

```
In [ ]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from pmdarima import auto_arima
from statsmodels.distributions import chi2
from sklearn.metrics import mean_absolute_error
import warnings
```

Ex. 1: MA model

```
In [ ]: def MA(steps, df: np.array, c, phi: np.array, burnin):
    #generating white noise
    np.random.seed(100)
    noise = np.random.normal(0, 1, steps + burnin)

    res = df

    #start calculating the MA model
    for i in range(len(df) - 1, steps + burnin):
        new = c
        #adding previous values of error
        for j in range(i, len(phi)):
            new += phi[j] * noise[i - (j + 1)]

        #adding white noise
        new += noise[i]

        #appending new value
        res = np.append(res, new)

    #discarding first n values
    del res[:burnin]
    res = np.delete(res, del, 0)

    return res
```

```
In [ ]: def AR(steps, df: np.array, c, phi: np.array, burnin):
    #generating white noise
    np.random.seed(100)
    noise = np.random.normal(0, 1, steps + burnin)

    res = df

    #start calculating the AR model
    for i in range(len(df) - 1, steps + burnin):
        new = c + noise[i]
        #adding previous values of res
        for j in range(i, len(phi)):
            new += phi[j] * res[i - j]

        #appending new value
        res = np.append(res, new)

    #discarding first n values
    del res[:burnin]
    res = np.delete(res, del, 0)

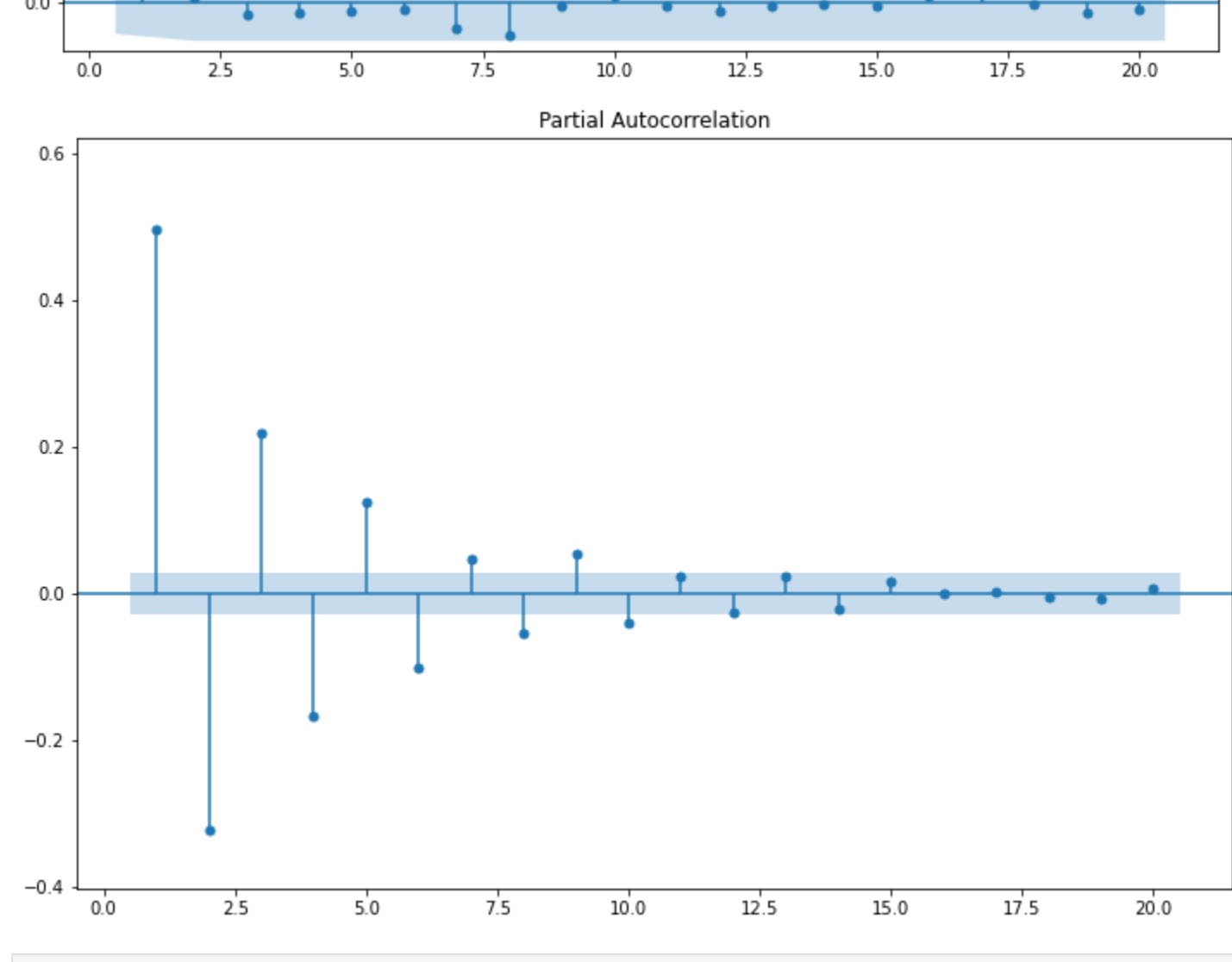
    return res
```

Y_t = 20 + ε_t + 0.8ε_{t-1}

```
In [ ]: df = MA(5000, np.array([1]), 20, np.array([0.8]), 200)

plt.rc("figure", figsize=(12,8))
plot_acf(df, lags = 20, zero = False, auto_vlins = True);
plot_pacf(df, lags = 20, zero = False, auto_vlins = True);
```

