Practical 10 - Solution

September 14, 2022

1 First Name:

2 Last Name:

3 Import Libraries

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
```

4 Read in champagne.CSV File

[2]:
```python
champagne = pd.read_csv('champagne.csv')
champagne.head()
```

[2]:
```
     Month  champagne
0  1964-01       2815
1  1964-02       2672
2  1964-03       2755
3  1964-04       2721
4  1964-05       2946
```

Read in data from csv file, and showing the first five rows

5 Data Management

6 convert champagne['Month'] to datetime format

[3]:
```python
from datetime import datetime champagne['Month'] =
pd.to_datetime(champagne['Month'], format='%Y-%m')
champagne.head()
```

[3]:
```
       Month  champagne
0 1964-01-01       2815
1 1964-02-01       2672
2 1964-03-01       2755
3 1964-04-01       2721
4 1964-05-01       2946
```

Reformat datetime to use as index for timeseries later on and showing the first five rows.

7 Set ‘Month’ column as index

```
[4]: champagne.set_index('Month', inplace=True)
     champagne.head()
```

```
[4]:          champagne
    Month
    1964-01-       2815
    01
    1964-02-       2672
    01
    1964-03-       2755
    01
    1964-04-       2721
    01
    1964-05-       2946
    01
```

Setting ‘Month’ as index for timeseries and showing the first five rows.

8 Convert champagne[‘champagne’] to numeric and print the description of champagne[‘champagne’] column

```
[9]: champagne['champagne'] = pd.to_numeric(champagne['champagne'])
     print(champagne.describe())
```

```
        champagne

count   105.000000
mean   4761.152381
std    2553.502601
min    1413.000000
25%    3113.000000
50%    4217.000000
75%    5221.000000
max   13916.000000
```

9 print the index of champagne

