

Project1_TimeSeries

October 29, 2019

Importing all the necessary libraries

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
import seaborn as sns
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
sns.set(font_scale=1.4)
import math
```

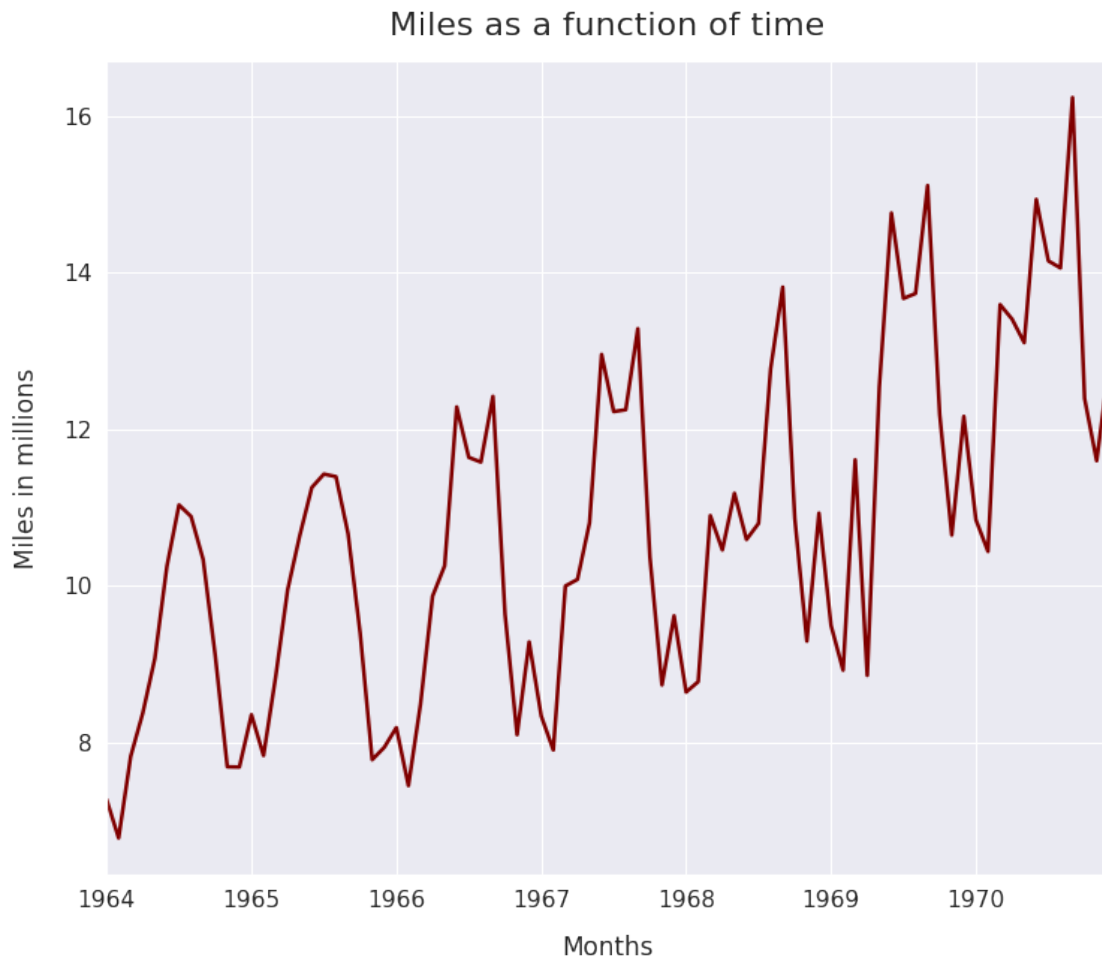
Importing the data in and converting the date coulumn into a date time series

```
In [2]: data = pd.read_excel("Project1_DataSet.xlsx")
data['Month'] = pd.to_datetime(data['Month'])
series = data["Miles, in Millions"]
time = data['Month']
```

1 Q1 Solution

