### 딥러닝 모델 구현해 보기

### 학습 내용

- 정신 건강 설문 조사 데이터를 사용하여 개인의 우울증을 경험할 수 있는 요인을 탐색
- 첫번째 데이터 셋: 자전거 공유 업체 시간대별 데이터
- 두번째 데이터 셋: 타이타닉 데이터 셋(PyTorch)
- 세번째 데이터 셋:정신 건강 설문 조사 데이터

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## 01. 사전 환경 설치

목차로 이동하기

# GPU 버전 PyTorch 설치

```
# 가상환경 만들기
conda create --name gpuDL python=3.10

# Jupyter Notebook
conda install -c conda-forge notebook jupyter

# 추가 설치
pip install pandas scikit-learn

# PyTorch 설치하기
# 01 Anaconda 사용 시
conda install pytorch=2.5.1 torchvision torchaudio pytorch-
cuda=12.1 -c pytorch -c nvidia

# 02 pip 사용 시
pip3 install torch==2.5.1 torchvision torchaudio --index-url
https://download.pytorch.org/whl/cu121
```

In [1]: import torch
import sys
import numpy
import torch

```
print("Python version:", sys.version)
print("NumPy version:", numpy.__version__)
print("PyTorch version:", torch.__version__)

# CUDA 사용 가능 여부 확인
print(torch.cuda.is_available())

# 사용 가능한 GPU 장치 수 확인
print(torch.cuda.device_count())
```

Python version: 3.11.10 | packaged by Anaconda, Inc. | (main, Oct 3 2024, 07:22:

26) [MSC v.1929 64 bit (AMD64)]

NumPy version: 2.1.3

PyTorch version: 2.5.1+cpu

False 0

PyTorch 버전	권장 CUDA 버전
1.13.x	11.7
2.0.x	11.8
2.1.x	12.1

```
import torch
import sklearn

print(torch.__version__)
print(sklearn.__version__)
```

2.5.1+cpu 1.5.2

## 02. 라이브러리 및 데이터 불러오기

#### 목차로 이동하기

```
import numpy as np
import pandas as pd
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
```

```
In [4]: import os
    os.getcwd()
```

Out[4]: 'd:\\github\\DeepLearning\_Basic\_Class'

```
In [5]: # 시드 고정
torch.manual_seed(42)
np.random.seed(42)

# 1. 데이터 준비
# 상대 경로로 데이터 로드
```

```
train = pd.read_csv('./datasets/health_mental_24/train.csv')
test = pd.read_csv('./datasets/health_mental_24/test.csv')
sub = pd.read_csv('./datasets/health_mental_24/test.csv')
# 데이터 shape 확인
print("훈련 데이터 shape:", train.shape)
print("테스트 데이터 shape:", test.shape)
# 데이터 정보 확인
print("\n훈련 데이터 정보:")
print(train.info())

print("\n테스트 데이터 정보:")
print(test.info())
```

훈련 데이터 shape: (140700, 20) 테스트 데이터 shape: (93800, 19)

#### 훈련 데이터 정보:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 140700 entries, 0 to 140699
Data columns (total 20 columns):

Duca	coramis (cocar zo coramis).		
#	Column	Non-Null Count	Dtype
0	id	140700 non-null	int64
1	Name	140700 non-null	object
2	Gender	140700 non-null	object
3	Age	140700 non-null	float64
4	City	140700 non-null	object
5	Working Professional or Student	140700 non-null	object
6	Profession	104070 non-null	object
7	Academic Pressure	27897 non-null	float64
8	Work Pressure	112782 non-null	float64
9	CGPA	27898 non-null	float64
10	Study Satisfaction	27897 non-null	float64
11	Job Satisfaction	112790 non-null	float64
12	Sleep Duration	140700 non-null	object
13	Dietary Habits	140696 non-null	object
14	Degree	140698 non-null	object
15	Have you ever had suicidal thoughts ?	140700 non-null	object
16	Work/Study Hours	140700 non-null	float64
17	Financial Stress	140696 non-null	float64
18	Family History of Mental Illness	140700 non-null	object
19	Depression	140700 non-null	int64

dtypes: float64(8), int64(2), object(10)

memory usage: 21.5+ MB

None

#### 테스트 데이터 정보:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 93800 entries, 0 to 93799
Data columns (total 19 columns):

