R09546042 TSA HW 02

October 10, 2021

0.0.1 import used library

```
[1]: import numpy as np
  import matplotlib.pyplot as plt
  import pandas as pd
  from sklearn.linear_model import LinearRegression
  from statsmodels.tsa.holtwinters import ExponentialSmoothing as HWES
```

1 Q1

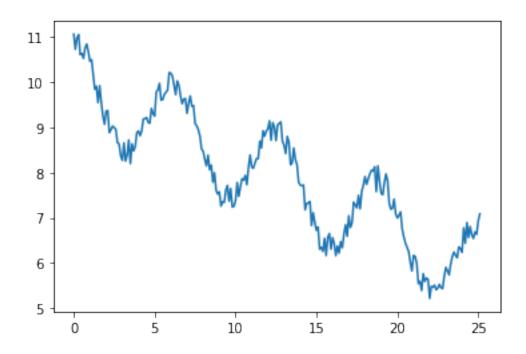
- 1.1 a. Explain how you design the disturbance.
- 1.1.1 Use $\cos()$ for changing time-series, -x/6 for dwindling trend, 10 as label, and normal distribution(-0.3~0.3) for noise.

```
[2]: x = np.arange(0,8*np.pi,0.1)
y = 10+np.cos(x)-x/6

# generate noise
y_noise = []

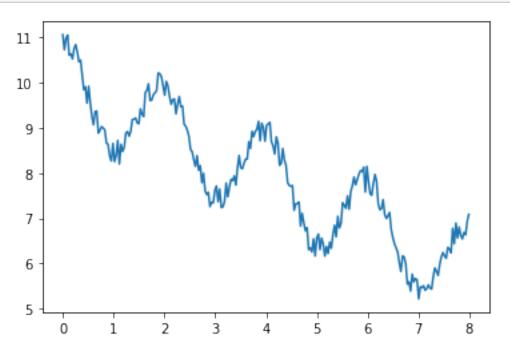
for i in y:
    n = 0.3
    noise = np.random.uniform(-n,n)
    y_noise.append(i + noise)

plt.plot(x,y_noise)
plt.show()
```



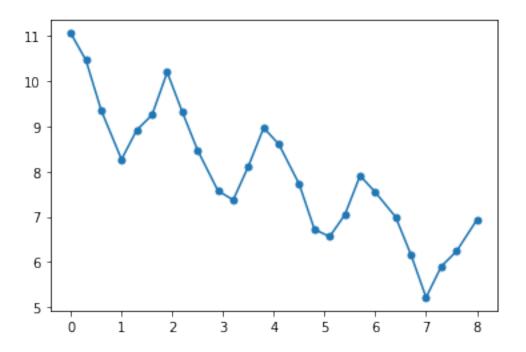
- $1.2\,$ b. Identify the number of periods in a season and then deseasonalize the series.
- 1.2.1 Change x scale into #pi, making observation easier

[3]: plt.plot(x/np.pi,y_noise) plt.show()



- 1.2.2 As the creator of this time-series, we know that its period is 3.14(by cos()), which means there are 3 interger data points in one period.
- 1.2.3 Leading us to assume period roughly close to 3.

```
[4]: df_original_series = pd.DataFrame({
         'period': x,
         'demand': y_noise
     })
     # include average interger.
     df_interger series = df_original_series[df_original_series['period'] % 1 == 0]
     df_interger_series['period'] = df_interger_series['period'].div(np.pi).round(1)
     plt.plot(df_interger_series['period'],df_interger_series['demand'],u
      →marker='o',markersize=5)
     # deseasonalize
     series deseasonalization = df interger series.loc[:, 'demand'].rolling(3).
     →mean().dropna()
     series_deseasonalization=series_deseasonalization.
     drop([series_deseasonalization.index[22],series_deseasonalization.index[23]])
     # deseasonalize dataframe
     df_deseasonalization = pd.DataFrame({
         'Quater': sum([[1,2,3]*8,[1,2]],[]),
         'Period': df_interger_series['period'] ,
         'Demand': df_interger_series['demand'] ,
         'Deseasonalized_Demand': series_deseasonalization
     })
    <ipython-input-4-ab869889bd6c>:8: SettingWithCopyWarning:
    A value is trying to be set on a copy of a slice from a DataFrame.
    Try using .loc[row_indexer,col_indexer] = value instead
    See the caveats in the documentation: https://pandas.pydata.org/pandas-
    docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
      df_interger_series['period'] =
    df_interger_series['period'].div(np.pi).round(1)
```