```
In [3]: data.set_index('Month')['Miles, in Millions'].plot(figsize=(12, 10), linewidth=2.5, color='red')
plt.xlabel("Months", labelpad=15)
plt.ylabel("Miles in millions", labelpad=15)
plt.title("Miles as a function of time", y=1.02, fontsize=22)
```

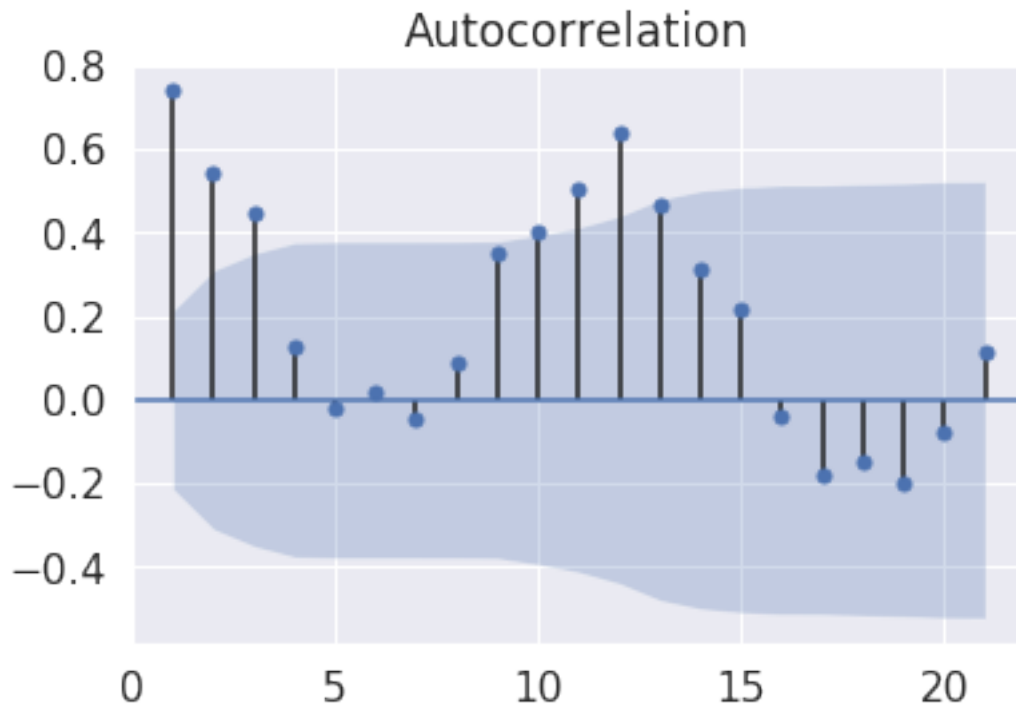
```
Out[3]: Text(0.5, 1.02, 'Miles as a function of time')
```



2 Q2 Solution

2.0.1 ACF plotted for the series.

```
In [4]: n_lags = np.round(len(series)/4)
        plot_acf(series,lags=n_lags, zero=False)
        plt.show()
```



2.0.2 Q2

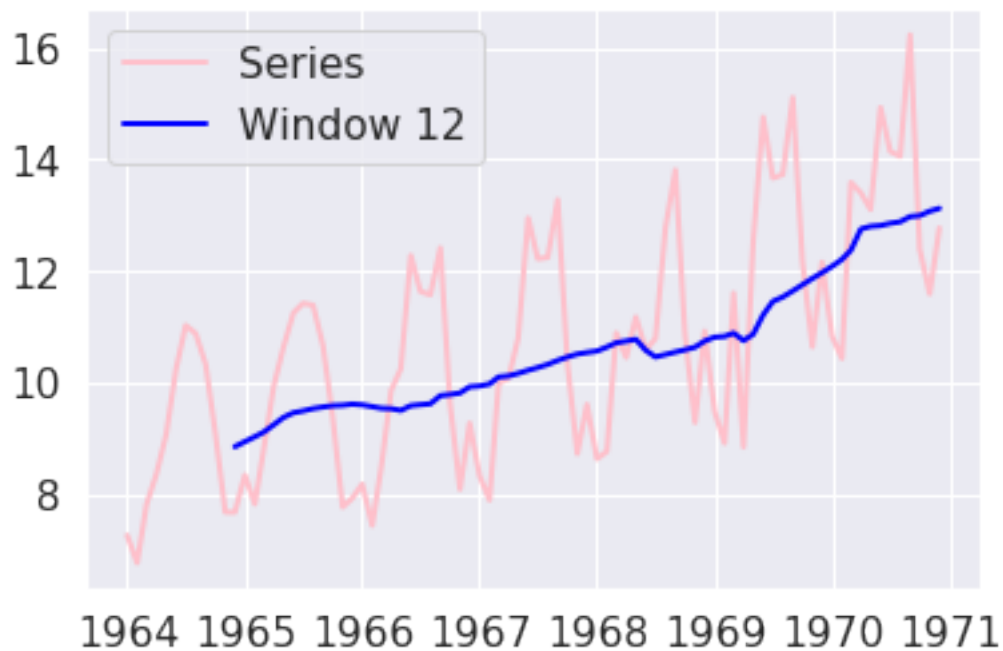
2.0.3 The season period is 12 months.

2.0.4 The highest significant lag in the ACF is at 12 which denotes the seasonal period (except lag 1).

3 Q3 Solution

