
STOCHASTIC PROCESSES

HW03

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Stochastic processes course

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1 Abstract

In this exercise, we want to check the second-order stationarity of a data. We have used two data, one is normal data generated by ourselves and the other is Autoregressive data. To check the second-order stationary, for first method we must first separate the data into windows of length L , where L is from 3 (because variance can be obtained from 3 numbers of data) to $1/5$ of number of data and obtain the variance of each window, then take the average of the variance of windows. Then draw the plot of average variances according to L . If this graph converges towards a number, then we can say that this data is second-order stationary (because we have used variance) and the length of the second-order stationary is the point where the plot starts to converge.

The second method is to check the second-order stationarity of the data at different levels of confidence through p-value.

2 Results

First, let's go to the normal data with a different number of data to check the stationery second order for them and get its length.

2.1 Normal distribution

2.1.1 Normal distribution $n=10^2$

2.1.1.1 First method

For 10^2 data, the length of the second-order stationary is 26. (This value will be output to you if you run the code for the number of data you want.)

In order to show a better plot when drawing the error bars, in addition to drawing the original data, we have also drawn a smoother data along with the error bars, which we obtained from summarizing the original data. With less numbers of data, these two plots are identical.

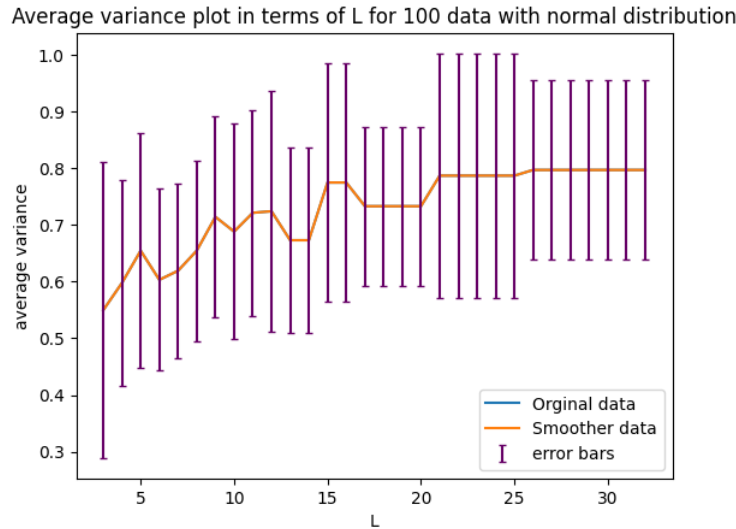


Figure 1: Average variance plot in terms of L for 10^2 data with normal distribution

2.1.1.2 Second method

Augmented Dickey-Fuller Statistic: -9.669236

p-value: 0.000000

critical values at different levels:

1%: -3.498

5%: -2.891

10%: -2.583

2.1.2 Normal distribution $n=10^3$

2.1.2.1 First method

For 10^3 data, the length of the second-order stationary is 251.

Average variance plot in terms of L for 1000 data with normal distribution

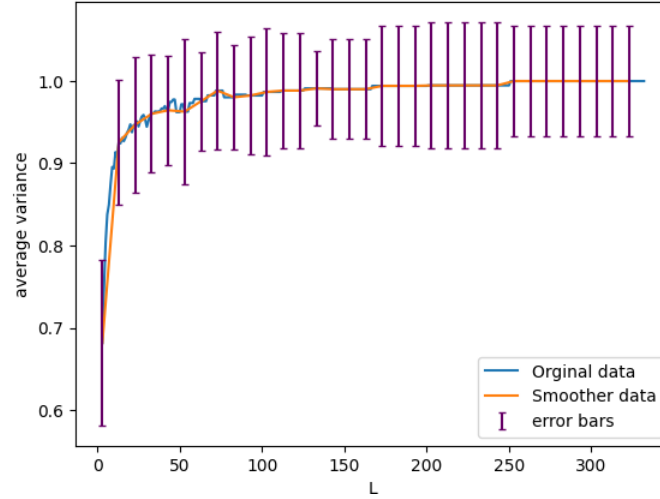


Figure 2: Average variance plot in terms of L for 10^3 data with normal distribution

2.1.2.2 Second method

Augmented Dickey-Fuller Statistic: -13.113123

p-value: 0.000000

critical values at different levels:

1%: -3.437

5%: -2.864

10%: -2.568

2.1.3 Normal distribution $n=10^4$

2.1.3.1 First method

For 10^4 data, the length of the second-order stationary is 25001.

