```
In []: import numpy as np
import matplotlib.pyplot as plt

from statsmodels.stats.diagnostic import acorr_ljungbox
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller

from ma_model import ma_series
from ar_model import ar_series
```

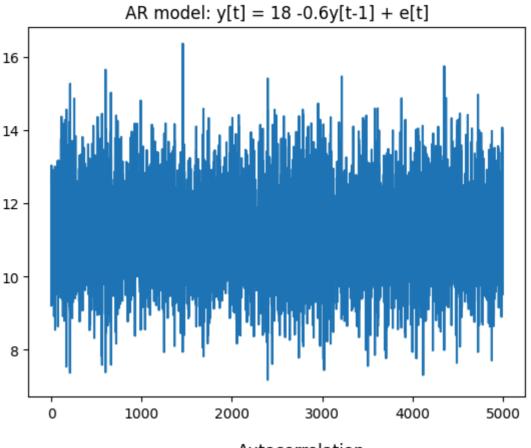
Constants setup

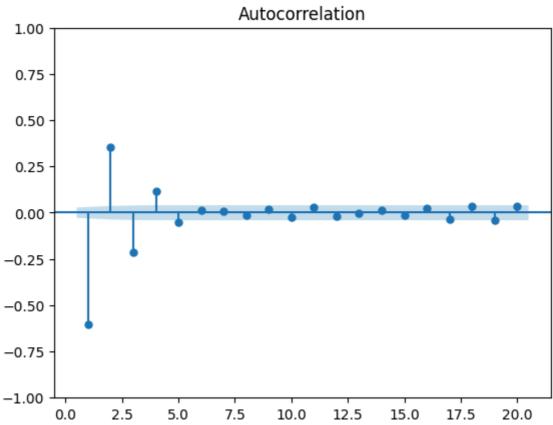
```
In []: BURNIN = 500
N = 5000
SEED = 42
```

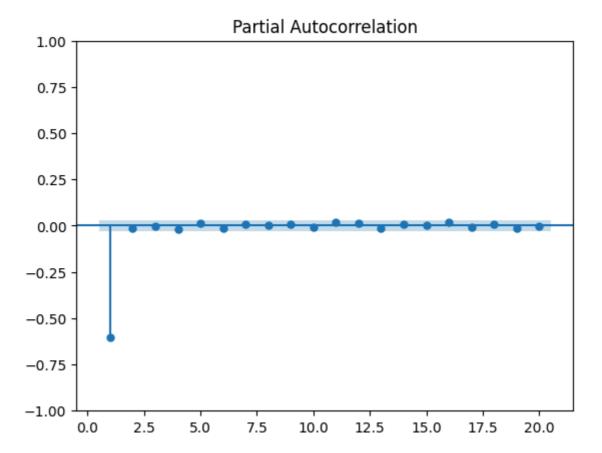
Correlations in AR model

Out[]: lb_stat lb_pvalue **1** 1826.691767 0.0 2 2457.314658 0.0 **3** 2680.744180 0.0 **4** 2745.886276 0.0 0.0 **5** 2759.040234 **6** 2759.780959 0.0 **7** 2760.340900 0.0 **8** 2761.579899 0.0 **9** 2763.715950 0.0 **10** 2766.282141 0.0 **11** 2770.698410 0.0 **12** 2772.212735 0.0 **13** 2772.214016 0.0 **14** 2773.041093 0.0 **15** 2774.122868 0.0 **16** 2777.749506 0.0 **17** 2783.438981 0.0 **18** 2790.330182 0.0 **19** 2798.411716 0.0