```
In [5]: ma_13 = (series).rolling(window=12).mean()
plt.plot( time, series, color='pink', linewidth=2, label= "Series")
plt.plot( time, ma_13,marker='', color='blue', linewidth=2, label="Window 12")
plt.legend()
```

Out[5]: <matplotlib.legend.Legend at 0x2ba569db71d0>



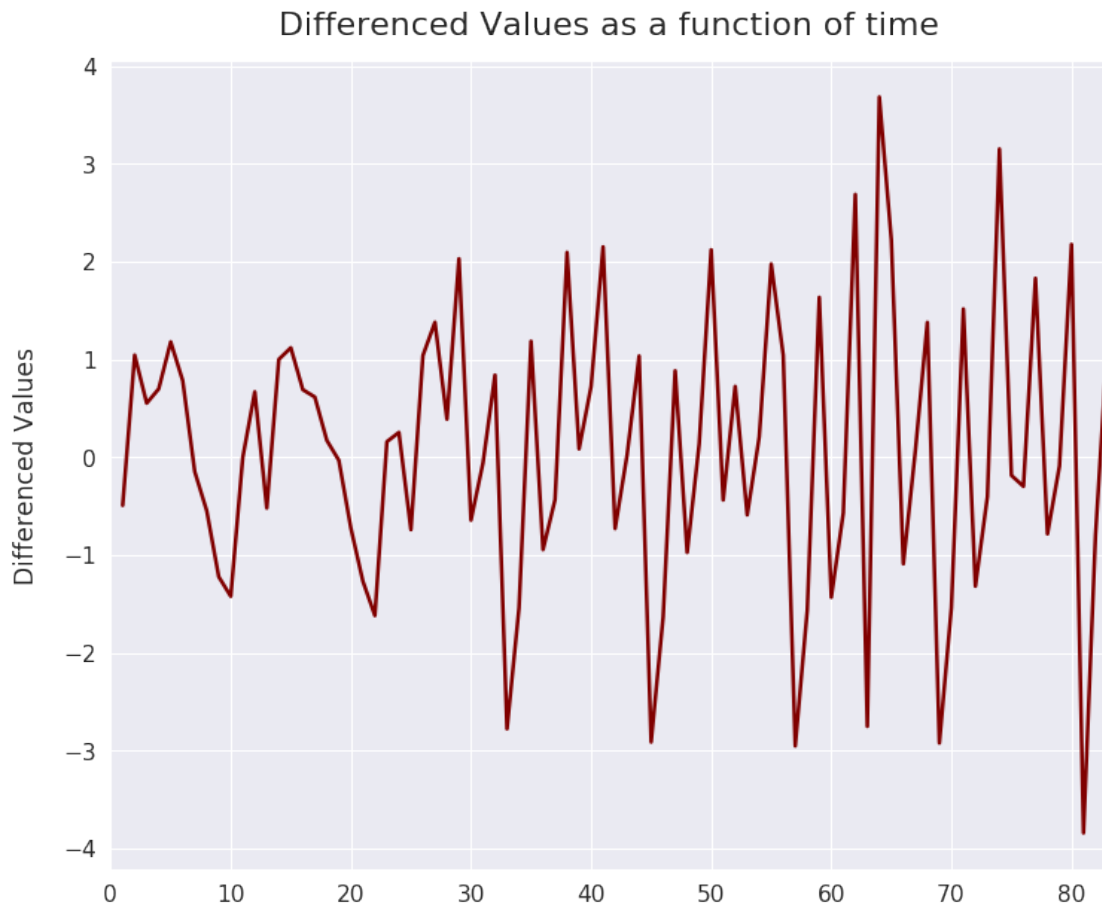