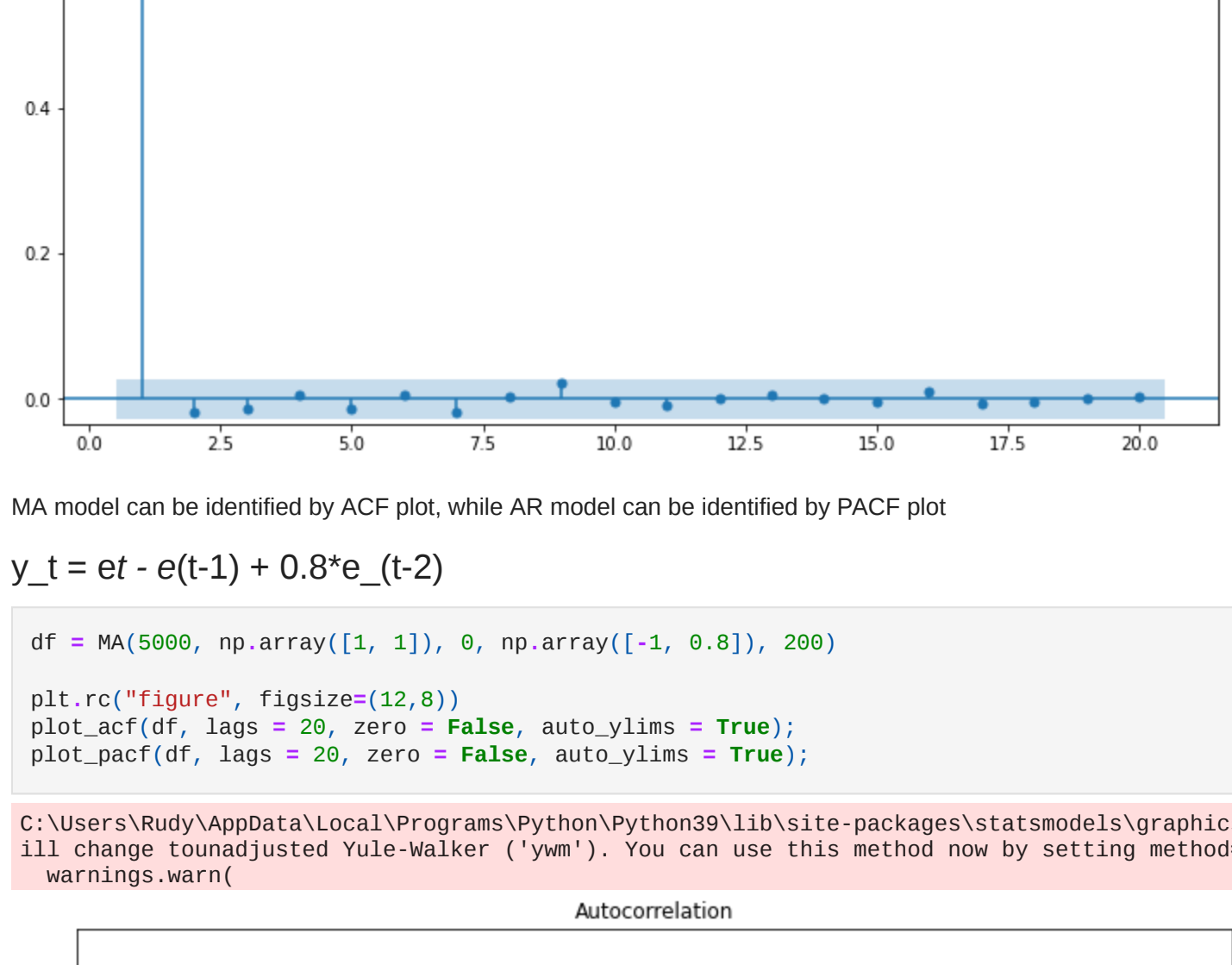
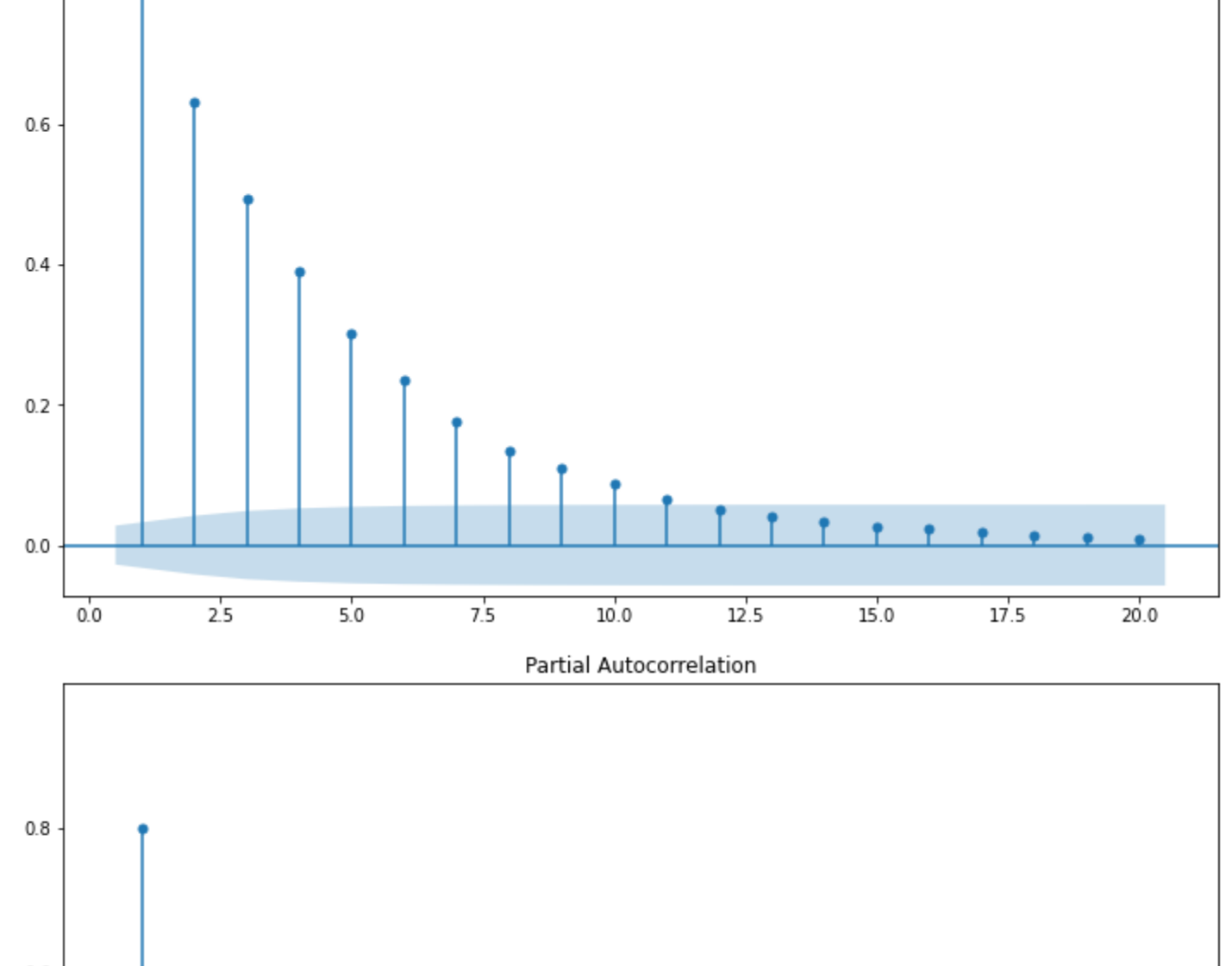
C:\Users\khu\AppData\Local\Programs\Python\Python39\lib\site-packages\statsmodels\graphics\taplots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to adjusted Vuille-Walker ('yw'). You can use this method now by setting method='yw'.
warnings.warn



```
In [ ]: df2 = AR(5000, np.array([1]), 20, np.array([0.8]), 200)

plt.rc("figure", figsize=(12,8))
plot_acf(df2, lags = 20, zero = False, auto_vlins = True);
plot_pacf(df2, lags = 20, zero = False, auto_vlins = True);
```