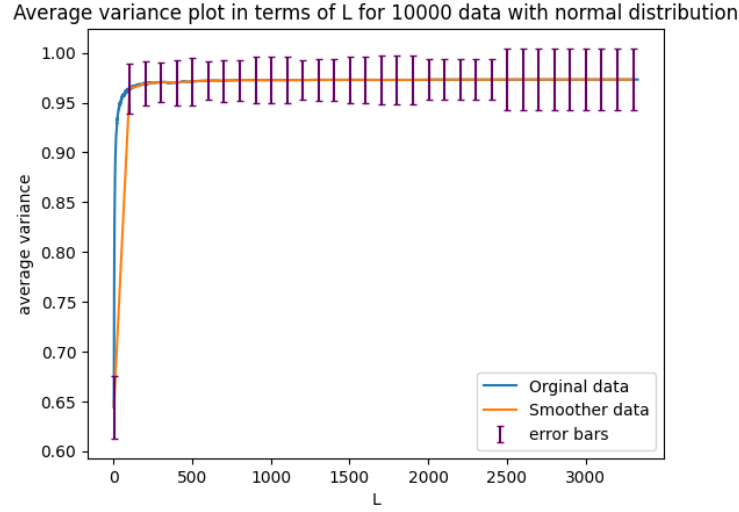


Figure 3: Average variance plot in terms of L for 10^4 data with normal distribution

2.1.3.2 Second method

Augmented Dickey-Fuller Statistic: -99.162574

p-value: 0.000000

critical values at different levels:

1%: -3.431

5%: -2.862

10%: -2.567

2.1.4 Normal distribution $n=10^5$

2.1.4.1 First method

For 10^5 data, the length of the second-order stationary is 2501.

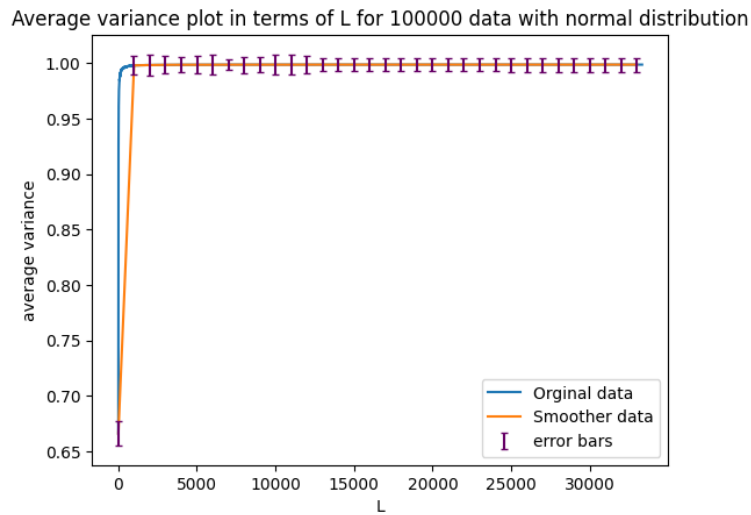


Figure 4: Average variance plot in terms of L for 10^5 data with normal distribution

2.1.4.2 Second method

Augmented Dickey-Fuller Statistic: -100.721542

p-value: 0.000000

critical values at different levels:

1%: -3.430

5%: -2.862

10%: -2.567

2.2 Autoregressive Process

2.2.0.1 First method

For Autoregressive data, we cannot define the length of the second-order stationary well, because in every interval, the data becomes second-order stationary and grows again, and this process repeats.

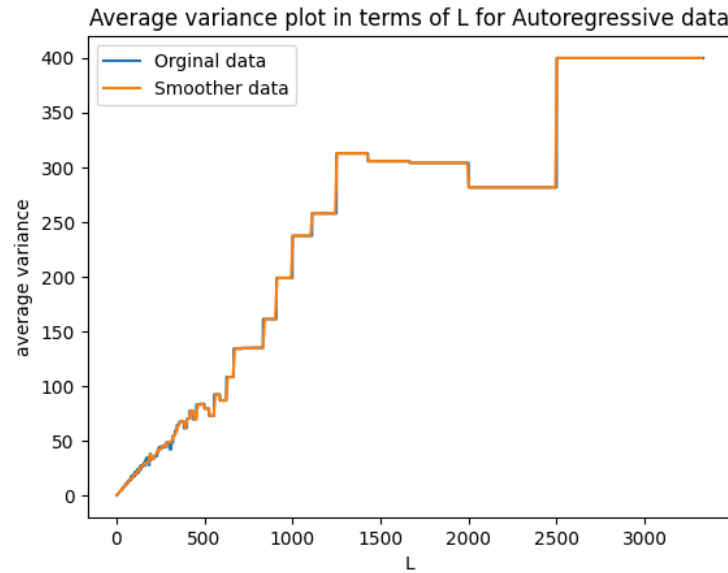


Figure 5: Average variance plot in terms of L for Autoregressive data

2.2.0.2 Second method

Augmented Dickey-Fuller Statistic: -2.249658

p-value: 0.188718

critical values at different levels:

1%: -3.431

5%: -2.862

10%: -2.567

2.3 Exercise 4 data

2.3.0.1 First method

For exercise 4 data, the length of the second-order stationary is 2501.