3.0.1 The moving average window should be 12 since the seasonal period is 12 months. It also provides a smoother plot than a 13 month window.

4 Q4 Solution

4.0.1 There is an increasing trending as we can clearly see from the moving average and time series graph.

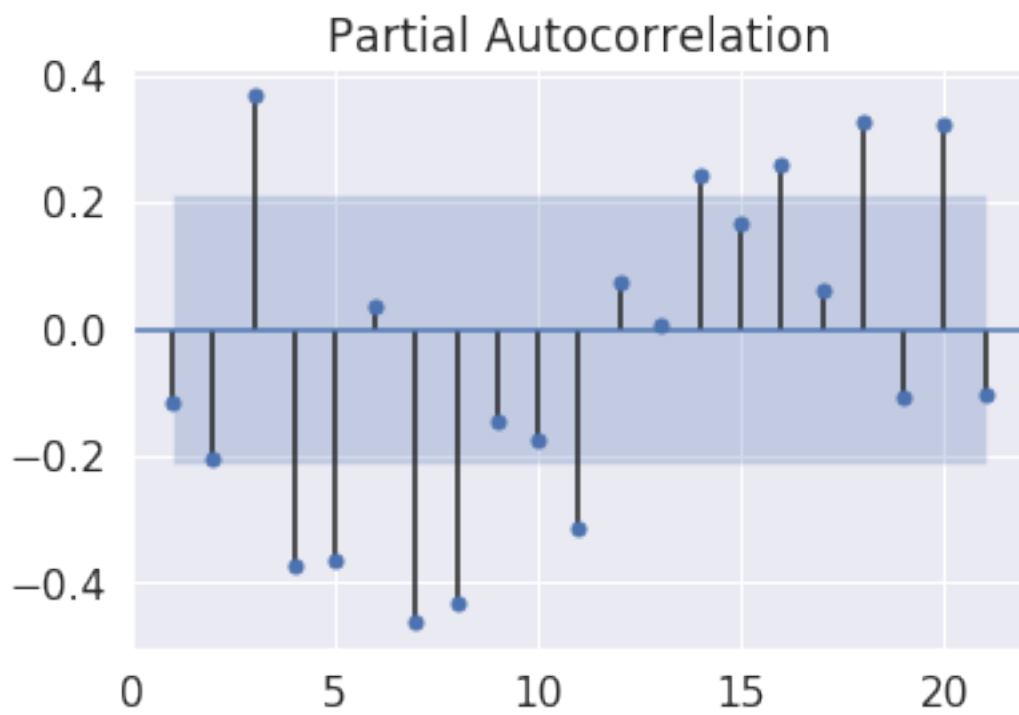
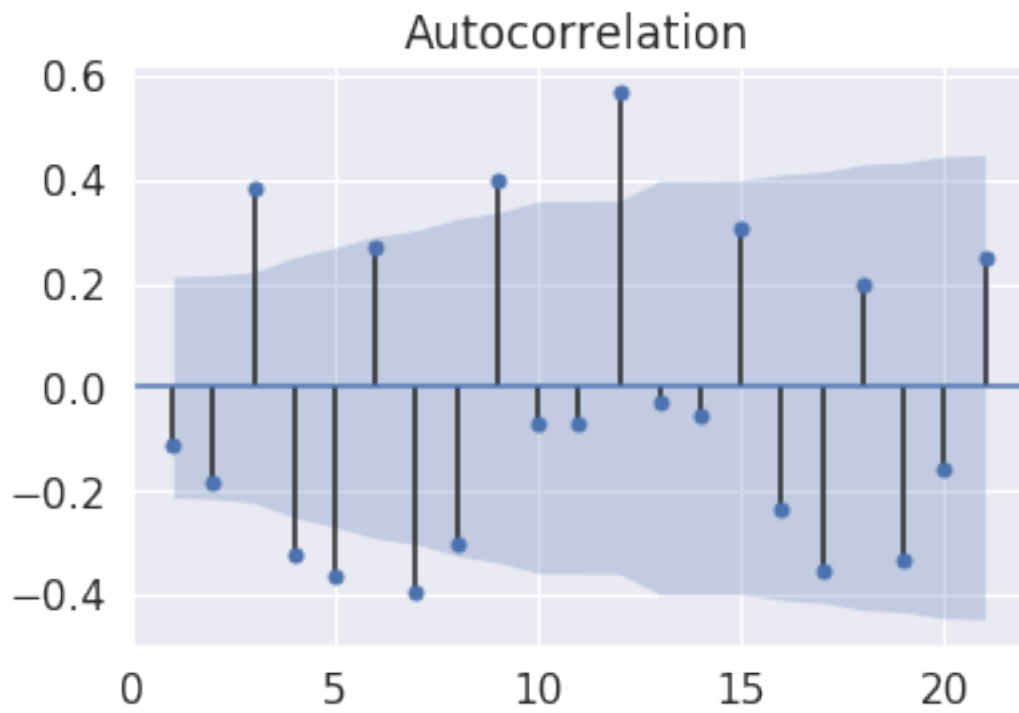
5 Q5 Solution