```
[10]: champagne.index
```

```
[10]: DatetimeIndex(['1964-01-01', '1964-02-01', '1964-03-01',
'1964-04-01', '1964-05-01', '1964-06-01', '1964-07-01', '1964-08-
                                                             01',
                  '1964-09-01', '1964-10-01',
                  …
                  '1971-12-01', '1972-01-01', '1972-02-01', '1972-03-
                  01',
                  '1972-04-01', '1972-05-01', '1972-06-01', '1972-07-
                  01',
                  '1972-08-01', '1972-09-01'],
                 dtype='datetime64[ns]', name='Month', length=105,
                 freq=None)
```

10 Print rows from 1965-07-01 to 1965-12-01

[11]:
```
champagne['1965-07-01':'1965-12-01']
```

[11]:

	champagne
Month	
1965-07-01	3028
1965-08-01	1759
1965-09-01	3595
1965-10-01	4474
1965-11-01	6838
1965-12-01	8357

11 Print from begining of data till 1966-07-01

[12]:
```
champagne[:'1966-07-01']
```

[12]:

	champagne
Month	
1964-01-01	2815
1964-02-01	2672
1964-03-01	2755
1964-04-01	2721
1964-05-01	2946
1964-06-01	3036
1964-07-01	2282
1964-08-01	2212
1964-09-01	2922
1964-10-01	4301
1964-11-01	5764
1964-12-01	7312

1965-01-01	2541
1965-02-01	2475
1965-03-01	3031
1965-04-01	3266
1965-05-01	3776
1965-06-01	3230
1965-07-01	3028
1965-08-01	1759
1965-09-01	3595
1965-10-01	4474
1965-11-01	6838
1965-12-01	8357
1966-01-01	3113
1966-02-01	3006
1966-03-01	4047
1966-04-01	3523
1966-05-01	3937
1966-06-01	3986
1966-07-01	3260

12 Print data for the entire year 1972

[13]:
```
champagne['1972']
```

[13]:

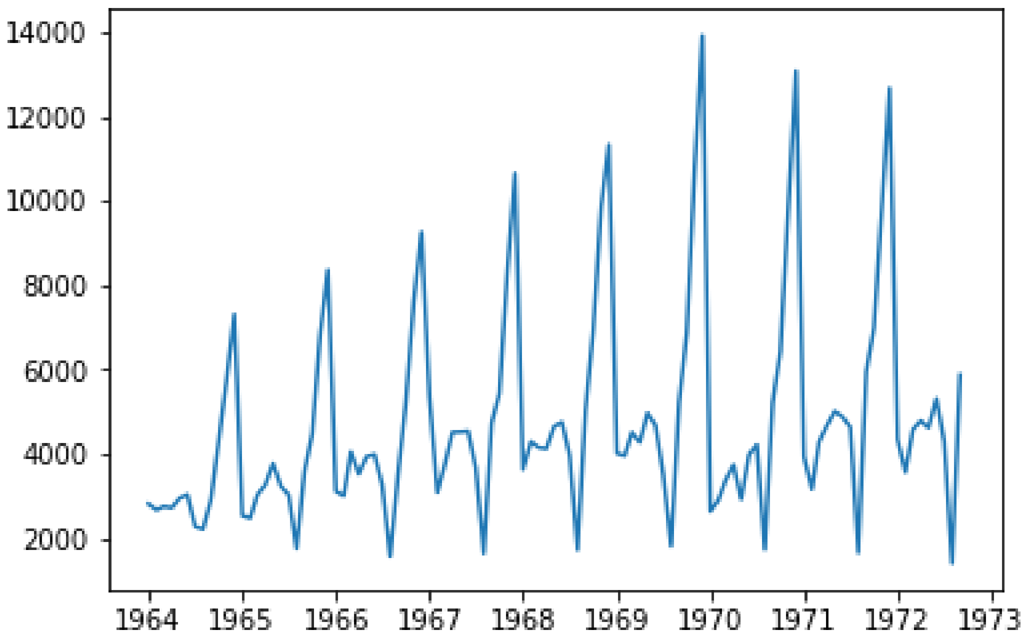
	champagne
Month	
1972-01-01	4348
1972-02-01	3564
1972-03-01	4577
1972-04-01	4788
1972-05-01	4618

1972-06-01	5312
1972-07-01	4298
1972-08-01	1413
1972-09-01	5877

13 1. Plot champagne Time Series

[14]:
```
%matplotlib inline
plt.plot(champagne)
```

[14]: [<matplotlib.lines.Line2D at 0x1b971cfa58>]



The time series showing a recurring pattern of champagne sales, and the sales seems growing from 1964 until 1970.

14 Create a column called 'Month' that is just the month of sale

[15]:
```
champagne['Month'] = champagne.index.month
champagne.head()
```

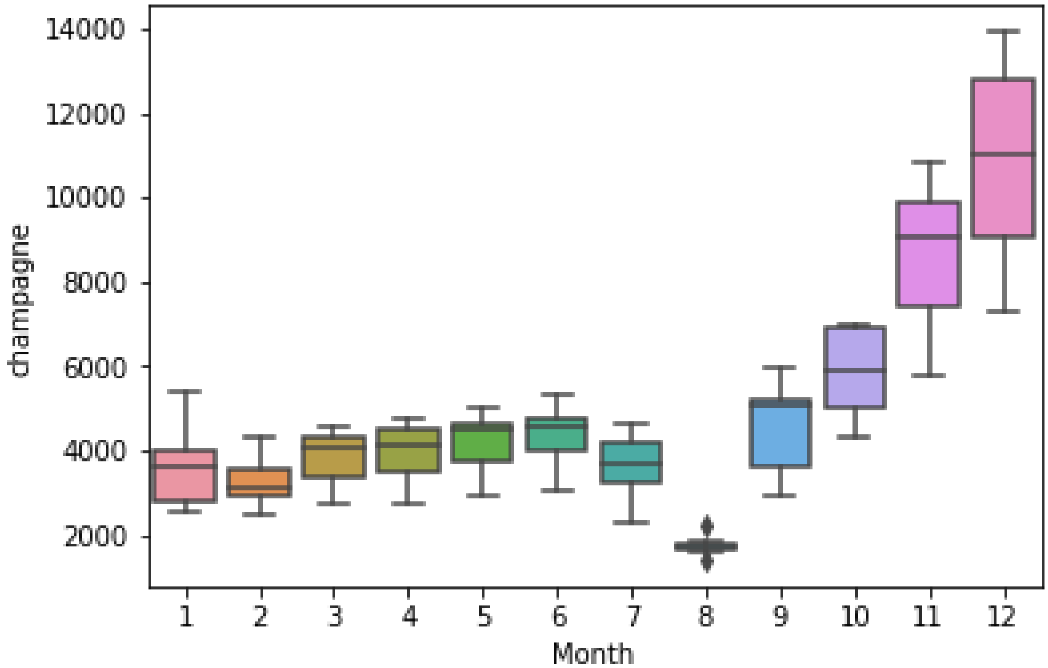
[15]:

	champagne	Month
Month		
1964-01-01	2815	1
1964-02-01	2672	2
1964-03-01	2755	3
1964-04-01	2721	4

