HW1

Charles Dotson

September 7, 2022

Contents

[170]:
```
'''Importing Packages'''
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as plt
from IPython.display import Markdown as md
import statsmodels.tsa.stattools as ts
import datetime
from loess import loess_1d
from statsmodels.graphics.tsaplots import plot_acf
from openpyxl import Workbook, load_workbook
%matplotlib inline
```

1 Figure 1.1 The market yield on US Treasury Securities at 10-year constant maturity

1.1 a) load and reconstruct the series data

[171]:
```
'''Reading in Data'''

data_yield = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪1-10YTCM')
data_yield
```

[171]:
```
          Month  Rate, %    Month.1  Rate, %.1    Month.2  Rate, %.2  \
0    1953-04-01     2.83 1966-10-01       5.01 1980-04-01      11.47
1    1953-05-01     3.05 1966-11-01       5.16 1980-05-01      10.18
2    1953-06-01     3.11 1966-12-01       4.84 1980-06-01       9.78
3    1953-07-01     2.93 1967-01-01       4.58 1980-07-01      10.25
4    1953-08-01     2.95 1967-02-01       4.63 1980-08-01      11.10
..          …        …          …         …          …          …
157  1966-05-01     4.78 1979-11-01      10.65 1993-05-01       6.04
158  1966-06-01     4.81 1979-12-01      10.39 1993-06-01       5.96
159  1966-07-01     5.02 1980-01-01      10.80 1993-07-01       5.81
160  1966-08-01     5.22 1980-02-01      12.41 1993-08-01       5.68
161  1966-09-01     5.18 1980-03-01      12.75 1993-09-01       5.36

        Month.3  Rate, %.3
0    1993-10-01       5.33
1    1993-11-01       5.72
2    1993-12-01       5.77
3    1994-01-01       5.75
4    1994-02-01       5.97
..          …        …
157  2006-11-01       4.60
158  2006-12-01       4.56
```

```
159 2007-01-01       4.76
160 2007-02-01       4.72
161        NaT        NaN

[162 rows x 8 columns]
```

1.2 (b) convert the data into xts object

pandas automatically can read data types in python and create an index of date times. the work is done to create one dataframe stacked by the month columns.

[172]:
```
month_columns = ['Month', 'Month.1', 'Month.2', 'Month.3']
rates_columns = ['Rate, %', 'Rate, %.1', 'Rate, %.2', 'Rate, %.3']
index_list = []
rates_list = []

for i in month_columns:
    for t in range(len(data_yield[i])):
        if data_yield[i].iloc[t] not in index_list:
            index_list.append(data_yield[i].iloc[t])


for i in rates_columns:
    for t in range(len(data_yield[i])):
            rates_list.append(data_yield[i].iloc[t])

data_yield_fixed = pd.DataFrame(index=index_list, columns=['Rates'])
data_yield_fixed['Rates'] = rates_list
data_yield_fixed = data_yield_fixed.dropna(axis=0)
data_yield_fixed.index.name = 'Month'
```

1.2.1 Recreating the time series graph first

[173]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.scatter(data_yield_fixed.index, data_yield_fixed['Rates'])
    plt.plot(data_yield_fixed)
    ax.set_xlabel('Month')
    ax.set_ylabel('Rate, %')
    plt.show()
```

1.3 (c) generate the time series plot with loess smoothed curve overlapped.

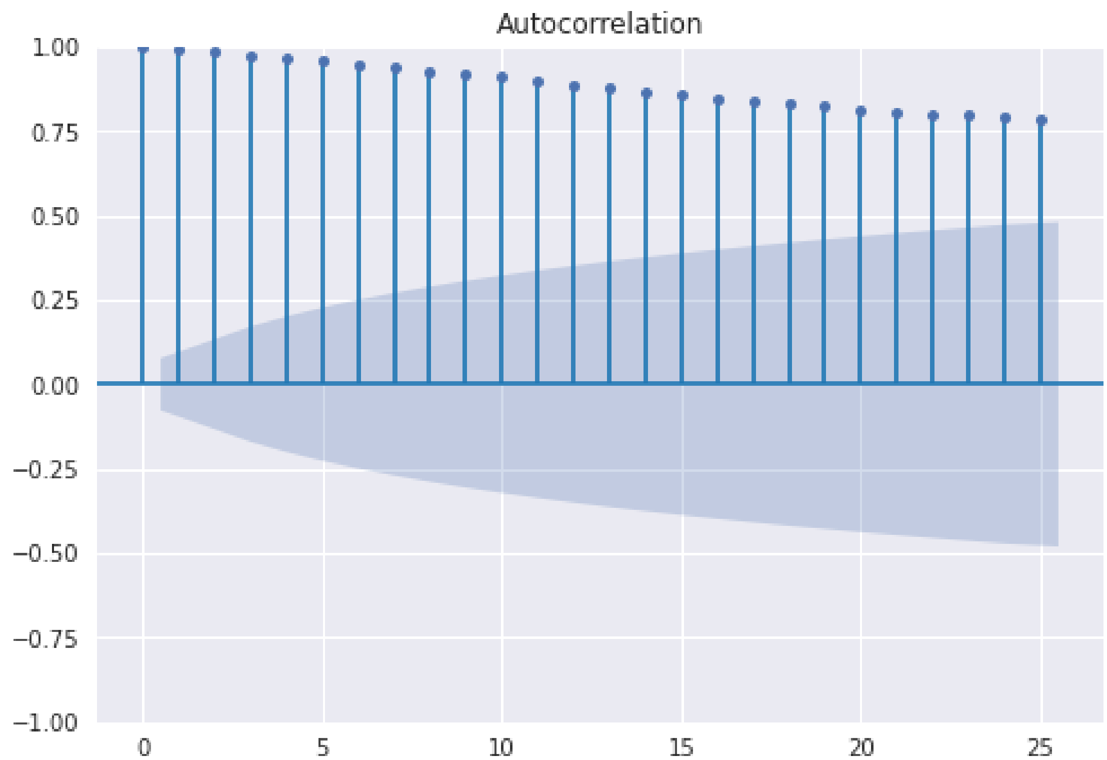
[174]:
```
data_yield_fixed.index = pd.to_datetime(data_yield_fixed.index)
data_yield_fixed['Month_num'] = [i for i in range(len(data_yield_fixed))]
x = np.array(data_yield_fixed['Month_num'])
y = np.array(data_yield_fixed['Rates'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_yield_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_yield_fixed.index)
smoothed['Rates_sm'] = data_yield_fixed['smoothed']
```

[175]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_yield_fixed.index, data_yield_fixed['Rates'])
    ax.set_xlabel('Month')
    ax.set_ylabel('Rate, %')
    plt.legend()
    plt.show()
```

1.4 (d) generate the ACF plot (up to and including 25 lags)

[176]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_yield_fixed['Rates'], lags=25)
```

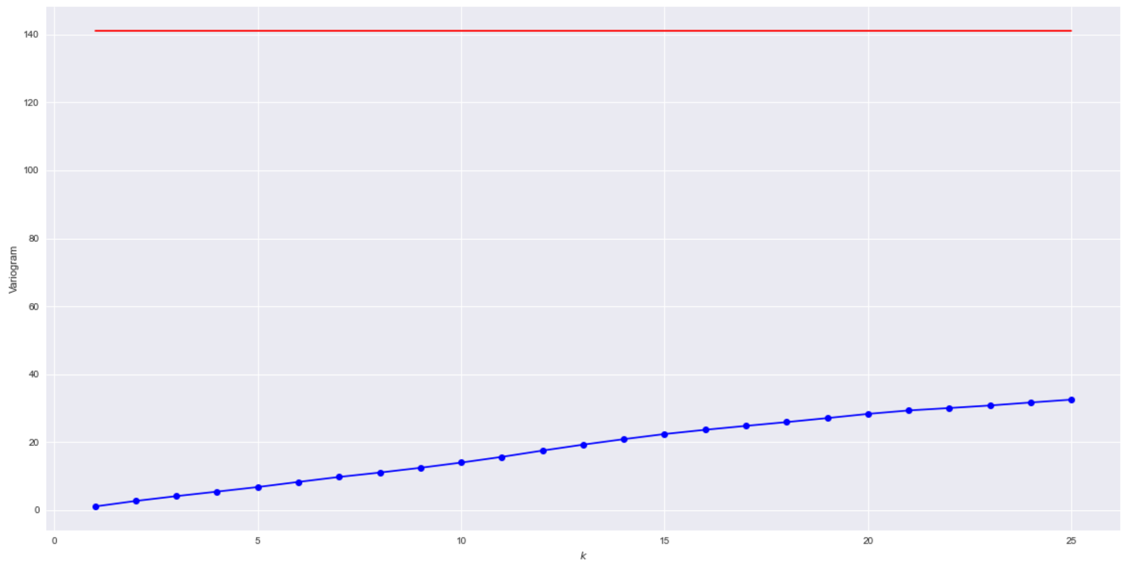
```
<Figure size 1440x720 with 0 Axes>
```



1.5 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[177]:
```
r1 = ts.acf(data_yield_fixed['Rates'], nlags=25)[1]
base_var  = np.var(data_yield_fixed['Rates'])

variogram = pd.DataFrame(index = [i for i in range(1,26)])
variogram['lagged'] = [np.var(np.array(data_yield_fixed['Rates'].iloc[i:]) - np.
↪array(data_yield_fixed['Rates'].iloc[:-i]))/np.var(np.
↪diff(data_yield_fixed['Rates'])) for i in range(1,26)]
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[178]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



1.6 (f) Comment on the stationarity of the series.

Based on the Variogram we can say this is most likely not Stationary.

2 FIGURE 1.2 Pharmaceutical product sales.

2.1 (a) load and reconstruct the series data / (b) convert the data into xts object

[179]:
```
data_pharma = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪2-PHAR')
data_pharma
```

[179]:
```
    Week  Sales, in Thousands  Week.1  Sales, in Thousands.1  Week.2  \
0      1              10618.1      31                10334.5      61
1      2              10537.9      32                10480.1      62
2      3              10209.3      33                10387.6      63
3      4              10553.0      34                10202.6      64
4      5               9934.9      35                10219.3      65
5      6              10534.5      36                10382.7      66
6      7              10196.5      37                10820.5      67
7      8              10511.8      38                10358.7      68
8      9              10089.6      39                10494.6      69
9     10              10371.2      40                10497.6      70
10    11              10239.4      41                10431.5      71
11    12              10472.4      42                10447.8      72
12    13              10827.2      43                10684.4      73
13    14              10640.8      44                10176.5      74
```

14	15	10517.8	45	10616.0	75
15	16	10154.2	46	10627.7	76
16	17	9969.2	47	10684.0	77
17	18	10260.4	48	10246.7	78
18	19	10737.0	49	10265.0	79
19	20	10430.0	50	10090.4	80
20	21	10689.0	51	9881.1	81
21	22	10430.4	52	10449.7	82
22	23	10002.4	53	10276.3	83
23	24	10135.7	54	10175.2	84
24	25	10096.2	55	10212.5	85
25	26	10288.7	56	10395.5	86
26	27	10289.1	57	10545.9	87
27	28	10589.9	58	10635.7	88
28	29	10551.9	59	10265.2	89
29	30	10208.3	60	10551.6	90

