

Homework: GLM and MLE

▼ Problem 1

▼ Step 1: Preparation of data

```
1 from google.colab import drive
2 drive.mount('/content/drive')
```

Mounted at /content/drive

G:\내 드라이브\Class\Programming_2023_Pytorch\New_2024_Chapter_5_MLE_and_GLM\HW

```
1 import pandas as pd
2 import torch
3 import numpy as np
4 from torch.utils.data import DataLoader, TensorDataset
5
6 df = pd.read_csv(r"/content/drive/MyDrive/24-2프로그래밍/competition_awards_data.csv", sep=',')
7 df.head()
```

	Awards	Math Score	grid icon
0	0	43	grid icon
1	0	38	
2	0	41	
3	0	33	
4	0	39	

다음 단계: [df 변수로 코드 생성](#) [추천 차트 보기](#) [New interactive sheet](#)

```
1 x = torch.tensor(df['Math Score'].values, dtype=torch.float32)
2 n = len(x)
3 #정규화
4 x_mean = torch.mean(x)
5 x_std = torch.std(x)
6 xx = (x-x_mean)/x_std
7
8 y = df['Awards'].values
9
10 ones = torch.ones([n])
11 X = torch.stack([ones, xx], axis=1)
12 Y = torch.tensor(y.reshape([n,1]), dtype=torch.float32)
13
14 dataset = TensorDataset(X,Y)
15 trainloader = DataLoader(dataset=dataset, batch_size=32, shuffle=True)
16
17
18
```

```
1 print(X.shape, Y.shape)
2
3 torch.Size([200, 2]) torch.Size([200, 1])
```

```
1 from sklearn.model_selection import train_test_split
2
3 # Split the data into training and test sets
4 X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
5 # Convert the data to TensorDataset to use with DataLoader
```

```

6 train_dataset = TensorDataset(X_train, Y_train)
7 test_dataset = TensorDataset(X_test, Y_test)
8
9 train_loader = DataLoader(dataset=train_dataset, batch_size=32, shuffle=True)
10 test_loader = DataLoader(dataset=test_dataset, batch_size=32, shuffle=True)

```

1 코딩을 시작하거나 AI로 코드를 생성하세요.

▼ Step 2: Model 1

Using the data above, we want to build the poisson regression model to predict the number of awards.

Model 1

```
Awards ~ exp(beta0 + beta1 * MathScore)
```

Answer the following questions.

1. Train the model.
2. You want to predict the number of awards for people having Math Score = 47, 40, 80. Calculated the predicted number of awards for these people.

```

1 #step 1: definition of the model
2 beta=torch.tensor(torch.randn([2,1]), requires_grad=True)
3
4 def forward(xx):
5     temp=torch.exp(xx@beta)
6     return temp
7
8 def criterion(yhat,yy):
9     temp=-torch.mean(-yhat+yy*torch.log(yhat))
10    return temp
11
12 optimizer = torch.optim.SGD([beta], lr=0.01)

→ <ipython-input-6-80cbd61bf6cf>:2: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.cl
beta=torch.tensor(torch.randn([2,1]), requires_grad=True)

```

```

1 #training
2 epochs=100
3 history=[]
4 n=len(train_loader.dataset)
5
6 for epoch in range(epochs):
7     LOSS_sum=0
8     for xx,yy in train_loader:
9         yhat=forward(xx)
10        loss=criterion(yhat,yy)
11        LOSS_sum=LOSS_sum+loss*len(yy)
12
13        optimizer.zero_grad()
14        loss.backward()
15        optimizer.step()
16
17    history.append(LOSS_sum.item()/n)
18

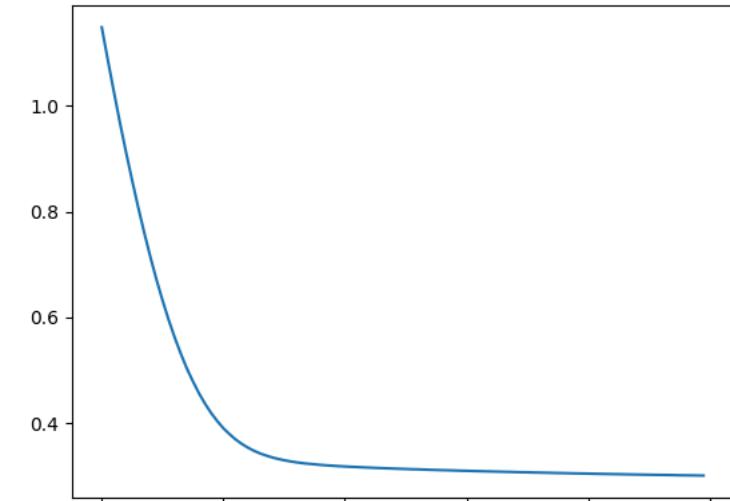
```

```

1 import matplotlib.pyplot as plt
2 plt.plot(history)
3