```
1964-05-01      2946      5
```

15 Box plot of monthly champange sale

[16]:
```python
import seaborn as sns
ax = sns.boxplot(data = champagne, x='Month',y='champagne')
```



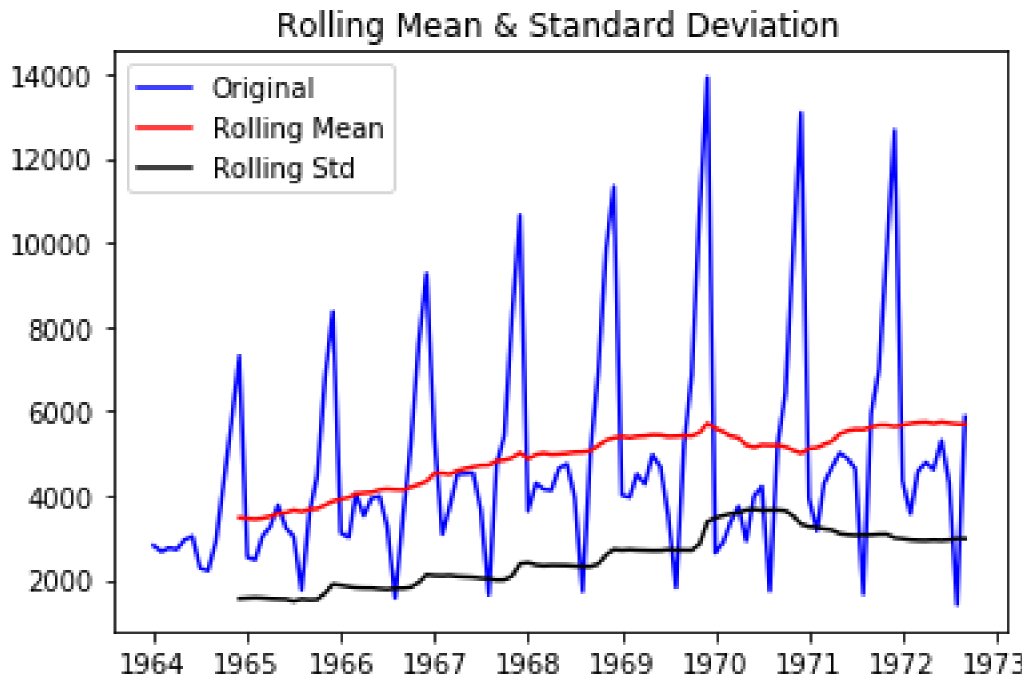
The box plot shows there is a big sales drop during August.

16 2. Stationarity - Check

[18]:
```python
def test_stationarity(timeseries):