C:\Users\khu\AppData\Local\Programs\Python\Python39\lib\site-packages\statsmodels\graphics\taplots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to adjusted Vuille-Walker ('yw'). You can use this method now by setting method='yw'.
warnings.warn



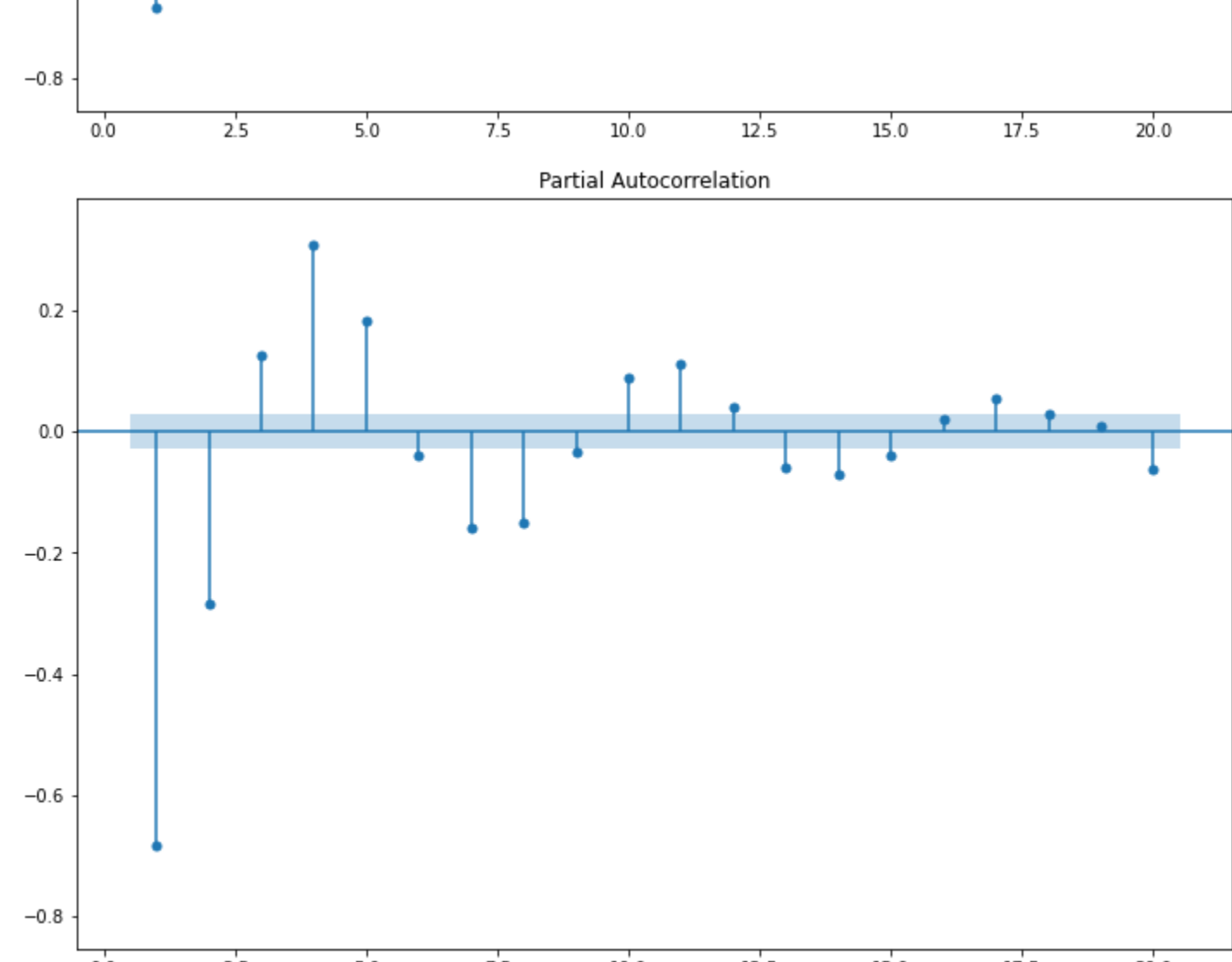
MA model can be identified by ACF plot, while AR model can be identified by PACF plot

Y_t = ε_t - ε_{t-1} + 0.8ε_{t-2}

```
In [ ]: df = MA(5000, np.array([1, -1]), 0, np.array([-1, 0.8]), 200)

plt.rc("figure", figsize=(12,8))
plot_acf(df, lags = 20, zero = False, auto_vlins = True);
plot_pacf(df, lags = 20, zero = False, auto_vlins = True);
```

C:\Users\khu\AppData\Local\Programs\Python\Python39\lib\site-packages\statsmodels\graphics\taplots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to adjusted Vuille-Walker ('yw'). You can use this method now by setting method='yw'.
warnings.warn