Data	columns (colar 19 columns):						
#	Column	Non-Null Count	Dtype				
0	id	93800 non-null	int64				
1	Name	93800 non-null	object				
2	Gender	93800 non-null	object				
3	Age	93800 non-null	float64				
4	City	93800 non-null	object				
5	Working Professional or Student	93800 non-null	object				
6	Profession	69168 non-null	object				
7	Academic Pressure	18767 non-null	float64				
8	Work Pressure	75022 non-null	float64				
9	CGPA	18766 non-null	float64				
10	Study Satisfaction	18767 non-null	float64				
11	Job Satisfaction	75026 non-null	float64				
12	Sleep Duration	93800 non-null	object				
13	Dietary Habits	93795 non-null	object				
14	Degree	93798 non-null	object				
15	Have you ever had suicidal thoughts ?	93800 non-null	object				
16	Work/Study Hours	93800 non-null	float64				
17	Financial Stress	93800 non-null	float64				
18	Family History of Mental Illness	93800 non-null	object				
<pre>dtypes: float64(8), int64(1), object(10)</pre>							

memory usage: 13.6+ MB

None

In [6]: train.head()

Out[6]:

	id	Name	Gender	Age	City	Working Professional or Student	Profession	Academic Pressure	Pre
0	0	Aaradhya	Female	49.0	Ludhiana	Working Professional	Chef	NaN	
1	1	Vivan	Male	26.0	Varanasi	Working Professional	Teacher	NaN	
2	2	Yuvraj	Male	33.0	Visakhapatnam	Student	NaN	5.0	
3	3	Yuvraj	Male	22.0	Mumbai	Working Professional	Teacher	NaN	
4	4	Rhea	Female	30.0	Kanpur	Working Professional	Business Analyst	NaN	
4									Þ
test.head(3)									

In [7]: test.head(3)

Out[7]:

In [8]:

	id	Name	Gender	Age	City	Working Professional or Student	Profession	Academic Pressure
0	140700	Shivam	Male	53.0	Visakhapatnam	Working Professional	Judge	NaN
1	140701	Sanya	Female	58.0	Kolkata	Working Professional	Educational Consultant	NaN
2	140702	Yash	Male	53.0	Jaipur	Working Professional	Teacher	NaN
4								•
sub *head()								

```
Out[8]:
               id Depression
         0 140700
                           0
         1 140701
                           0
         2 140702
                           0
         3 140703
                           0
         4 140704
                           0
In [9]: train.columns
Out[9]: Index(['id', 'Name', 'Gender', 'Age', 'City',
                'Working Professional or Student', 'Profession', 'Academic Pressure',
                'Work Pressure', 'CGPA', 'Study Satisfaction', 'Job Satisfaction',
                'Sleep Duration', 'Dietary Habits', 'Degree',
                'Have you ever had suicidal thoughts ?', 'Work/Study Hours',
                'Financial Stress', 'Family History of Mental Illness', 'Depression'],
               dtype='object')
In [40]: import numpy as np
         import pandas as pd
         from sklearn.impute import SimpleImputer
         from sklearn.preprocessing import LabelEncoder, StandardScaler
         #필요한 피처 선택
         features = [
             'Age', 'Work/Study Hours', 'Financial Stress', # 숫자형 변수
             'Gender', 'Working Professional or Student', 'City',
             'Sleep Duration', 'Dietary Habits', 'Degree', # 범주형 변수
             'Academic Pressure', 'Work Pressure', 'CGPA',
             'Study Satisfaction', 'Job Satisfaction' # 결측치 있는 숫자형 변수
         1
         target = 'Depression'
In [42]: # 전처리 함수 정의
         def preprocess_data(df, gubun='train'):
            # 데이터프레임 복사
            data = df.copy()
            # 범주형 변수 인코딩
             categorical_features = [
                 'Gender',
                 'Working Professional or Student',
                'City',
                 'Sleep Duration',
                 'Dietary Habits',
                'Degree'
             1
            # 라벨 인코더 초기화
            le = LabelEncoder()
            # 범주형 변수 인코딩
            for col in categorical_features:
                # NaN 값을 문자열로 변환 후 인코딩
                data[col] = data[col].fillna('Unknown')
```

```
numeric_features = [
                'Age', 'Work/Study Hours', 'Financial Stress',
                'Academic Pressure', 'Work Pressure', 'CGPA',
                'Study Satisfaction', 'Job Satisfaction'
            1
            # 결측값 처리
            imputer = SimpleImputer(strategy='median')
            # 숫자형 변수 결측값 대체
            numeric_data = imputer.fit_transform(data[numeric_features])
            # 스케일러로 숫자형 변수 표준화
            scaler = StandardScaler()
            scaled_numeric_data = scaler.fit_transform(numeric_data)
            # 범주형 변수와 숫자형 변수 결합
            X = np.column_stack([
               scaled_numeric_data, # 표준화된 숫자형 변수
               data[categorical_features].values # 인코딩된 범주형 변수
            ])
            if gubun=="train":
               # 타겟 변수 추출
               y = data[target].values
               return X, y
            else:
               return X
        # 전처리 적용
        X, y = preprocess_data(train)
In [43]: # 스케일링
        scaler = StandardScaler()
        X = scaler.fit_transform(X)
        # 데이터 분할
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=0.2, random_state=42
        # NumPy to PyTorch Tensor 변환
        # X train이라는 NumPy 배열을 PyTorch의 FloatTensor로 변환.
        # FloatTensor는 32비트 부동 소수점 숫자로 구성된 텐서를 생성.
        # 이 변환은 PyTorch 모델에서 데이터를 처리할 수 있도록 준비하는 단계
        X_train = torch.FloatTensor(X_train)
```