    #Determing rolling statistics rolmean =
    timeseries.rolling(window=12).mean()
    rolstd =
    timeseries.rolling(window=12).std()

    #Plot rolling statistics:
    orig = plt.plot(timeseries,
    color='blue',label='Original') mean =
    plt.plot(rolmean, color='red', label='Rolling
    Mean') std = plt.plot(rolstd, color='black', label
    = 'Rolling Std') plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)
```

17 Perform test_stationarity on champagne sale

[19]:
```
test_stationarity(champagne['champagne'])
```




```
A rolling
mean shows
the sales
suffer a drop
in 1970, and
std increased
significantly
at the same
time.
```

[20]:
```
from statsmodels.tsa.stattools import adfuller

#Perform Dickey-Fuller test:
def test_Dickey_Fuller(timeseries):
    print('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries,
    autolag='AIC')
         dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-
                                                          value','#Lags␣
 ↪Used','Number of Observations
    Used']) for key,value in
    dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
```

18 Perform test_Dickey_Fuller on champagne sale

[21]:
```
test_Dickey_Fuller(champagne['champagne'])
```

```
Results of Dickey-Fuller Test:
```

```
Test Statistic    -1.833593 p-value
 0.363916 #Lags Used    11.000000
Number of Observations Used 93.000000