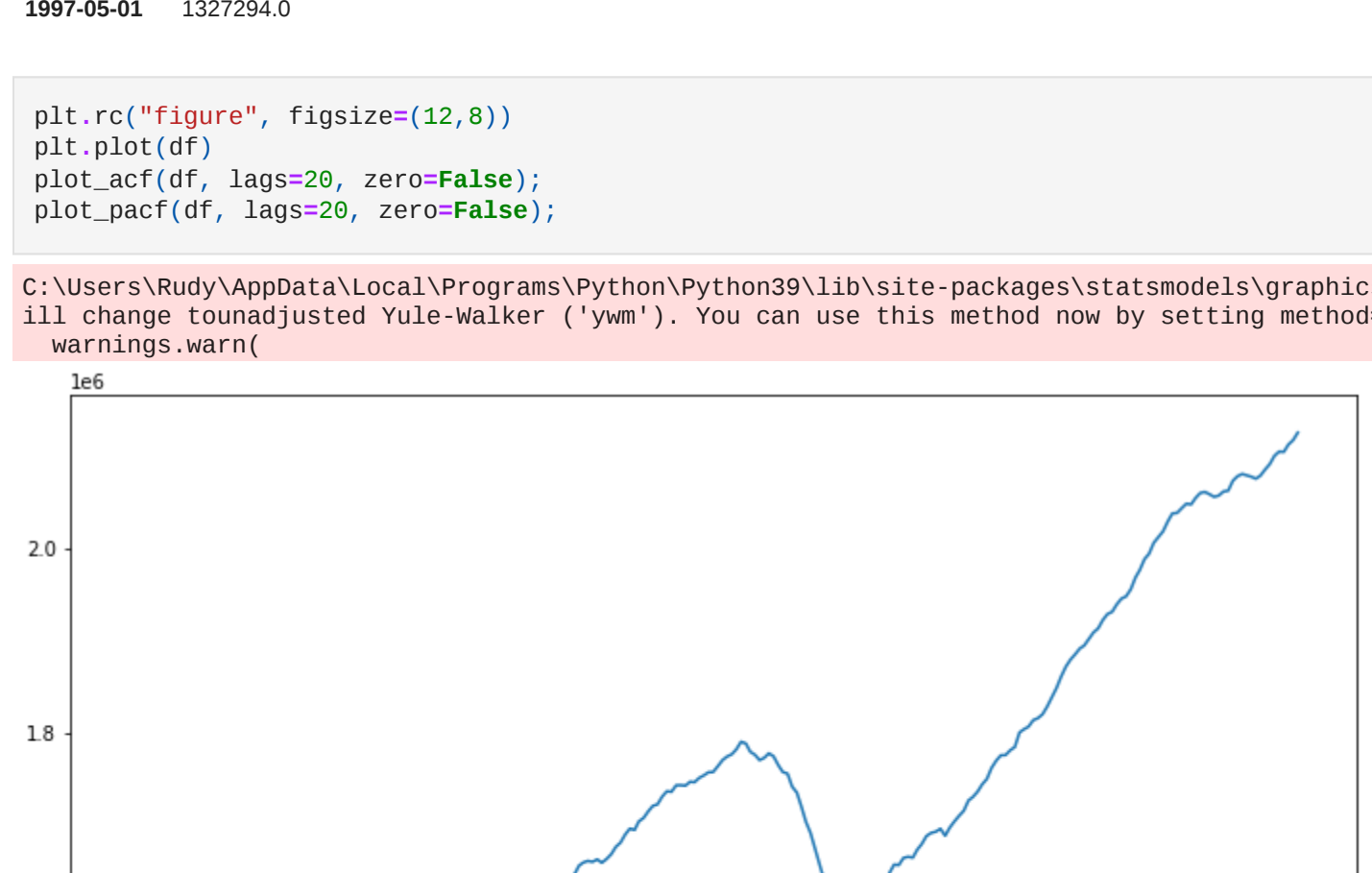


AR(2) model with these parameters overflows - k just increases to infinity

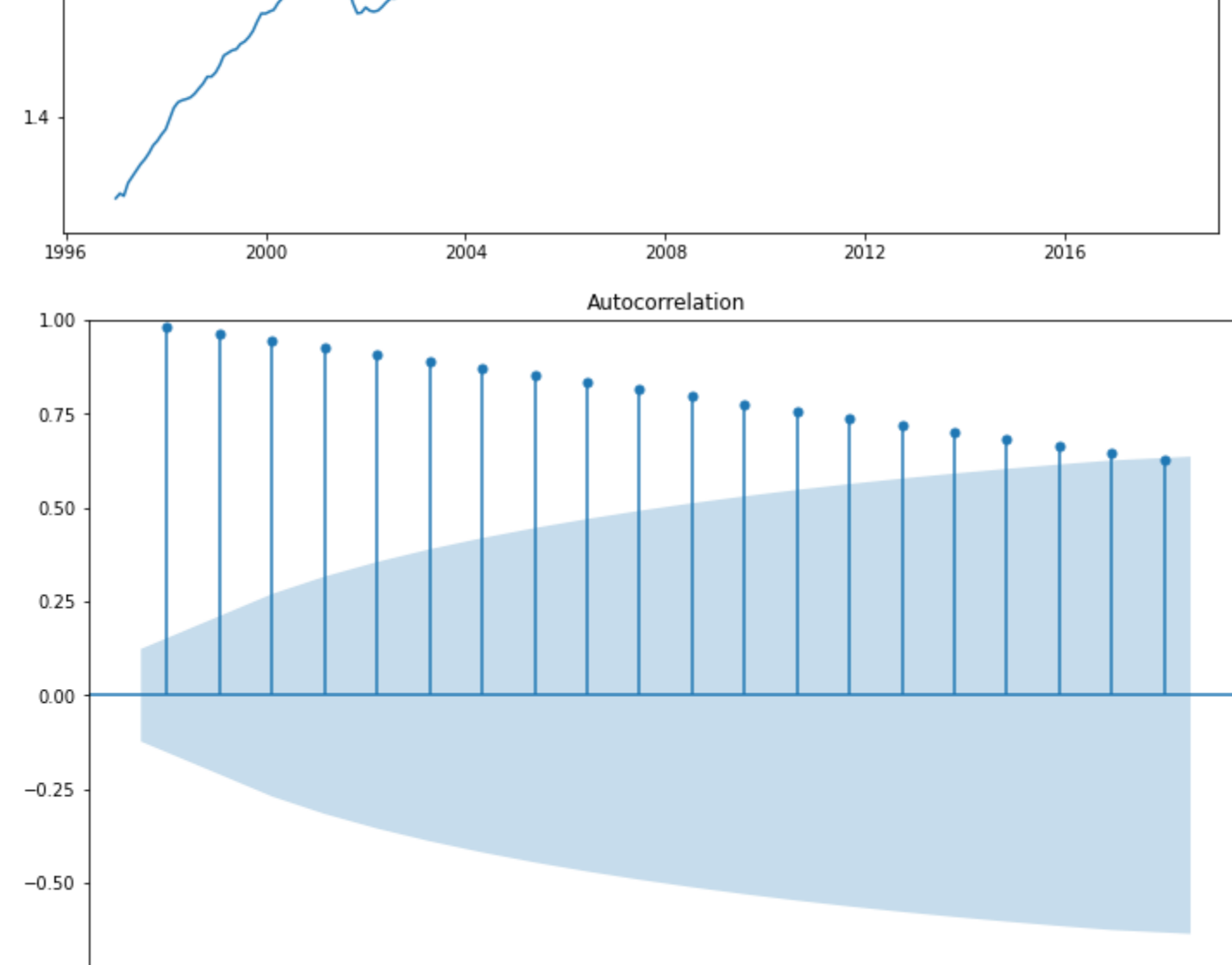
Ex. 2: ARIMA forecasting

```
In [ ]: df=pd.read_csv('INVCWMHT.csv', index_col='DATE', parse_dates=True)
df.index.freq = 'MS'
df.head()
```