1.3 c. Calculate the seasonality factors

```
[5]: #build up regressing model
     reg = LinearRegression().fit(np.asarray(df_deseasonalization.loc[20:230,_
     → 'Period']).reshape(-1, 1),
                                 df_deseasonalization.loc[:,u
     →'Deseasonalized_Demand'].dropna())
     #predict nan value
     values = pd.Series(reg.predict(np.asarray(df_deseasonalization.loc[:,__
     → 'Period']).reshape(-1,1)))
     #fill up nan value
     df_deseasonalization.loc[0,['Deseasonalized_Demand']] = values[0]
     df_deseasonalization.loc[10,['Deseasonalized_Demand']] = values[10]
     df_deseasonalization.loc[240,['Deseasonalized_Demand']] = values[24]
     df_deseasonalization.loc[250,['Deseasonalized_Demand']] = values[25]
     # calculate seansonality factor
     df_deseasonalization.loc[:, 'Seasonality'] = (df_deseasonalization.loc[:, |
     → 'Demand'] / df_deseasonalization.loc[:, 'Deseasonalized_Demand'])
     df_Seasonality_bar= pd.DataFrame({
         'Quater': sum([[1,2,3]*8,[1,2]],[]),
         'Period': df_interger_series['period'] ,
         'Demand': df_interger_series['demand'] ,
```

[6]: df_deseasonalization

[6]:		Quater	Period	Demand	Deseasonalized_Demand	Seasonality	\
[0].	0	1	0.0	11.053918	10.119166	1.092374	`
	9	2	0.3	10.455796	8.455223	1.236608	
	18	3	0.6	9.349128	10.286280	0.908893	
	1	1	1.0	8.266442	9.357122	0.883439	
	10	2	1.3	8.915853	8.843808	1.008146	
	19	3	1.6	9.245860	8.809385	1.049547	
	2	1	1.9	10.191551	9.451088	1.078347	
	11	2	2.2	9.306449	9.581287	0.971315	
	20	3	2.5	8.466014	9.321338	0.908240	
	3	1	2.9	7.573053	8.448505	0.896378	
	12	2	3.2	7.370566	7.803211	0.944555	
	21	3	3.5	8.116188	7.686602	1.055888	
	4	1	3.8	8.964254	8.150336	1.099863	
	13	2	4.1	8.599915	8.560119	1.004649	
	22	3	4.5	7.721453	8.428541	0.916108	
	5	1	4.8	6.722205	7.681191	0.875151	
	14	2	5.1	6.559955	7.001204	0.936975	
	23	3	5.4	7.043282	6.775147	1.039576	
	6	1	5.4	7.043262	7.170449	1.102875	
	15	2	6.0	7.541343	7.170449	1.005837	
		3					
	24		6.4	6.994145	7.481199	0.934896	
	7	1	6.7	6.166982	6.900824	0.893659	
	16	2	7.0	5.216677	6.125935	0.851572	
	25	3	7.3	5.902539	5.762066	1.024379	
	8	1	7.6	6.237170	6.167302	1.011329	
	17	2	8.0	6.930420	5.959309	1.162957	

Seasonality_bar
0 0.992602
9 1.013624
18 0.979691
1 0.992602
10 1.013624
19 0.979691
2 0.992602

```
11
           1.013624
20
           0.979691
3
           0.992602
12
            1.013624
21
           0.979691
4
           0.992602
13
           1.013624
22
           0.979691
5
           0.992602
14
           1.013624
23
           0.979691
6
           0.992602
15
           1.013624
24
           0.979691
7
           0.992602
16
           1.013624
25
           0.979691
           0.992602
17
           1.013624
```

[7]: df_seasonality

```
[7]: Quater Seasonality_bar
0 1 0.992602
1 2 1.013624
2 3 0.979691
```

1.4 d. Finalize the model and evaluate the performance via MSE and MAPE

Time-Series Model:

MSE: 0.524

MAPE: 7.853

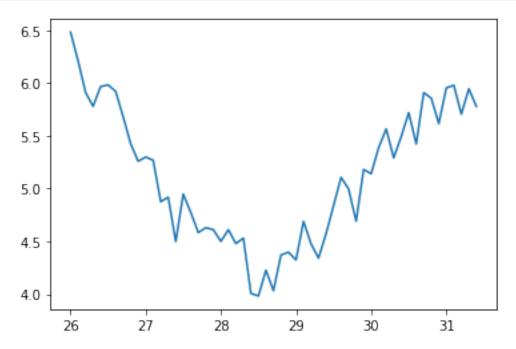
- 1.5 e. Use the static model to predict $\ , = 25, \dots , 30.$ Use the "true" model to simulate $25, \dots , 30$ and calculate the MSE and MAPE accordingly.
- 1.5.1 Construct further more data points(y=26~31)

```
[9]: x = np.arange(26.0,10*np.pi,0.1)
y = 10+np.cos(x)-x/6

y_noise = []

for i in y:
    n = 0.3
    noise = np.random.uniform(-n,n)
    y_noise.append(i + noise)

plt.plot(x,y_noise)
plt.show()
```



1.5.2 Predicting while using true model

```
[10]: #true model
df_true_model = pd.DataFrame({
    'Period': x,
    'Demand': y_noise,
```

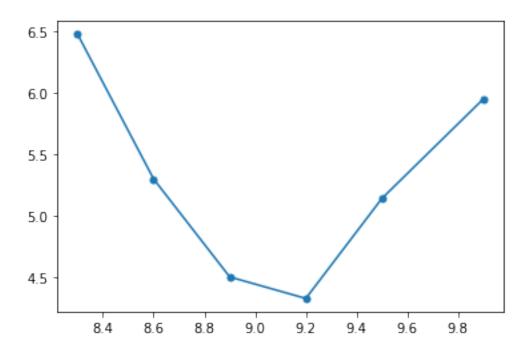
True Model(y=26~31): MSE: 0.031 MAPE: 3.02

1.5.3 Predicting while using constructed model

```
[11]: #time-series model
     df_time_series_model = pd.DataFrame({
         'Period': x,
         'Demand': y_noise
     })
     df_interger_series = df_time_series_model[df_time_series_model['Period'].
      \rightarrowround(1) % 1.0 == 0]
     df_interger_series['Period'] = df_interger_series['Period'].div(np.pi).round(1)
     plt.plot(df interger series['Period'],df interger series['Demand'],
      →marker='o',markersize=5)
     df_time_series_deseasonalization= pd.DataFrame({
     df time series deseasonalization = pd.
      →merge(df_interger_series,df_deseasonalization, how="outer").
      ⇔sort values('Period')
     df_time_series_deseasonalization.loc[:,'Quater']=sum([[1,2,3]*10,[1,2]],[])
     {\tt df\_time\_series\_deseasonalization} = {\tt df\_time\_series\_deseasonalization}.

→drop(['Seasonality_bar'], axis=1)
     df_time_series_deseasonalization = pd.
      ⇔sort_values('Period')
```

```
df_time_series_deseasonalization.loc[:, 'Forecast'] = (reg.predict(np.
 →asarray(df_time_series_deseasonalization.loc[:, 'Period']).reshape(-1,1)) *__
 →df_time_series_deseasonalization.loc[:, 'Seasonality_bar'])
df time series deseasonalization.loc[:, 'Error'] = ___
 →(df_time_series_deseasonalization.loc[:,__
 →'Demand']-df time series deseasonalization.loc[:, 'Forecast'])
df_time_series_deseasonalization.loc[:, 'Error_Squre'] = __
 → (df_time_series_deseasonalization.loc[:,__
 →'Error']*df_time_series_deseasonalization.loc[:, 'Error'])
MSE = df_time_series_deseasonalization['Error_Squre'].sum()/
 →len(df_time_series_deseasonalization)
MAPE = ((abs(df_time_series_deseasonalization.loc[:, 'Error']) /__
 →abs(df_time_series_deseasonalization.loc[:, 'Demand'])).sum())*100/
 →len(df_deseasonalization)
print("Time-Series Model(y=26~31):")
print("MSE:",MSE.round(3))
print("MAPE:",MAPE.round(3))
Time-Series Model(y=26~31):
MSE: 0.536
MAPE: 10.853
<ipython-input-11-c8e5766bbe8b>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df interger series['Period'] =
df_interger_series['Period'].div(np.pi).round(1)
```