Critical Value (1%)         -3.502705
Critical Value (5%)         -2.893158
Critical Value (10%)        -2.583637
dtype: float64
```

A high p-value indicates we have to accept null hypothesis

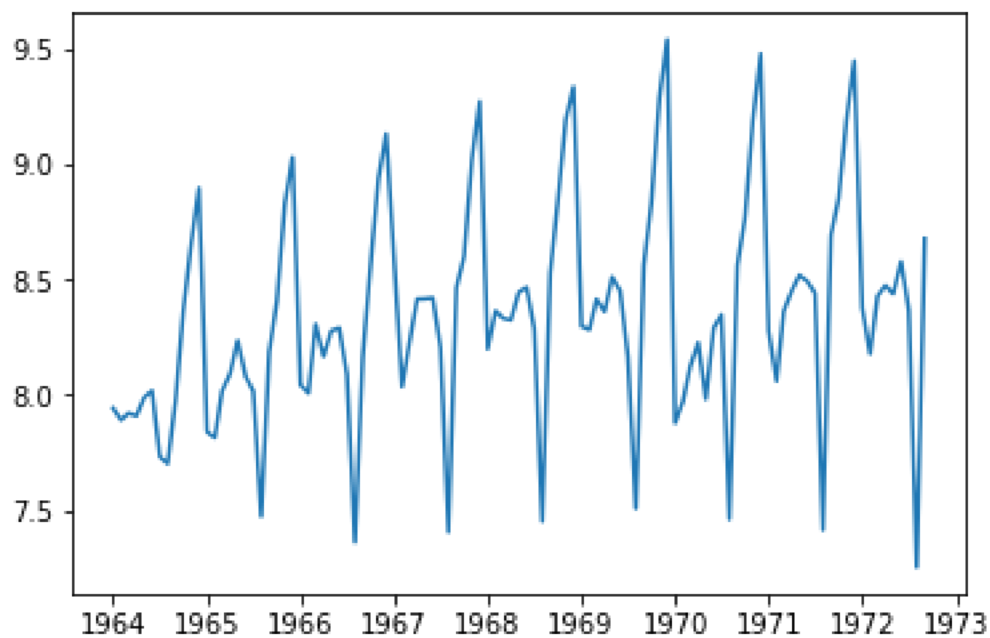
19 Make Time Series Stationary

20 Decomposing

21 get log of champagne sales and print the log time series (ts_log)

[22]:
```
ts_log = np.log(champagne['champagne'])
plt.plot(ts_log)
```

[22]: [<matplotlib.lines.Line2D at 0x1b9c643080>]



The time series showing a recurring pattern of champagne sales, and the sales seems growing from 1964 until 1970.

22 Decompose log of champagne sales to obtain trend, seasonal, residual

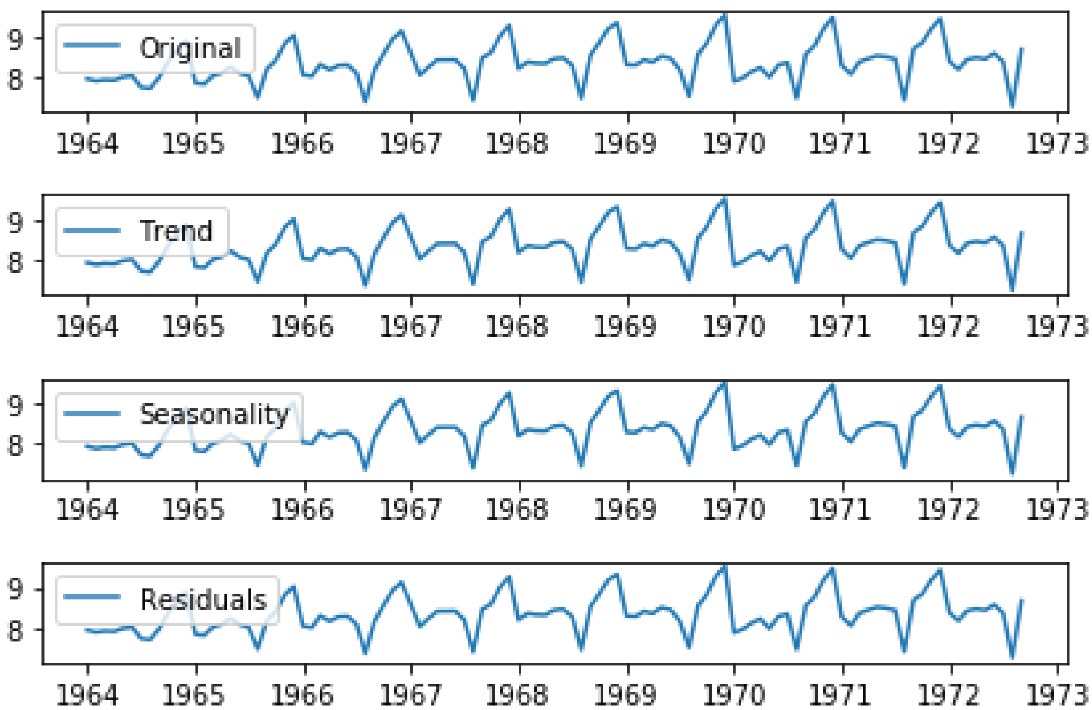
23 plot 'Original' (ts_log)

24 plot trend

25 plot seasonality

26 plot residuals

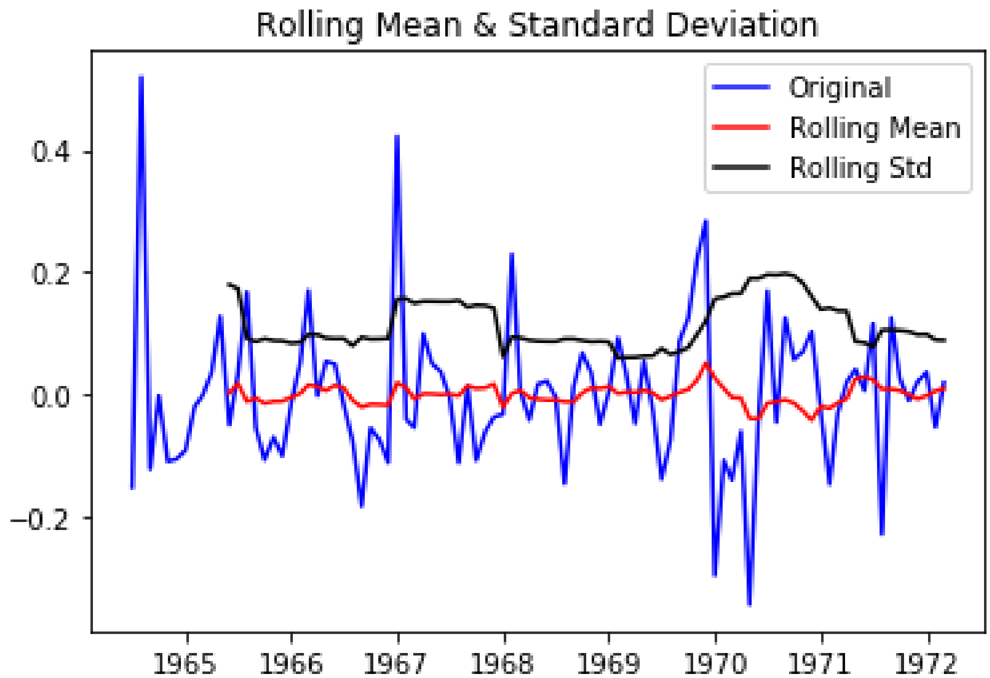
[24]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

decomposition = seasonal_decompose(ts_log)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

plt.subplot(411)
plt.plot(ts_log, label='Original')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(ts_log, label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(ts_log,label='Seasonality')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(ts_log, label='Residuals')
plt.legend(loc='best')
plt.tight_layout()
```




```
Perform seasonal decomposition of time series to further analyze
tread and residuals.
```