data[col] = le.fit\_transform(data[col].astype(str))

# 숫자형 변수 분리

# 03. 신경망 모델 정의

X\_test = torch.FloatTensor(X\_test)

y\_train = torch.FloatTensor(y\_train).unsqueeze(1)
y\_test = torch.FloatTensor(y\_test).unsqueeze(1)

- 딥러닝의 이해를 위해 일부 특징(변수)만 지정하였음.
- 이미지를 사용할 때는 지정된 이미지 전체를 입력 데이터로 사용하는 경우가 대부분.

```
In [35]: # 학습 진행
         epochs = 1000
         for epoch in range(epochs):
            # 순전파
            outputs = model(X_train)
            loss = criterion(outputs, y_train)
            # 정확도 계산
            with torch.no_grad():
                # 이진 분류의 경우
                predicted = (outputs > 0.5).float()
                accuracy = (predicted == y_train).float().mean()
            # 역전파
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            # 20번마다 손실과 정확도 출력
            if (epoch + 1) % 20 == 0:
                print(f'Epoch [{epoch+1}/{epochs}], '
                      f'Loss: {loss.item():.4f},
                      f'Accuracy: {accuracy.item():.4f}')
```

```
Epoch [20/1000], Loss: 0.1903, Accuracy: 0.9216
        Epoch [40/1000], Loss: 0.1895, Accuracy: 0.9219
        Epoch [60/1000], Loss: 0.1891, Accuracy: 0.9217
        Epoch [80/1000], Loss: 0.1887, Accuracy: 0.9216
        Epoch [100/1000], Loss: 0.1885, Accuracy: 0.9218
        Epoch [120/1000], Loss: 0.1883, Accuracy: 0.9219
        Epoch [140/1000], Loss: 0.1882, Accuracy: 0.9218
        Epoch [160/1000], Loss: 0.1880, Accuracy: 0.9219
        Epoch [180/1000], Loss: 0.1879, Accuracy: 0.9219
        Epoch [200/1000], Loss: 0.1878, Accuracy: 0.9221
        Epoch [220/1000], Loss: 0.1877, Accuracy: 0.9222
        Epoch [240/1000], Loss: 0.1875, Accuracy: 0.9222
        Epoch [260/1000], Loss: 0.1874, Accuracy: 0.9223
        Epoch [280/1000], Loss: 0.1873, Accuracy: 0.9223
        Epoch [300/1000], Loss: 0.1872, Accuracy: 0.9224
        Epoch [320/1000], Loss: 0.1872, Accuracy: 0.9224
        Epoch [340/1000], Loss: 0.1871, Accuracy: 0.9224
        Epoch [360/1000], Loss: 0.1870, Accuracy: 0.9224
        Epoch [380/1000], Loss: 0.1869, Accuracy: 0.9225
        Epoch [400/1000], Loss: 0.1868, Accuracy: 0.9224
        Epoch [420/1000], Loss: 0.1868, Accuracy: 0.9224
        Epoch [440/1000], Loss: 0.1867, Accuracy: 0.9225
        Epoch [460/1000], Loss: 0.1866, Accuracy: 0.9225
        Epoch [480/1000], Loss: 0.1865, Accuracy: 0.9225
        Epoch [500/1000], Loss: 0.1865, Accuracy: 0.9225
        Epoch [520/1000], Loss: 0.1864, Accuracy: 0.9225
        Epoch [540/1000], Loss: 0.1863, Accuracy: 0.9226
        Epoch [560/1000], Loss: 0.1862, Accuracy: 0.9226
        Epoch [580/1000], Loss: 0.1862, Accuracy: 0.9226