```

↳ [`<matplotlib.lines.Line2D at 0x7e2a58d41870>`]



```
1 #step 2 mathscore= 47, 40, 80
2
3 forward(torch.tensor([[1,47],[1,40],[1,80]],dtype=torch.float32))
→ tensor([[4.5239e+24],
       [8.0004e+20],
       [        inf]], grad_fn=<ExpBackward0>)
```

1 beta

```
→ tensor([[-1.2415],
       [ 1.2343]], requires_grad=True)
```

```
1 #test MSE
2 MSE_sum=0
3 n_test=len(test_loader.dataset)
4 for xx, yy in test_loader:
5     yhat=forward(xx)
6     mse=torch.sum((yhat-yy)**2)
7     MSE_sum+=mse.item()
8
9 MSE_sum/n_test
```

```
→ 0.04800056889653206
```

✓ Step 3: Model 2

You are also considering the following model

Model 2

`Awards ~ exp(beta0 + beta1 * MathScore + beta2 * MathScore**2)`

3. Train the model.

4. You want to predict the number of awards for people having Math Score = 47, 40, 80. Calculated the predicted number of awards for these people.

5. Calculate the Test MSE for each model. Which model is better in terms of Test MSE?

```
1 x = torch.tensor(df['Math Score'].values, dtype=torch.float32)
2 n = len(x)
3 #정규화
4 x_mean = torch.mean(x)
5 x_std = torch.std(x)
6 xx = (x-x_mean)/x_std
7
```

```

8 y = df['Awards'].values
9
10 x2=df['Math Score'].values
11
12 x2=torch.tensor(x2**2, dtype=torch.float32)
13 x2_mean = torch.mean(x2)
14 x2_std = torch.std(x2)
15 x3 = (x2-x2_mean)/x2_std
16
17 ones = torch.ones([n])
18 X = torch.stack([ones, xx, x3], axis=1)
19 Y = torch.tensor(y.reshape([n,1]), dtype=torch.float32)
20
21 dataset = TensorDataset(X,Y)
22 trainloader = DataLoader(dataset=dataset, batch_size=32, shuffle=True)

```

더블클릭 또는 Enter 키를 눌러 수정

1 X.shape

torch.Size([200, 3])

```

1 #데이터 셋 넣기
2 dataset = TensorDataset(X,Y)
3 trainloader = DataLoader(dataset=dataset, batch_size=32, shuffle=True)
4
5 from sklearn.model_selection import train_test_split
6
7 # Split the data into training and test sets
8 X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
9 # Convert the data to TensorDataset to use with DataLoader
10 train_dataset = TensorDataset(X_train, Y_train)
11 test_dataset = TensorDataset(X_test, Y_test)
12
13 train_loader = DataLoader(dataset=train_dataset, batch_size=32, shuffle=True)
14 test_loader = DataLoader(dataset=test_dataset, batch_size=32, shuffle=True)

```

1 #model2

2

3 beta=torch.tensor(torch.randn([3,1]), requires_grad=True)

4

5 def forward(xx):

6 temp=torch.exp(xx@beta)

7 return temp

8

9 def criterion(yhat,yy):

10 temp=-torch.mean(-yhat+yy*torch.log(yhat))

11 return temp

12

13 optimizer = torch.optim.SGD([beta], lr=0.01)

14

<ipython-input-102-5b449b6fcfd2>:3: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.
beta=torch.tensor(torch.randn([3,1]), requires_grad=True)

1 #training

2 epochs=100

3 history=[]

4 n=len(train_loader.dataset)

5

6 for epoch in range(epochs):

7 LOSS_sum=0

8 for xx,yy in train_loader:

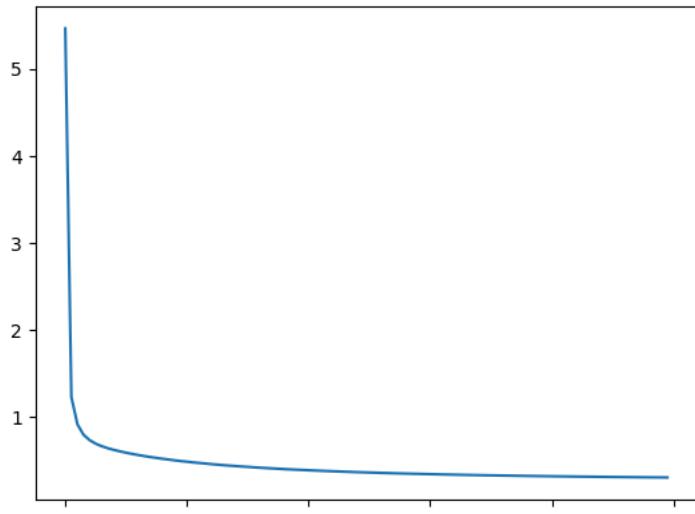
```

9     yhat=forward(xx)
10    loss=criterion(yhat,yy)
11    LOSS_sum=LOSS_sum+loss*len(yy)
12
13    optimizer.zero_grad()
14    loss.backward()
15    optimizer.step()
16
17 history.append(LOSS_sum.item()/n)
18
19
20

```

```
1 plt.plot(history)
```

↳ [matplotlib.lines.Line2D at 0x7e2a51220df0]



```
1 beta
```

↳ tensor([[-0.9299],
 [0.5249],
 [0.5035]], requires_grad=True)

```
1 #Math Score = 47, 40, 80
```

```
2
3 # 정규화 되돌리기
4 x_ori=x_std*47+x_mean
5 x_ori1=x_std*40+x_mean
6 x_ori2=x_std*80+x_mean
7 forward(torch.tensor([[1,x_ori,x_ori**2],[1,x_ori1,x_ori1**2],[1,x_ori2,x_ori2**2]]),dtype
8
```

↳ tensor([[inf],
 [inf],
 [inf]], grad_fn=<ExpBackward0>)

```

1 #test MSE
2 MSE_sum=0
3 n_test=len(test_loader.dataset)
4 for xx, yy in test_loader:
5     yhat=forward(xx)
6     mse=torch.sum((yhat-yy)**2)
7     MSE_sum+=mse.item()
8
9 MSE_sum/n_test

```

↳ 0.03132881969213486

1 # 모델 2의 성능이 더 좋음
2

▼ Problem 2:

Under the same dataset in Problem 1, answer the following questions.

Problem 2.1.

You want to use

```
torch.nn.Linear(... , ..., bias=True)
```

to modify `forward` function. Repeat procedure in Step 3 of Problem 1 using `torch.nn.Linear`. Redefine the `train_loader` and `test_loader` if necessary.

Problem 2.2.

You want to use

```
torch.nn.Linear(... , ..., bias=False)
```

to modify `forward` function. Repeat procedure in Step 3 of Problem 1 using `torch.nn.Linear`. Redefine the `train_loader` and `test_loader` if necessary.

Problem 2.3.

Repeat procedure in Step 3 in Problem 1 by modifying the following function. Furthermore, do not use

`torch.distributions.poisson.Poisson` in defining the loss function. Redefine the `train_loader` and `test_loader` if necessary.

```
class linear_regression(torch.nn.Module):
    def __init__(self, input_size, output_size):
        super().__init__()
        #####
        self.linear = torch.nn.Linear(input_size, output_size)
        #####
    def forward(self,x):
        #####
        yhat = self.linear(x)
        return yhat
        #####
forward = linear_regression(2,1)
```

▼ Problem 3.

You are given the following data. Answer the following questions.