```
In [6]: diff = series.diff()
diff.plot(figsize=(12, 10), linewidth=2.5, color='maroon')
plt.ylabel("Differenced Values", labelpad=15)
plt.title("Differenced Values as a function of time", y=1.02, fontsize=22)
plt.show()
```



5.0.1 Plotting the ACF and the PACF of the differences series

```
In [7]: diff[[0]] = 0
        n_lags = np.round(len(diff)/4)
        plot_acf(diff.astype(int),lags=n_lags,zero=False)
        plot_pacf(diff.astype(int),lags=n_lags,zero=False)
        plt.show()
```

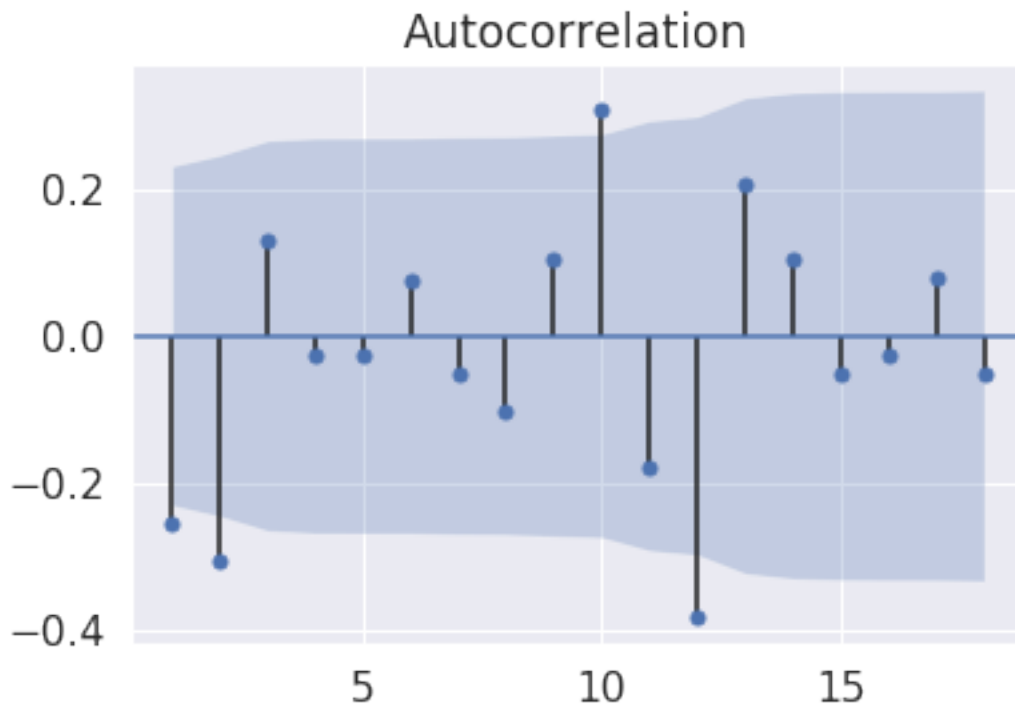


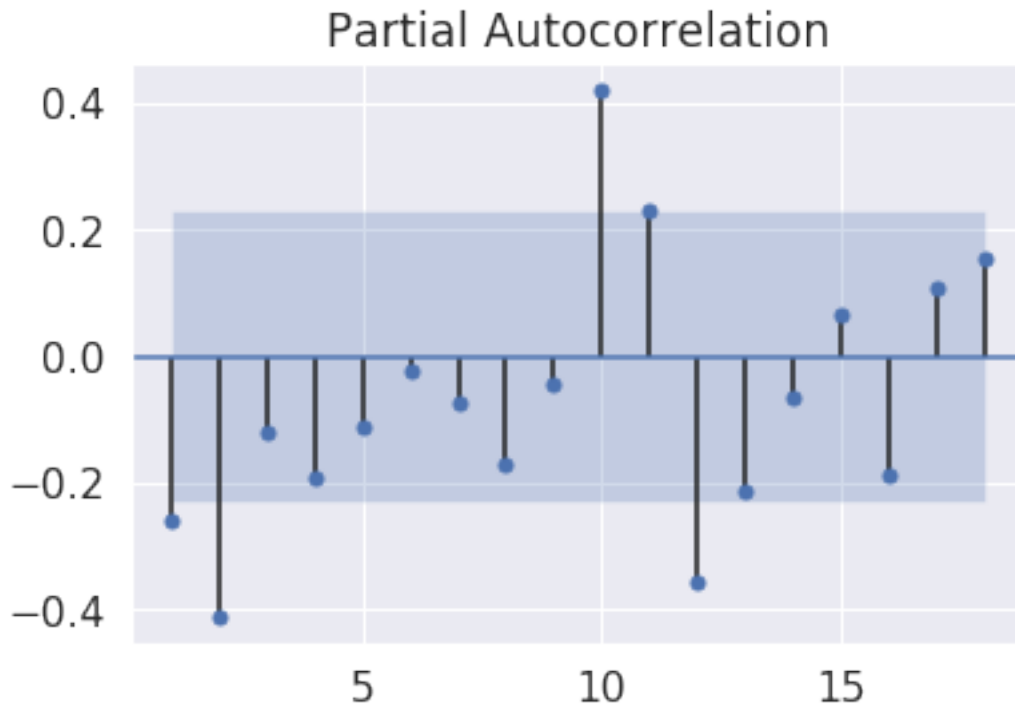
5.0.2 The significant lags in the ACF are 3, 4, 5, 7, 9 and 12

5.0.3 The significant lags in the PACF are 3, 4, 5, 7, 8, 11 and more

6 Q6 Solution

