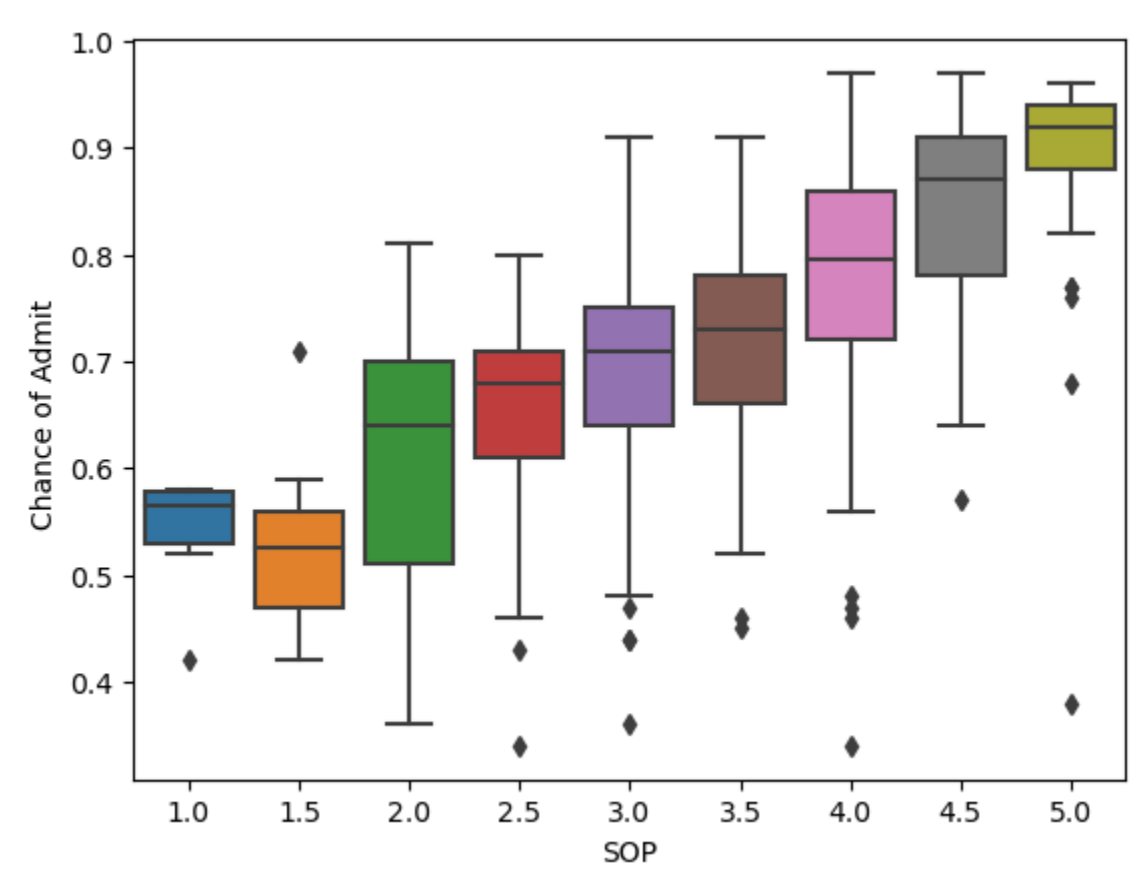
```python
# 大学评分与入学承认率的关系
sns.boxplot(x='University Rating', y='Chance of Admit ', data=data)
```

```
<AxesSubplot:xlabel='University Rating', ylabel='Chance of Admit '>
```



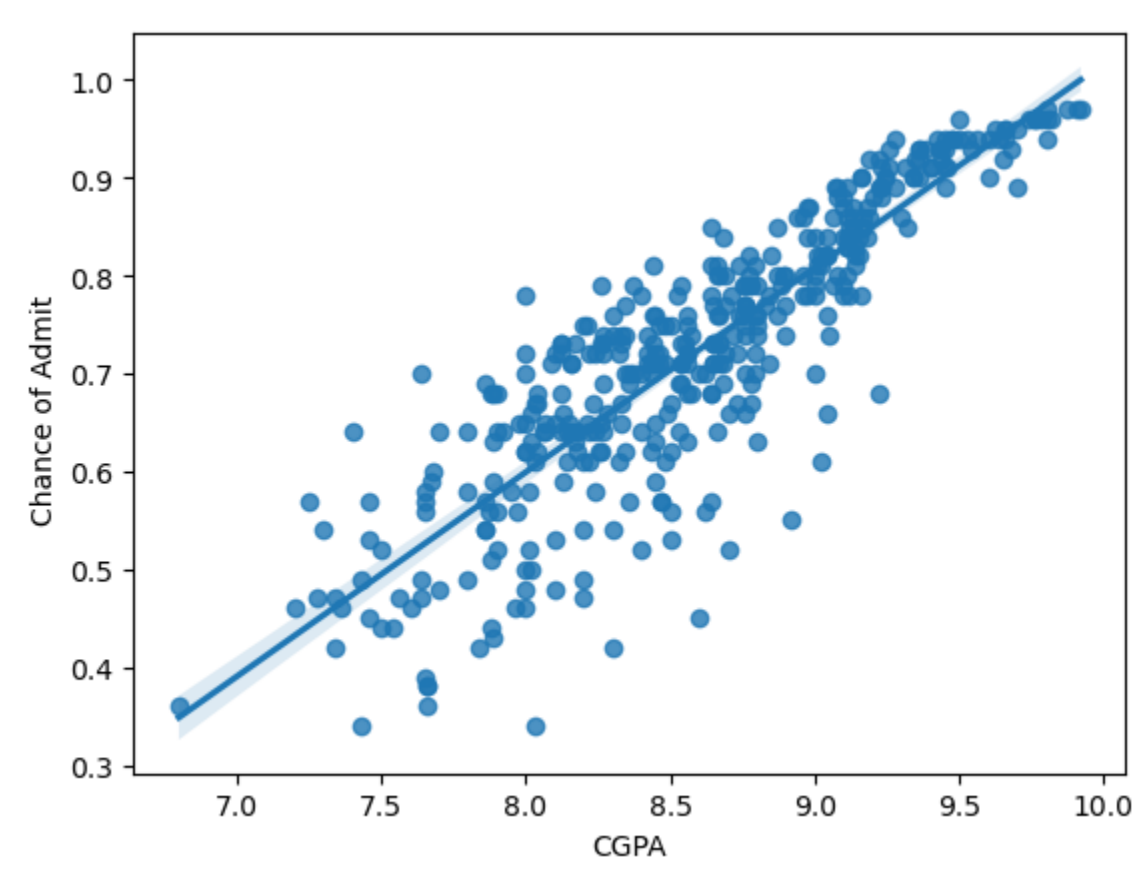
```python
# 算目的陈述与入学承认率的关系
sns.boxplot(x='SOP', y='Chance of Admit ', data=data)
```

```
<AxesSubplot:xlabel='SOP', ylabel='Chance of Admit '>
```



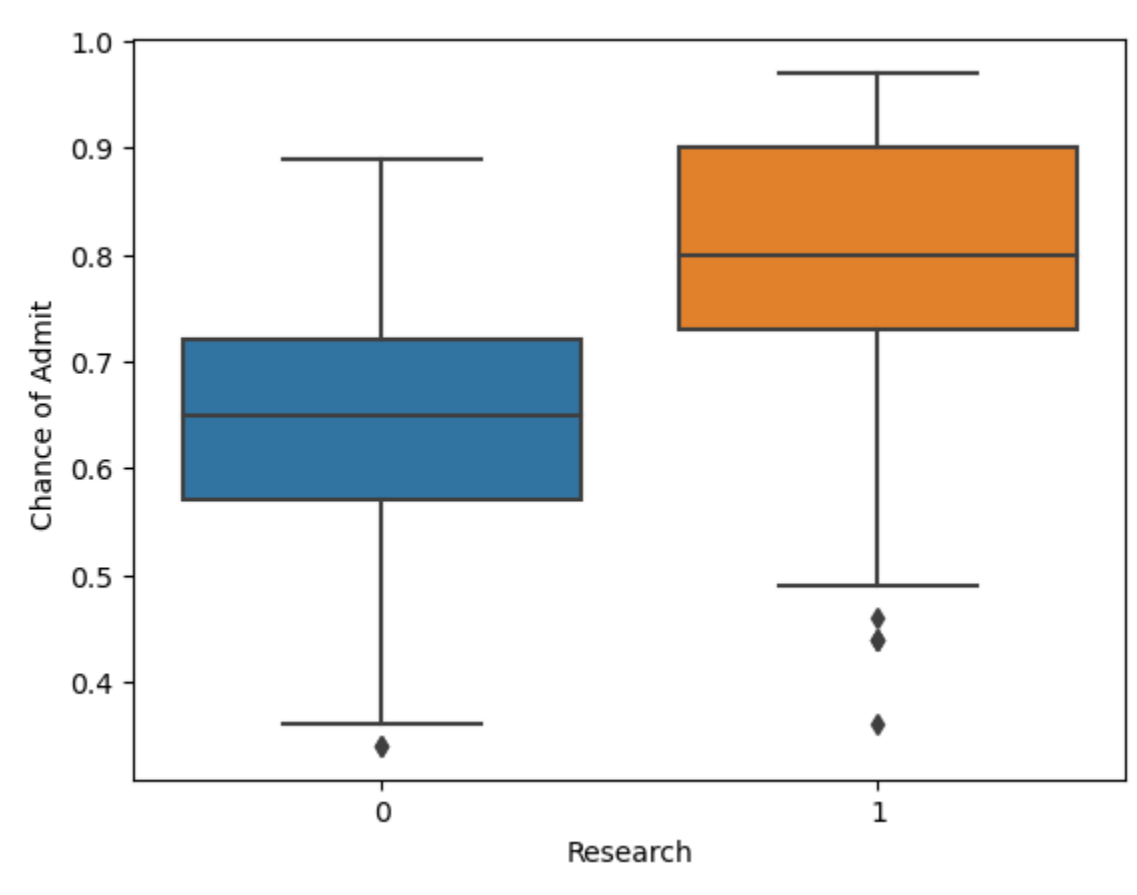
```python
# 本科GPA与入学承认率的关系
sns.regplot(x='CGPA', y='Chance of Admit ', data=data)
```

```
<AxesSubplot:xlabel='CGPA', ylabel='Chance of Admit '>
```



```python
# 研究经历与入学承认率的关系
sns.boxplot(x='Research', y='Chance of Admit ', data=data)
```

```
<AxesSubplot:xlabel='Research', ylabel='Chance of Admit '>
```



通过可视化，上述 field 的字段中与 'Chance of Admit' 的都有一定的相关性，且相关性均超过0.5，即上述特征均考虑在预测模型中

```python
# 用迭代增加特征的模型优化对特征的选择
lm = linear_model.LinearRegression()
features = ['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA', 'Research']
y = data['Chance of Admit ']

selected_features = []