Out[]: INVCWMHT



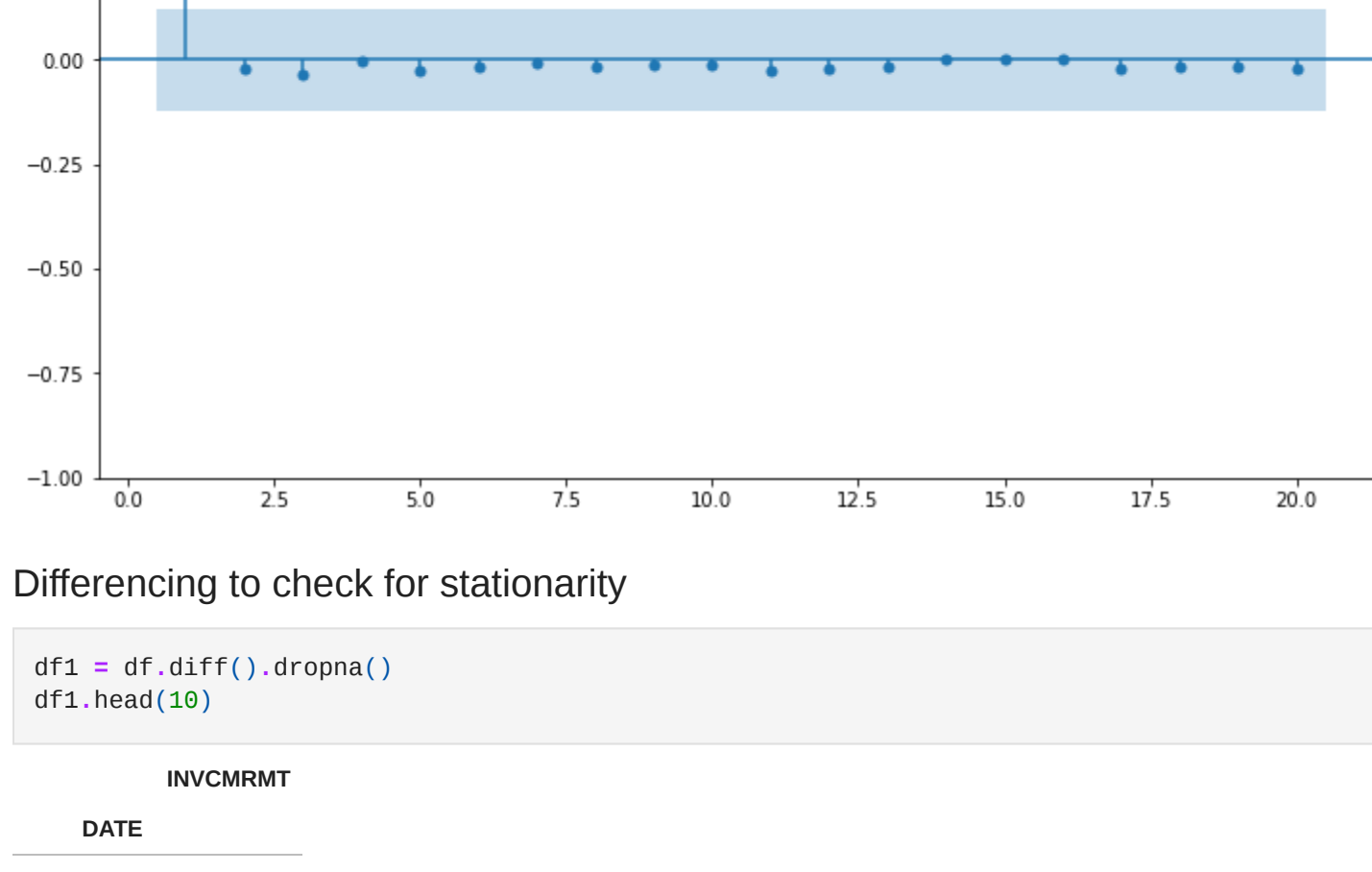
C:\Users\khu\AppData\Local\Programs\Python\Python39\lib\site-packages\statsmodels\graphics\taplots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to adjusted Vuille-Walker ('yw'). You can use this method now by setting method='yw'.
warnings.warn



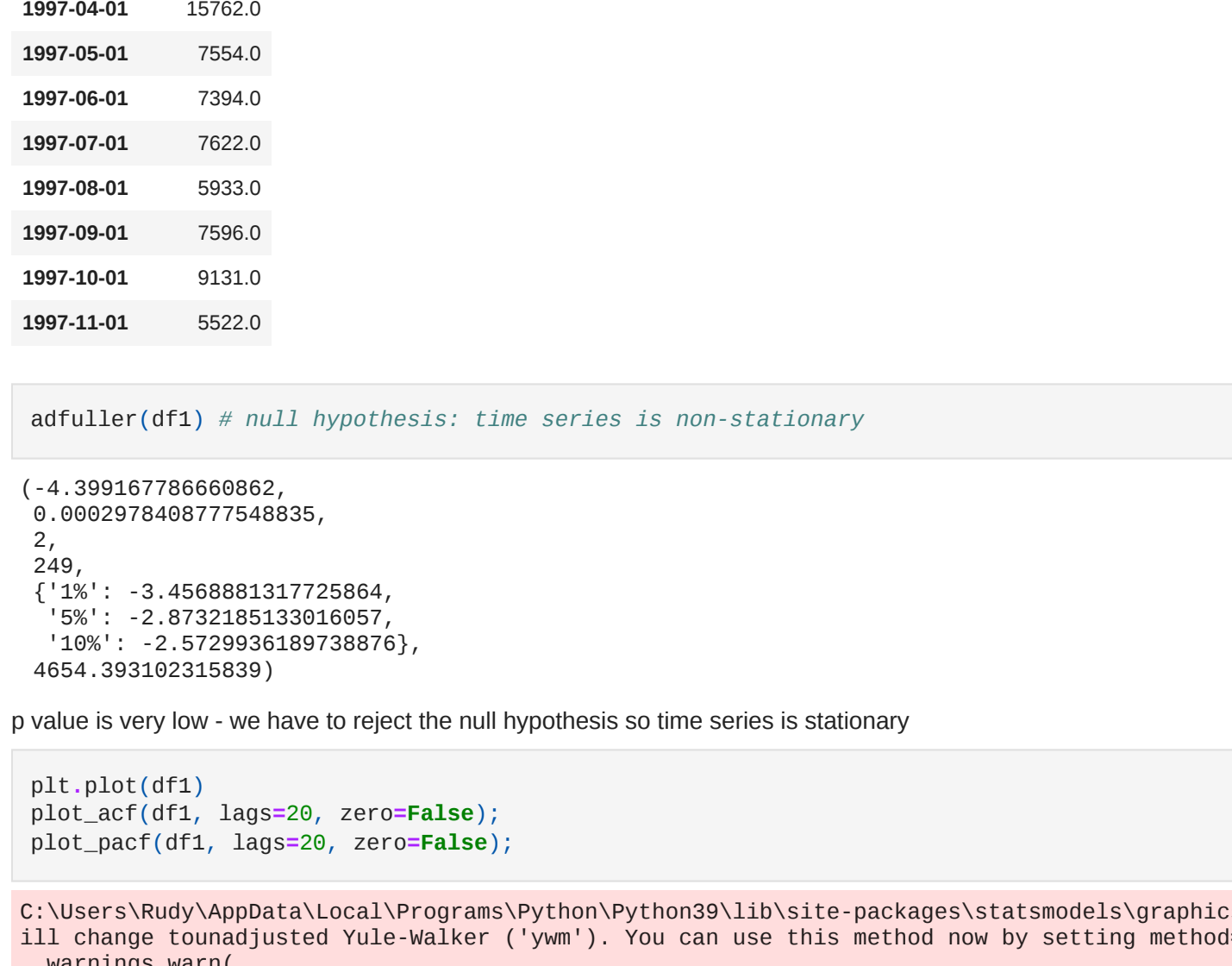
Differencing to check for stationarity

```
In [ ]: df1 = df.diff().dropna()
df1.head(10)
```

