15장, 다중 회귀 분석 과제

In [1]:

!pip install seaborn

Requirement already satisfied: seaborn in c:\u00edusers\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdata_mining \u00fclib\u00afsite-packages (0.11.1)

Requirement already satisfied: matplotlib>=2.2 in c:\u00edusers\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdata _mining\u00fclib\u00fcsite-packages (from seaborn) (3.3.4)

Requirement already satisfied: scipy>=1.0 in c:\u00edusers\u00edghkrg\u00fcanaconda3\u00fcenvs\u00fcdata_mining\u00fclib\u00asite-packages (from seaborn) (1.6.3)

Requirement already satisfied: pandas>=0.23 in c:\u00edusers\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdata_ming\u00fclib\u00asite-packages (from seaborn) (1.2.3)

Requirement already satisfied: numpy>=1.15 in c:\u00edusers\u00edghkrg\u00fcanaconda3\u00fcenvs\u00fcdta_min ing\u00fclib\u00fcsite-packages (from seaborn) (1.20.1)

Requirement already satisfied: cycler>=0.10 in c:\u00edusers\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdata_mi ning\u00fclib\u00edsite-packages (from matplotlib>=2.2->seaborn) (0.10.0)

Requirement already satisfied: python-dateutil>=2.1 in c:\u00e4users\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdtenvs\u00e4data_mining\u00fclib\u00fcsite-packages (from matplotlib>=2.2->seaborn) (2.8.1)

Requirement already satisfied: kiwisolver>=1.0.1 in c:\u00edusers\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdata_mining\u00fclib\u00edsite-packages (from matplotlib>=2.2->seaborn) (1.3.1)

Requirement already satisfied: pillow>=6.2.0 in c:\u00edusers\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdta_m ining\u00fclib\u00edsite-packages (from matplotlib>=2.2->seaborn) (8.1.2)

Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in c:\u00edusers \u00edghkrg\u00edanaconda3\u00edenvs\u00eddata_mining\u00edlib\u00edsite-packages (from matplotlib>=2.2->seaborn) (2.4.7)

Requirement already satisfied: six in c:\u00edusers\u00fcgkanaconda3\u00fcenvs\u00fcdata_mining\u00fclib \u00dfusers\u00edusers=0.10-\u00dfusers\u00fclib>=2.2-\u00dfusers\u00fcn) (1.15.0)

Requirement already satisfied: pytz>=2017.3 in c:\u00edusers\u00fcghkrg\u00fcanaconda3\u00fcenvs\u00fcdata_ming\u00fclib\u00fcsite-packages (from pandas>=0.23->seaborn) (2021.1)

1. 데이터셋

1.1 데이터셋 읽기 (Graduate Admission)

- 특징 : GRE Scores, TOEFL, CGPA, SOP Rating, LOR Rating, Research Papers, University Ratings
- 타겟 : Chance of Admit (대학원 입학 허가 확률)
- https://www.kaggle.com/mohansacharya/graduate-admissions (https://www.kaggle.com/mohansacharya/graduate-admissions)

In [2]:

```
import os
import pandas as pd

path1 = os.path.join('data', 'Admission_Predict_Ver1.1.csv')
path2 = os.path.join('data', 'Admission_Predict.csv')

data1 = pd.read_csv(path1)
data2 = pd.read_csv(path2)

dataset = pd.concat([data1, data2])

dataset.sample(5)
```

Out[2]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
322	323	314	107	2	2.5	4.0	8.27	0	0.72
372	373	336	119	4	4.5	4.0	9.62	1	0.95
131	132	303	105	5	5.0	4.5	8.65	0	0.77
149	150	311	106	2	3.5	3.0	8.26	1	0.79
344	345	295	96	2	1.5	2.0	7.34	0	0.47

1.2 Series No 컬럼 삭제 (Q1)

샘플마다 유일하게 존재하는 ID 역할을 하는 컬럼은 학습에 방해가 되므로 삭제하시오.