20 2803.689824







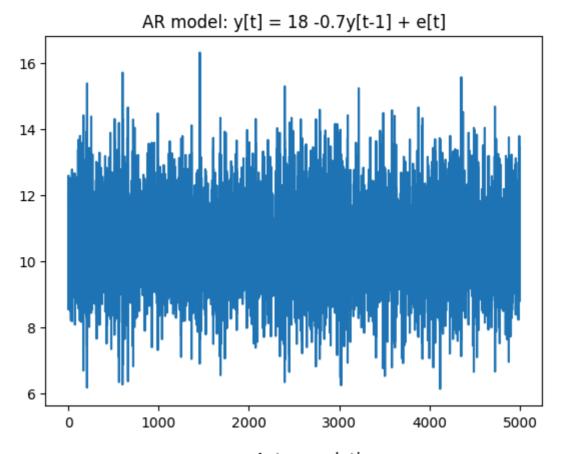
```
In []: ar_series_2, ar_formula_2 = ar_series(burnin=BURNIN, n=N, c=18, o=np.array([-0.7]), seed=SEED)

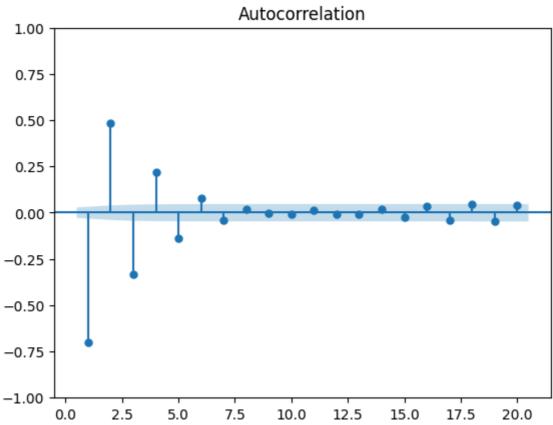
plt.title(ar_formula_2)
  plt.plot(ar_series_2)
  fig = plot_acf(ar_series_2, lags=20, zero=False)
  fig = plot_pacf(ar_series_2, lags=20, zero=False)
  acorr_ljungbox(ar_series_2, lags=20, return_df=True)

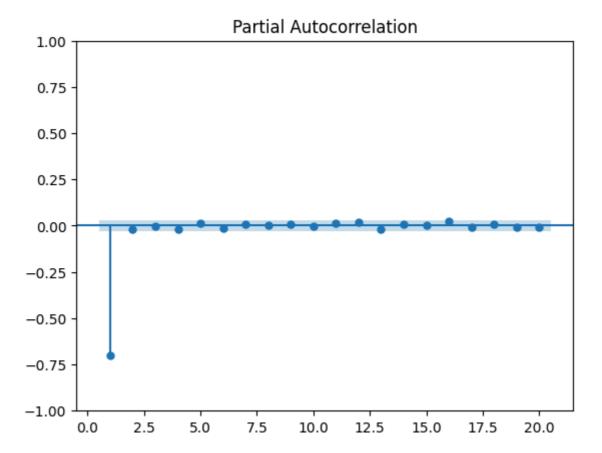
AR_model: v[t] = 18 -0 7v[t=1] + e[t]
```

Out[]: lb_stat lb_pvalue **1** 2457.161149 0.0 **2** 3618.631995 0.0 **3** 4171.256316 0.0 **4** 4410.741539 0.0 **5** 4503.375498 0.0 **6** 4533.555290 0.0 **7** 4540.866228 0.0 **8** 4542.458437 0.0 **9** 4542.497862 0.0 **10** 4542.678069 0.0 **11** 4543.788489 0.0 **12** 4544.032652 0.0 **13** 4544.284701 0.0 **14** 4545.944316 0.0 **15** 4548.386706 0.0 **16** 4553.932734 0.0 **17** 4562.044687 0.0 **18** 4571.686722 0.0 **19** 4582.347496 0.0

20 4590.199335







```
In []: ar_series_3, ar_formula_3 = ar_series(burnin=BURNIN, n=N, c=18, o=np.array([-0.8]), seed=SEED)

plt.title(ar_formula_3)
  plt.plot(ar_series_3)
  fig = plot_acf(ar_series_3, lags=20, zero=False)
  fig = plot_pacf(ar_series_3, lags=20, zero=False)
  acorr_ljungbox(ar_series_3, lags=20, return_df=True)

AR_model: v[t] = 18 = 0.8v[t=1] + e[t]
```