	Sales, in Thousands.2	Week.3	Sales, in Thousands.3
0	10538.2	91	10375.4
1	10286.2	92	10123.4
2	10171.3	93	10462.7
3	10393.1	94	10205.5
4	10162.3	95	10522.7
5	10164.5	96	10253.2
6	10327.0	97	10428.7
7	10365.1	98	10615.8
8	10755.9	99	10417.3
9	10463.6	100	10445.4
10	10080.5	101	10690.6
11	10479.6	102	10271.8
12	9980.9	103	10524.8
13	10039.2	104	9815.0
14	10246.1	105	10398.5
15	10368.0	106	10553.1
16	10446.3	107	10655.8
17	10535.3	108	10199.1
18	10786.9	109	10416.6
19	9975.8	110	10391.3
20	10160.9	111	10210.1
21	10422.1	112	10352.5
22	10757.2	113	10423.8
23	10463.8	114	10519.3
24	10307.0	115	10596.7
25	10134.7	116	10650.0
26	10207.7	117	10741.6
27	10488.0	118	10246.0
28	10262.3	119	10354.4

```
29                10785.9     120                10155.4
```

[180]:
```
month_columns = ['Week', 'Week.1', 'Week.2', 'Week.3']
sales_column = ['Sales, in Thousands', 'Sales, in Thousands.1', 'Sales, in␣
 ↪Thousands.2', 'Sales, in Thousands.3']
index_list = []
Sales_list = []

for i in month_columns:
    for t in range(len(data_pharma[i])):
        if data_pharma[i].iloc[t] not in index_list:
            index_list.append(data_pharma[i].iloc[t])


for i in sales_column:
    for t in range(len(data_pharma[i])):
            Sales_list.append(data_pharma[i].iloc[t])

data_pharma_fixed = pd.DataFrame(index=index_list, columns=['Sales'])
data_pharma_fixed['Sales'] = Sales_list
data_pharma_fixed = data_pharma_fixed.dropna(axis=0)
data_pharma_fixed.index.name = 'Week'
```

[181]:
```
data_pharma_fixed
```

[181]:
```
        Sales
Week
1     10618.1
2     10537.9
3     10209.3
4     10553.0
5      9934.9
…        …
116   10650.0
117   10741.6
118   10246.0
119   10354.4
120   10155.4

[120 rows x 1 columns]
```

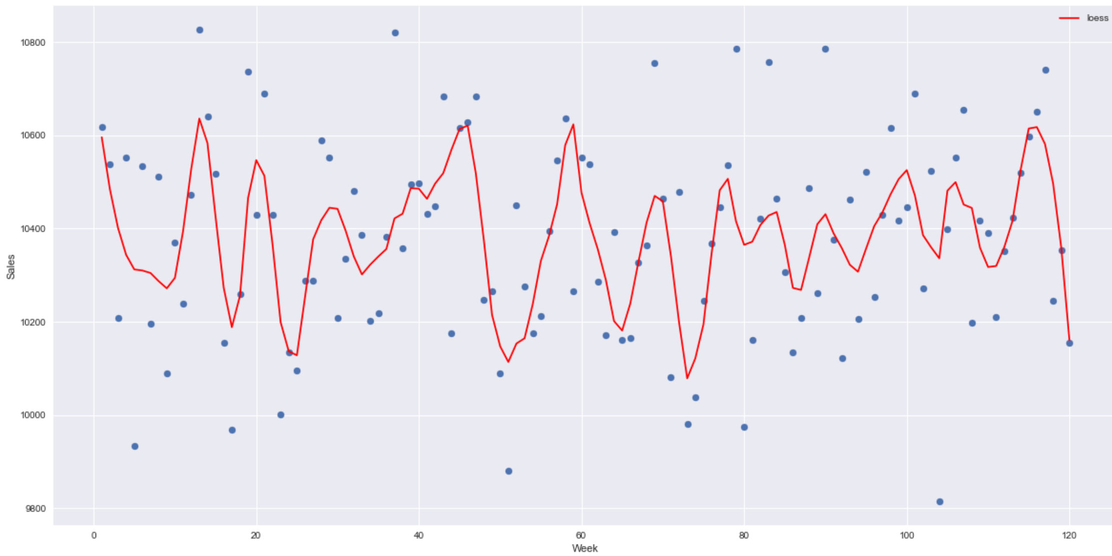
2.2 (c) generate the time series plot with loess smoothed curve overlapped.

[182]:
```
x = np.array(data_pharma_fixed.index)
y = np.array(data_pharma_fixed['Sales'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)
```

```
data_pharma_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_pharma_fixed.index)
smoothed['Sales'] = data_pharma_fixed['smoothed']
```

[183]:

```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_pharma_fixed.index, data_pharma_fixed['Sales'])
    ax.set_xlabel('Week')
    ax.set_ylabel('Sales')
    plt.legend()
    plt.show()
```

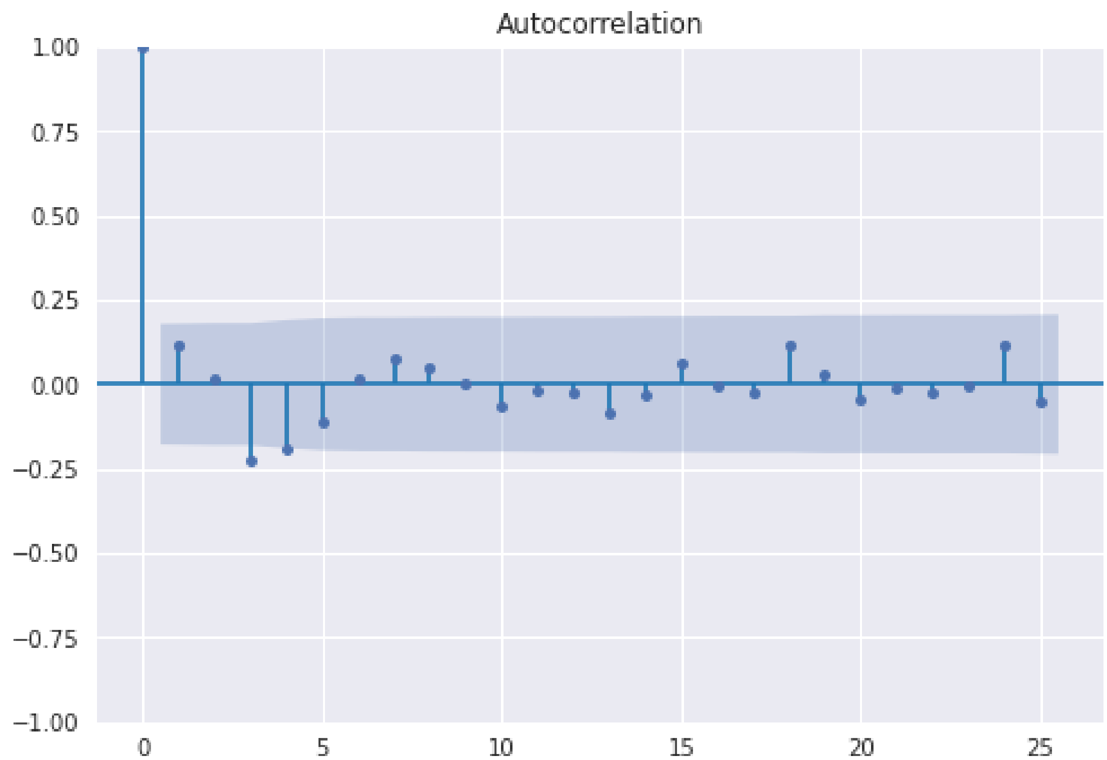


2.3 (d) generate the ACF plot (up to and including 25 lags)

[184]:

```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_pharma_fixed['Sales'], lags=25)
```

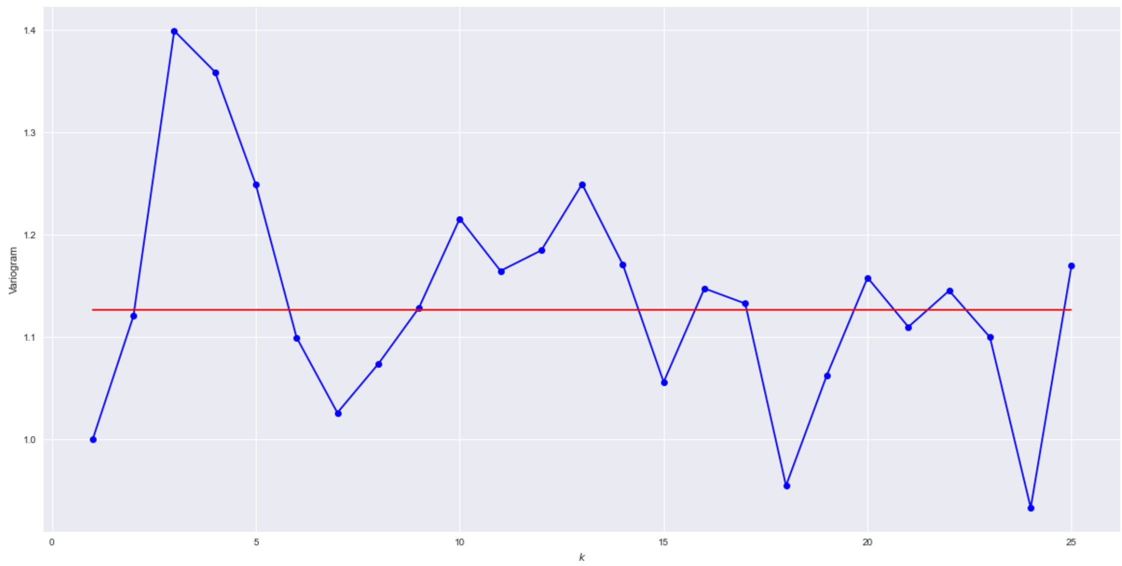
```
<Figure size 1440x720 with 0 Axes>
```



2.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[185]:
```
r1 = ts.acf(data_pharma_fixed['Sales'], nlags=25)[1]
base_var  = np.var(data_pharma_fixed['Sales'])

variogram = pd.DataFrame(index = [i for i in range(1,26)])
variogram['lagged'] = [np.var(np.array(data_pharma_fixed['Sales'].iloc[i:]) -
 ↪np.array(data_pharma_fixed['Sales'].iloc[:-i]))/np.var(np.
 ↪diff(data_pharma_fixed['Sales'])) for i in range(1,26)]
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[186]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



2.5 (f) Comment on the stationarity of the series.

Based on the Variogram, we can say this series is most likely stationary

3 FIGURE 1.3 Chemical process viscosity readings.

3.1 (a) load and reconstruct the series data / (b) convert the data into xts object

[187]:
```
data_visc = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.3-VISC')
data_visc

month_columns = ['Time Period', 'Time Period.1', 'Time Period.2', 'Time Period.
 ↪3']
reading_column = ['Reading', 'Reading.1', 'Reading.2', 'Reading.3']
index_list = []
reading_list = []

for i in month_columns:
    for t in range(len(data_visc[i])):
        if data_visc[i].iloc[t] not in index_list:
            index_list.append(data_visc[i].iloc[t])


for i in reading_column:
    for t in range(len(data_visc[i])):
            reading_list.append(data_visc[i].iloc[t])
```

