

Function that calculates the values of AR(p) model/parameter burnin determines how many initial values are discarded):

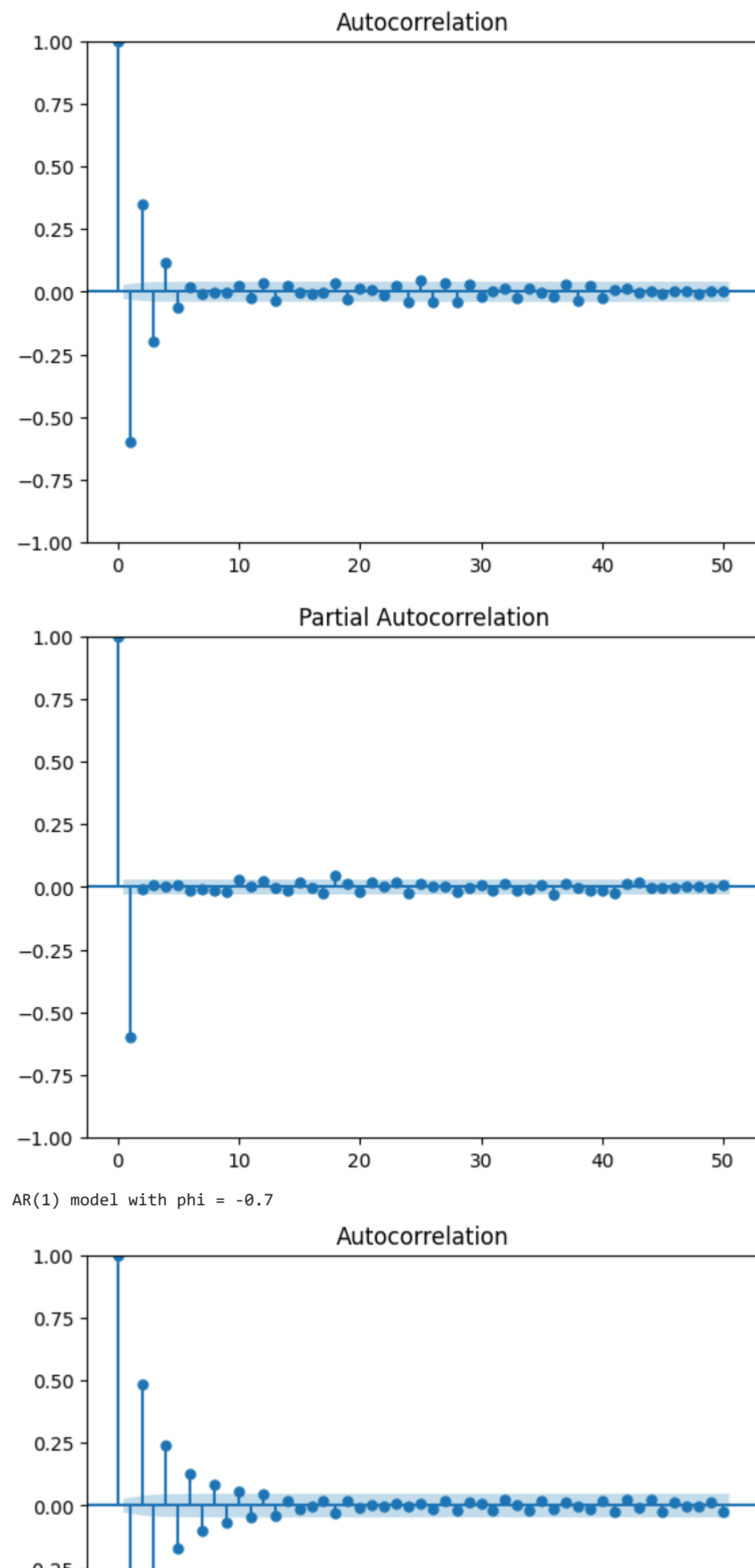
```
In [39]: import numpy as np
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

def ar_model(p, phi, c, n, burnin=100):
    y = np.zeros(n + burnin)
    # generate the time series according to the AR(p) model
    for t in range(p, n + burnin):
        y[t] = c + np.dot(phi, y[t-p:t][:-1]) + np.random.normal()
    # discard the initial values
    return y[burnin:]

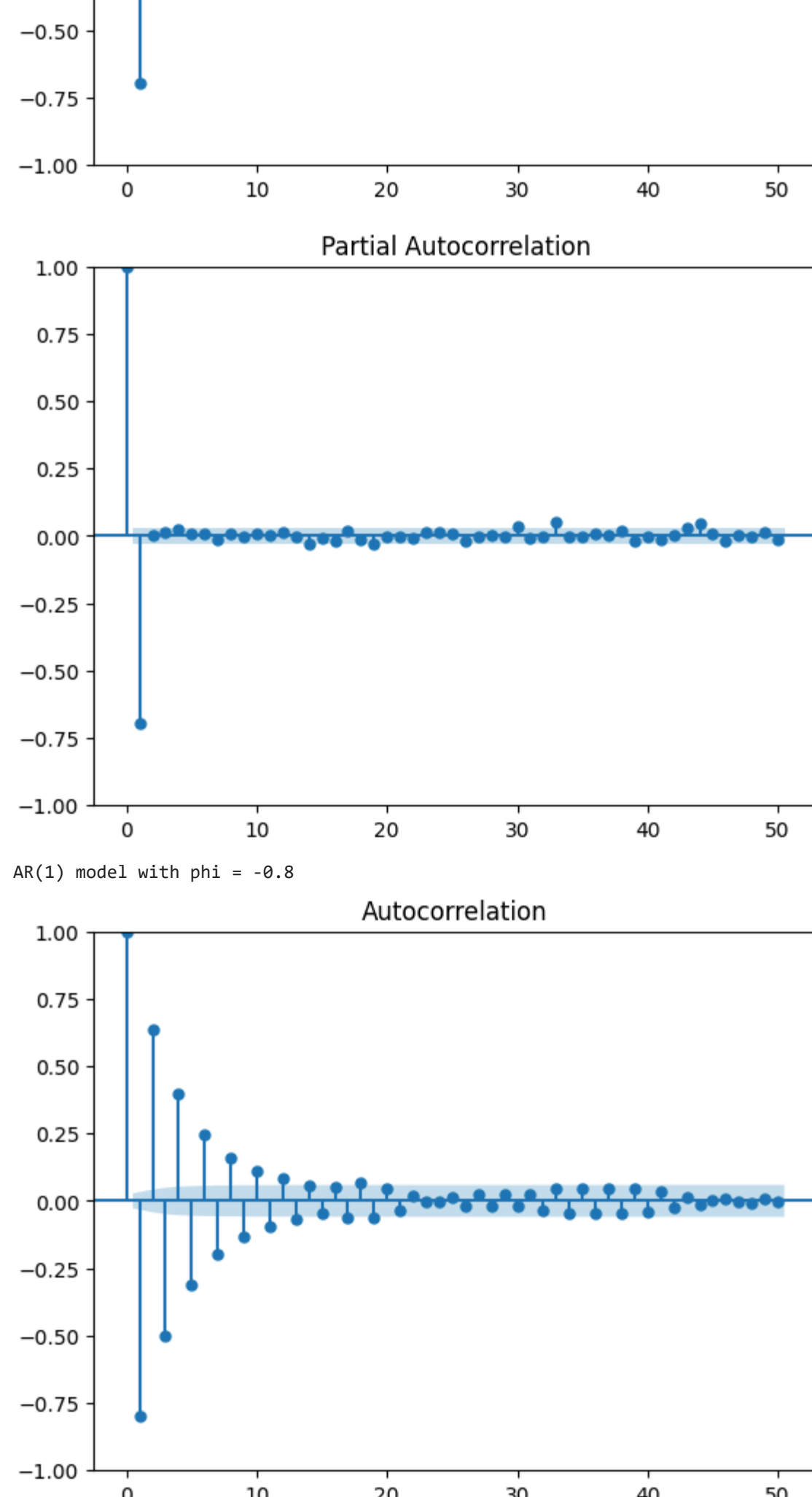
a) calculate 5000 values of the AR(1) model with such coefficients: -0.6, -0.7, -0.8, -0.9 b) calculate the autocorrelation (ACF) and partial autocorrelation (PACF) function for this time series
```

```
In [40]: for phi in [-0.6, -0.7, -0.8, -0.9]: # a
    y = ar_model(1, [phi], 10, 5000)
    print("AR(1) model with phi = {phi}")
    plot_acf(y, lags=50) # a
    plt.show()
    plot_pacf(y, lags=50) # b
    plt.show()
```