In [3]:

```
# your code
dataset = dataset.drop('Serial No.', axis=1)
```

2. 데이터 탐색

2.1 요약 통계량

In [4]:

dataset.describe()

Out[4]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Ch
count	900.000000	900.000000	900.000000	900.000000	900.00000	900.000000	900.000000	900
mean	316.621111	107.288889	3.102222	3.385556	3.47000	8.586433	0.554444	0
std	11.369700	6.073968	1.143048	0.997612	0.91319	0.600822	0.497303	0
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.140000	0.000000	0
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.570000	1.000000	0
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.052500	1.000000	0
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0

2.2 누락 데이터 확인

In [5]:

dataset.isnull().sum()

Out[5]:

GRE Score	0
TOEFL Score	0
University Rating	0
SOP	0
LOR	0
CGPA	0
Research	0
Chance of Admit	0
dtype: int64	

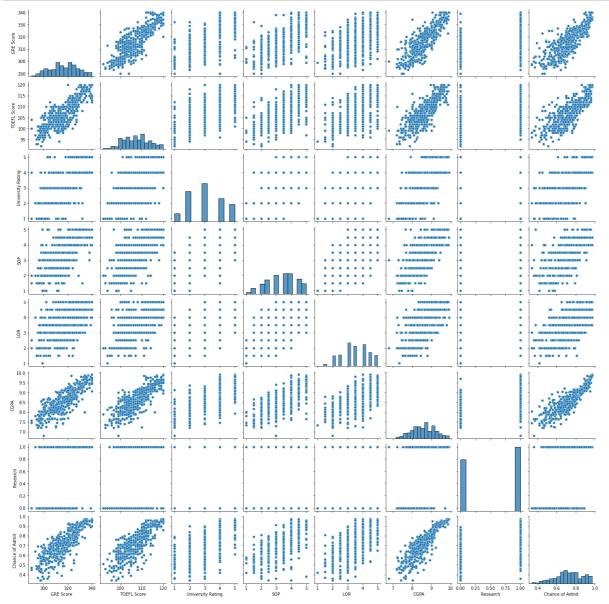
2.3 산포도 행렬

• 행렬의 대각 방향 : 히스토그램

• 행렬의 나머지 셀 : 두 변수 간의 상관성 분석을 위한 산포도

In [6]:

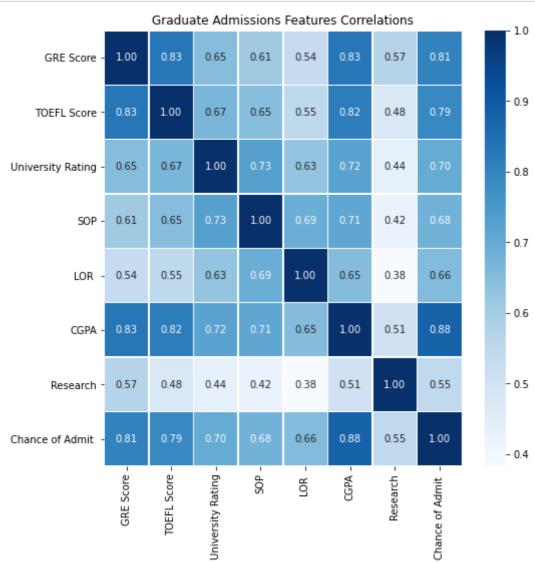
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.pairplot(dataset)
plt.show()
```



2.4 히트맵

In [7]:

```
fig, ax = plt.subplots(figsize=(8, 8))
sns.heatmap(dataset.corr(), linewidths=.5, annot=True, fmt=".2f", cmap='Blues')
plt.title('Graduate Admissions Features Correlations')
plt.show()
```



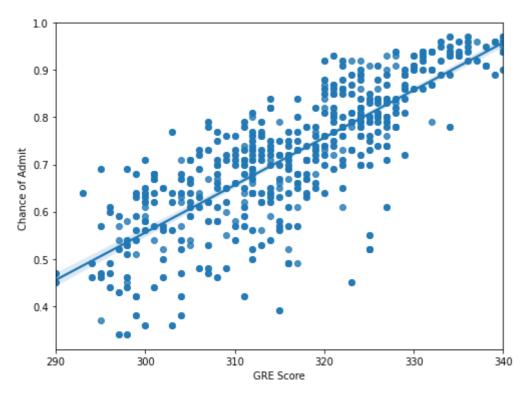
2.5 산포도와 단순 회귀선

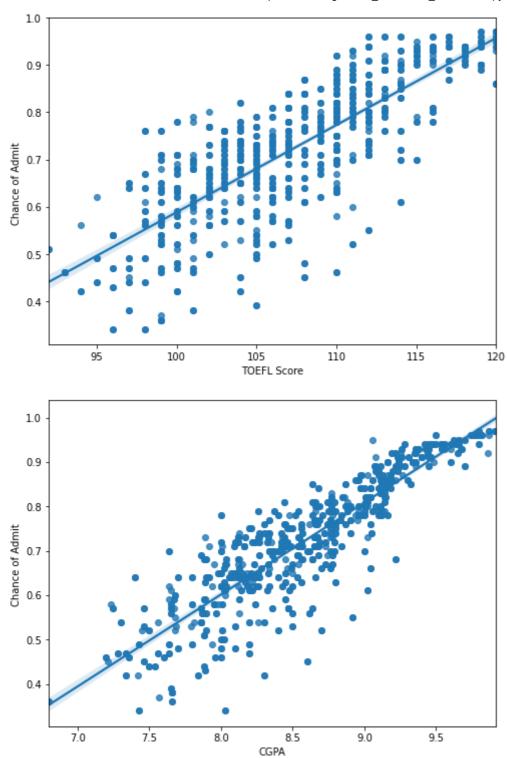
In [8]:

```
plt.subplots(figsize=(8,6))
sns.regplot(x="GRE Score", y="Chance of Admit ", data=dataset)
plt.subplots(figsize=(8,6))
sns.regplot(x="TOEFL Score", y="Chance of Admit ", data=dataset)
plt.subplots(figsize=(8,6))
sns.regplot(x="CGPA", y="Chance of Admit ", data=dataset)
```

Out[8]:

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





3. 데이터 전처리

3.1 입력 및 타겟 데이터 추출

In [9]:

```
X = dataset.iloc[:,:-1].values
y = dataset.iloc[:,-1].values # Chance of Admit
```

입력 데이터에 상수 항에 대한 입력 1 추가

In [10]:

```
X = [[1.0] + list(row[:]) for row in X]
```

3.2 데이터셋 분리

In [11]:

```
import random
from scratch.machine_learning import train_test_split

random.seed(12)
X_train, X_test, y_train, y_test = train_test_split(X, y, 0.25)
print('train dataset :', len(X_train))
print('test dataset :', len(X_test))
```

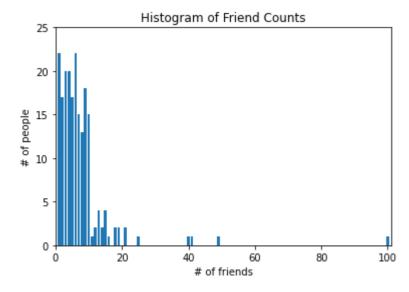
train dataset : 675 test dataset : 225

3.3 데이터 표준화 (Q2)

훈련 데이터의 평균과 표준 편차로 테스트 데이터를 표준화 하도록 normalization() 함수를 작성해 보시오.

In [12]:

```
from scratch.working_with_data import scale
from scratch.linear_algebra import vector_mean
from scratch.statistics import standard_deviation
from scratch.linear_algebra import Vector
from typing import List
def normalization(data: List[Vector].
                 means : Vector = None,
                 stdevs : Vector = None) -> List[Vector]:
   # your code
   dim = Ien(data[0])
   if means == None or stdevs == None:
       means, stdevs = scale(data)
   rescaled = [v[:] for v in data]
   for v in rescaled:
        for i in range(dim):
            if stdevs[i] > 0:
               v[i] = (v[i] - means[i]) / stdevs[i]
   return rescaled, means, stdevs
```



In [13]:

```
X_train_normed, X_train_means, X_train_stdevs = normalization(X_train)
X_test_normed, _, _ = normalization(X_test, X_train_means, X_train_stdevs)
```

4. 선형 회귀 분석 (Linear Regression)

4.1 예측 (Q3)

모델 예측 코드를 작성해 보시오.

In [14]:

```
# your code
from scratch.linear_algebra import dot, Vector

def predict(x: Vector, beta: Vector) -> float:
    return dot(x, beta)
```

4.2 손실 함수 (Q4)

손실 함수와 그래디언트를 작성해 보시오.

In [15]:

```
from typing import List

def error(x: Vector, y: float, beta: Vector) -> float:
    return predict(x, beta) - y
```

In [16]:

```
def squared_error(x: Vector, y: float, beta: Vector) -> float:
  return error(x, y, beta) ** 2
```

In [17]:

```
# your code
def sqerror_gradient(x: Vector, y: float, beta: Vector) -> Vector:
    err = error(x, y, beta)
    return [2 * err * x_i for x_i in x]
```

4.3 모델 훈련 (Q5)

최소 자승법

선형 회귀의 최소 자승법을 경사 하강법으로 구현하시오.

In [18]:

```
# your code
import random
import tqdm
from scratch.linear_algebra import vector_mean
from scratch.gradient_descent import gradient_step
def least_squares_fit(xs: List[Vector],
   ys: List[float],
    learning_rate: float = 0.001,
    num\_steps: int = 1000,
   batch_size: int = 1) -> Vector:
    # Start with a random guess
    guess = [random.random() for _ in xs[0]]
    for _ in tqdm.trange(num_steps, desc="least squares fit"):
        for start in range(0, len(xs), batch_size):
           batch_xs = xs[start:start+batch_size]
           batch_ys = ys[start:start+batch_size]
           gradient = vector_mean([sqerror_gradient(x, y, guess) for x, y in zip(batch_xs, batch_y
           guess = gradient_step(guess, gradient, -learning_rate)
    return guess
```

In [19]:

```
learning_rate = 0.001
beta = least_squares_fit(X_train_normed, y_train, learning_rate, 5000, 50)
```

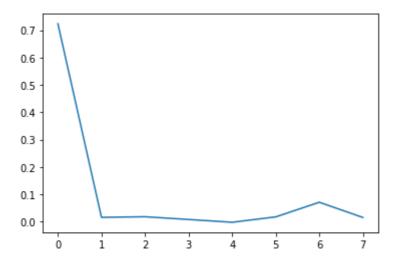
least squares fit: 100% 5000/5000 [00:17<00:00, 281.21it/s]

β 확인

In [20]:

```
print("beta = ", beta)
plt.plot(beta)
plt.show()
```

 $\begin{array}{lll} \text{beta} = & [0.7230369263767936, \ 0.01589118373524194, \ 0.018101419703239086, \ 0.008113360737764688, \ -0.002073350176785202, \ 0.017606264994132734, \ 0.0710238708099809, \ 0.015511699194081541] \end{array}$



4.4 모델 테스트 (Q6)

테스트 데이터를 이용해서 예측을 해보고 SSE를 계산해 보시오.

In [21]:

```
def test(xs: List[Vector], ys: List[float], beta : Vector) -> float:

# your code
pred_y = []
sse_list = []
for i in xs:
    pred_y.append(dot(i, beta))
    sse_list.append(dot(i, beta))

c = 0
for j in ys:
    sse_list[c] -= j
    sse_list[c] = sse_list[c] ** 2
    c += 1

SSE = sum(sse_list)
return pred_y, SSE
```

In [22]:

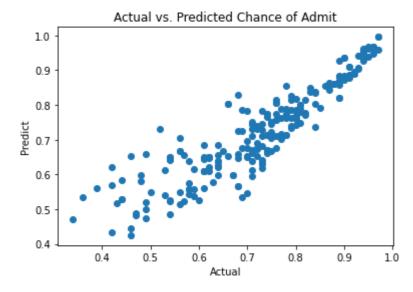
```
pred_y, SSE = test(X_test_normed, y_test, beta)
print("SSE = ", SSE)
```

SSE = 0.8671732654574079

실제 값과 예측 값의 상관 관계

In [23]:

```
plt.scatter(y_test, pred_y)
plt.title("Actual vs. Predicted Chance of Admit")
plt.xlabel("Actual")
plt.ylabel("Predict")
plt.show()
```



4.5 모델 적합도 (goodness-of-fit)

결정계수

In [24]:

In [25]:

```
r_squared = multiple_r_squared(X_test_normed, y_test, beta)
print(r_squared)
```

0.8189390601208067