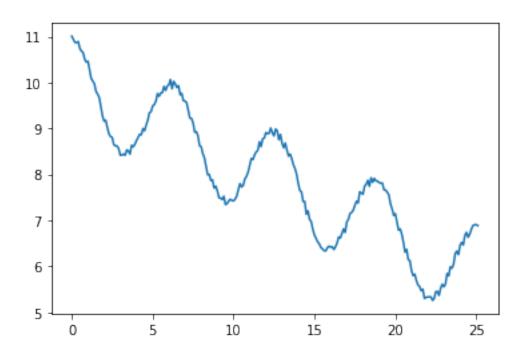
- 1.6 f. Modify the disturbance in (a) to change series (can be more or less fluctuating). Re-run the questions (b)-(d). What can you conclude when comparing to the results in (d) with the previous disturbance.
- 1.6.1 Change noise factor from 0.3 to 0.1.

```
[12]: x = np.arange(0,8*np.pi,0.1)
y = 10+np.cos(x)-x/6

y_noise = []

for i in y:
    n = 0.1
    noise = np.random.uniform(-n,n)
    y_noise.append(i + noise)

plt.plot(x,y_noise)
plt.show()
```



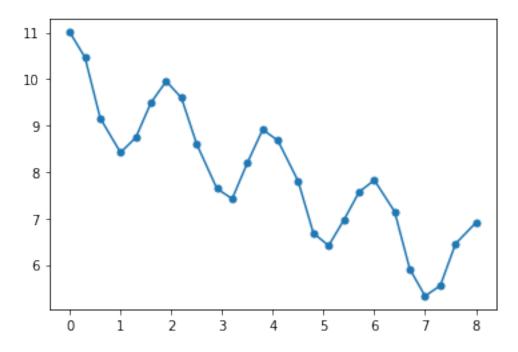
```
[13]: df_original_series = pd.DataFrame({
          'period': x,
          'demand': y_noise
      })
      # include average interger.
      df_interger_series = df_original_series[df_original_series['period'] % 1 == 0]
      df_interger_series['period'] = df_interger_series['period'].div(np.pi).round(1)
      plt.plot(df_interger_series['period'],df_interger_series['demand'],__
       →marker='o',markersize=5)
      # deseasonalize
      series_deseasonalization = df_interger_series.loc[:, 'demand'].rolling(3).
      →mean().dropna()
      series_deseasonalization=series_deseasonalization.

→drop([series_deseasonalization.index[22],series_deseasonalization.index[23]])
      # deseasonalize dataframe
      df_deseasonalization = pd.DataFrame({
          'Quater': sum([[1,2,3]*8,[1,2]],[]),
          'Period': df_interger_series['period'] ,
          'Demand': df_interger_series['demand'] ,
          'Deseasonalized_Demand': series_deseasonalization
      })
```

<ipython-input-13-ab869889bd6c>:8: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy df_interger_series['period'] = df_interger_series['period'].div(np.pi).round(1)



```
df Seasonality bar= pd.DataFrame({
        'Quater': sum([[1,2,3]*8,[1,2]],[]),
        'Period': df_interger_series['period'] ,
        'Demand': df_interger_series['demand'] ,
        'Deseasonalized_Demand': series_deseasonalization
    })
    df seasonality = df deseasonalization.groupby(['Quater'], as index=False).mean()
    df_seasonality.loc[:, 'Seasonality_bar'] = df_seasonality.loc[:, 'Seasonality']
    df_seasonality = df_seasonality[['Quater','Seasonality_bar']]
    df_deseasonalization = pd.merge(df_deseasonalization,df_seasonality).
     →sort_values('Period')
[15]: df_deseasonalization.loc[:, 'Forecast'] = (reg.predict(np.
     →asarray(df_deseasonalization.loc[:, 'Period']).reshape(-1,1)) *__
     →df_deseasonalization.loc[:, 'Seasonality_bar'])
    → 'Demand']-df_deseasonalization.loc[:, 'Forecast'])
    MSE = df_deseasonalization['Error_Squre'].sum()/len(df_deseasonalization)
```

Time-Series Model(less disturbance): MSE: 0.546

print("MSE:",MSE.round(3))
print("MAPE:",MAPE.round(3))

print("Time-Series Model(less disturbance):")

MAPE: 8.679

1.6.2 In this disturbance data simulation, we have better performance in both MSE and MAPE than previous model

MAPE = ((abs(df_deseasonalization.loc[:, 'Error']) / abs(df_deseasonalization.