Out[]: lb_stat lb_pvalue **1** 3179.440748 0.0 **2** 5153.628248 0.0 **3** 6381.691046 0.0 **4** 7116.220653 0.0 0.0 **5** 7542.085628 **6** 7782.280436 0.0 **7** 7915.230636 0.0 **8** 7992.213703 0.0

9 8035.684801

11 8074.438005

12 8086.052397

13 8099.027810

14 8113.513082

15 8127.766880

16 8144.869785

17 8163.670219

18 8182.816382

19 8201.503074

20 8216.212460

8060.743535

0.0

0.0

0.0

0.0

0.0

0.0

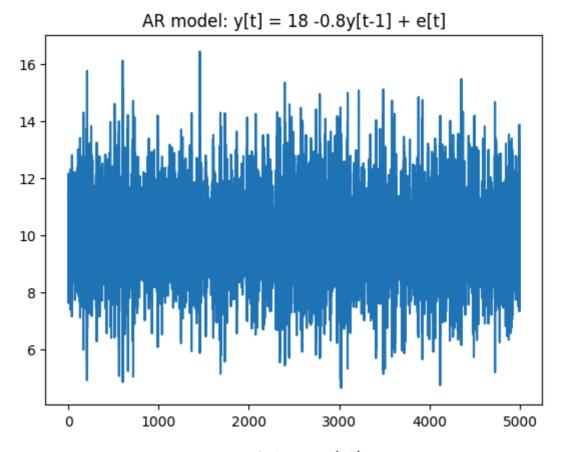
0.0

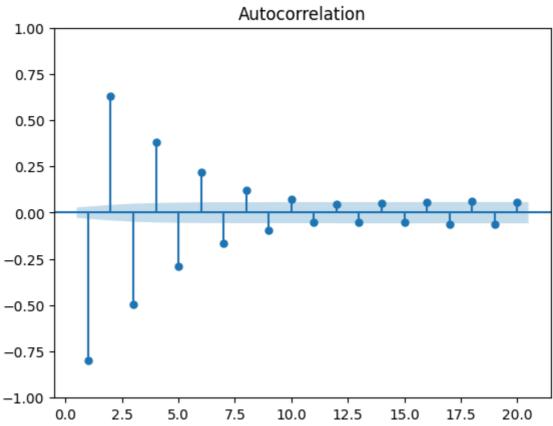
0.0

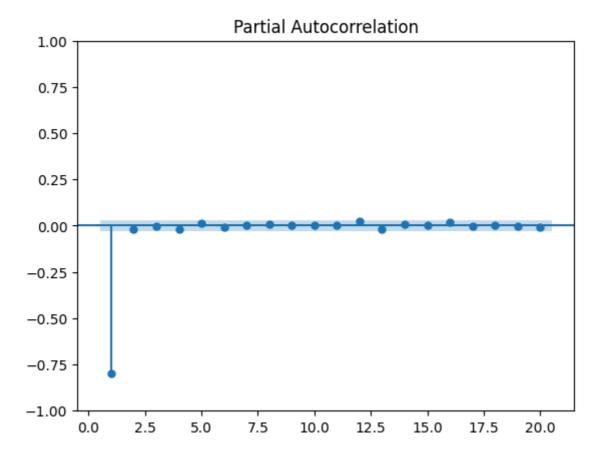
0.0

0.0

0.0







```
In []: ar_series_4, ar_formula_4 = ar_series(burnin=BURNIN, n=N, c=18, o=np.array([-0.9]), seed=SEED)

plt.title(ar_formula_4)
  plt.plot(ar_series_4)
  fig = plot_acf(ar_series_4, lags=20, zero=False)
  fig = plot_pacf(ar_series_4, lags=20, zero=False)
  acorr_ljungbox(ar_series_4, lags=20, return_df=True)

AR_model: v[t] = 18 -0 9v[t-1] + e[t]
```