rest_features = features[:]
best_acc = -0x7f7f7f7f
while len(rest_features)>0:
    temp_best_i = ''
    temp_best_acc = -0x7f7f7f7f
    for feature_i in rest_features:
        temp_features = selected_features + [feature_i]
        X = data[temp_features]
        scores = cross_val_score(lm, X, y, cv=5, scoring='neg_mean_absolute_error') # 负均方差来作为分数评价标准
        acc = np.mean(scores)
        if acc > temp_best_acc:
            temp_best_acc = acc
            temp_best_i = feature_i
    print("select",temp_best_i,"acc:",temp_best_acc)
    if temp_best_acc > best_acc:
        best_acc = temp_best_acc
        selected_features += [temp_best_i]
        rest_features.remove(temp_best_i)
    else:
        break
print("best feature set: ",selected_features,"acc: ",best_acc)

# 因为用交叉检验得到的 scores 是负值且结果均大于负无穷

# 所以 temp_best_acc 和 best_acc 的起始值设置为负无穷
```

```
select CGPA acc: -0.052544478165713907
select GRE Score acc: -0.050741512059l4499
select LOR  acc: -0.04893266934603155
select TOEFL Score acc: -0.04847770855315416
select Research acc: -0.048381681109844143
select SOP acc: -0.04842869515572236
best feature set:  ['CGPA', 'GRE Score', 'LOR ', 'TOEFL Score', 'Research'] acc:  -0.048381681109844143
```

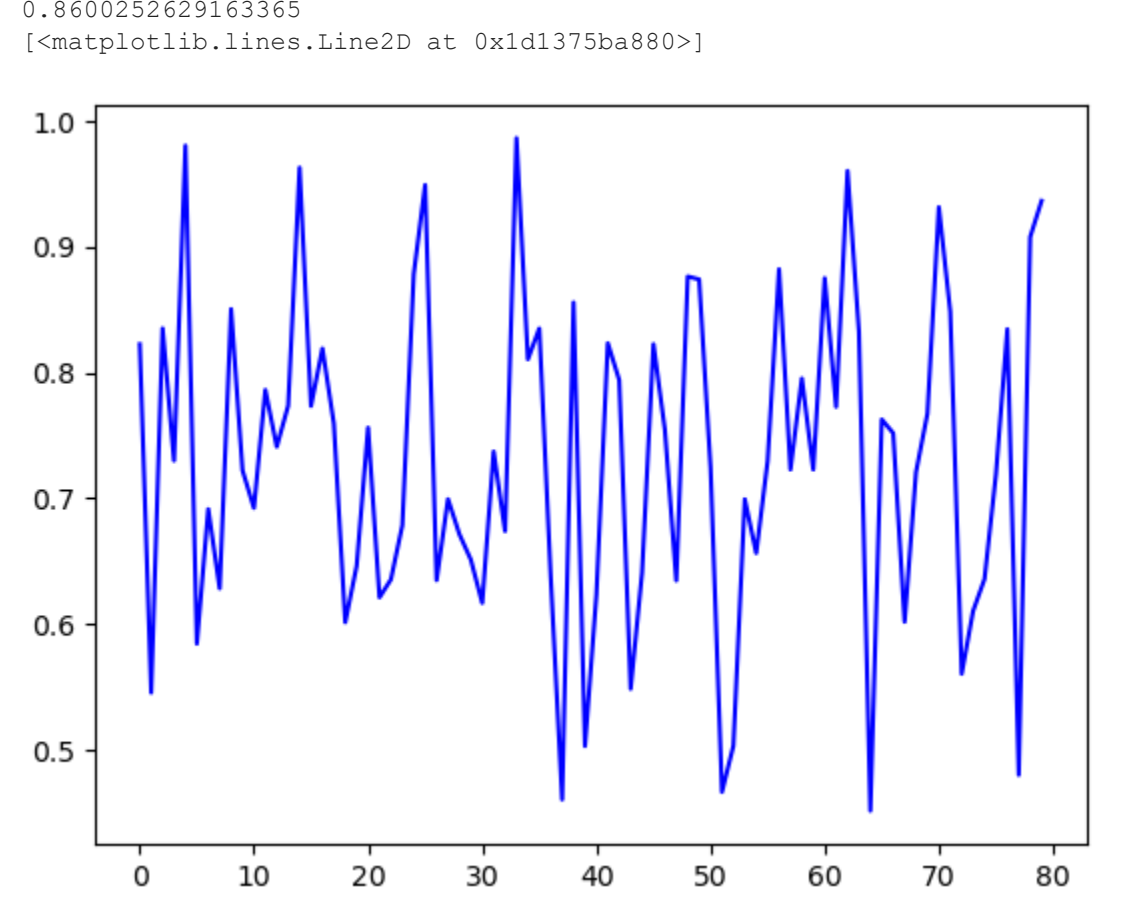
通过上述模型，我们能得到 best_feature = ['CGPA', 'GRE Score', 'LOR ', 'TOEFL Score', 'Research']

```python
# 对原始数据进行测试集和训练集的划分
best_features = ['CGPA', 'GRE Score', 'LOR ', 'TOEFL Score', 'Research']

# 对原始数据进行测试集和训练集的划分
char_data = data[best_features]
X_train, X_test, y_train, y_test = train_test_split(char_data, data['Chance of Admit '], train_size=0.8)
# 建立线性回归模型
model = lm.fit(X_test, y_test)
a = list(zip(best_features, model.coef_))
b = model.intercept_
print(f'回归系数: {a}', f'截距: {b}')
```

```
回归系数: [('CGPA', 0.19679873470548737), ('GRE Score', -0.0013725299837086297), ('LOR ', 0.008505992924868566), ('TOEFL Score', 0.0015098297196899512), ('Research', 0.04404154072065522)] 截距: -0.749817501794831
```

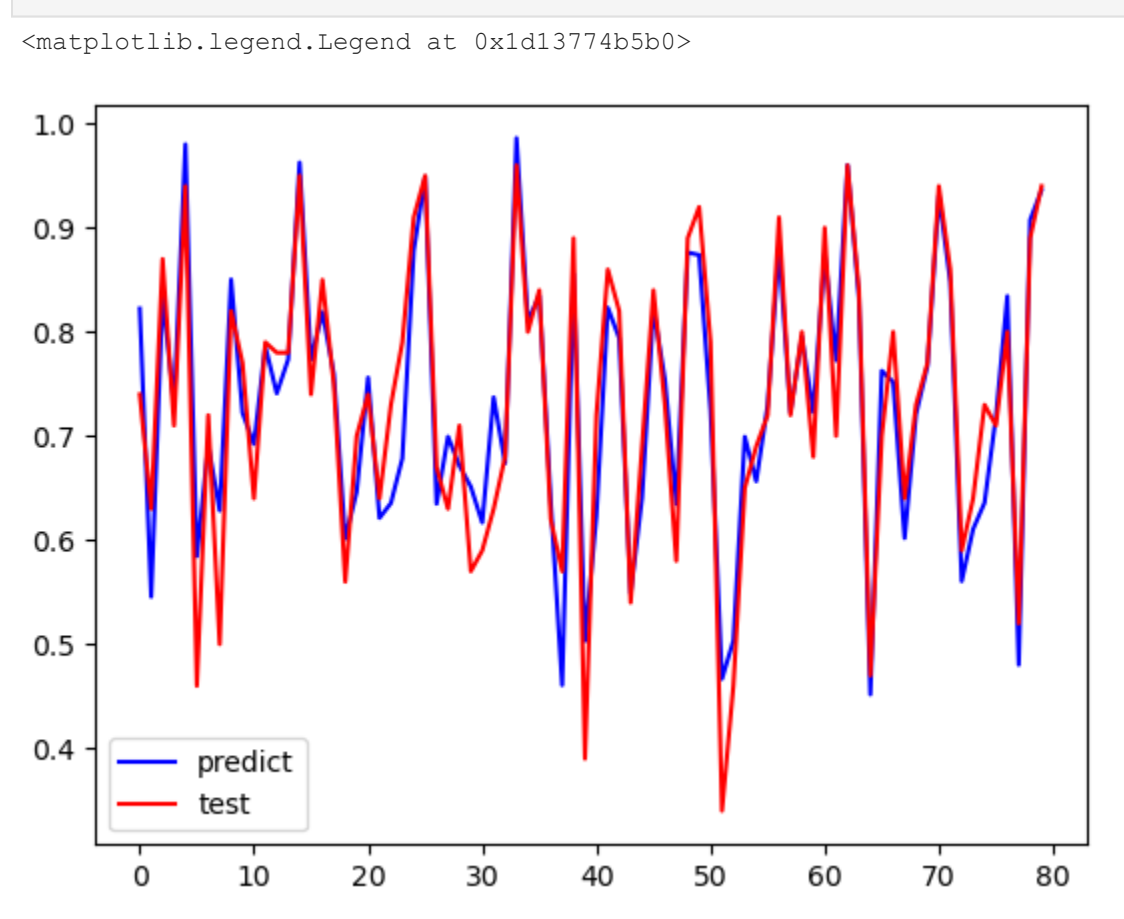
```python
# 评估模型的精确度
score = model.score(X_test, y_test)
print(score)