→loc[:, 'Demand'])).sum())*100/len(df deseasonalization)

2 Q2

2.0.1 rearrange the data

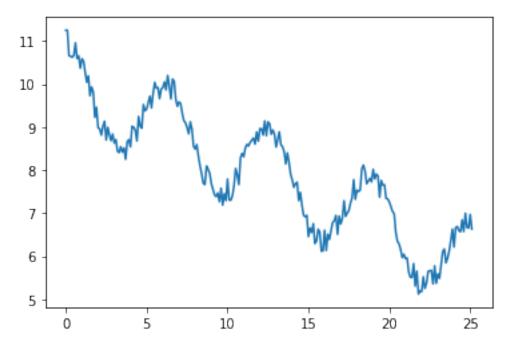
```
[16]: x = np.arange(0,8*np.pi,0.1)
y = 10+np.cos(x)-x/6

y_noise = []

for i in y:
    n = 0.3
```

```
noise = np.random.uniform(-n,n)
y_noise.append(i + noise)

plt.plot(x,y_noise)
plt.show()
```

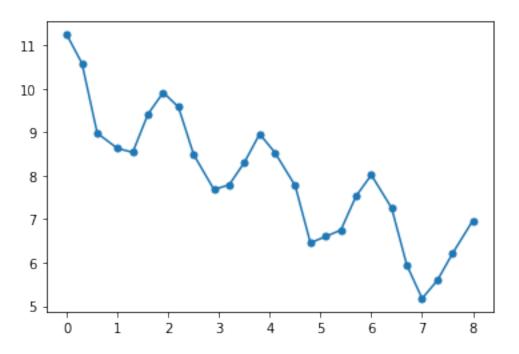


docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

df interger series['Period'] =

df_interger_series['Period'].div(np.pi).round(1)

[17]: [<matplotlib.lines.Line2D at 0x16ba3c51f10>]



```
[18]: # train the data with Holt-Winters algorithms with statsmodels module.

HWES_model = HWES(df_interger_series.loc[:, 'Demand'], seasonal_periods=3,

→trend='add', seasonal='mul')

HWES_fit_report = HWES_model.fit()

print(HWES_fit_report.summary())
```

ExponentialSmoothing Model Results

Dep. Variable:	Demand	No. Observations:	26						
Model:	ExponentialSmoothing	SSE	13.224						
Optimized:	True	AIC	-3.578						
Trend:	Additive	BIC	5.229						
Seasonal:	Multiplicative	AICC	7.672						
Seasonal Periods:	3	Date:	Sun, 10 Oct 2021						
Box-Cox:	False	Time:	22:34:05						
Box-Cox Coeff.:	None								
=============			=======================================						
=									
	coeff	code	optimized						
-									
smoothing_level	1.000000	alpha							
True									
smoothing_trend	4.8631e-13	beta							

True			
${\tt smoothing_seasonal}$	1.5746e-09	gamma	
True			
initial_level	7.1094084	1.0	
True			
initial_trend	-0.1086316	b.0	
True			
<pre>initial_seasons.0</pre>	1.6064587	s.0	
True			
initial_seasons.1	1.6246751	s.1	
True			
initial_seasons.2	1.5939570	s.2	
True			

_

packages\statsmodels\tsa\base\tsa_model.py:578: ValueWarning: An unsupported index was provided and will be ignored when e.g. forecasting.

warnings.warn('An unsupported index was provided and will be'

C:\Users\TerryYang\anaconda3\envs\TENSORFLOW\lib\site-

packages\statsmodels\tsa\holtwinters\model.py:427: FutureWarning: After 0.13 initialization must be handled at model creation

warnings.warn(

C:\Users\TerryYang\anaconda3\envs\TENSORFLOW\lib\site-