Time-Series Modelling

```
import pandas as pd
import numpy as np
import matplotlib
from matplotlib import pyplot as plt
import statsmodels
import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
# splitting TS into components
from sklearn.metrics import mean_squared_error
# calculate RMSE
from math import sqrt
```

```
from google.colab import files
uploaded=files.upload()
# CDAC_DataBook.xlsx
# to be used with google colab

# import os
# os.chdir(r'C:\Users\surya\Downloads\PG-DBDA-Mar23\Datasets')
# os.getcwd()
# to change current working directory to specified path
# to be used while running on local system
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving CDAC_DataBook.xlsx to CDAC_DataBook.xlsx
```

```
df = pd.read_excel('CDAC_DataBook.xlsx', sheet_name='birth')
df.head
```

```
<bound method NDFrame.head of      BirthRate
0       26.663
1       23.598
2       26.931
3       24.740
4       25.806
..         ...
163     30.000
164     29.261
165     29.012
166     26.992
167     27.897
```

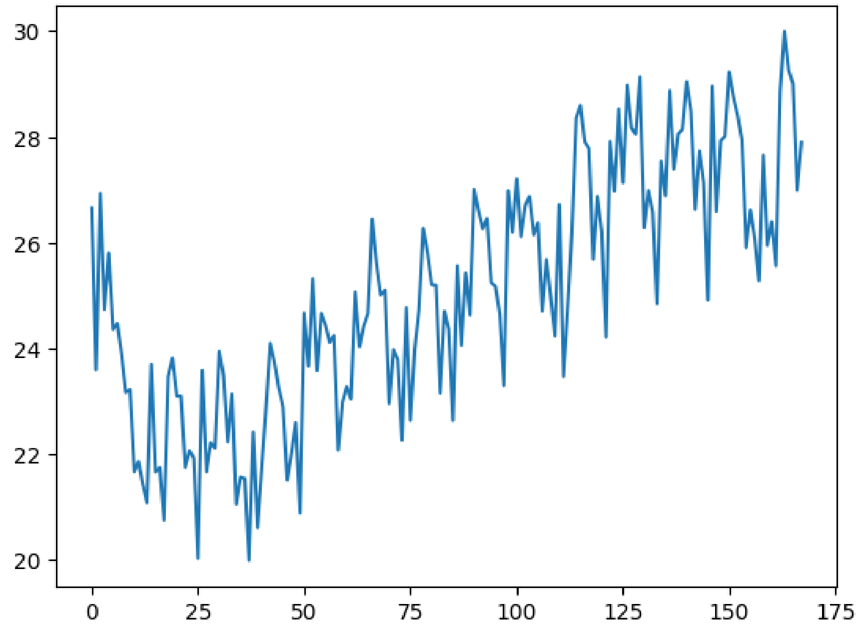
```
[168 rows x 1 columns]>
```

```
df.columns
```

```
Index(['BirthRate'], dtype='object')
```

```
df.BirthRate.plot()
# plotting the time series
```

```
<Axes: >
```




```
df_train = df.iloc[:144]
# splitting 12 years data to training data
df_test = df.iloc[144:]
# splitting 02 years data to test data

# created training & testing data manually without train_test_split(),
# because we do not want it to select row randomly
# as randomization in Time-Series Modelling will impact results
```

```
df_train.shape
```

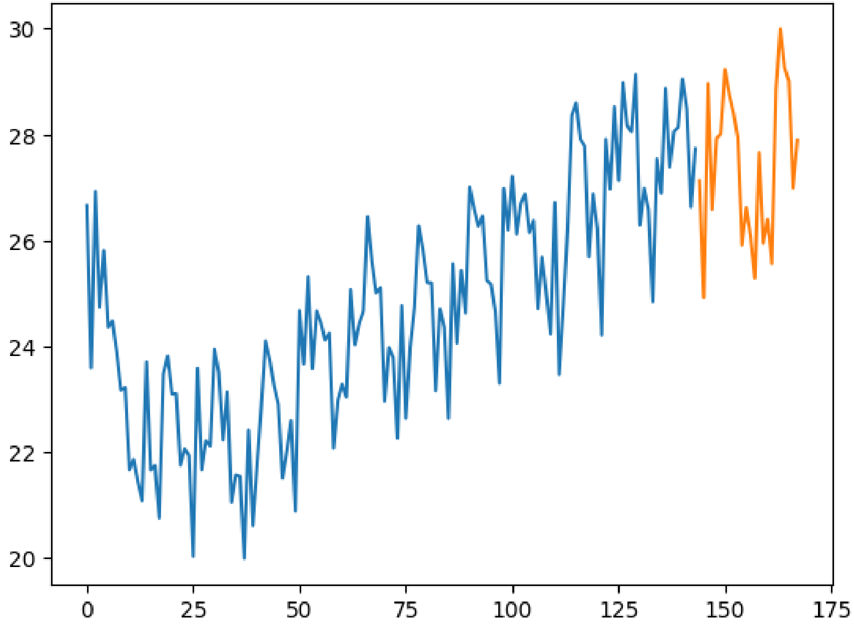
```
(144, 1)
```

```
df_test.shape
```

```
(24, 1)
```