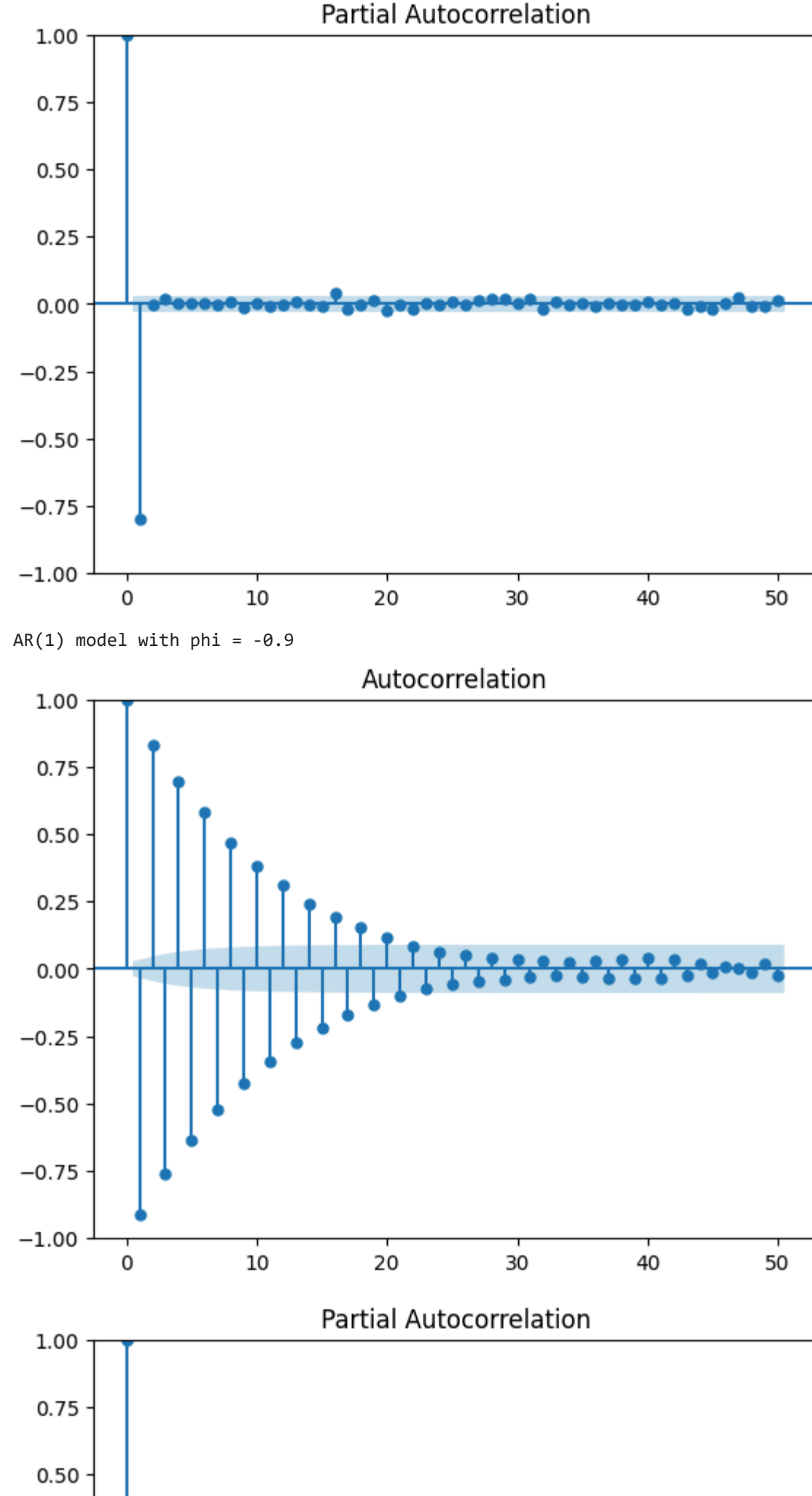
AR(1) model with phi = -0.6



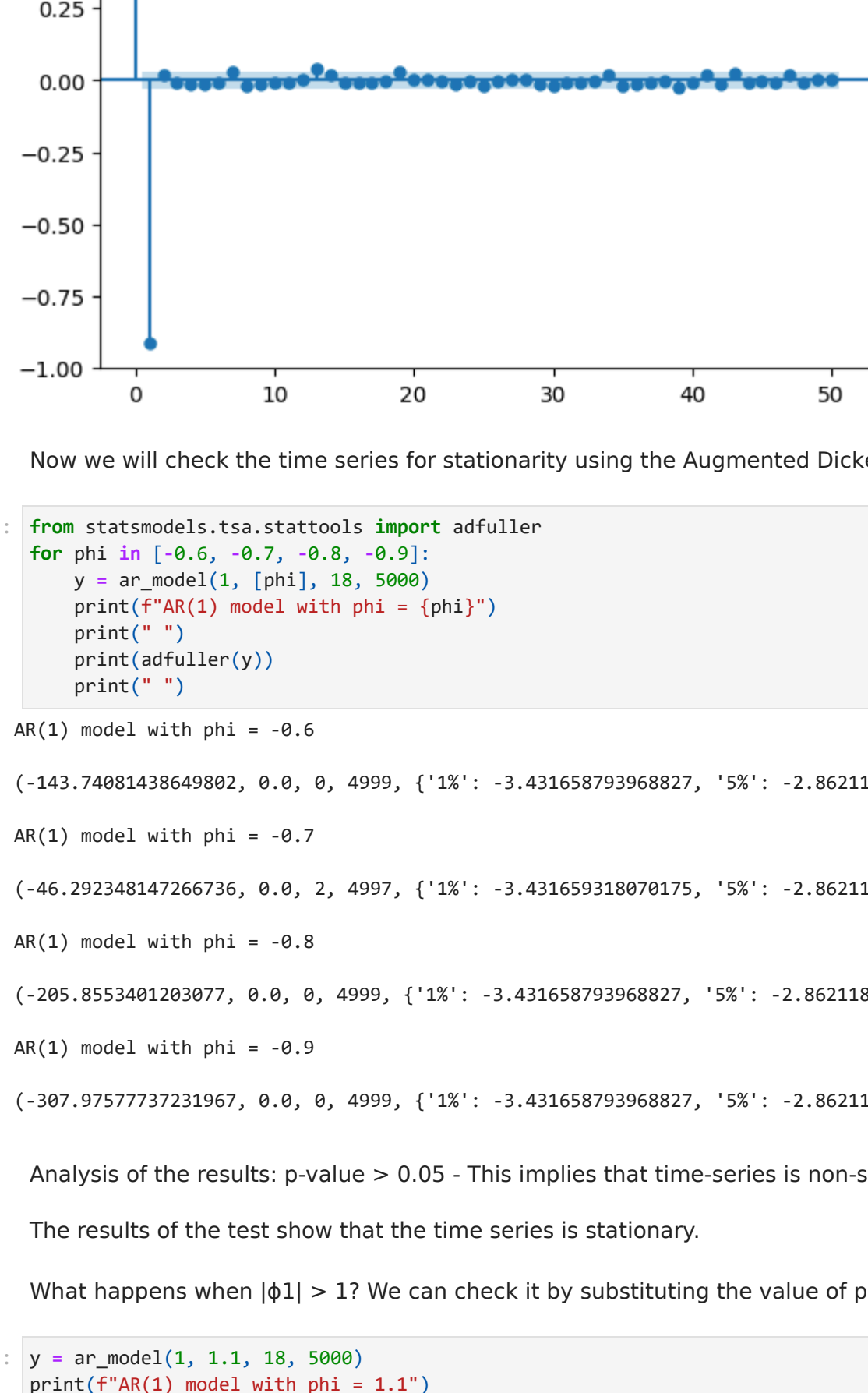
AR(1) model with phi = -0.7



AR(1) model with phi = -0.8



AR(1) model with phi = -0.9



Now we will check the time series for stationarity using the Augmented Dickey-Fuller test.

```
In [41]: from statsmodels.tsa.stattools import adfuller
for phi in [-0.6, -0.7, -0.8, -0.9]:
    y = ar_model(1, [phi], 10, 5000)
    print("AR(1) model with phi = {phi}")
    print(adfuller(y))
    print(" ")

AR(1) model with phi = -0.6
(-243.74881438649802, 0.0, 0.4999, ('1X': -3.431658793968827, '5X': -2.8621183451810484, '10X': -2.567877853953267), 14014.671388204191)

AR(1) model with phi = -0.7
(-46.29234847426676, 0.0, 2.4997, ('1X': -3.431658793968827, '5X': -2.8621183451810484, '10X': -2.567877853953267), 14008.15459356985)

AR(1) model with phi = -0.8
(-285.8513481263077, 0.0, 0.4999, ('1X': -3.431658793968827, '5X': -2.8621183451810484, '10X': -2.567877853953267), 14168.137917089623)

AR(1) model with phi = -0.9
(-387.9757737231967, 0.0, 0.4999, ('1X': -3.431658793968827, '5X': -2.8621183451810484, '10X': -2.567877853953267), 14159.9281657359)
```