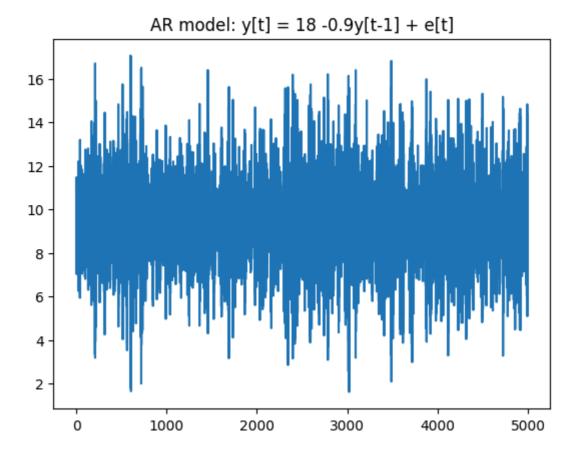
 Out[]:
 Ib_stat
 Ib_pvalue

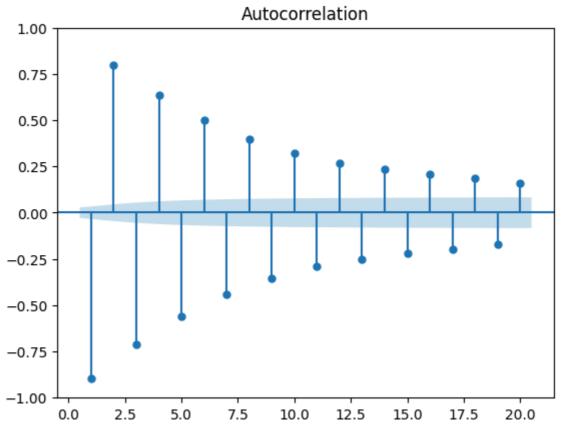
 1
 4015.633406
 0.0

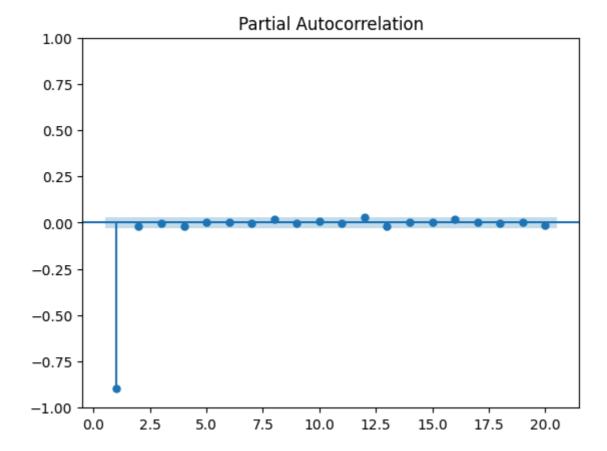
 2
 7210.041258
 0.0

 3
 9757.877470
 0.0

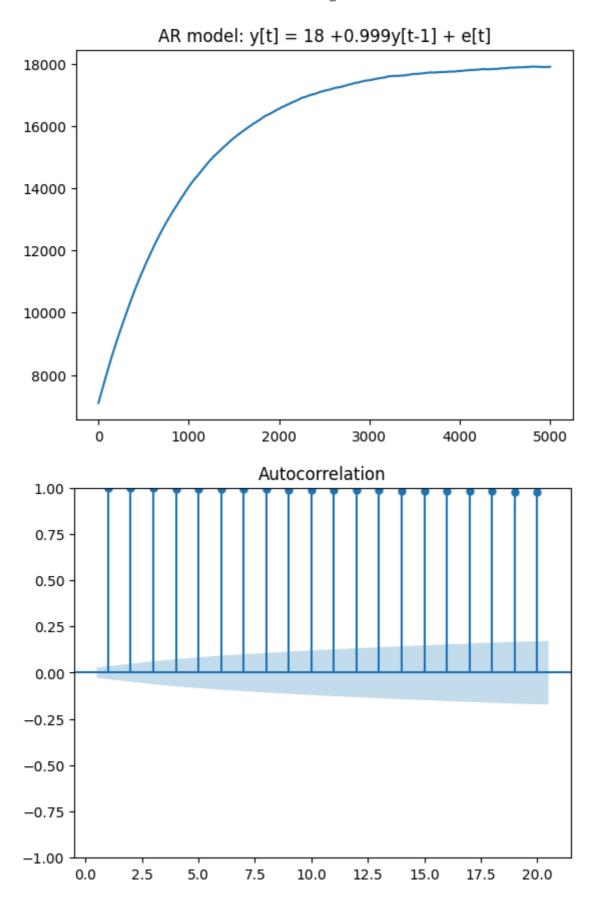
 4
 11768.875817
 0.0

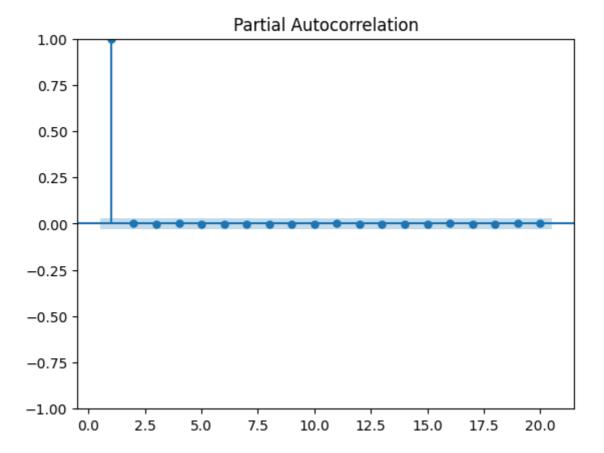






Is stationary if |theta| > 1?