```
In [8]: seasonal_diff = diff - diff.shift(12)
n_lags = np.round(len(seasonal_diff[12:])/4)
plot_acf(seasonal_diff[12:].astype(int),lags=n_lags,zero=False)
plot_pacf(seasonal_diff[12:].astype(int),lags=n_lags,zero=False)
plt.show()
```





6.0.1 The significant lags in the ACF are 1, 2, 10 and 12

6.0.2 The significant lags in the PACF are 1, 2, 10 and 12

7 Q7

7.0.1 From question 4 will know that we need to apply first order differencing since there is a trend and from question 6 we know that the AR model order needs to be between 1 and 4 while the MA model order also needs to be between 1 and 4. Along with the seasonal difference.

```
In [9]: score = math.inf
```

```
Order = []
```

```
Seasonal_Order = []
```

```
AIC_score = []
```

```
for p in range(0,5):
```

```
    for q in range(0,5):
```

```
        for P in range(0,5):
```

```
            for Q in range(0,5):
```

```
                try:
```



```

o = (p,1,q)
s_order = (P,1,Q,12)

model = SARIMAX(series[:72], order = o, seasonal_order=s_order)
results = model.fit()
AIC = results.aic
AIC_score.append(AIC)

Order.append(o)

Seasonal_Order.append(s_order)

if AIC < score:
    score = AIC
    #print(AIC)
    best_order = o
    best_seasonal_order = s_order
else:
    pass
except:
    pass

print("The best order is",best_order)

print("The best seasonal order is",best_seasonal_order)

print("The lowest AIC is",score)

/software/anaconda3/2019.03/lib/python3.7/site-packages/statsmodels/tsa/statespace/representat
    return matrix[[slice(None)]*(matrix.ndim-1) + [0]]
/software/anaconda3/2019.03/lib/python3.7/site-packages/statsmodels/base/model.py:508: Converge
    "Check mle_retvals", ConvergenceWarning)
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/software/anaconda3/2019.03/lib/python3.7/site-packages/statsmodels/base/model.py:508: Converge
    "Check mle_retvals", ConvergenceWarning)

```



```

/software/anaconda3/2019.03/lib/python3.7/site-packages/statsmodels/base/model.py:508: ConvergenceWarning:
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  "Check mle_retvals", ConvergenceWarning)
/software/anaconda3/2019.03/lib/python3.7/site-packages/statsmodels/base/model.py:508: ConvergenceWarning:
  "Check mle_retvals", ConvergenceWarning)

```

```

The best order is (2, 1, 3)
The best seasonal order is (1, 1, 0, 12)
The lowest AIC is 147.28340552146926

```

```

In [10]: AIC_table = pd.DataFrame()
        AIC_table['Order'] = Order
        AIC_table['Seasonal Order'] = Seasonal_Order
        AIC_table['AIC'] = AIC_score
        AIC_table.sort_values(by=['AIC'])

```