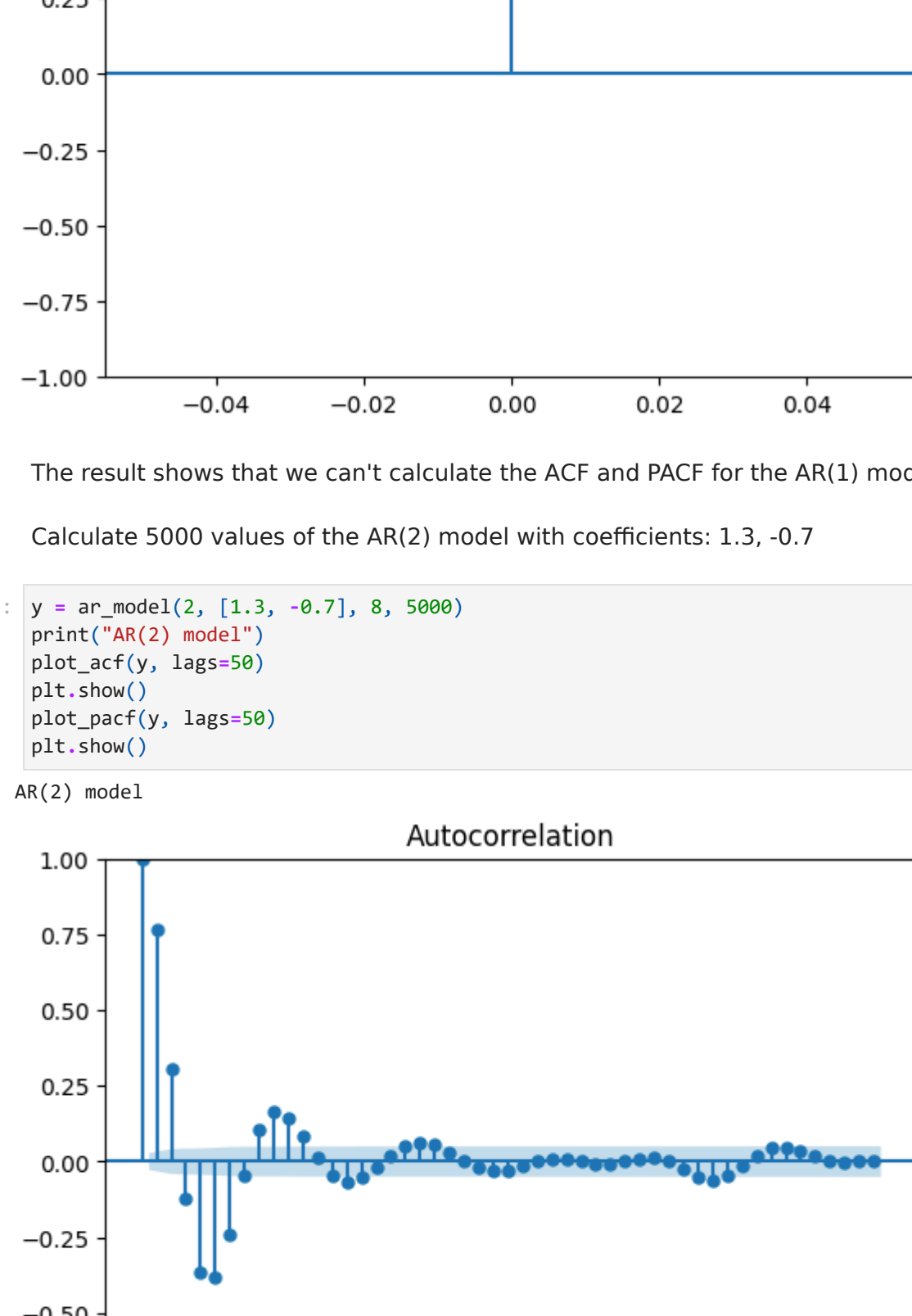
Analysis of the results: p-value > 0.05 - This implies that time-series is non-stationary. p-value <= 0.05 - This implies that time-series is stationary

The results of the test show that the time series is stationary.