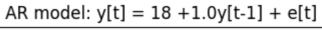


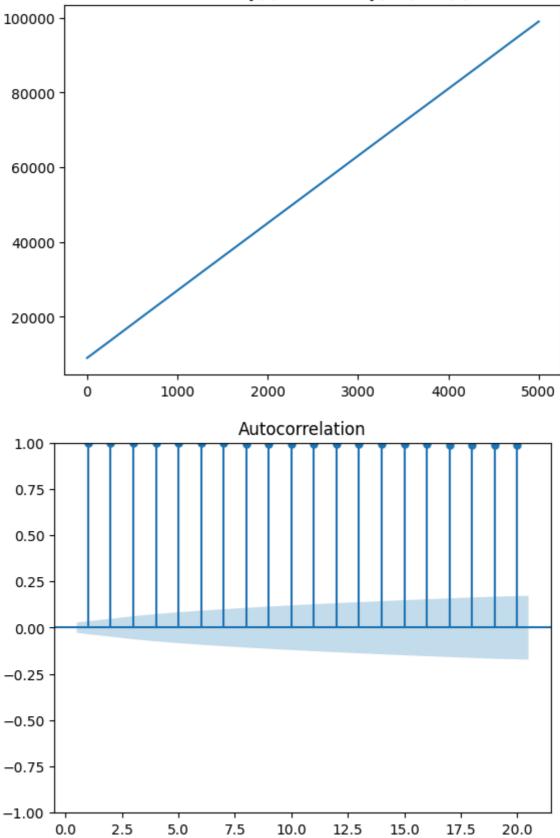
```
In []: ar_series_5, ar_formula_5 = ar_series(burnin=BURNIN, n=N, c=18, o=np.array([1.0]), seed=SEED)

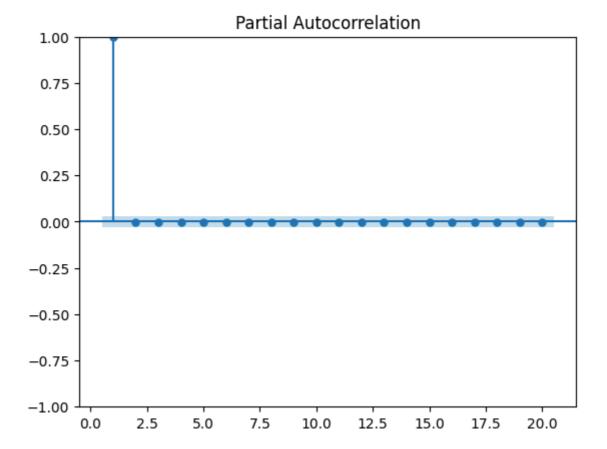
plt.title(ar_formula_5)
  plt.plot(ar_series_5)
  fig = plot_acf(ar_series_5, lags=20, zero=False)

fig = plot_pacf(ar_series_5, lags=20, zero=False)
```