```

Out[10]:
   Order Seasonal Order  AIC
93  (2, 1, 3)  (1, 1, 0, 12) 147.283406
92  (2, 1, 3)  (0, 1, 1, 12) 147.796169
16  (0, 1, 2)  (1, 1, 0, 12) 148.968651
99  (2, 1, 4)  (0, 1, 1, 12) 148.986842
15  (0, 1, 2)  (0, 1, 1, 12) 149.224977
95  (2, 1, 3)  (2, 1, 0, 12) 149.236361
100 (2, 1, 4)  (1, 1, 0, 12) 149.457987
94  (2, 1, 3)  (1, 1, 1, 12) 149.578717
121 (3, 1, 3)  (1, 1, 0, 12) 149.699652
51  (1, 1, 2)  (1, 1, 0, 12) 149.858222
50  (1, 1, 2)  (0, 1, 1, 12) 149.995964
23  (0, 1, 3)  (1, 1, 0, 12) 150.102492
14  (0, 1, 2)  (0, 1, 0, 12) 150.105497
22  (0, 1, 3)  (0, 1, 1, 12) 150.170875
120 (3, 1, 3)  (0, 1, 1, 12) 150.440980
18  (0, 1, 2)  (2, 1, 0, 12) 150.964349

```

44	(1, 1, 1)	(1, 1, 0, 12)	151.040104
17	(0, 1, 2)	(1, 1, 1, 12)	151.043874
96	(2, 1, 3)	(3, 1, 0, 12)	151.140487
102	(2, 1, 4)	(2, 1, 0, 12)	151.185886
30	(0, 1, 4)	(1, 1, 0, 12)	151.310332
29	(0, 1, 4)	(0, 1, 1, 12)	151.549688
147	(4, 1, 3)	(0, 1, 1, 12)	151.647972
123	(3, 1, 3)	(2, 1, 0, 12)	151.684866
43	(1, 1, 1)	(0, 1, 1, 12)	151.698195
91	(2, 1, 3)	(0, 1, 0, 12)	151.723697
133	(4, 1, 1)	(0, 1, 1, 12)	151.768707
53	(1, 1, 2)	(2, 1, 0, 12)	151.771099
86	(2, 1, 2)	(1, 1, 0, 12)	151.857864
58	(1, 1, 3)	(1, 1, 0, 12)	151.858090
..
83	(2, 1, 1)	(3, 1, 1, 12)	158.005940
152	(4, 1, 3)	(3, 1, 1, 12)	158.066265
131	(4, 1, 0)	(3, 1, 1, 12)	158.113051
109	(3, 1, 0)	(2, 1, 0, 12)	158.127160
75	(2, 1, 0)	(3, 1, 0, 12)	158.128318
108	(3, 1, 0)	(1, 1, 1, 12)	158.145728
118	(3, 1, 1)	(3, 1, 1, 12)	158.230148
66	(1, 1, 4)	(1, 1, 1, 12)	158.689664
69	(1, 1, 4)	(3, 1, 1, 12)	159.073136
105	(3, 1, 0)	(0, 1, 0, 12)	159.554038
145	(4, 1, 2)	(3, 1, 1, 12)	159.698557
76	(2, 1, 0)	(3, 1, 1, 12)	160.073622
110	(3, 1, 0)	(3, 1, 0, 12)	160.127077
7	(0, 1, 1)	(0, 1, 0, 12)	160.295406