Out[]: INVCWMHT



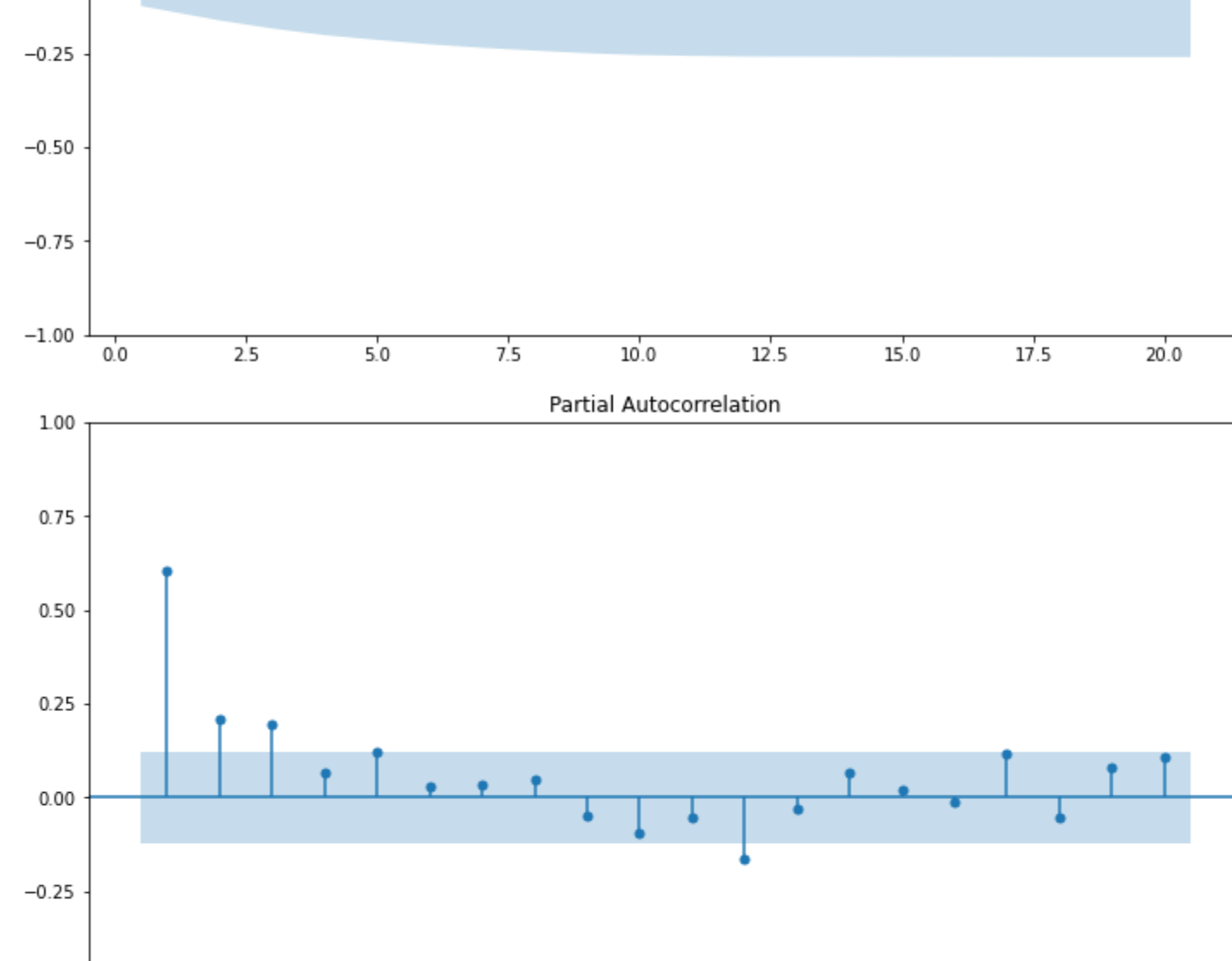
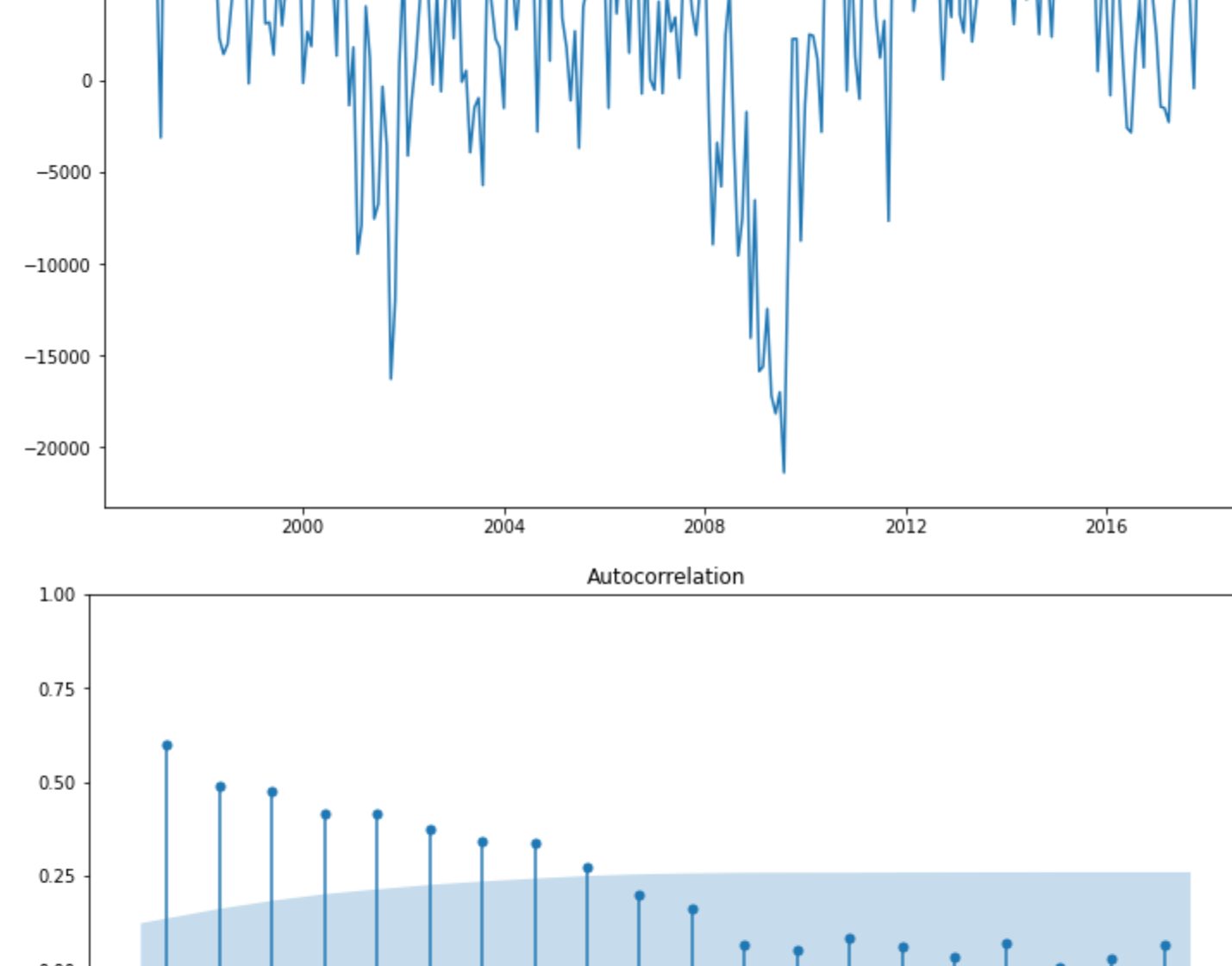
C:\Users\khu\AppData\Local\Programs\Python\Python39\lib\site-packages\statsmodels\graphics\taplots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to adjusted Vuille-Walker ('yw'). You can use this method now by setting method='yw'.
warnings.warn