R model: y[t] = 18 +1.0y[t-1] + e[t]



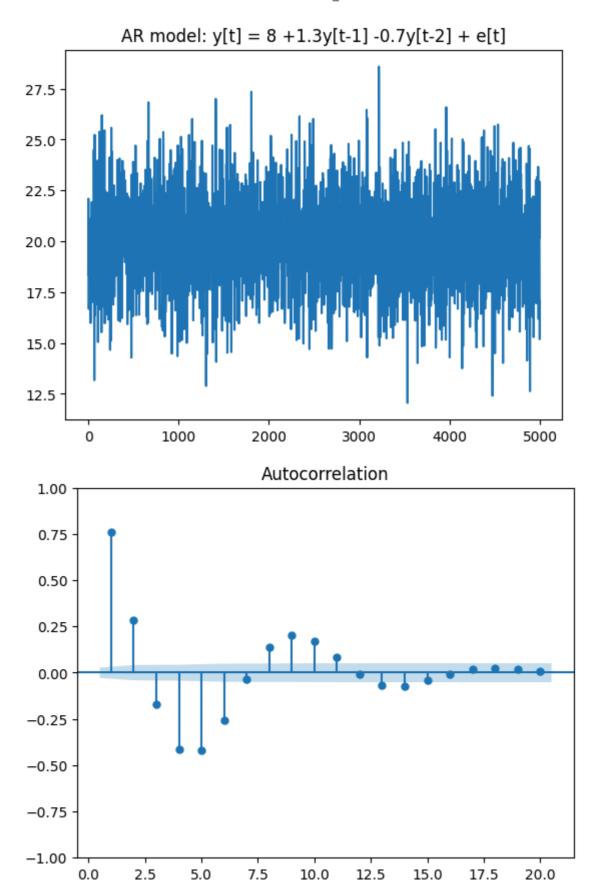


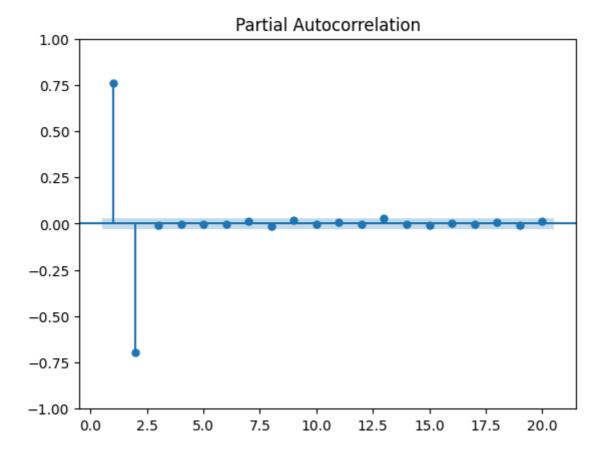


We can observe that if theta get closer to one then the series becomes more and more non stationary and even becomes a linear function.