1 !pip install ISLP

```
→ Collecting ISLP
  Downloading ISLP-0.4.0-py3-none-any.whl.metadata (7.0 kB)
Requirement already satisfied: numpy>=1.7.1 in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.26.4)
Requirement already satisfied: scipy>=0.9 in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.13.1)
Requirement already satisfied: pandas>=0.20 in /usr/local/lib/python3.10/dist-packages (from ISLP) (2.2.2)
Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages (from ISLP) (4.9.4)
Requirement already satisfied: scikit-learn>=1.2 in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.5.2)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from ISLP) (1.4.2)
Requirement already satisfied: statsmodels>=0.13 in /usr/local/lib/python3.10/dist-packages (from ISLP) (0.14.4)
Collecting lifelines (from ISLP)
  Downloading lifelines-0.29.0-py3-none-any.whl.metadata (3.2 kB)
Collecting pygam (from ISLP)
  Downloading pygam-0.9.1-py3-none-any.whl.metadata (7.1 kB)
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (from ISLP) (2.5.0+cu121)
```

```

Collecting pytorch-lightning (from ISLP)
  Downloading pytorch_lightning-2.4.0-py3-none-any.whl.metadata (21 kB)
Collecting torchmetrics (from ISLP)
  Downloading torchmetrics-1.5.1-py3-none-any.whl.metadata (20 kB)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.20->ISLP)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.20->ISLP) (20)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.20->ISLP) (2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=1)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13->ISLP)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13->ISLP)
Requirement already satisfied: matplotlib>=3.0 in /usr/local/lib/python3.10/dist-packages (from lifelines->ISLP) (3.3)
Requirement already satisfied: autograd>=1.5 in /usr/local/lib/python3.10/dist-packages (from lifelines->ISLP) (1.7.0)
Collecting autograd-gamma>=0.3 (from lifelines->ISLP)
  Downloading autograd-gamma-0.5.0.tar.gz (4.0 kB)
  Preparing metadata (setup.py) ... done
Collecting formulaic>=0.2.2 (from lifelines->ISLP)
  Downloading formulaic-1.0.2-py3-none-any.whl.metadata (6.8 kB)
Requirement already satisfied: progressbar2<5.0.0,>=4.2.0 in /usr/local/lib/python3.10/dist-packages (from pygam->ISLP)
Collecting scipy>=0.9 (from ISLP)
  Downloading scipy-1.11.4-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (60 kB)
  60.4/60.4 kB 4.6 MB/s eta 0:00:00
Requirement already satisfied: tqdm>=4.57.0 in /usr/local/lib/python3.10/dist-packages (from pytorch-lightning->ISLP)
Requirement already satisfied: PyYAML>=5.4 in /usr/local/lib/python3.10/dist-packages (from pytorch-lightning->ISLP)
Requirement already satisfied: fsspec>=2022.5.0 in /usr/local/lib/python3.10/dist-packages (from fsspec[http]>=2022.5)
Requirement already satisfied: typing-extensions>=4.4.0 in /usr/local/lib/python3.10/dist-packages (from pytorch-lightning->ISLP)
Collecting lightning-utilities>=0.10.0 (from pytorch-lightning->ISLP)
  Downloading lightning_utilities-0.11.8-py3-none-any.whl.metadata (5.2 kB)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch->ISLP) (3.16.1)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch->ISLP) (3.4.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch->ISLP) (3.1.4)
Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.10/dist-packages (from torch->ISLP) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from sympy==1.13.1->torch)
Collecting interface-meta>=1.2.0 (from formulaic>=0.2.2->lifelines->ISLP)
  Downloading interface_meta-1.3.0-py3-none-any.whl.metadata (6.7 kB)
Requirement already satisfied: wrapt>=1.0 in /usr/local/lib/python3.10/dist-packages (from formulaic>=0.2.2->lifelines)
Requirement already satisfied: aiohttp!=4.0.0a0,!=4.0.0a1 in /usr/local/lib/python3.10/dist-packages (from fsspec[http])
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from lightning-utilities>=0.10)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
Requirement already satisfied: numpy>=1.21 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)

```

```

1 import ISLP
2 Bikeshare = ISLP.load_data("Bikeshare")

```

▼ Problem 3.1.

You are given Model 1

$$Y_i \sim Pois(\mu_i)$$

where $\mu_i = \exp(b_0 + b_1 X_{1,i} + \dots + b_4 X_{4,i})$ and

$$\begin{cases} Y = \text{bikers} \\ X_1 = \text{mnth} \\ X_2 = \text{hr} \\ X_3 = \text{temp} \\ X_4 = \text{weathersit} \end{cases}$$

and Model 2:

$$Y_i \sim Pois(\mu_i)$$

where $\mu_i = \exp(b_0 + b_1 X_{1,i} + \dots + b_4 X_{4,i})$ and

$$\begin{cases} Y = \text{bikers} \\ X_1 = \text{mnth} \\ X_2 = \text{hr} \\ X_3 = \text{workingday} \\ X_4 = \text{temp} \\ X_5 = \text{weathersit} \end{cases}$$

Which is better model in terms of TEST MSE?

1 코딩을 시작하거나 AI로 코드를 생성하세요.