```
data_visc_fixed = pd.DataFrame(index=index_list, columns=['reading'])
data_visc_fixed['reading'] = reading_list
data_visc_fixed = data_visc_fixed.dropna(axis=0)
data_visc_fixed.index.name = 'Time Period'
```

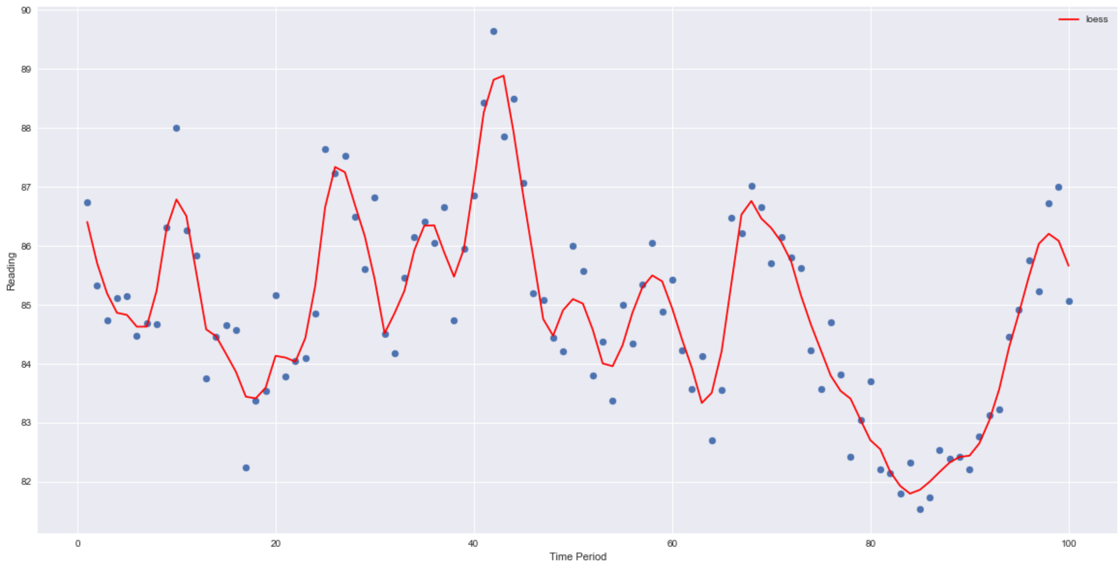
[188]:
```
data_visc_fixed
```

[188]:
```
             reading
Time Period
1            86.7418
2            85.3195
3            84.7355
4            85.1113
5            85.1487
…              …
96           85.7609
97           85.2302
98           86.7312
99           87.0048
100          85.0572

[100 rows x 1 columns]
```

3.2 (c) generate the time series plot with loess smoothed curve overlapped.

[189]:
```
x = np.array(data_visc_fixed.index)
y = np.array(data_visc_fixed['reading'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_visc_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_visc_fixed.index)
smoothed['reading'] = data_visc_fixed['smoothed']
```

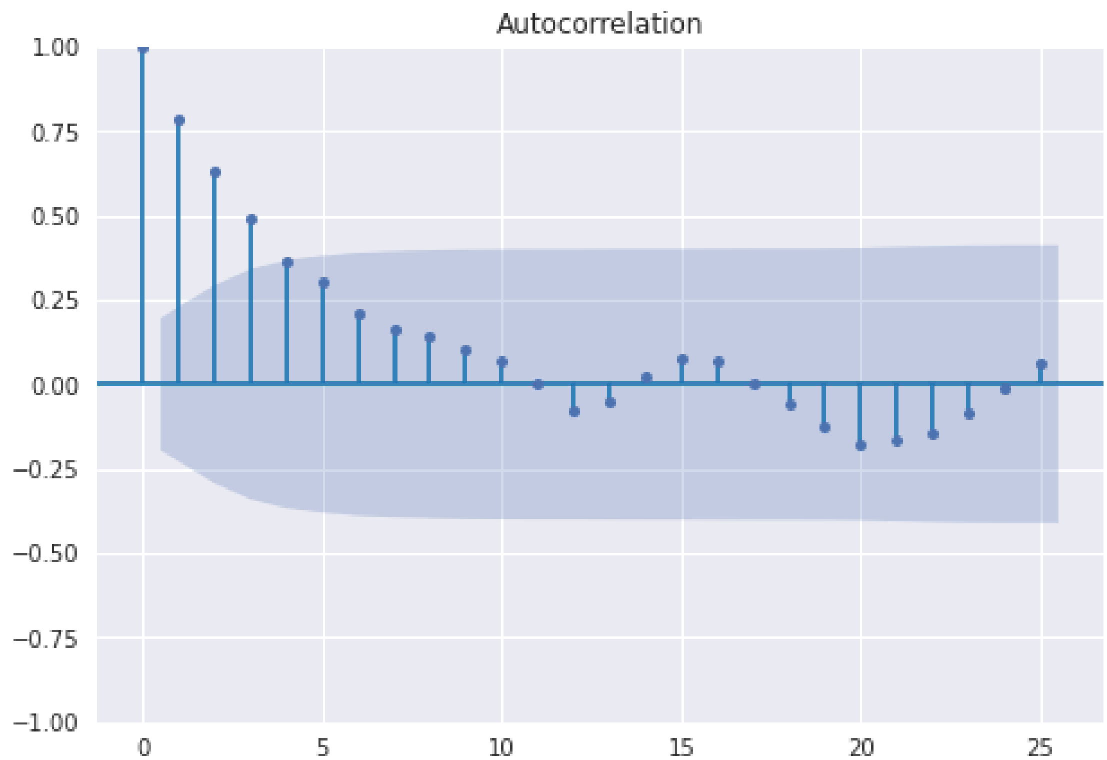
[190]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_visc_fixed.index, data_visc_fixed['reading'])
    ax.set_xlabel('Time Period')
    ax.set_ylabel('Reading')
    plt.legend()
    plt.show()
```



3.3 (d) generate the ACF plot (up to and including 25 lags)

[191]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_visc_fixed['reading'], lags=25)
```

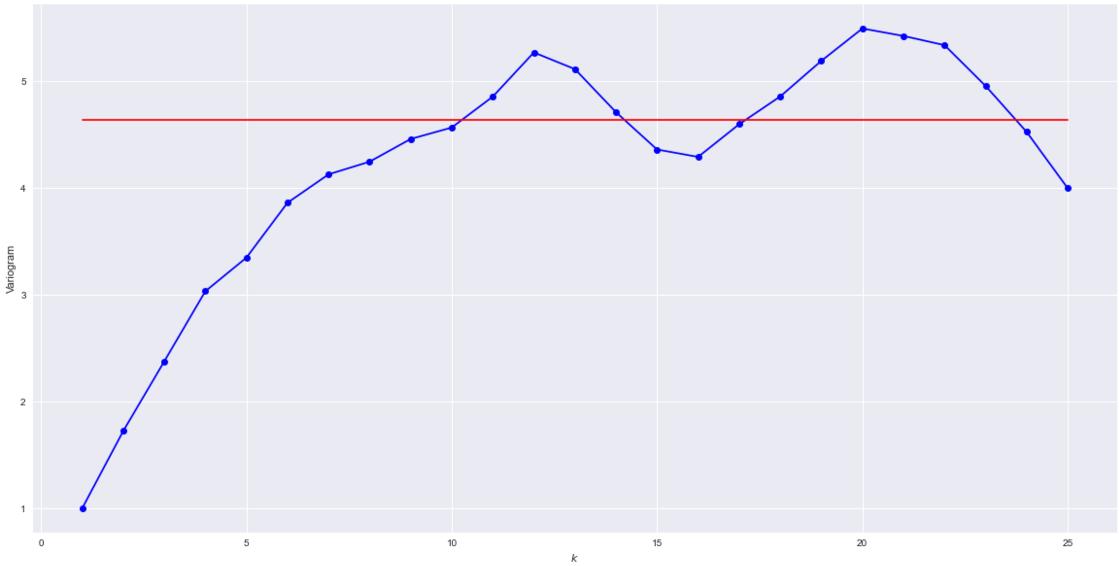
```
<Figure size 1440x720 with 0 Axes>
```



3.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[192]:
```
r1 = ts.acf(data_visc_fixed['reading'], nlags=25)[1]
base_var  = np.var(data_visc_fixed['reading'])

variogram = pd.DataFrame(index = [i for i in range(1,26)])
variogram['lagged'] = [np.var(np.array(data_visc_fixed['reading'].iloc[i:]) -
 ↪np.array(data_visc_fixed['reading'].iloc[:-i]))/np.var(np.
 ↪diff(data_visc_fixed['reading'])) for i in range(1,26)]
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[193]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



3.5 (f) Comment on the stationarity of the series.

Based on the Variogram, we can say this is most likely stationary.

4 FIGURE 1.4 TheUS annual production of blue and gorgonzola cheeses.

4.1 (a) load and reconstruct the series data / (b) convert the data into xts object

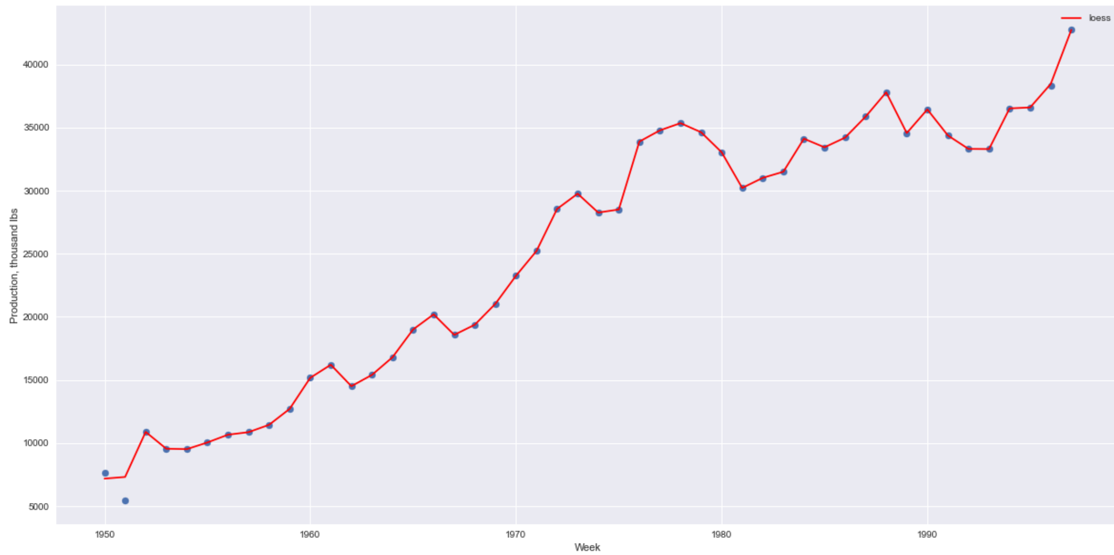
[194]:
```
data_blue = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪4-BLUE', index_col='Year')
```

4.2 (c) generate the time series plot with loess smoothed curve overlapped.