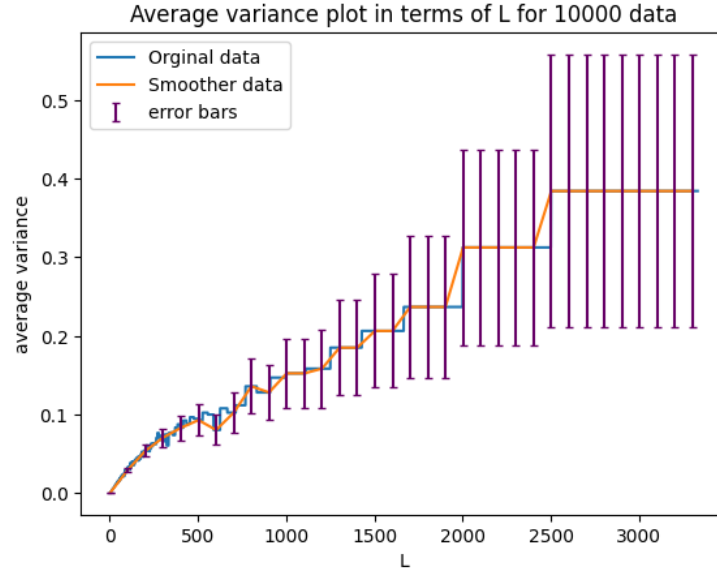


Figure 6: Average variance plot in terms of L for exercise 4 data

2.3.0.2 Second method

Augmented Dickey-Fuller Statistic: -2.133389

p-value: 0.231302

critical values at different levels:

1%: -3.431

5%: -2.862

10%: -2.567

3 Code

```
1 # Import needed libraries
2 import numpy as np
3 from numpy import inf
4 import matplotlib.pyplot as plt
5 from scipy import stats
6
7 # Generate n random numbers with normal distribution
8 datanumbers = int(input('Enter numbers of random data you want to generate: '
9 ))
10 random_number = np.random.normal(0, 1, 1000000)
11 data = np.random.choice(random_number, datanumbers, replace = False)
12
13 #read Autoregressive data
14 data = np.loadtxt('mydataset.txt')
15
16 def split_array(array, l):
17     # Calculate the number of parts
18     num_parts = len(array) // l
19
20     # Split the array into parts of length l
21     parts = np.array_split(array, num_parts)
22
23     return parts
24
25 # Specify the length of each part
26 length_of_each_part = 3
27 errors = []
28 average_variance = []
29 l = []
30 while length_of_each_part <= (int(len(data)/3)-1):
31     l.append(length_of_each_part)
32     result = split_array(data, length_of_each_part)
33     variance = []
34     for i in range(len(result)):
35         vari = np.var(result[i])
36         variance.append(vari)
37     av_vari = sum(variance) / len(variance)
38     average_variance.append(av_vari)
39     variance = np.array(variance)
40     error = np.sqrt((np.sum(((variance**2)) - av_vari**2)) / (len(variance)*(
41         len(variance)-1)))
42     errors.append(error)
43     length_of_each_part = length_of_each_part + 1
44
45 errors = np.array(errors)
46
47 from numpy import inf
48 errors[errors == inf] = 0
49
50 for ele in average_variance:
51     if ele == average_variance[-1]:
52         n = average_variance.index(ele)
53         print('Second Order Stationary Length:',l[n])
54         break
```



```

53 l = np.array(l)
54 average_variance = np.array(average_variance)
55 errors = np.array(errors)
56
57 plt.plot(l,average_variance , label='Orginal data')
58
59 slicenumber = 1000
60 lnew = l[::slicenumber]
61 errorsnew = errors[::slicenumber]
62 average_variancenew =average_variance[::slicenumber]
63
64 plt.plot(lnew,average_variancenew, label='Smoother data')
65 plt.errorbar(lnew, average_variancenew, yerr=errorsnew, fmt='none', color='
    #660066', capsize=2, label='error bars')
66 plt.legend()
67 plt.xlabel("L")
68 plt.ylabel("average variance")
69 plt.title(f'Average variance plot in terms of L for {datanumbers} data with
    normal distribution')
70 plt.show()
71
72 import pandas as pd
73 from statsmodels.tsa.stattools import adfuller
74
75
76 res = adfuller(data)
77
78 # Printing the statistical result of the adfuller test
79 print('Augmneted Dickey_fuller Statistic: %f' % res[0])
80 print('p-value: %f' % res[1])
81
82 # printing the critical values at different alpha levels.
83 print('critical values at different levels:')
84 for k, v in res[4].items():
85     print('\t%s: %.3f' % (k, v))

```