What happens when $|\phi| > 1$? We can check it by substituting the value of $\phi = 1.1$ in our function.

```
In [42]: y = ar_model(1, [1.1], 10, 5000)
print("AR(1) model with phi = 1.1")
plot_acf(y, lags=50) # a
plt.show()
plot_pacf(y, lags=50) # b
plt.show()

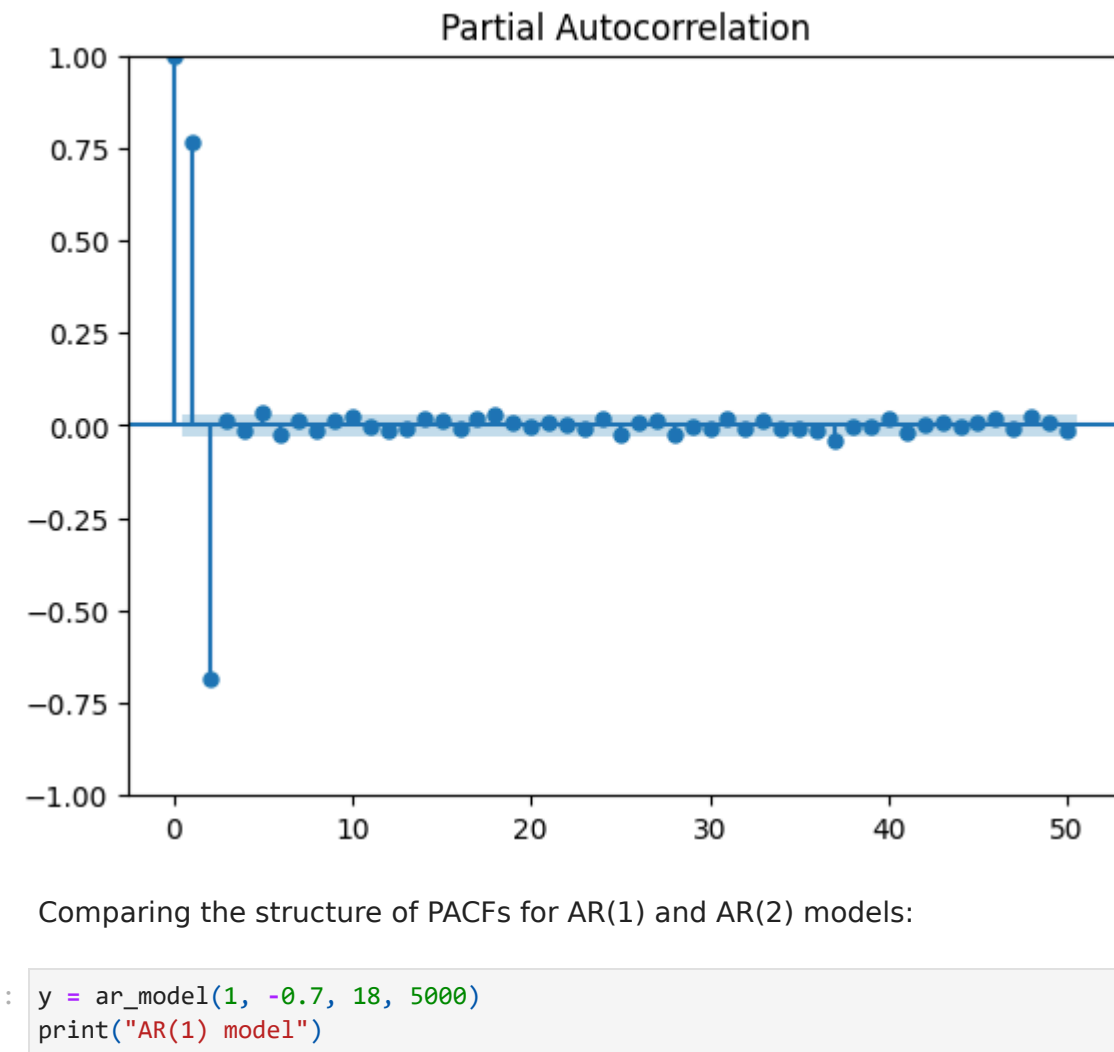
AR(1) model with phi = 1.1
/Users/muryabovoy/Desktop/semestr-4/Time Series Analysis/lab4/lib/python3.12/site-packages/statsmodels/regression/linear_model.py:1483: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation. (Deprecated NumPy 1.25.)
y[t] = c + np.dot(phi, y[t-p:t][:-1]) + np.random.normal(1.25)
/Users/muryabovoy/Desktop/semestr-4/Time Series Analysis/lab4/lib/python3.12/site-packages/statsmodels/regression/linear_model.py:1483: RuntimeWarning: Invald value encountered in reduce
acf = acf/(lags + 1) / avf[0]
```



The result shows that we can't calculate the ACF and PACF for the AR(1) model with $\phi = 1.1$.

Calculate 5000 values of the AR(2) model with coefficients: 1.3, -0.7

```
In [43]: y = ar_model(2, [1.3, -0.7], 8, 5000)
print("AR(2) model")
plot_acf(y, lags=50)
plt.show()
plot_pacf(y, lags=50)
plt.show()
```