[195]:
```
x = np.array(data_blue.index)
y = np.array(data_blue['Production, thousand lbs'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_blue['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_blue.index)
smoothed['Production, thousand lbs'] = data_blue['smoothed']
```

[196]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
```

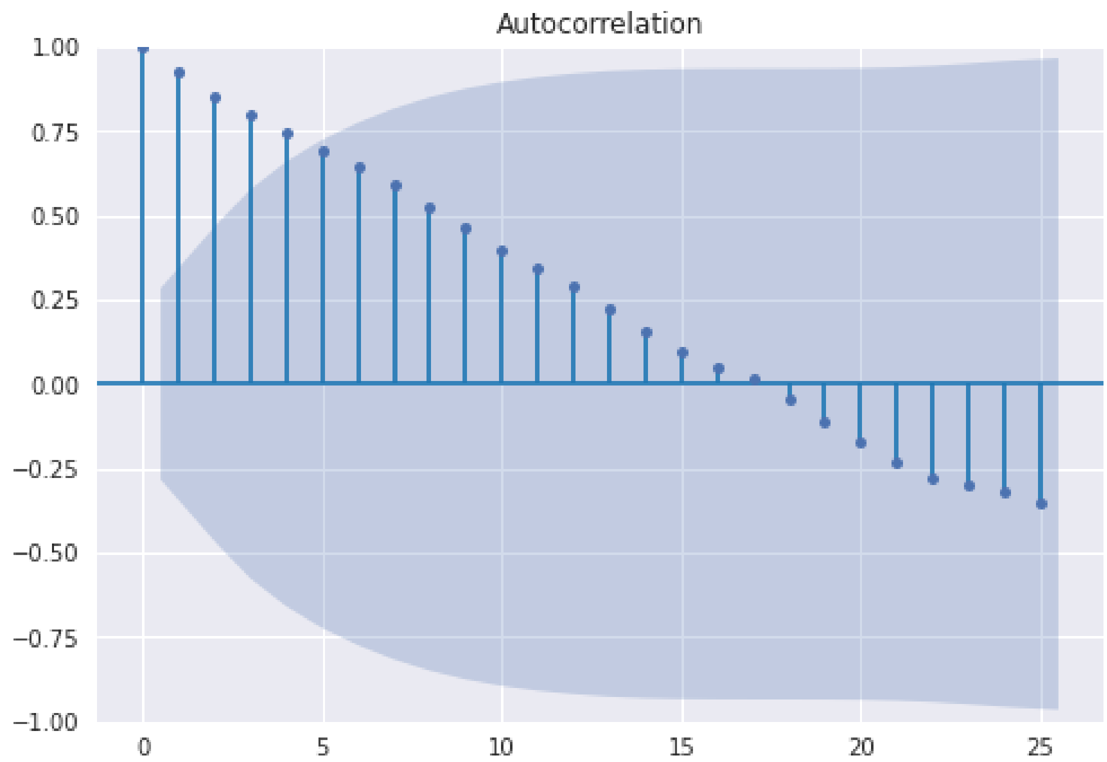
```
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_blue.index, data_blue['Production, thousand lbs'])
    ax.set_xlabel('Week')
    ax.set_ylabel('Production, thousand lbs')
    plt.legend()
    plt.show()
```



4.3 (d) generate the ACF plot (up to and including 25 lags)

[197]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_blue['Production, thousand lbs'], lags=25)
```

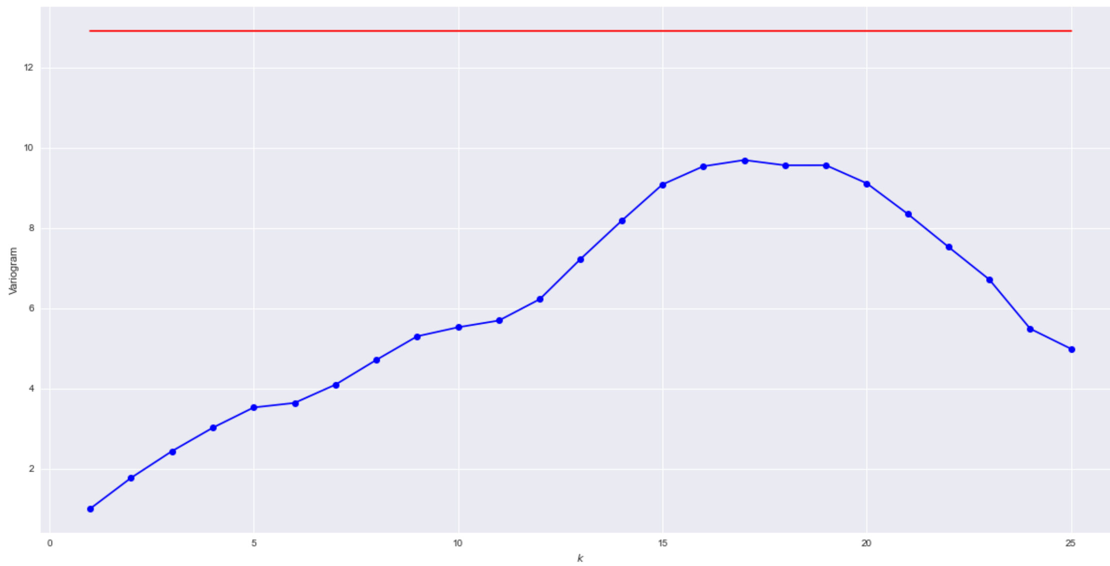
```
<Figure size 1440x720 with 0 Axes>
```



4.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[198]:
```
r1 = ts.acf(data_blue['Production, thousand lbs'], nlags=25)[1]
base_var  = np.var(data_blue['Production, thousand lbs'])

variogram = pd.DataFrame(index = [i for i in range(1,26)])
variogram['lagged'] = [np.var(np.array(data_blue['Production, thousand lbs'].
 ↪iloc[i:]) - np.array(data_blue['Production, thousand lbs'].iloc[:-i]))/np.
 ↪var(np.diff(data_blue['Production, thousand lbs'])) for i in range(1,26)]
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[199]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



4.5 (f) Comment on the stationarity of the series.

Based on the Variogram we can say this is most likely not Stationary.

5 FIGURE 1.5 The US beverage manufacturer monthly product shipments

5.1 (a) load and reconstruct the series data / (b) convert the data into xts object

[200]:
```
data_bev = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.5-BEV')
```

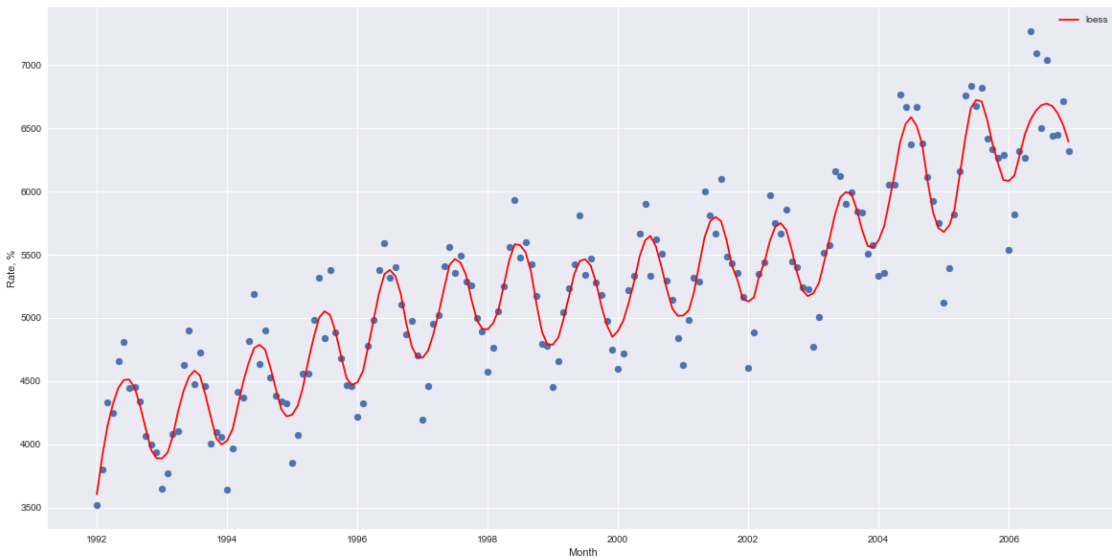
[201]:
```
month_columns = ['Month', 'Month.1', 'Month.2', 'Month.3']
dollars_column = ['Dollars, in Millions', 'Dollars, in Millions.1', 'Dollars,␣
↪in Millions.2', 'Dollars, in Millions.3']
index_list = []
dollars_list = []

for i in month_columns:
    for t in range(len(data_bev[i])):
        if data_bev[i].iloc[t] not in index_list:
            index_list.append(data_bev[i].iloc[t])


for i in dollars_column:
    for t in range(len(data_bev[i])):
            dollars_list.append(data_bev[i].iloc[t])
```

```
data_bev_fixed = pd.DataFrame(index=index_list, columns=['Dollars, in␣
↪Millions'])
data_bev_fixed['Dollars, in Millions'] = dollars_list
data_bev_fixed = data_bev_fixed.dropna(axis=0)
data_bev_fixed.index.name = 'Month'
```

5.2 (c) generate the time series plot with loess smoothed curve overlapped.

[202]:
```
data_bev_fixed.index = pd.to_datetime(data_bev_fixed.index)
data_bev_fixed['Month_num'] = [i for i in range(len(data_bev_fixed))]
x = np.array(data_bev_fixed['Month_num'])
y = np.array(data_bev_fixed['Dollars, in Millions'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_bev_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_bev_fixed.index)
smoothed['Dollars, in Millions'] = data_bev_fixed['smoothed']
```

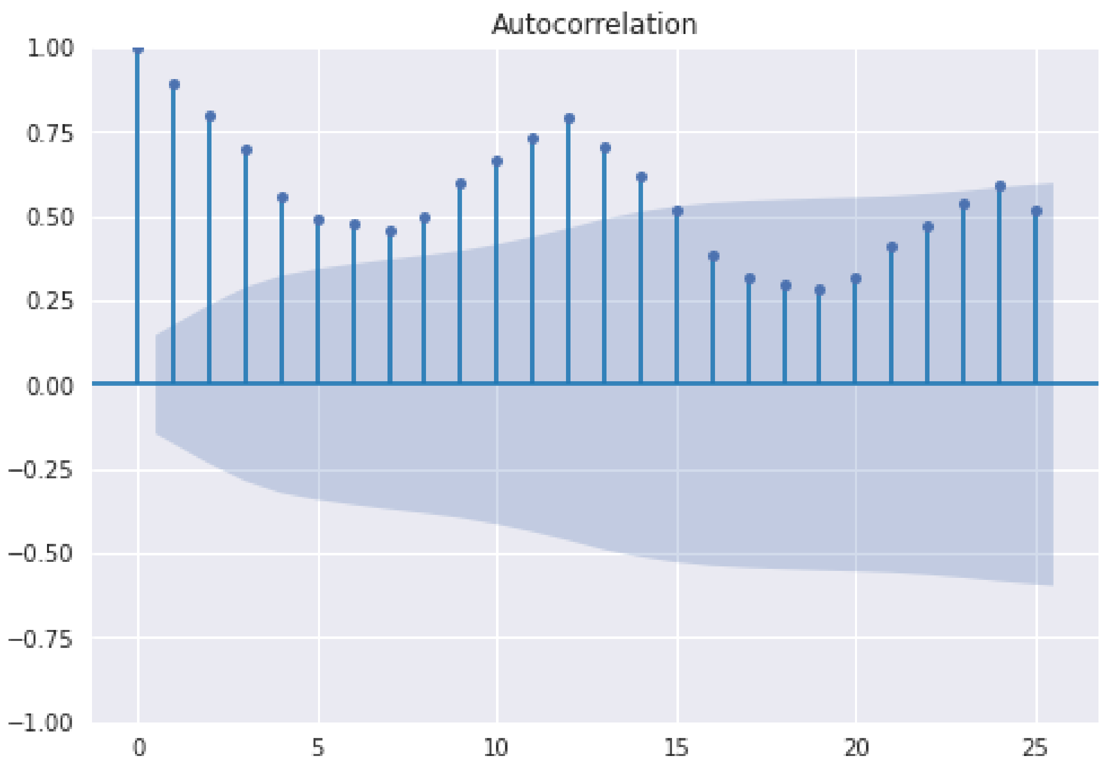
[203]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_bev_fixed.index, data_bev_fixed['Dollars, in Millions'])
    ax.set_xlabel('Month')
    ax.set_ylabel('Rate, %')
    plt.legend()
    plt.show()
```