27 Perform test_stationarity on residual of champagne sale

[25]:
```
#use only residual data
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
test_stationarity(ts_log_decompose)
```



Calculating rolling mean and std on log of original data, to reduce variances.

28 Perform test_Dickey_Fuller on residual of champagne sale

[26]:
```
test_Dickey_Fuller(ts_log_decompose)
```

```
Results of Dickey-Fuller Test:
Test Statistic   -6.275488e+00 p-value
 3.910002e-08 #Lags Used    7.000000e+00
Number of Observations Used 8.500000e+01
Critical Value (1%)        -3.509736e+00
Critical Value (5%)    -2.896195e+00
Critical Value (10%)   -2.585258e+00
dtype: float64
```

29 Plot ACF & PACF chart & find optimal parameter

[27]:
```
from statsmodels.tsa.stattools import acf, pacf
```

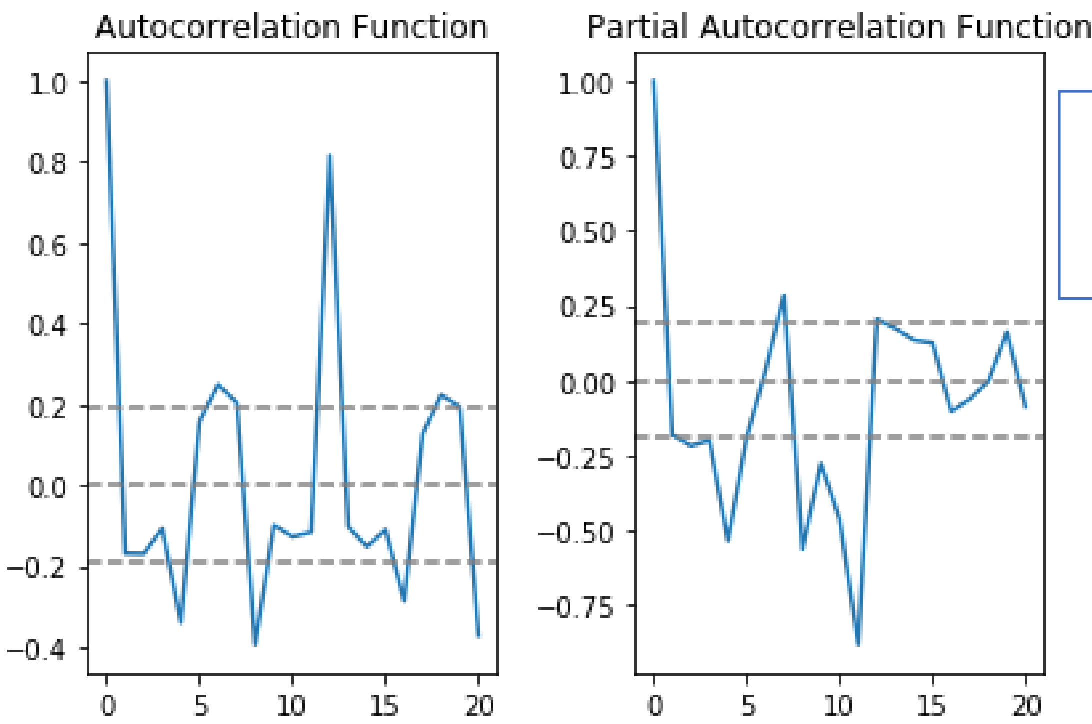
30 Obtain partical autocorrelation (pacf) and autocorrelation