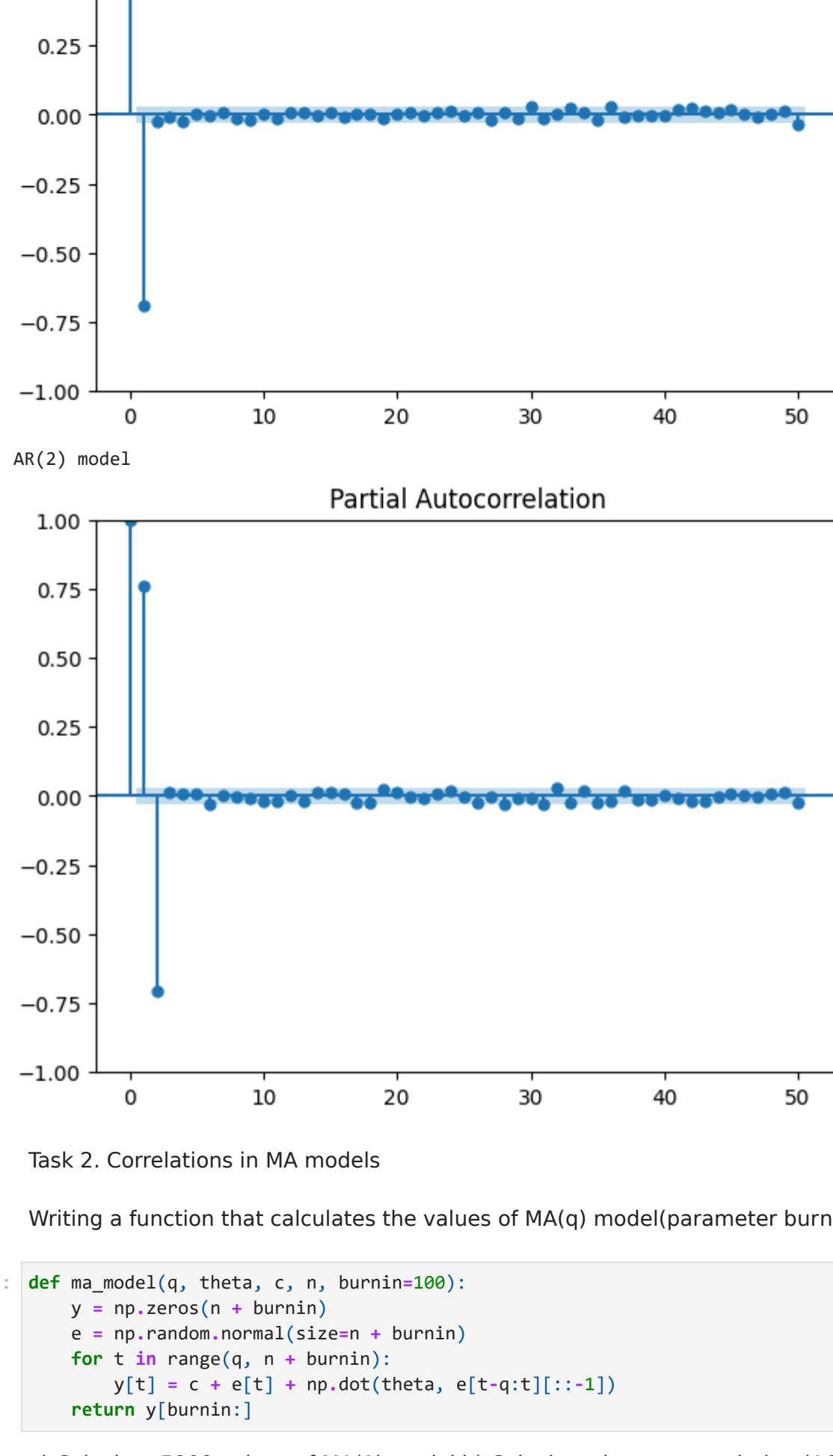
Comparing the structure of PACFs for AR(1) and AR(2) models:

```
In [44]: y = ar_model(1, [-0.7, 10, 5000])
print("AR(1) model")
plot_acf(y, lags=50)
plt.show()

y = ar_model(2, [1.3, -0.7], 8, 5000)
print("AR(2) model")
plot_acf(y, lags=50)
plt.show()

AR(1) model
/Users/muryabovoy/Desktop/semestr-4/Time Series Analysis/lab4/lib/python3.12/site-packages/statsmodels/regression/linear_model.py:1483: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation. (Deprecated NumPy 1.25.)
y[t] = c + np.dot(phi, y[t-p:t][:-1]) + np.random.normal()

AR(2) model
```