5.3 (d) generate the ACF plot (up to and including 25 lags)

[204]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_bev_fixed['Dollars, in Millions'], lags=25)
```

```
<Figure size 1440x720 with 0 Axes>
```

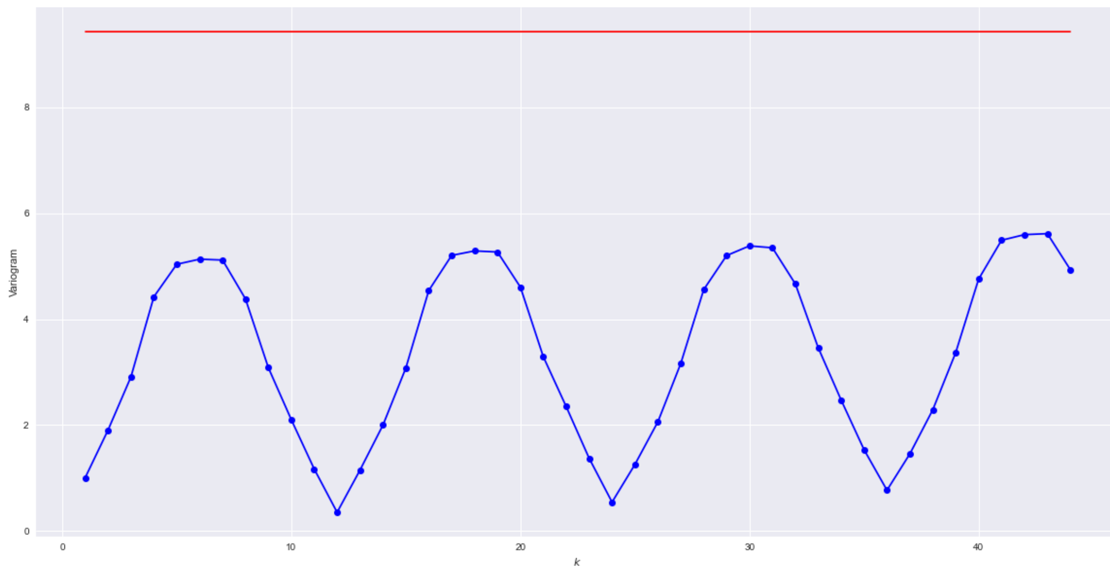


5.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[205]:
```
r1 = ts.acf(data_bev_fixed['Dollars, in Millions'], nlags=25)[1]
base_var  = np.var(data_bev_fixed['Dollars, in Millions'])

variogram = pd.DataFrame(index = [i for i in range(1,int(len(data_bev_fixed)/
 ↪4))])
variogram['lagged'] = [np.var(np.array(data_bev_fixed['Dollars, in Millions'].
 ↪iloc[i:]) - np.array(data_bev_fixed['Dollars, in Millions'].iloc[:-i]))/np.
 ↪var(np.diff(data_bev_fixed['Dollars, in Millions'])) for i in␣
 ↪range(1,int(len(data_bev_fixed)/4))]
```

```
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[206]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



5.5 (f) Comment on the stationarity of the series.

Based on the Variogram we can say this is most likely not Stationary.

6 FIGURE 1.6 Global mean surface air temperature annual anomaly.

6.1 (a) load and reconstruct the series data / (b) convert the data into xts object

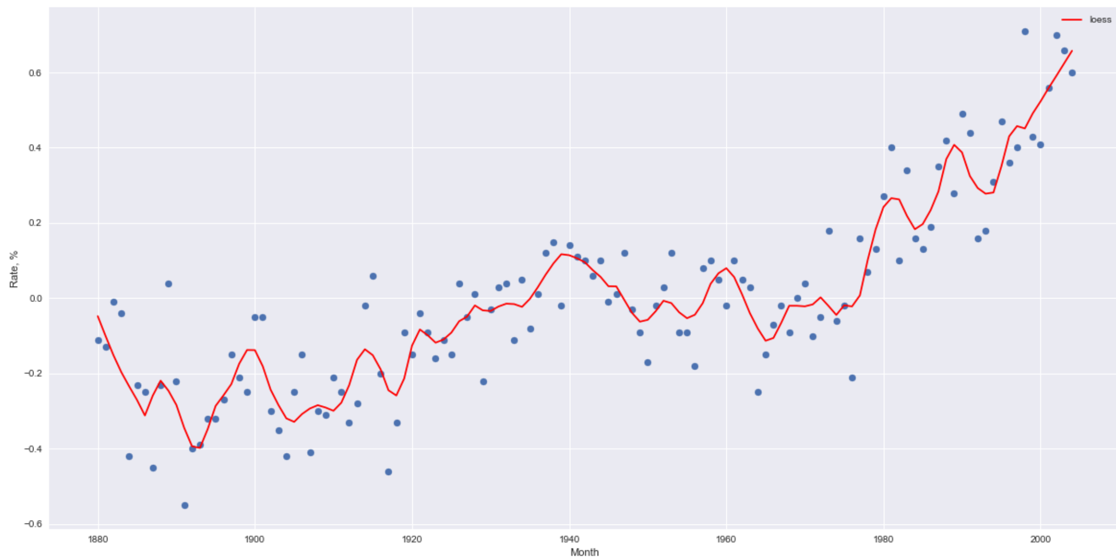
[207]:
```
data_temp_1 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪6-GSAT-CO2', nrows= 43, usecols = 'A:C')
data_temp_2 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪6-GSAT-CO2', nrows= 43, usecols = 'D:F')
data_temp_3 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪6-GSAT-CO2', nrows= 42, usecols = 'G:I')
```

```
data_temp_2.columns = data_temp_1.columns.tolist()
data_temp_3.columns = data_temp_1.columns.tolist()

data_temp_1 = data_temp_1.set_index('Year')
data_temp_2 = data_temp_2.set_index('Year')
data_temp_3 = data_temp_3.set_index('Year')

data_temp_fixed = pd.concat([data_temp_1,data_temp_2,data_temp_3], axis=0)
data_temp_fixed = data_temp_fixed.dropna(axis=0)
data_temp_fixed = data_temp_fixed.drop(['CO2, ppmv'], axis = 1)
```

6.2 (c) generate the time series plot with loess smoothed curve overlapped.

[208]:
```
x = np.array(data_temp_fixed.index)
y = np.array(data_temp_fixed['Anomaly, C'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_temp_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_temp_fixed.index)
smoothed['Anom'] = data_temp_fixed['smoothed']
```

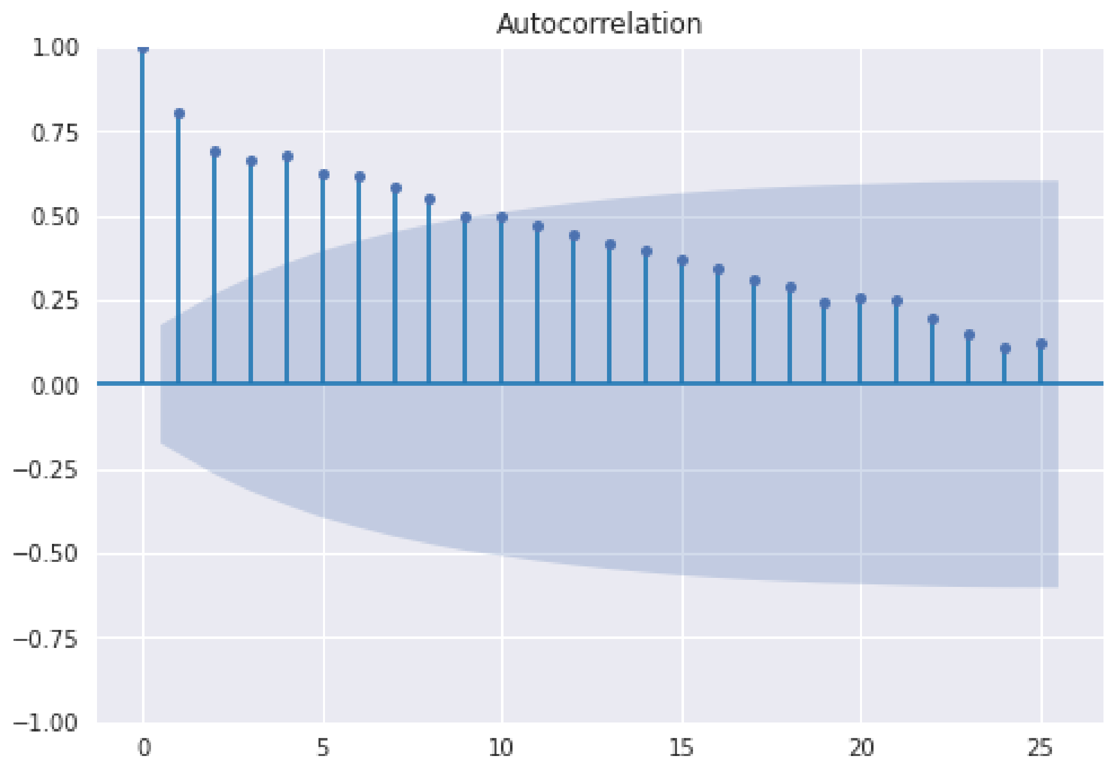
[209]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_temp_fixed.index, data_temp_fixed['Anomaly, C'])
    ax.set_xlabel('Month')
    ax.set_ylabel('Rate, %')
    plt.legend()
    plt.show()
```



6.3 (d) generate the ACF plot (up to and including 25 lags)

[210]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_temp_fixed['Anomaly, C'], lags=25)
```

