ADP_Red\stats\7.time_series.py

```
1 | ## Time Series Analysis
 2
   # %% 0. Load Libraries and Dataset
 3 import numpy as np
 4 import pandas as pd
   import seaborn as sns
 5
   import matplotlib.pyplot as plt
 7
8
   import scipy.stats as stats
9
   # data encoding type: 'utf-8', 'euc-kr'
10
   df = pd.read_csv('../../ADP_Python/data/서울특별시 코로나19.csv')
11
   date_column = '날짜'
12
13
14
   # Check data properties
15 print(df.head())
16 print(df.info())
17
18 | # # Change datatype to datetime
   df[date column] = pd.to datetime(df[date column], format='%Y-%m-%d')
19
   df.set_index(date_column, inplace=True)
20
21
22 print(df.dtypes)
   print(df.head())
23
24
25 # EDA Visualization
26 plt.plot(df)
27
   plt.show()
28
29
30 # %% 1. Time Series Decomposition
31 # (Trend, Seasonality, Residual)
32 # - 'additive'
   # - 'multiplicative'
33
34
35
   from statsmodels.tsa.seasonal import seasonal_decompose
36
   decomp_add = seasonal_decompose(df, model='additive')
37
   decomp mul = seasonal decompose(df, model='multiplicative')
38
39
40
   decomp_add.plot()
41
   decomp mul.plot()
   plt.show()
42
43
44
   # %% 2. Stationarize the Series
45
46
   # %% 2-1. Durbin-Watson Test
47
   from statsmodels.stats.stattools import durbin watson
48
   print(durbin watson(df))
49
50
51 # %% 2-2. Augmented Dickey-Fuller Test (d)
52 | # Stationary Test
53 from statsmodels.tsa.stattools import adfuller
54
55 # train, test data split
56 | df train = df[:'2016-12-01']
57 | df_test = df.drop(df_train.index)
```

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```
59 print(df_train)
     print(df_test)
     adf = adfuller(df_train, regression='ct')
     print(f'ADF Statistic: {adf[0]}')
     print(f'p-value: {adf[1]}')
     if adf[1] < 0.05:</pre>
         print('stationary time-series data')
         print('WARNING: non-stationary time-serie data')
         print('WARNING: differentiation or log transformation needed')
     # %% 2-3. Differentiation
     # First-order differentiation
 75 | df diff1 = df train.diff(1)
    df_diff1 = df_diff1.dropna()
 78 | df diff1.plot()
     plt.show()
     adf1 = adfuller(df_diff1)
     print(f'ADF Statistic: {adf1[0]}')
     print(f'p-value: {adf1[1]}')
     # Second-order differentiation
     df diff2 = df train.diff(2)
 87
    df_diff2 = df_diff2.dropna()
 88
 89
 90 | df_diff2.plot()
 91
    plt.show()
 92
     adf2 = adfuller(df diff2)
 93
 94
     print(f'ADF Statistic: {adf2[0]}')
95
 96
     print(f'p-value: {adf2[1]}')
97
98 # 2-3. Log Transformation
99
     # 2-4. Box-Cos Transformation
100
101
102
     # %% 3. Plot ACF/PACF Charts and Find Optimal Parameters
     from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
103
104
     # %% 3-1. AR (Auto Regressive) Model: AR(p)
105
106 # PACF (p)
107
    plot_pacf(df_diff1)
108
     plt.show()
109
110 | # %% 3-2. MA (Moving Average) Model: MA(q)
111 | # ACF (q)
     plot_acf(df_diff1)
112
113
    plt.show()
114
     # %% 3-3. Grid Search: p, q
115
116
     from pmdarima import auto arima
117
```

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118 auto ar
```

```
118 | auto_arima_model = auto_arima(df_train,
119
                                   start_p=0, max_p=5,
120
                                   start_q=0, max_q=5,
121
                                   seasonal=True,
122
                                   d=1,
123
                                   trace=True,
124
                                   error action='ignore',
125
                                   suppress_warnings=True,
126
                                   stepwise=False)
127
128
    # %% 4. Build the ARIMA Model
129
130 \# %% 4-0. ARMA Model: AR(p) + MA(q)
131 | # %% 4-1. ARIMA Model: AR(p) + differentiation(d) + MA(q)
132 | from statsmodels.tsa.arima.model import ARIMA
133
    model = ARIMA(df train, order=(5,1,0))
134
135 result = model.fit()
    result.summary()
136
137
138
139
    # %% 4-2. SARIMA Model
140
141 # %% 5. Make Predictions
142 # %% 5-1. Model Prediction
143
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))
144
145 | valid_y = result.predict()
146
    axes[0].plot(valid_y, label='prediction')
    axes[0].plot(df train, label='target')
147
148
149
    axes[0].legend(loc='upper left')
150
151
    # 학습데이터 세트로부터 테스트 데이터 길이(len(df test))만큼 예측
152
     pred_y = result.forecast(steps=len(df_test), alpha=0.05)
153
154
    axes[1].plot(pred y, label='prediction')
    axes[1].plot(df_test, label='target')
155
156
    axes[1].legend(loc='upper right')
157
    plt.tight_layout()
158
159
    plt.show()
160
161
    # %% 5-2. Model Evaluation
162
    from sklearn.metrics import mean_squared_error, r2_score
163
    print(f'r2_score: {r2_score(df_test, pred_y)}')
                                                                     # R^2
164
     print(f'RMSE: {np.sqrt(mean squared error(df test, pred y))}') # Root Mean Squared Error
165
166
167
    # %%
168 true index = list(df.index)
169
    predict index = list(df test.index)
170
171
    true value = np.array(list(df.price))
172
173
    # plot
174
175
    plt.plot(true_index, true_value, label='True')
176
    plt.plot(predict index, pred y, label='Prediction')
177
    plt.vlines(pd.Timestamp('2017-01-01'), 0, 10000, linestyle='--')
```

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178 plt.show() 179

180 # %% References

[[머신러닝][시계열] AR, MA, ARMA, ARIMA의 모든 것 - 개념편](https://velog.io/@euisuk-chung/%EB%A8%B8%EC%8B%A0%EB%9F%AC%EB%8B%9D%EC%8B%9C%EA%B3%84%EC%97%B4-AR-MA-ARMA-ARIMA%EC%9D%98-%EB%AA%A8%EB%93%A0-%EA%B2%83-%EA%B0%9C%EB%85%90%ED%8E%B8)

[[머신러닝][시계열] AR, MA, ARMA, ARIMA의 모든 것 - 실습편](https://velog.io/@euisuk-chung/%EB%A8%B8%EC%8B%A0%EB%9F%AC%EB%8B%9D%EC%8B%9C%EA%B3%84%EC%97%B4-AR-MA-ARMA-ARIMA%EC%9D%98-%EB%AA%A8%EB%93%A0-%EA%B2%83-%EC%8B%A4%EC%8A%B5%ED%8E%B8)