p value is very low - we have to reject the null hypothesis so time series is stationary

In []: plt.plot(df1)

C:\Users\khu\AppData\Local\Programs\Python\Python39\lib\site-packages\statsmodels\graphics\taplots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change to adjusted Vuille-Walker ('yw'). You can use this method now by setting method='yw'.
warnings.warn



LLR test

```
In [ ]: def LLR_test(m1, m2, DF = 1):
    L1 = m1.llf
    L2 = m2.llf
    L = 2 * (L2 - L1)
    p = chi2.sf(L, DF).round(3)
    return p
```

ARIMA models grid search based on AIC

```
In [ ]: #ignoring warnings
with warnings.catch_warnings():
    warnings.simplefilter("ignore")

    #starting model, should be the worst one
    model = ARIMA(df1, order = (0, 0, 0)) fit()
    aic = model.aic
    p = 0
    q = 0

    #loop to test different models
    for j in range(0, 5):
        for i in range(0, 5):
            print('Testing model (" + str(p) + ", 0, " + str(q) + ")")
            model = ARIMA(df1, order = (i, 0, j)) fit()

            #if the aic is lower, model is better
            if model.aic < aic:
                aic = model.aic
                p = i
                q = j

    print('Best model based on AIC: ARIMA(" + str(p) + ", 0, " + str(q) + ")')

Testing model (0, 0, 0)
Testing model (0, 0, 1)
Testing model (0, 0, 2)
Testing model (0, 0, 3)
Testing model (0, 0, 4)
Testing model (1, 0, 0)
Testing model (1, 0, 1)
Testing model (1, 0, 2)
Testing model (1, 0, 3)
Testing model (1, 0, 4)
Testing model (2, 0, 0)
Testing model (2, 0, 1)
Testing model (2, 0, 2)
Testing model (2, 0, 3)
Testing model (2, 0, 4)
Testing model (3, 0, 0)
Testing model (3, 0, 1)
Testing model (3, 0, 2)
Testing model (3, 0, 3)
Testing model (3, 0, 4)
Testing model (4, 0, 0)
Testing model (4, 0, 1)
Testing model (4, 0, 2)
Testing model (4, 0, 3)
Testing model (4, 0, 4)
Best model based on AIC: ARIMA(2, 0, 2)
```

Comparing with auto arima

```
In [ ]: auto_arima(df1, seasonal = False, trace = True).summary()
```

Performing stepwise search to minimize aic
ARIMA(2,0,2)(0,0,0)[0] : AIC=5301.127, Time=0.01 sec
ARIMA(1,0,0)(0,0,0)[0] : AIC=5023.256, Time=0.01 sec
ARIMA(1,0,1)(0,0,0)[0] : AIC=5080.244, Time=0.05 sec
ARIMA(2,0,0)(0,0,0)[0] : AIC=5089.769, Time=0.02 sec
ARIMA(1,0,1)(0,0,0)[0] : AIC=4986.973, Time=0.05 sec
ARIMA(2,0,2)(0,0,0)[0] : AIC=4995.907, Time=0.07 sec
ARIMA(1,0,2)(0,0,0)[0] : AIC=4980.051, Time=0.05 sec
ARIMA(1,0,2)(0,0,0)[0] : AIC=4904.562, Time=0.05 sec
ARIMA(1,0,2)(0,0,0)[0] : AIC=4970.771, Time=0.05 sec
ARIMA(1,0,2)(0,0,0)[0] : AIC=4980.074, Time=0.07 sec
ARIMA(1,0,2)(0,0,0)[0] : AIC=4907.643, Time=0.09 sec
ARIMA(1,0,2)(0,0,0)[0] : AIC=4917.686=29 sec
ARIMA(1,0,2)(0,0,0)[0] Intercept : AIC=4995.940, Time=0.06 sec
Best model: ARIMA(1,0,2)(0,0,0)[0]
Total fit time: 0.994 seconds
SARIMAX Results