(acf)

[29]:
```
ts_log_diff = ts_log -
ts_log.shift()
ts_log_diff.dropna(inplace=True)
lag_acf = acf(ts_log_diff,
nlags=20)
lag_pacf = pacf(ts_log_diff, nlags=20, method='ols')
```

31 Plot partical autocorrelation (pacf) and autocorrelation (acf)

[30]:
```
#Plot ACF:
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--
',color='gray')
plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--
',color='gray') plt.title('Autocorrelation Function')

#Plot PACF:
plt.subplot(122)
plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--
',color='gray')
plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--
',color='gray') plt.title('Partial Autocorrelation Function')
plt.tight_layout()
```



Use acf and pacf to calculate p,q values for ARIMA model

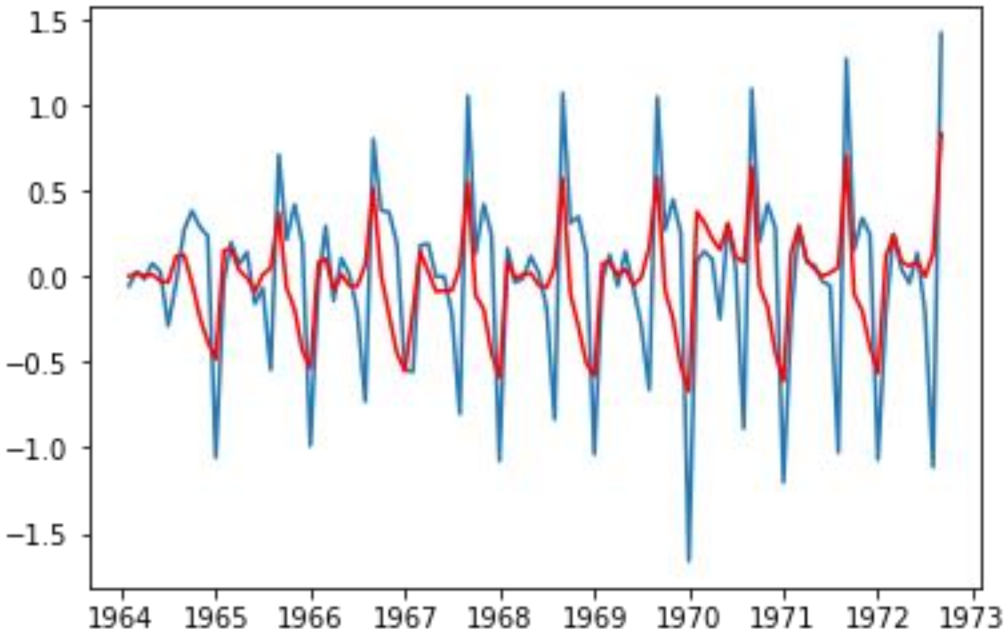
[31]:
```
from statsmodels.tsa.arima_model import ARIMA
```