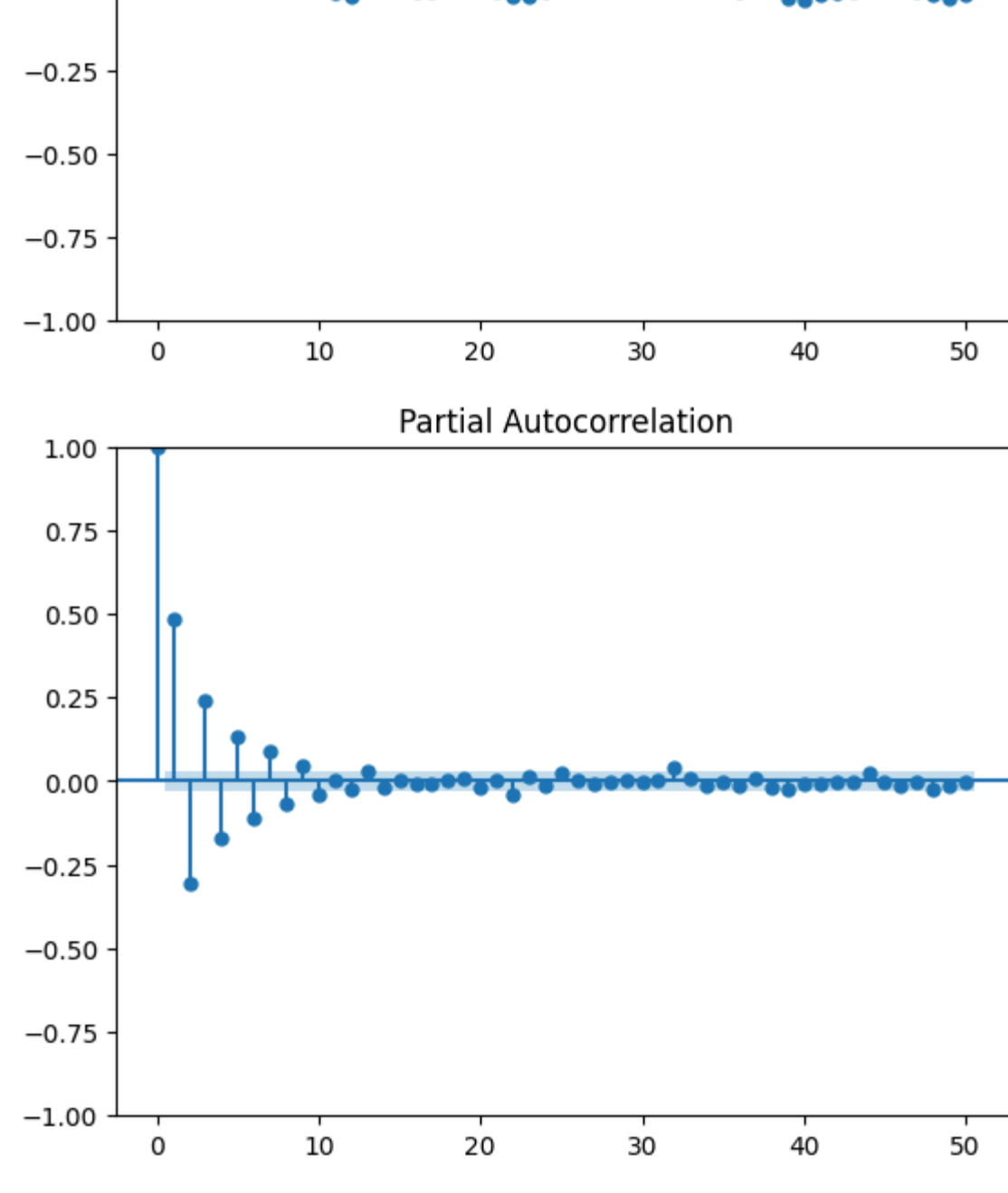
Task 2: Correlations in MA models

Writing a function that calculates the values of MA(q) model/parameter burnin determines how many initial values are discarded)

```
In [45]: def ma_model(q, theta, c, n, burnin=100):
    y = np.zeros(n + burnin)
    # generate the time series according to the MA(q) model
    for t in range(q, n + burnin):
        y[t] = c + np.dot(theta, y[t-q:t][:-1])
    return y[burnin:]

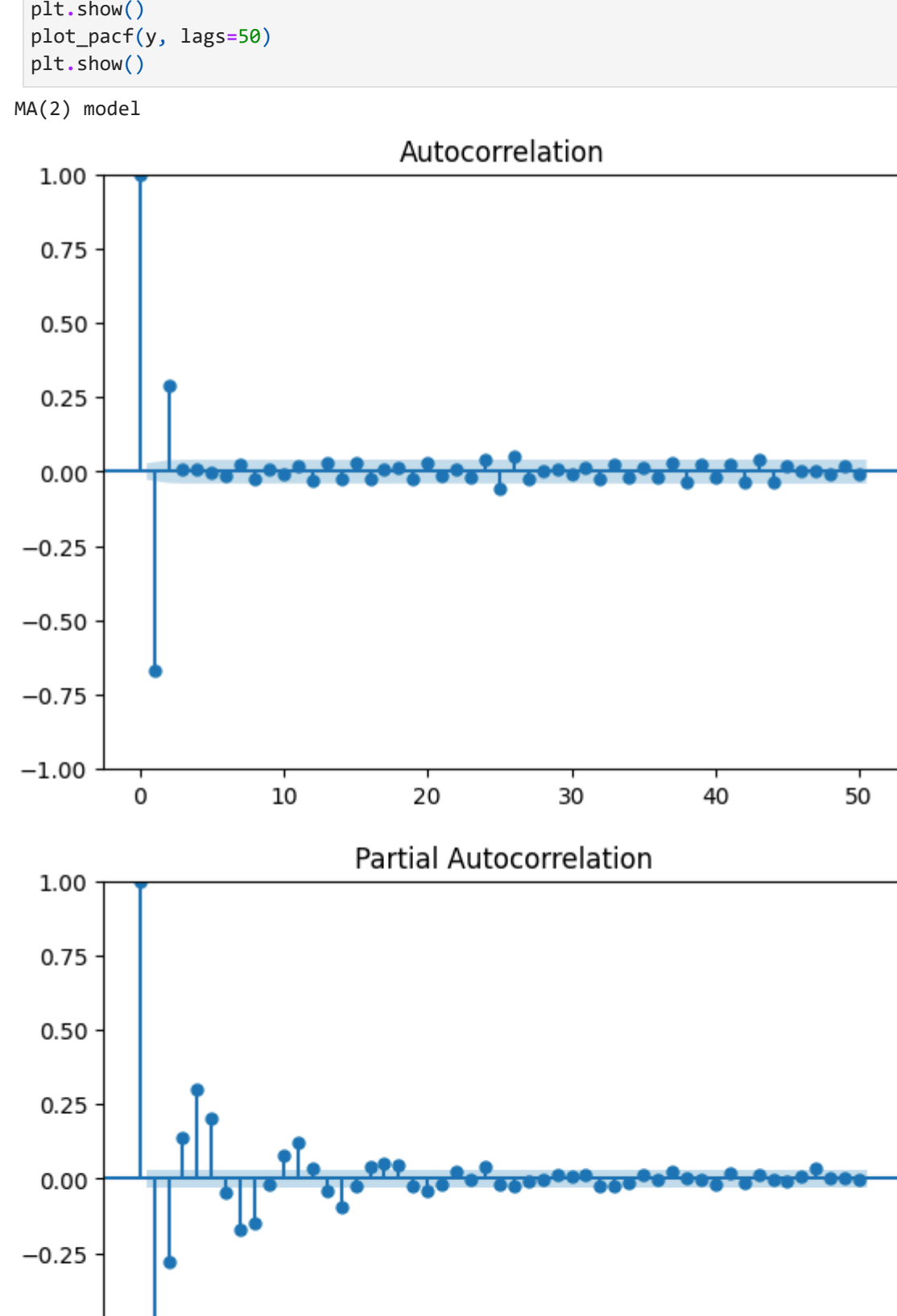
a) Calculate 5000 values of MA(1) model b) Calculate the autocorrelation (ACF) and partial autocorrelation (PACF) function for this time series.
```

```
In [46]: y = ma_model(1, [0.8], 10, 5000) # a
print("MA(1) model")
plot_acf(y, lags=50) # a
plt.show()
plot_pacf(y, lags=50) # b
plt.show()
```