111	(3, 1, 0)	(3, 1, 1, 12)	162.070138
37	(1, 1, 0)	(1, 1, 0, 12)	163.307685
36	(1, 1, 0)	(0, 1, 1, 12)	163.789152
39	(1, 1, 0)	(2, 1, 0, 12)	165.132139
38	(1, 1, 0)	(1, 1, 1, 12)	165.210748
2	(0, 1, 0)	(1, 1, 0, 12)	165.333070
1	(0, 1, 0)	(0, 1, 1, 12)	165.608301
40	(1, 1, 0)	(3, 1, 0, 12)	166.409535
0	(0, 1, 0)	(0, 1, 0, 12)	166.902178
35	(1, 1, 0)	(0, 1, 0, 12)	167.195685
4	(0, 1, 0)	(2, 1, 0, 12)	167.321479
3	(0, 1, 0)	(1, 1, 1, 12)	167.327523
41	(1, 1, 0)	(3, 1, 1, 12)	168.408456
5	(0, 1, 0)	(3, 1, 0, 12)	168.571740
6	(0, 1, 0)	(3, 1, 1, 12)	170.533949
24	(0, 1, 3)	(1, 1, 1, 12)	1223.309950

[153 rows x 3 columns]

8 Q8 Solution

```
In [11]: model = SARIMAX(series[:72], order = best_order, seasonal_order=best_seasonal_order)
         model_fit = model.fit()
         #print(model_fit.summary())
         yhat = model_fit.forecast(12)
         error = np.sum(np.square(yhat-series[-12:]))/(12)
         print("The mean squared error for forecast is",error)
```

The mean squared error for forecast is 0.7383706098643396

```
In [12]: print("Dataframe with actual and forecasted: \n")
         forecast = pd.DataFrame()
         forecast['Ground Truth'] = series[-12:]
         forecast['Forecasted'] = yhat
         print(forecast)
```

Dataframe with actual and forecasted:

	Ground Truth	Forecasted
72	10.840	10.936182
73	10.436	10.014992
74	13.589	12.995767
75	13.402	10.836447
76	13.103	13.520746
77	14.933	14.359624
78	14.147	13.914507
79	14.057	14.774762
80	16.234	15.999929
81	12.389	13.090693
82	11.594	11.502247
83	12.772	13.106475

8.0.1 The forecast can be improved if we had more data by using another model order. We are not able to explore many combinations of model orders because of the scarcity of data.