y_pred = model.predict(X_test)
plt.plot(range(len(y_pred)),y_pred,'b',label="predict")
```

```
0.8600252629163365
[<matplotlib.lines.Line2D at 0x1d1375ba880>]
```



```python
# 预测集与源数据集进行对比
plt.plot(range(len(y_pred)),y_pred,'b',label="predict")
plt.plot(range(len(y_pred)),y_test,'r',label="test")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x1d13774b5b0>
```



通过一些列的建模与分析，我们可以知道GRE成绩，本科GPA，托福成绩都，推荐信强度，研究经历这些特征的选取，对模型的分数会有一个极大的提高，但是模型的分数并不理想，需要进一步去优化模型。

为了考虑决策树的模型是否更优于线性回归模型，下面进行决策树的建模：

```python
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import pandas as pd
import numpy as np
import graphviz
import os


# 对承认机会进行人工分类，超过0.8的为录取，0.5-0.8之间的为待考虑，低于0.5为不录取
data['Admit_level'] = np.nan  # 创建Admit_level列并初始化为NaN
data['Admit_level'] = data['Admit_level'].astype(str)
data.iloc[data['Chance of Admit '] >= 0.8, data.columns.get_loc('Admit_level')] = 'Admission'
data.iloc[(data['Chance of Admit '] >= 0.5) & (data['Chance of Admit '] < 0.8), data.columns.get_loc('Admit_level')] = 'Pending consideration'
data.iloc[data['Chance of Admit '] < 0.5, data.columns.get_loc('Admit_level')] = 'Not admitted'
print(data['Admit_level'].unique())

features = ['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA', 'Research']
y = data['Admit_level']
X = data[features]  # 选择正确的特征数据集
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) # 随机种子
dt_classifier = DecisionTreeClassifier(random_state=42)
dt_classifier.fit(X_train, y_train)
y_pred = dt_classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
import os

# 指定 Graphviz 可执行文件路径
os.environ["PATH"] += os.pathsep + 'D:\ProgramData\Anaconda3\Lib\site-packages\Graphviz-10.0.1-win64\bin'


dot_data = export_graphviz(
    dt_classifier,
    out_file=None,
    feature_names=features,
    class_names=['Admission', 'Pending consideration', 'Not admitted'],
    filled=True,
    rounded=True,
    special_characters=True,

)

graph = graphviz.Source(dot_data)

engine='dot'
graph.render("decision_tree")
graph.view()
```

```
['Admission' 'Pending consideration' 'Not admitted']
Accuracy: 0.8
'decision_tree.pdf'
```