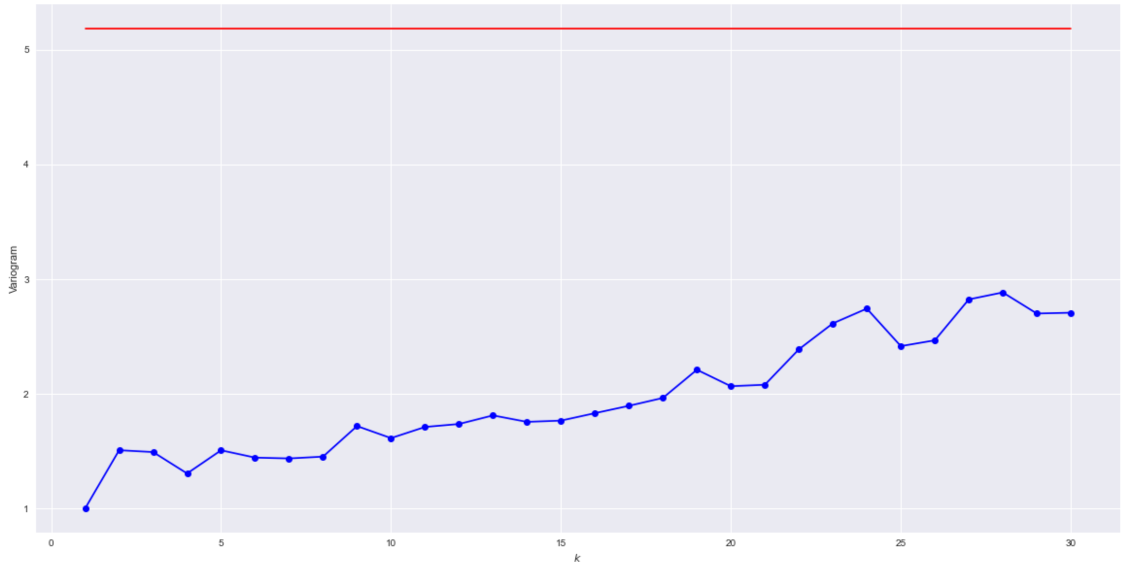
```
<Figure size 1440x720 with 0 Axes>
```



6.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[211]:
```
r1 = ts.acf(data_temp_fixed['Anomaly, C'], nlags=25)[1]
base_var  = np.var(data_temp_fixed['Anomaly, C'])

variogram = pd.DataFrame(index = [i for i in range(1,int(len(data_temp_fixed)/
 ↪4))])
variogram['lagged'] = [np.var(np.array(data_temp_fixed['Anomaly, C'].iloc[i:])␣
 ↪- np.array(data_temp_fixed['Anomaly, C'].iloc[:-i]))/np.var(np.
 ↪diff(data_temp_fixed['Anomaly, C'])) for i in␣
 ↪range(1,int(len(data_temp_fixed)/4))]
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[212]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



6.5 (f) Comment on the stationarity of the series.

Based on the Variogram we can say this is most likely not Stationary.

7 FIGURE 1.7 Whole foods market stock price

7.1 (a) load and reconstruct the series data / (b) convert the data into xts object

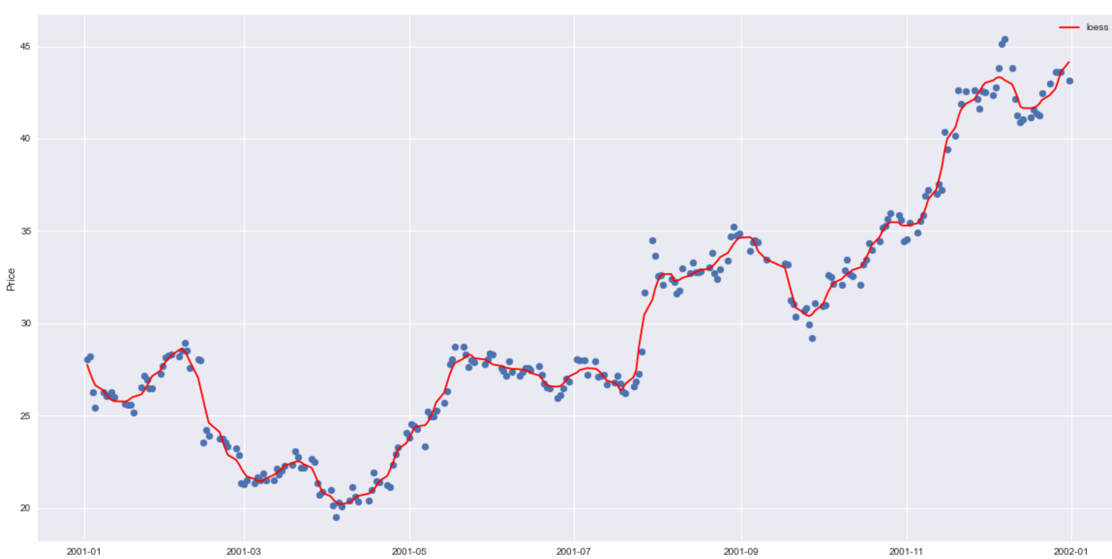
[213]:
```
data_WFMI_1 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪7-WFMI', nrows= 51, usecols = 'A:B')
data_WFMI_2 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪7-WFMI', nrows= 51, usecols = 'C:D')
data_WFMI_3 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪7-WFMI', nrows= 51, usecols = 'E:F')
data_WFMI_4 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪7-WFMI', nrows= 51, usecols = 'G:H')
data_WFMI_5 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
↪7-WFMI', nrows= 49, usecols = 'I:J')

data_WFMI_2.columns = data_WFMI_1.columns.tolist()
data_WFMI_3.columns = data_WFMI_1.columns.tolist()
data_WFMI_4.columns = data_WFMI_1.columns.tolist()
data_WFMI_5.columns = data_WFMI_1.columns.tolist()

data_WFMI_1 = data_WFMI_1.set_index('Date')
data_WFMI_2 = data_WFMI_2.set_index('Date')
data_WFMI_3 = data_WFMI_3.set_index('Date')
```

```
data_WFMI_4 = data_WFMI_4.set_index('Date')
data_WFMI_5 = data_WFMI_5.set_index('Date')

data_WFMI_fixed = pd.
↪concat([data_WFMI_1,data_WFMI_2,data_WFMI_3,data_WFMI_4,data_WFMI_5], axis=0)
data_WFMI_fixed = data_WFMI_fixed.dropna(axis=0)
```

7.2 (c) generate the time series plot with loess smoothed curve overlapped.

[214]:
```
data_WFMI_fixed.index = pd.to_datetime(data_WFMI_fixed.index)
data_WFMI_fixed['Month_num'] = [i for i in range(len(data_WFMI_fixed))]
x = np.array(data_WFMI_fixed['Month_num'])
y = np.array(data_WFMI_fixed['Dollars'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_WFMI_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_WFMI_fixed.index)
smoothed['Dollars_sm'] = data_WFMI_fixed['smoothed']
```

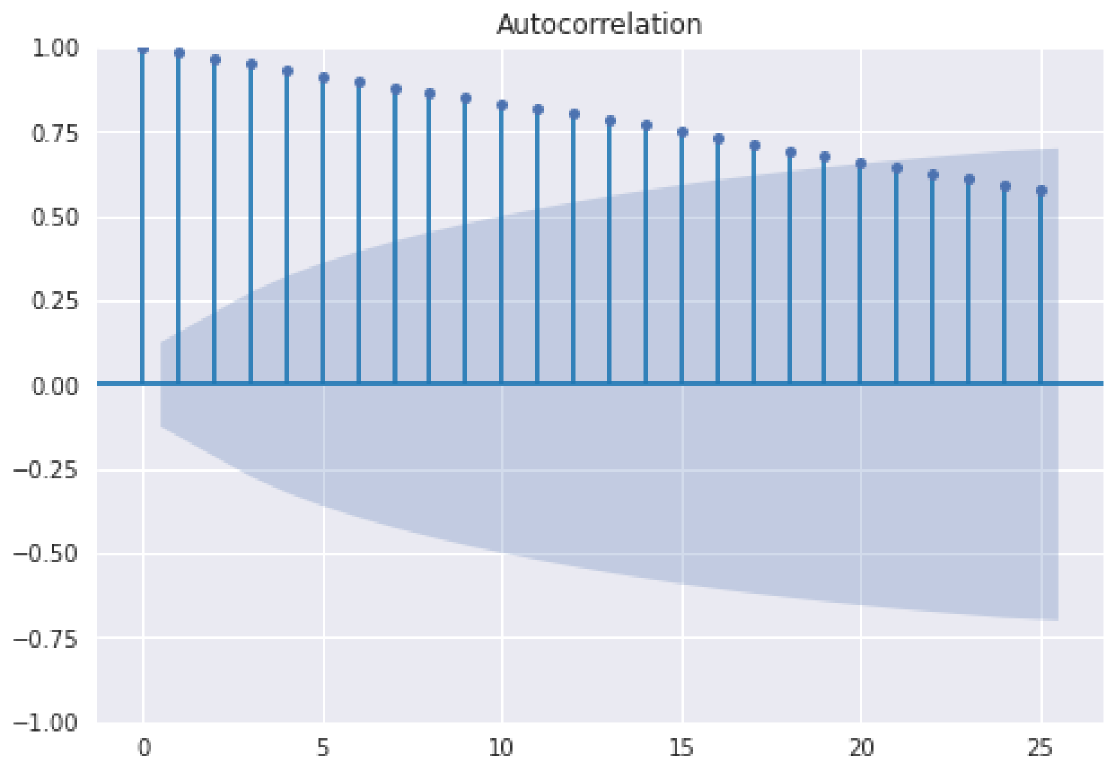
[215]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_WFMI_fixed.index, data_WFMI_fixed['Dollars'])
    ax.set_xlabel('Date')
    ax.set_ylabel('Price')
    plt.legend()
    plt.show()
```



7.3 (d) generate the ACF plot (up to and including 25 lags)

[216]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_WFMI_fixed['Dollars'], lags=25)
```

```
<Figure size 1440x720 with 0 Axes>
```

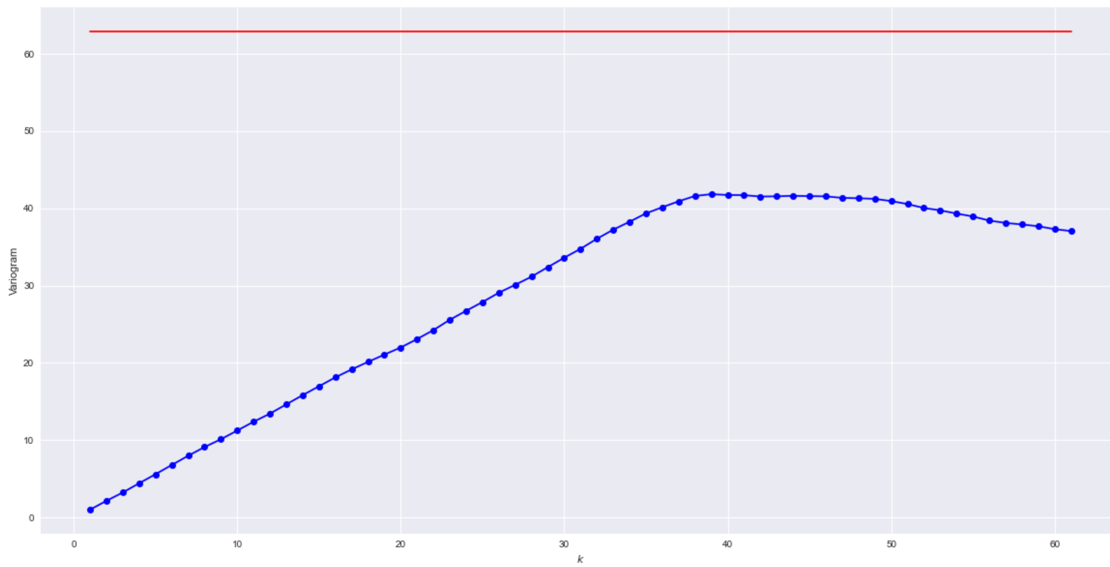


7.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[217]:
```
r1 = ts.acf(data_WFMI_fixed['Dollars'], nlags=25)[1]
base_var  = np.var(data_WFMI_fixed['Dollars'])

variogram = pd.DataFrame(index = [i for i in range(1,int(len(data_WFMI_fixed)/
 ↪4))])
variogram['lagged'] = [np.var(np.array(data_WFMI_fixed['Dollars'].iloc[i:]) -␣
 ↪np.array(data_WFMI_fixed['Dollars'].iloc[:-i]))/np.var(np.
 ↪diff(data_WFMI_fixed['Dollars'])) for i in range(1,int(len(data_WFMI_fixed)/
 ↪4))]
```

```
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[218]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



7.5 (f) Comment on the stationarity of the series.