Dep. Variable: y No. Observations: 252

Model: SARIMAX(1, 0, 2) Log Likelihood: -4903.262

Date: Tue, 20 Apr 2022 AIC: 4904.562

Time: 12:04:28 BIC: 5000.680

Sample: 0 HQIC: 5000.243

Covariance Type: oim

coef std err z P>|z| [0.025 0.975]

ma.L1 0.8610 0.027 35.079 0.000 0.809 1.003

ma.L2 -0.1068 0.002 -4.904 0.000 -0.039 -0.195

ma.L2 -2.01407 0.006 -1.615 0.106 -0.236 0.023

sigma2 2.414e+07 3.27e-10 6.84e-16 0.000 2.34e+07 2.46e+07

Ljung-Box (Ljung-Box) Prob(Q) 0.80 Jarque-Bera (JB) 0.95

Heteroskedasticity (H) Prob(Q) 0.76 Skew: -0.04

Prob(Q) (Bis-Statistic) 0.21 Kurtosis: 3.16

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[2] Covariance matrix is singular or near-singular, with condition number 2.41e+13. Standard errors may be unstable.

Auto ARIMA says that (1, 0, 2) is the best but according to my tests (2, 0, 2) is better.

```
In [ ]: train = df1.iloc[:12]
test = df1.iloc[12:]
start = len(train)
end = start + len(test) - 1
```

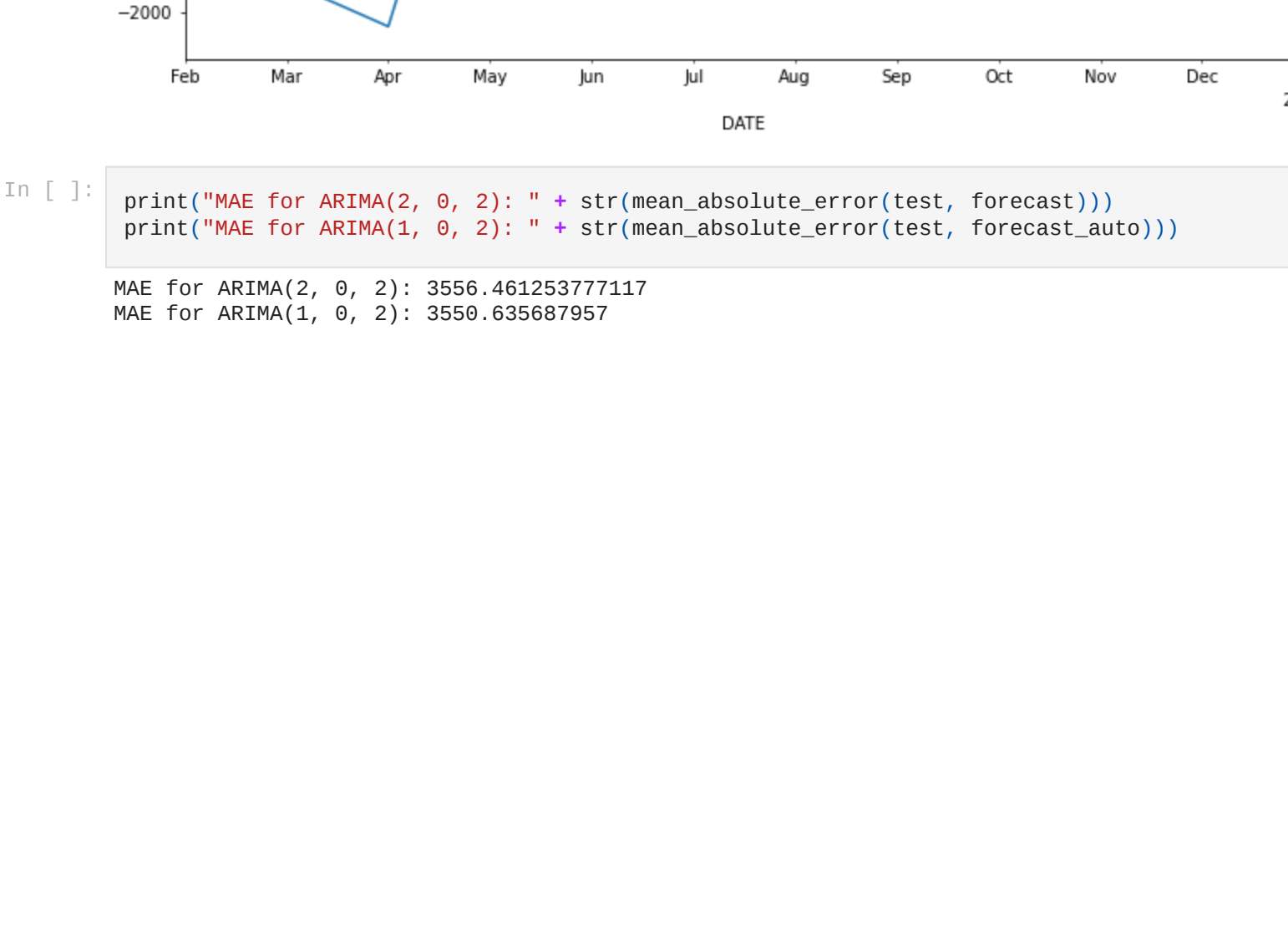
```
In [ ]: model = ARIMA(train, order = (2, 0, 2), enforce_invertibility = False)
res = model.fit()
model_auto = ARIMA(train, order = (1, 0, 2), enforce_invertibility = False)
res_auto = model_auto.fit()
```

```
In [ ]: forecast = res.predict(start = start, end = end, dynamic = False).rename('Forecast ARIMA(2, 0, 2)')
forecast_auto = res_auto.predict(start = start, end = end, dynamic = False).rename('Forecast ARIMA(1, 0, 2)')
```

```
In [ ]: ax = test.plot()
```

Forecast plot(ax = ax, legend = True)

forecast_auto.plot(ax = ax, legend = True)



```
In [ ]: print("MAE for ARIMA(2, 0, 2): " + str(mean_absolute_error(test, forecast)))
print("MAE for ARIMA(1, 0, 2): " + str(mean_absolute_error(test, forecast_auto)))
```

MAE for ARIMA(2, 0, 2): 3556.46125377117

MAE for ARIMA(1, 0, 2): 3556.435687957