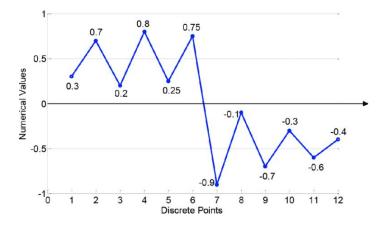
## LSTM을 이용한 Apple 주가 예측 모델

# 목차

- 모델링 배경
- Apple\_Stock\_Price Data
- 모델 구성

### 모델링 배경





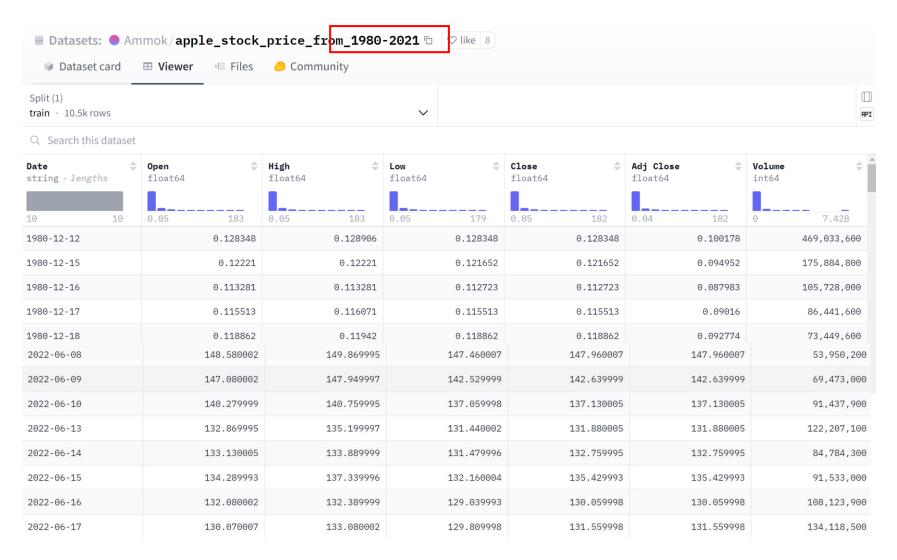
#### - 시계열 데이터(Time Series Data)

시간의 흐름에 따라 일정 시간 동안 수집되며, 순서대로 관측되는 데이터셋

- 연속 시계열(Continuous Time Series)

연속적으로 생성되는 시계열 자료로서, 관측 값들이 연속적으로 연결된 형태의 자료

### Apple\_Stock\_Price Data



#### Apple\_Stock\_Price Data

#### df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10468 entries, 0 to 10467
Data columns (total 7 columns):
```

#	Column	Non-Null Count	Dtype				
0	Date	10468 non-null	object				
1	Ореп	10468 non-null	float64				
2	High	10468 non-null	float64				
3	Low	10468 non-null	float64				
4	Close	10468 non-null	float64				
5	Adj Close	10468 non-null	float64				
6	Volume	10468 non-null	int64				
dtypes: float64(5), int64(1), object(1)							

memory usage: 572.6+ KB

- 10468개의 데이터

- Date column dtype : object

- Open(시가) : 주식 시장이 개장할 때 주식 가격

- High(고가): 주식이 특정 기간 동안 거래된 최고 가격

- Low(저가): 주식이 특정 기간 동안 거래된 최저 가격

- Close(종가): 주식 시장이 폐장할 때 주식 가격

- Adj Close(조정 종가) : 배당, 주식 분할 등 이벤트를 반영하여 조정된 종가

- Volume(거래량): 특정 기간 동안 거래된 주식의 총 수량

```
[1] pip install datasets
      숨겨진 출력 표시
    from datasets import load_dataset
     dataset = load dataset("Ammok/apple stock price from 1980-2021")
     숨겨진 출력 표시
     import pandas as pd
     import numpy as np
     from tensorflow import keras
     from tensorflow.keras.optimizers import Adam, SGD
[4] dataset
→ DatasetDict({
            features: ['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'],
            num rows: 10468
        })
     })
```