AR(2) model

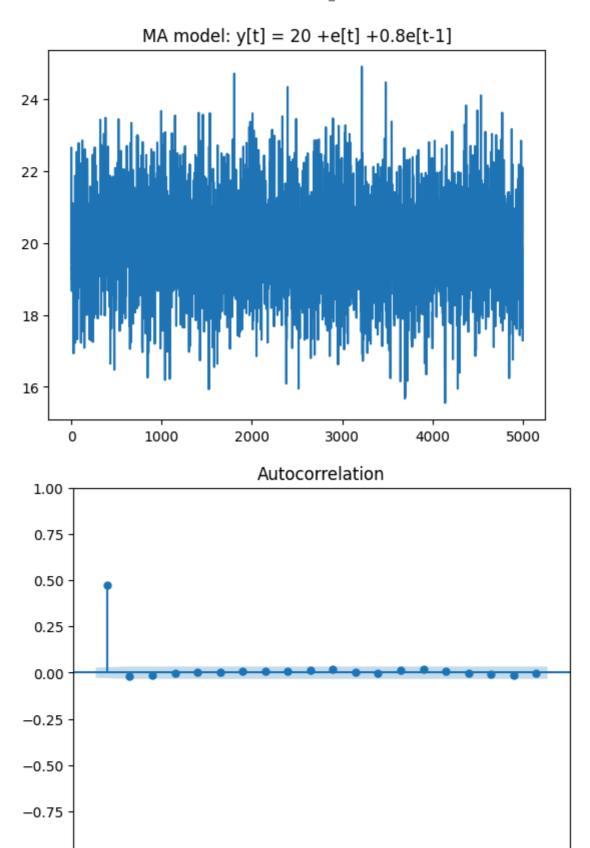
20 6055.81025





Correlations in MA model

Out[]:		lb_stat	lb_pvalue
	1	1129.790574	1.107010e-247
	2	1131.975101	1.565777e-246
	3	1133.188786	2.294328e-245
	4	1133.236673	4.729765e-244
	5	1133.265791	8.354605e-243
	6	1133.274595	1.317230e-241
	7	1133.847202	1.420233e-240
	8	1134.251392	1.533295e-239
	9	1134.399712	1.751250e-238
	10	1135.685184	1.068713e-237
	11	1137.975499	3.752398e-237
	12	1137.977906	3.903029e-236
	13	1138.042038	3.762776e-235
	14	1138.970869	2.268680e-234
	15	1140.740172	8.695084e-234
	16	1141.255433	5.983041e-233
	17	1141.258149	5.130238e-232
	18	1141.447332	3.889263e-231
	19	1142.279535	2.086163e-230
	20	1142.366340	1.571817e-229



-1.00

0.0

2.5

5.0

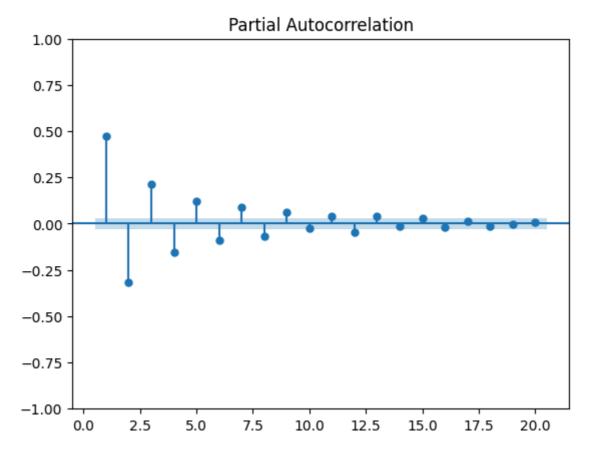
7.5

10.0

12.5

15.0

17.5



```
In []: ma_series_2, ma_formula_2 = ma_series(burnin=BURNIN, n=N, c=0, C=np.array([-1, 0.8]), seed=SEED)

plt.title(ma_formula_2)
plt.plot(ma_series_2)
fig = plot_acf(ma_series_2, lags=20, zero=False)
fig = plot_pacf(ma_series_2, lags=20, zero=False)
acorr_ljungbox(ma_series_2, lags=20, return_df=True)
```