Based on the Variogram we can say this is most likely not Stationary.

8 FIGURE 1.8 Monthly unemployment rate—full-time labor force.

8.1 (a) load and reconstruct the series data / (b) convert the data into xts object

[219]:
```
data_UNEMP_1 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
    ↪8-UNEMP', nrows= 85, usecols = 'A:B')
data_UNEMP_2 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
    ↪8-UNEMP', nrows= 85, usecols = 'C:D')
data_UNEMP_3 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
    ↪8-UNEMP', nrows= 85, usecols = 'E:F')
```

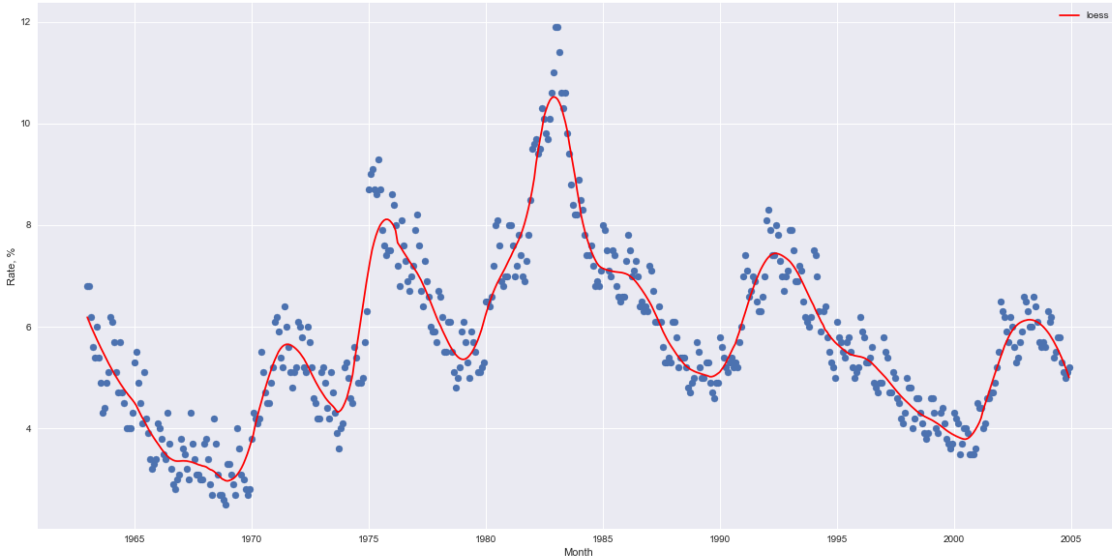
```
data_UNEMP_4 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
 ↪8-UNEMP', nrows= 85, usecols = 'G:H')
data_UNEMP_5 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
 ↪8-UNEMP', nrows= 85, usecols = 'I:J')
data_UNEMP_6 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
 ↪8-UNEMP', nrows= 85, usecols = 'K:L')

data_UNEMP_2.columns = data_UNEMP_1.columns.tolist()
data_UNEMP_3.columns = data_UNEMP_1.columns.tolist()
data_UNEMP_4.columns = data_UNEMP_1.columns.tolist()
data_UNEMP_5.columns = data_UNEMP_1.columns.tolist()
data_UNEMP_6.columns = data_UNEMP_1.columns.tolist()

data_UNEMP_1 = data_UNEMP_1.set_index('Month')
data_UNEMP_2 = data_UNEMP_2.set_index('Month')
data_UNEMP_3 = data_UNEMP_3.set_index('Month')
data_UNEMP_4 = data_UNEMP_4.set_index('Month')
data_UNEMP_5 = data_UNEMP_5.set_index('Month')
data_UNEMP_6 = data_UNEMP_6.set_index('Month')

data_UNEMP_fixed = pd.
 ↪concat([data_UNEMP_1,data_UNEMP_2,data_UNEMP_3,data_UNEMP_4,data_UNEMP_5,␣
 ↪data_UNEMP_6 ], axis=0)
data_UNEMP_fixed = data_UNEMP_fixed.dropna(axis=0)
```

8.2 (c) generate the time series plot with loess smoothed curve overlapped.

[220]:
```
data_UNEMP_fixed.index = pd.to_datetime(data_UNEMP_fixed.index)
data_UNEMP_fixed['Month_num'] = [i for i in range(len(data_UNEMP_fixed))]
x = np.array(data_UNEMP_fixed['Month_num'])
y = np.array(data_UNEMP_fixed['Rate %'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_UNEMP_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_UNEMP_fixed.index)
smoothed['Rate %'] = data_UNEMP_fixed['smoothed']
```

[221]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_UNEMP_fixed.index, data_UNEMP_fixed['Rate %'])
    ax.set_xlabel('Month')
    ax.set_ylabel('Rate, %')
    plt.legend()
```

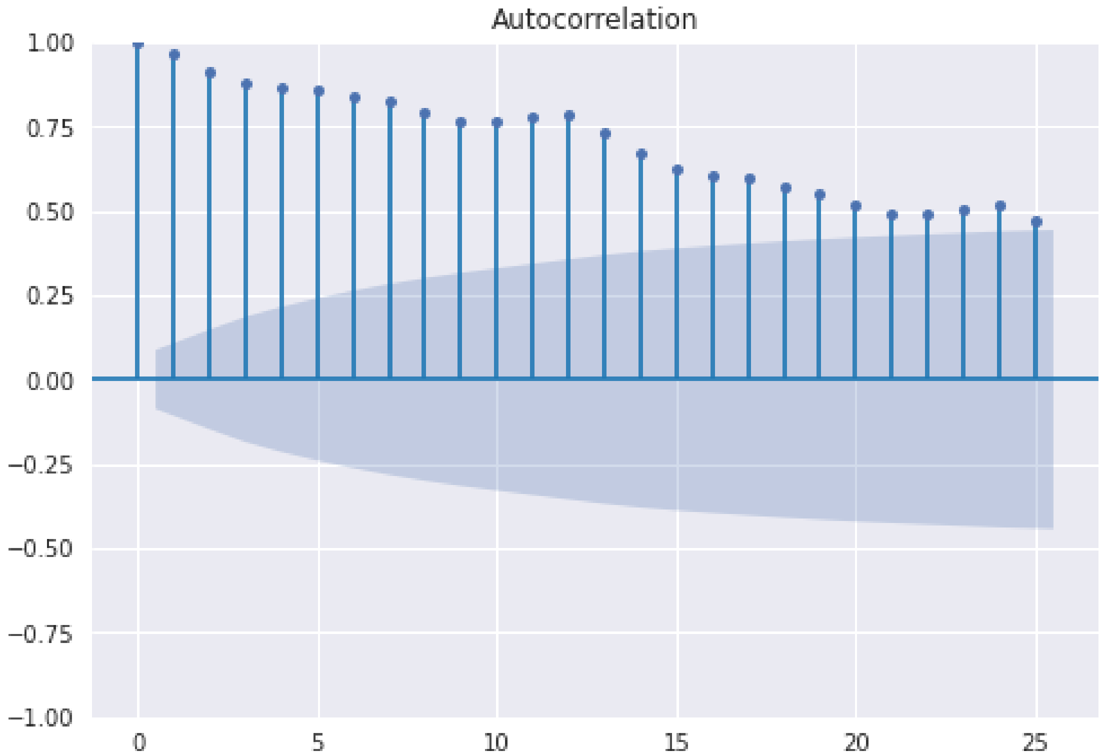
```
    plt.show()
```



8.3 (d) generate the ACF plot (up to and including 25 lags)

[222]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_UNEMP_fixed['Rate %'], lags=25)
```

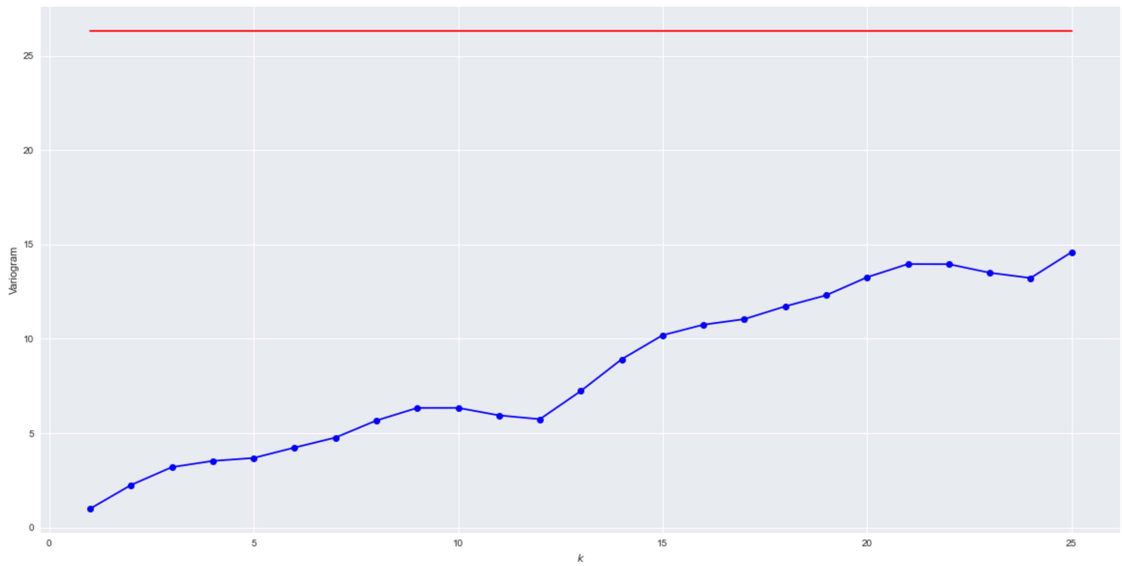
```
<Figure size 1440x720 with 0 Axes>
```