```
dataset.set_format(type='pandas')
    df = dataset['train'][:]
    print(df)
\overline{\mathbf{T}}
                                                                       Adj Close ₩
                 Date
                             Open
                                         High
                                                     Low
                                                               Close
           1980-12-12
                         0.128348
                                     0.128906
                                                0.128348
                                                            0.128348
                                                                        0.100178
           1980-12-15
                         0.122210
                                     0.122210
                                                0.121652
                                                            0.121652
                                                                        0.094952
                         0.113281
                                     0.113281
           1980-12-16
                                                0.112723
                                                            0.112723
                                                                        0.087983
                         0.115513
                                     0.116071
                                                0.115513
                                                            0.115513
                                                                        0.090160
           1980-12-18
                         0.118862
                                     0.119420
                                                0.118862
                                                            0.118862
                                                                        0.092774
           2022-06-13 132.869995
                                  135.199997
                                              131.440002
                                                          131.880005
           2022-06-14 133.130005 133.889999
                                              131.479996
                                                          132.759995
           2022-06-15 134.289993 137.339996
                                              132.160004
                                                          135.429993
                                                                      135.429993
                                                          130.059998
           2022-06-16 132.080002 132.389999
                                              129.039993
                                                                      130.059998
          2022-06-17 130.070007 133.080002 129.809998
                                                          131.559998 131.559998
              Volume
           469033600
           175884800
           105728000
            86441600
            73449600
    10463
           122207100
    10464
            84784300
            91533000
    10466 108123900
    10467 134118500
    [10468 rows x 7 columns]
```

[6] df.head()

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	Date	Open	High	Low	Close	Adj Close	Volume	
0	1980-12-12	0.128348	0.128906	0.128348	0.128348	0.100178	469033600	11.
1	1980-12-15	0.122210	0.122210	0.121652	0.121652	0.094952	175884800	
2	1980-12-16	0.113281	0.113281	0.112723	0.112723	0.087983	105728000	
3	1980-12-17	0.115513	0.116071	0.115513	0.115513	0.090160	86441600	
4	1980-12-18	0.118862	0.119420	0.118862	0.118862	0.092774	73449600	

```
[8] def convert_date_format(date_str):
    parts = date_str.split("-")
    return "".join(parts)

df['Date'] = df['Date'].apply(convert_date_format)
```

0

df



	Date	Open	High	Low	Close	Adj Close	Volume
0	19801212	0.128348	0.128906	0.128348	0.128348	0.100178	469033600
1	19801215	0.122210	0.122210	0.121652	0.121652	0.094952	175884800
2	19801216	0.113281	0.113281	0.112723	0.112723	0.087983	105728000
3	19801217	0.115513	0.116071	0.115513	0.115513	0.090160	86441600

```
[13] df['Date'] = pd.to_datetime(df['Date'])
[14] df.info()
    <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 10468 entries, 0 to 10467
     Data columns (total 7 columns):
         Column
                    Non-Null Count Dtype
                    10468 non-null datetime64[ns]
      0
         Date
                    10468 non-null float64
         Open .
         High
                    10468 non-null float64
         Low
                    10468 non-null float64
                    10468 non-null float64
         Close
         Adj Close 10468 non-null float64
         Volume
                    10468 non-null int64
```

dtypes: datetime64[ns](1), float64(5), int64(1)

memory usage: 572.6 KB

df						
	Open	High	Low	Close	Volume	Close2
0	0.128348	0.128906	0.128348	0.128348	469033600	0.128348
1	0.122210	0.122210	0.121652	0.121652	175884800	0.121652
2	0.113281	0.113281	0.112723	0.112723	105728000	0.112723
3	0.115513	0.116071	0.115513	0.115513	86441600	0.115513
4	0.118862	0.119420	0.118862	0.118862	73449600	0.118862
10463	132.869995	135.199997	131.440002	131.880005	122207100	131.880005
10464	133.130005	133.889999	131.479996	132.759995	84784300	132.759995

134.289993 137.339996 132.160004 135.429993 91533000 135.429993

132.080002 132.389999 129.039993 130.059998 108123900 130.059998

130.070007 133.080002 129.809998 131.559998 134118500 131.559998