32 Build ARIMA model using ts_log using p and q values from acf and pacf

[33]:
```
#ARIMA
model = ARIMA(ts_log, order=(1, 1, 1))  #(p,d,q)
results_ARIMA = model.fit(disp=-1)
plt.plot(ts_log_diff)
plt.plot(results_ARIMA.fittedvalues, color='red')
```

```
C:\ProgramData\Anaconda3\lib\sitepackages\statsmodels\tsa\base\t
sa_model.py:171: ValueWarning: No frequency information was
provided, so inferred frequency MS will be used. % freq,
ValueWarning)
C:\ProgramData\Anaconda3\lib\sitepackages\statsmodels\tsa\base\t
sa_model.py:171: ValueWarning: No frequency information was
provided, so inferred frequency MS will be used. % freq,
ValueWarning)
```

[33]: [<matplotlib.lines.Line2D at 0x1b9c539710>]



Close fit between log-difference and produced model

33 Make predictions

[34]:
```
predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues,
copy=True)
```

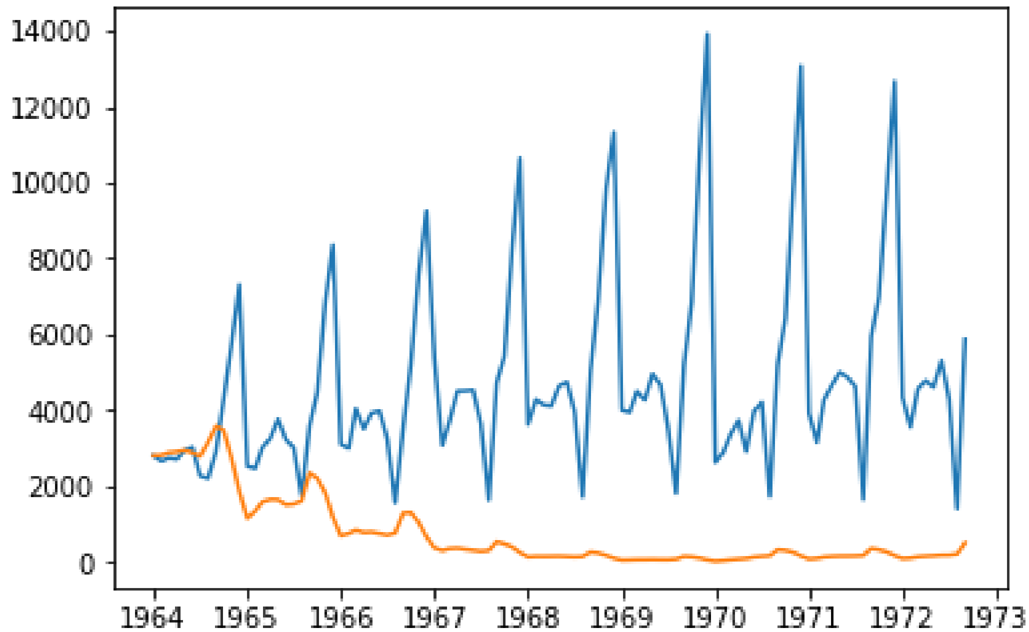
[35]:
```
predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
```

[36]:
```
predictions_ARIMA_log = pd.Series(ts_log.ix[0],
index=ts_log.index) predictions_ARIMA_log =
predictions_ARIMA_log.
↪add(predictions_ARIMA_diff_cumsum,fill_value=0)
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\ipykernel_launcher.py:1:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing
or .iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-
indexer-isdeprecated
  """Entry point for launching an IPython kernel.
```

[37]:
```
predictions_ARIMA = np.exp(predictions_ARIMA_log)
plt.plot(champagne['champagne'])
plt.plot(predictions_ARIMA)
```

[37]: [<matplotlib.lines.Line2D at 0x1b9c5f8eb8>]




```
The prediction model (orange) fits the actual data at beginning,
but drift apart quickly, and overall prediction is poor.
```