        Epoch [600/1000], Loss: 0.1861, Accuracy: 0.9226
        Epoch [620/1000], Loss: 0.1860, Accuracy: 0.9226
        Epoch [640/1000], Loss: 0.1860, Accuracy: 0.9226
        Epoch [660/1000], Loss: 0.1859, Accuracy: 0.9228
        Epoch [680/1000], Loss: 0.1859, Accuracy: 0.9228
        Epoch [700/1000], Loss: 0.1858, Accuracy: 0.9228
        Epoch [720/1000], Loss: 0.1858, Accuracy: 0.9228
        Epoch [740/1000], Loss: 0.1857, Accuracy: 0.9229
        Epoch [760/1000], Loss: 0.1857, Accuracy: 0.9228
        Epoch [780/1000], Loss: 0.1856, Accuracy: 0.9228
        Epoch [800/1000], Loss: 0.1856, Accuracy: 0.9229
        Epoch [820/1000], Loss: 0.1855, Accuracy: 0.9230
        Epoch [840/1000], Loss: 0.1855, Accuracy: 0.9230
        Epoch [860/1000], Loss: 0.1854, Accuracy: 0.9231
        Epoch [880/1000], Loss: 0.1854, Accuracy: 0.9231
        Epoch [900/1000], Loss: 0.1853, Accuracy: 0.9231
        Epoch [920/1000], Loss: 0.1853, Accuracy: 0.9232
        Epoch [940/1000], Loss: 0.1853, Accuracy: 0.9231
        Epoch [960/1000], Loss: 0.1852, Accuracy: 0.9231
        Epoch [980/1000], Loss: 0.1852, Accuracy: 0.9231
        Epoch [1000/1000], Loss: 0.1851, Accuracy: 0.9231
In [37]: # 4. 모델 평가
         model.eval() # 평가 모드
         with torch.no grad():
             test_outputs = model(X_test)
             predicted = (test outputs > 0.5).float()
             accuracy = (predicted == y_test).float().mean()
             print(f'Test Accuracy: {accuracy.item():.4f}')
```

Test Accuracy: 0.9231

# 04. 새로운 데이터로 예측

#### 목차로 이동하기

```
In [38]: # 필요한 피처 선택
        features = [
            'Age', 'Work/Study Hours', 'Financial Stress', # 숫자형 변수
            'Gender', 'Working Professional or Student', 'City',
            'Sleep Duration', 'Dietary Habits', 'Degree', # 범주형 변수
            'Academic Pressure', 'Work Pressure', 'CGPA',
            'Study Satisfaction', 'Job Satisfaction' # 결측치 있는 숫자형 변수
        ]
        # 선택한 피처로 test 데이터 준비
        X_predict = preprocess_data(test, gubun='test')
        # 결측값 처리
        X_predict = scaler.transform(X_predict)
        # 스케일링
        X_predict = scaler.transform(X_predict)
        # PyTorch Tensor로 변환
        X_predict = torch.FloatTensor(X_predict)
        # 예측 수행
        model.eval()
        with torch.no_grad():
            pred = model(X_predict)
            pred = (pred > 0.5).float()
        # submission 파일에 예측값 저장
        sub['Depression'] = pred.numpy()
        sub.to_csv('./datasets/health_mental_24/sub03.csv', index=False)
        print("예측 완료 및 sub 파일 저장.")
```

예측 완료 및 sub 파일 저장.

```
In [ ]:
```