```
from sklearn.preprocessing import
scaler = StandardScaler()
df.iloc[:, 0:5] = scaler.fit_transform(df.iloc[:, 0:5])
```

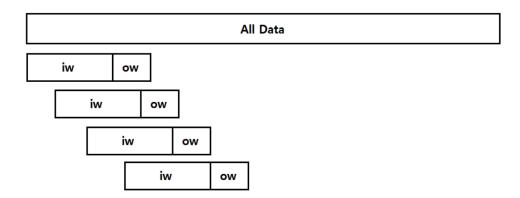
df.describe()

	Open	High	Low	Close	Volume	Close2
count	1.046800e+04	10468.000000	1.046800e+04	10468.000000	1.046800e+04	10468.000000
mean	4.344167e-17	0.000000	4.344167e-17	0.000000	2.172083e-17	14.763533
std	1.000048e+00	1.000048	1.000048e+00	1.000048	1.000048e+00	31.929489
min	-4.608932e-01	-0.460605	-4.611365e-01	-0.460863	-9.764575e-01	0.049107
25%	-4.535664e-01	-0.453183	-4.539184e-01	-0.453523	-6.111464e-01	0.283482
50%	-4.475931e-01	-0.447191	-4.479209e-01	-0.447510	-3.325890e-01	0.475446
<b>75</b> %	6.120328e-03	0.004201	3.110250e-03	0.004336	2.353143e-01	14.901964
max	5.260360e+00	5.203807	5.216003e+00	5.238244	2.092755e+01	182.009995

```
# 20일간의 주가 자료로 그 다음 날 종가를 예측
window_size = 20
x = []
y = []
for i in range(len(df) - window size):
  temp0 = df.iloc[i:i+window size, 0:5]
 x.append(temp0)
  temp1 = df.iloc[i+window_size, 5] # 20일 후 종가
 y.append(temp1)
x = np.array(x)
y = np.array(y)
split_point = begins_2022 - window_size
x train = x[:split point]
                         # (작년말 - 20개)까지의 데이터
x_test = x[split_point:] # (작년말 - 20개) 이후의 데이터
y_train = y[:split_point]
                         # 작년말까지의 주가
y test = y[split point:]
                         # 올해부터의 주가
```

#### - Sliding Window Dataset

시계열 예측을 위해 데이터의 일정한 길이의 input window, output window를 설정하고, 데이터의 처음 부분부터 끝부분까지 sliding 시켜 데이터셋을 생성



```
from sklearn.model_selection import train_test_split

x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size=0.2, shuffle=

print(x_train.shape, x_val.shape, x_test.shape)

print(y_train.shape, y_val.shape, y_test.shape)

(8265, 20, 5) (2067, 20, 5) (116, 20, 5)
(8265,) (2067,) (116,)
```

```
[37] es = keras.callbacks.EarlyStopping(
         patience=10,
         restore_best_weights=True)
[48] model = keras.Sequential()
     model.add(keras.layers.LSTM(
         48.
         activation='tanh',
         input_shape=(x_train.shape[1],x_train.shape[2])))
     model.add(keras.layers.Dropout(0.4))
     model.add(keras.layers.Dense(
         64.
         activation='relu'))
     model.add(keras.layers.Dropout(0.4))
     model.add(keras.layers.Dense(1))
     model.compile(loss = 'mae',
                   optimizer = Adam(0.01),
                   metrics = 'mae')
     history = model.fit(x_train, y_train,
                         epochs=150,
                         validation data=(x val, y val))
```

```
[49] score = model.evaluate(x_test, y_test, verbose=0)
    print('Test loss:', score[0])
    print('Test accuracy:', score[1])
```

Test loss: 5.548529624938965
Test accuracy: 5.548529624938965

```
y_pred = model.predict(x_test)
days_2022 = df.index[df.index >= begins_2022]

import matplotlib.pyplot as plt
plt.figure(figsize = (12, 8))
plt.title('Apple Stock 2022')
plt.plot(days_2022, y_test, 'orange', label='ground truth')
plt.plot(days_2022, y_pred, 'skyblue', label='prediction')
plt.ylabel('stock price')
plt.legend(loc='upper right')
```