8.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[223]:
```
r1 = ts.acf(data_UNEMP_fixed['Rate %'], nlags=25)[1]
base_var  = np.var(data_UNEMP_fixed['Rate %'])

variogram = pd.DataFrame(index = [i for i in range(1,26)])
variogram['lagged'] = [np.var(np.array(data_UNEMP_fixed['Rate %'].iloc[i:]) -␣
↪np.array(data_UNEMP_fixed['Rate %'].iloc[:-i]))/np.var(np.
↪diff(data_UNEMP_fixed['Rate %'])) for i in range(1,26)]
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[224]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



8.5 (f) Comment on the stationarity of the series.

Based on the Variogram we can say this is most likely not Stationary.

9 FIGURE 1.9 The international sunspot number

9.1 (a) load and reconstruct the series data / (b) convert the data into xts object

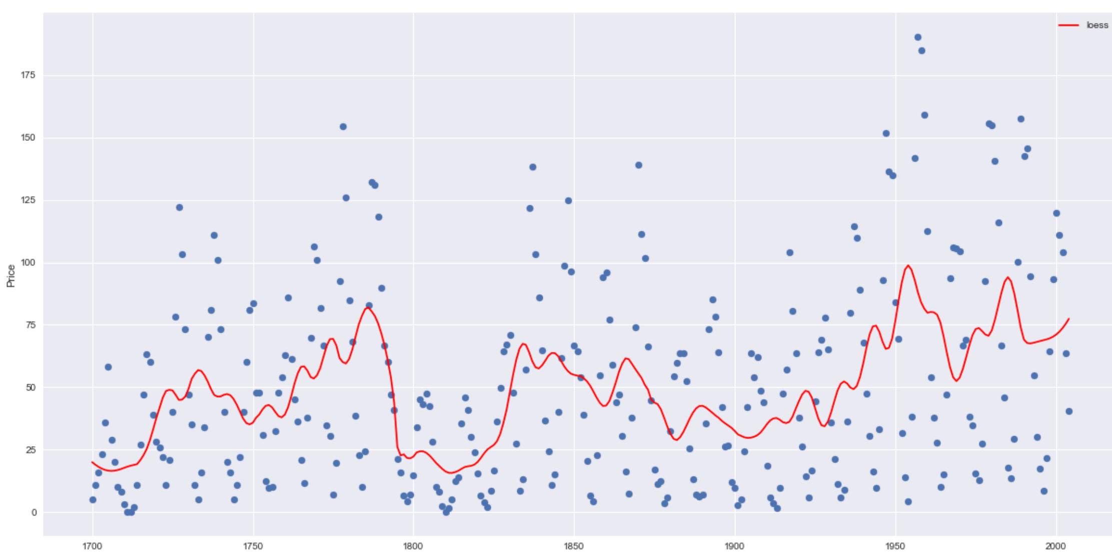
[225]:
```
data_SUNSPOT_1 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
  ↪9-SUNSPOT', nrows= 62, usecols = 'A:B')
data_SUNSPOT_2 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
  ↪9-SUNSPOT', nrows= 62, usecols = 'C:D')
data_SUNSPOT_3 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
  ↪9-SUNSPOT', nrows= 62, usecols = 'E:F')
data_SUNSPOT_4 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
  ↪9-SUNSPOT', nrows= 62, usecols = 'G:H')
data_SUNSPOT_5 = pd.read_excel('data_changed_for_import.xlsx', sheet_name='B.
  ↪9-SUNSPOT', nrows= 62, usecols = 'I:J')

data_SUNSPOT_2.columns = data_SUNSPOT_1.columns.tolist()
data_SUNSPOT_3.columns = data_SUNSPOT_1.columns.tolist()
data_SUNSPOT_4.columns = data_SUNSPOT_1.columns.tolist()
data_SUNSPOT_5.columns = data_SUNSPOT_1.columns.tolist()

data_SUNSPOT_1 = data_SUNSPOT_1.set_index('Year')
data_SUNSPOT_2 = data_SUNSPOT_2.set_index('Year')
data_SUNSPOT_3 = data_SUNSPOT_3.set_index('Year')
```

```
data_SUNSPOT_4 = data_SUNSPOT_4.set_index('Year')
data_SUNSPOT_5 = data_SUNSPOT_5.set_index('Year')

data_SUNSPOT_fixed = pd.
 ↪concat([data_SUNSPOT_1,data_SUNSPOT_2,data_SUNSPOT_3,data_SUNSPOT_4,data_SUNSPOT_5],␣
 ↪axis=0)
data_SUNSPOT_fixed = data_SUNSPOT_fixed.dropna(axis=0)
```

9.2 (c) generate the time series plot with loess smoothed curve overlapped.

[226]:
```
x = np.array(data_SUNSPOT_fixed.index)
y = np.array(data_SUNSPOT_fixed['Sunspot Number'])

l = loess_1d.loess_1d(x, y, frac = 0.1, degree=2)

data_SUNSPOT_fixed['smoothed'] = l[1]
smoothed = pd.DataFrame(index=data_SUNSPOT_fixed.index)
smoothed['Sunspot'] = data_SUNSPOT_fixed['smoothed']
```

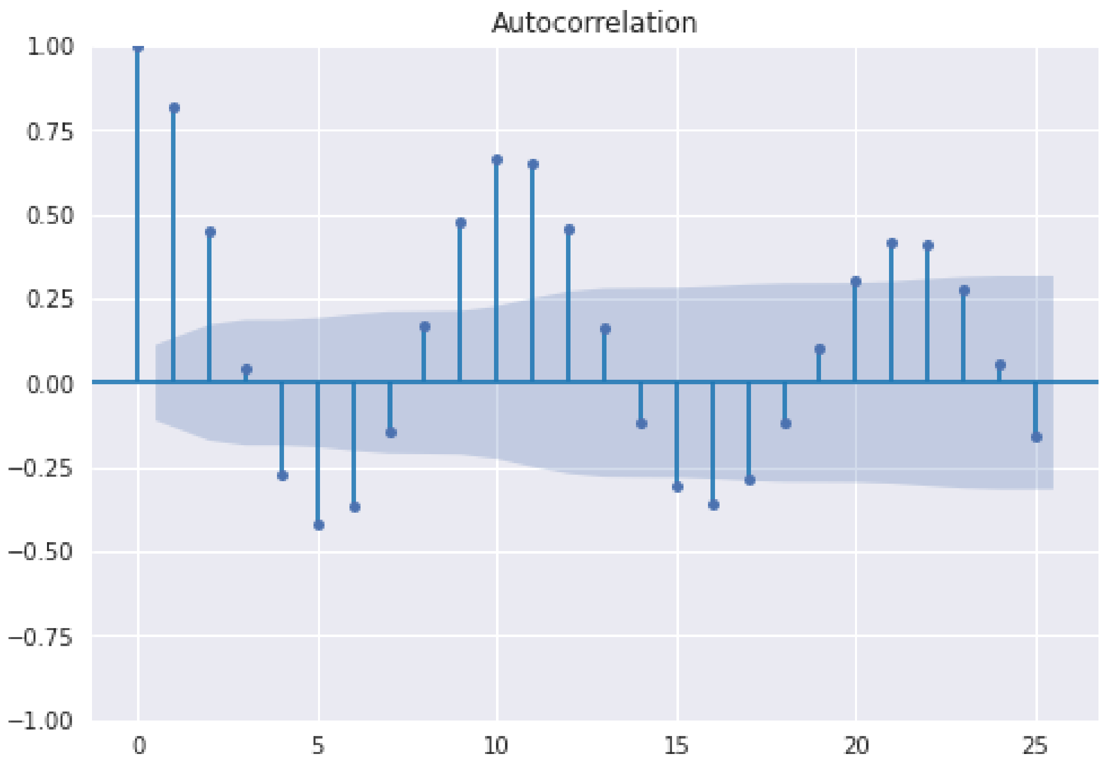
[227]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(smoothed, c = 'Red', label = 'loess')
    plt.scatter(data_SUNSPOT_fixed.index, data_SUNSPOT_fixed['Sunspot Number'])
    ax.set_xlabel('Date')
    ax.set_ylabel('Price')
    plt.legend()
    plt.show()
```



9.3 (d) generate the ACF plot (up to and including 25 lags)

[228]:
```
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    fig = plot_acf(data_SUNSPOT_fixed['Sunspot Number'], lags=25)
```

```
<Figure size 1440x720 with 0 Axes>
```

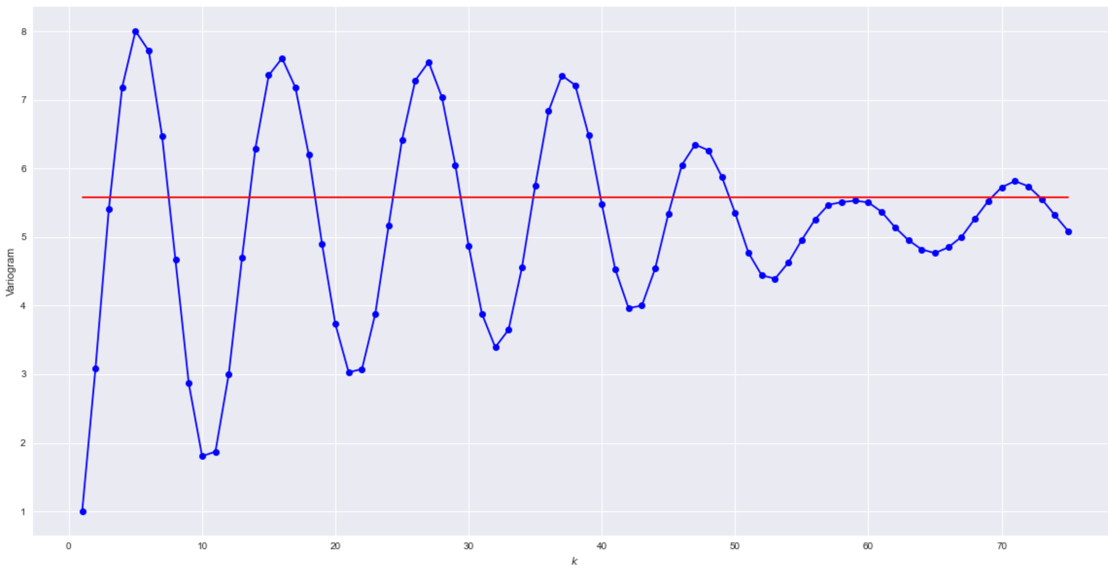


9.4 (e) generate the Variogram versus lag-k with asymptote $\frac{1}{1-r1}$ where r_1 is the lag-1 sample autocorrelation coefficient.

[229]:
```
r1 = ts.acf(data_SUNSPOT_fixed['Sunspot Number'], nlags=25)[1]
base_var  = np.var(data_SUNSPOT_fixed['Sunspot Number'])

variogram = pd.DataFrame(index = [i for i in␣
 ↪range(1,int(len(data_SUNSPOT_fixed)/4))])
variogram['lagged'] = [np.var(np.array(data_SUNSPOT_fixed['Sunspot Number'].
 ↪iloc[i:]) - np.array(data_SUNSPOT_fixed['Sunspot Number'].iloc[:-i]))/np.
 ↪var(np.diff(data_SUNSPOT_fixed['Sunspot Number'])) for i in␣
 ↪range(1,int(len(data_SUNSPOT_fixed)/4))]
variogram ['asymp'] = [1/(1-r1) for i in range(len(variogram))]
```

[230]:

```python
with plt.style.context('seaborn'):
    fig = plt.figure(figsize=(20,10))
    ax = plt.axes()
    plt.plot(variogram['lagged'], c = 'Blue', marker = 'o')
    plt.plot(variogram['asymp'], c = 'Red')
    ax.set_xlabel('$k$')
    ax.set_ylabel('Variogram')
    plt.show()
```



9.5 (f) Comment on the stationarity of the series.

Based on the Variogram, we can say this series is most likely stationary