Repeat the calculations for the MA(2) model with coefficients: -1, 0.8

```
In [47]: y = ma_model(2, [-1, 0.8], 0, 5000) # a
print("MA(2) model")
plot_acf(y, lags=50) # a
plt.show()
plot_pacf(y, lags=50) # b
plt.show()
```



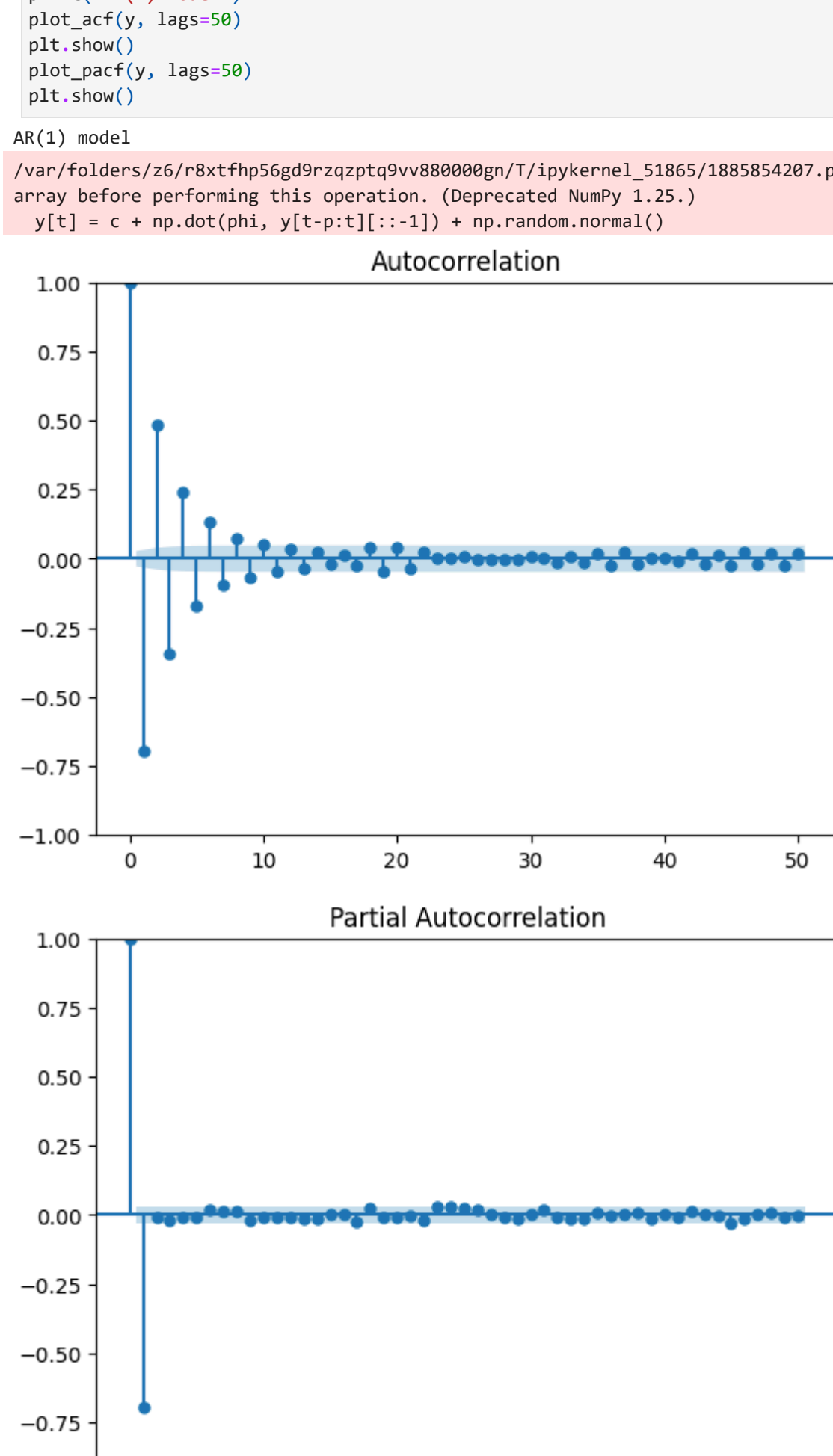
Comparing the structure of ACF/PACFs for AR and MA models (I will take the same values for AR and MA models for better understanding the differences)

```
In [48]: y = ar_model(1, [-0.7, 10, 5000])
print("AR(1) model")
plot_acf(y, lags=50)
plt.show()
plot_pacf(y, lags=50)
plt.show()

y = ma_model(1, [-0.7, 10, 5000])
print("MA(1) model")
plot_acf(y, lags=50)
plt.show()
plot_pacf(y, lags=50)
plt.show()

AR(1) model
/Users/muryabovoy/Desktop/semestr-4/Time Series Analysis/lab4/lib/python3.12/site-packages/statsmodels/regression/linear_model.py:1483: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation. (Deprecated NumPy 1.25.)
y[t] = c + np.dot(phi, y[t-p:t][:-1]) + np.random.normal()

MA(1) model
```



Repeat the calculations for the MA(2) model with coefficients: -1, 0.8

```
In [49]: y = ma_model(2, [-1, 0.8], 0, 5000) # a
print("MA(2) model")
plot_acf(y, lags=50) # a
plt.show()
plot_pacf(y, lags=50) # b
plt.show()

MA(2) model
```