NA model: v[t] = 0 +e[t] -1.0e[t-1] +0.8e[t-2]

Out[]: lb_stat lb_pvalue **1** 2359.502107 0.0 2 2820.291391 0.0 **3** 2820.301705 0.0 4 2820.839185 0.0 **5** 2823.601056 0.0 **6** 2829.526616 0.0 **7** 2835.963860 0.0 **8** 2839.452515 0.0 **9** 2842.469889 0.0 2846.285594 0.0 2851.851298 0.0 2853.786300 0.0 2853.803853 0.0 **14** 2854.645509 0.0 2855.868856 0.0 2858.372140 0.0 2863.102816 0.0

18 2870.138150

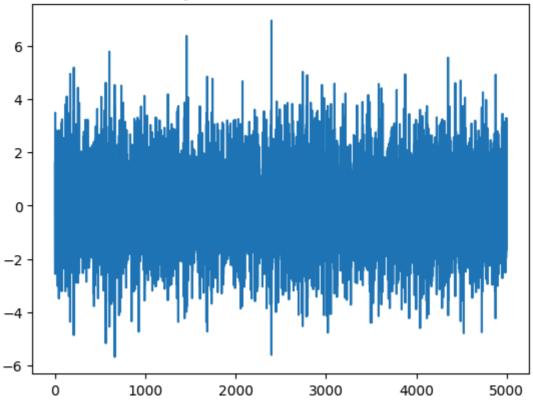
20 2880.845252

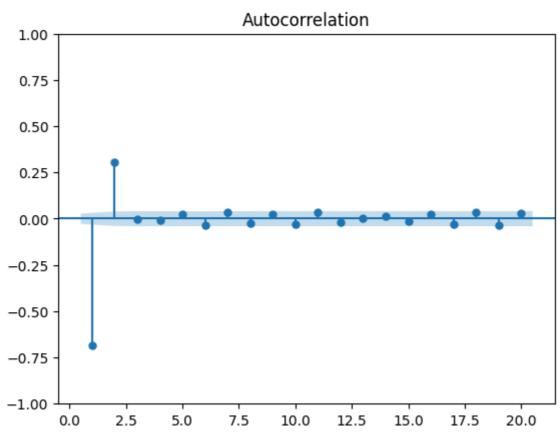
2876.604159

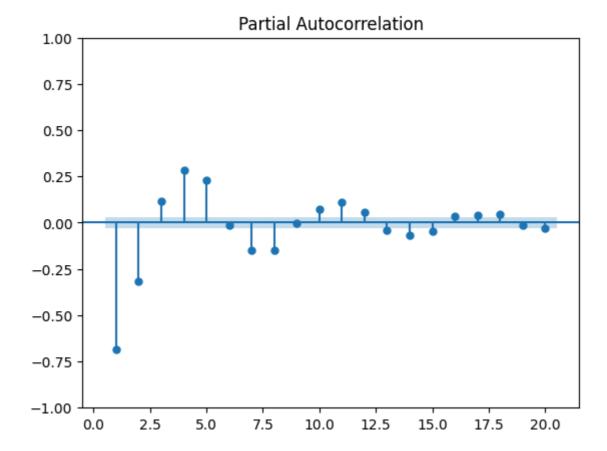
0.0

0.0









Comparison of AR and MA models

We can observe that ar models tend to have bigget autocorrelation and low partial autocorrelation. On the other hand, ma models behave the opposite way.

From the above we can conclude that usage of AR models is more suitable if we want to capture the direct influence of previous values on the current one. On the other hand, MA models are better in capturing the effects of past points without considerating possible fluctuations from closest points.