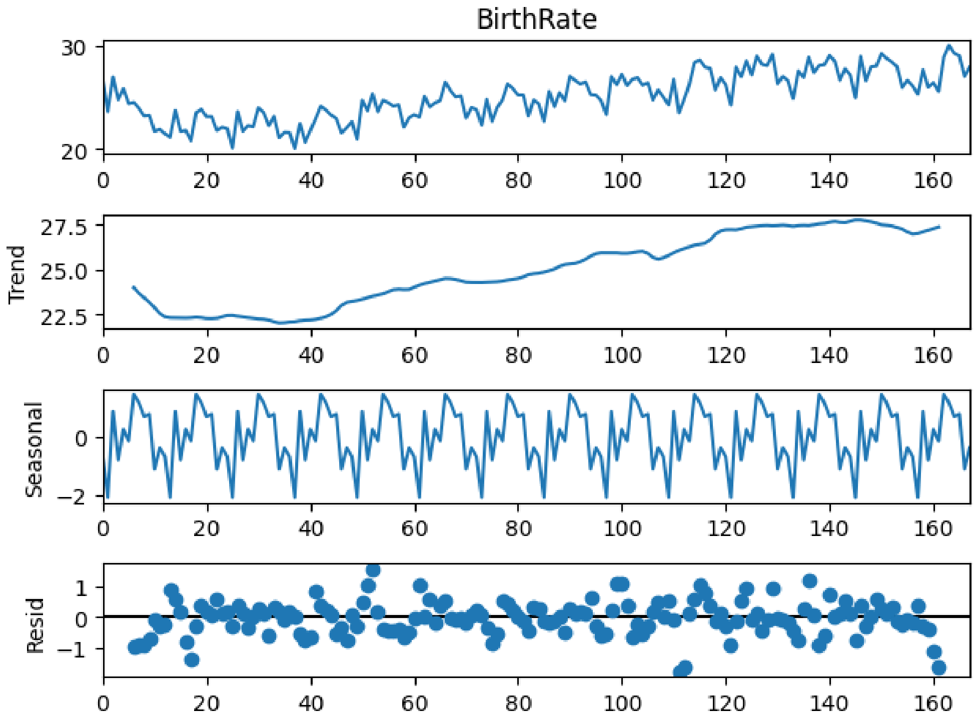
```
df_train.BirthRate.plot()
df_test.BirthRate.plot()
```

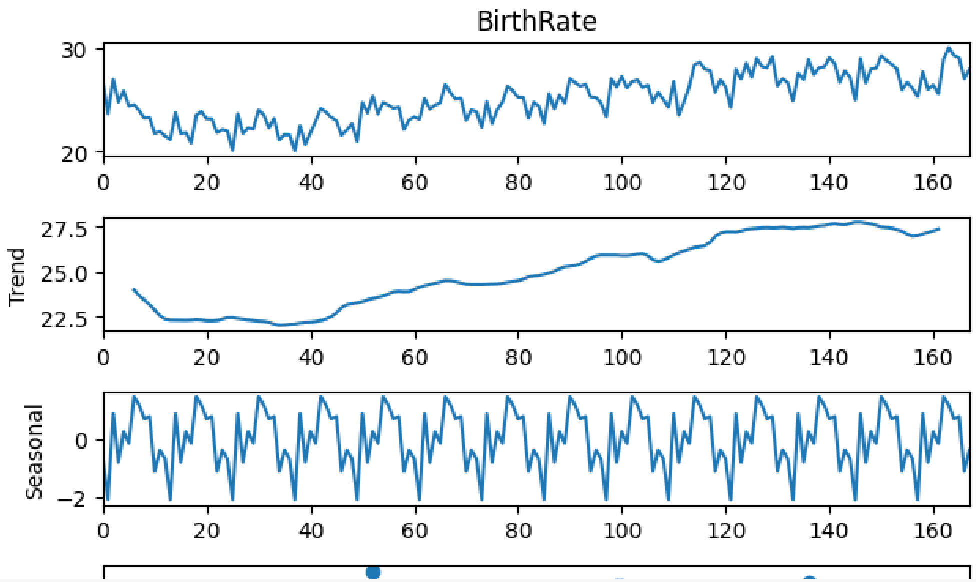
```
<Axes: >
```




```
from pandas.core.arrays import period
```

```
res = statsmodels.tsa.seasonal.seasonal_decompose(df.BirthRate, period=12)
# decomposes the TimeSeries into its components
res.plot()
# to plot & see the decomposed components of TImeSeries
```






```
type(res)
```

```
statsmodels.tsa.seasonal.DecomposeResult
```

Naive method

- assume that the last value from training data will keep on going for the future, then compare the forecast with the test data to find error

```
df_train.BirthRate.tail()
```

```
139    28.141
140    29.048
141    28.484
142    26.634
143    27.735
Name: BirthRate, dtype: float64
```

```
# Naive method
dd = np.array(df_train.BirthRate)
```

```
y_hat = df_test.copy()
# copying test data to y_hat
# y_hat : testing data
y_hat.head()
```

	BirthRate
144	27.132
145	24.924
146	28.963
147	26.589
148	27.931

```
y_hat['naive'] = dd[len(dd)-1]
# adds another column 'naive' with last value from ndarray 'dd'
# to get the last value
y_hat.tail()
```

	BirthRate	naive
163	30.000	27.735
164	29.261	27.735
165	29.012	27.735

```
plt.figure(figsize=(12, 8))
plt.plot(df_train.index, df_train.BirthRate, label='Train')
plt.plot(df_test.index, df_test.BirthRate, label='Test')
plt.plot(y_hat.index, y_hat.naive, label='Forecast')
plt.legend()
```

<matplotlib.legend.Legend at 0x7f08bf516800>

```
rms = sqrt(mean_squared_error(df_test.BirthRate, y_hat.naive))
# calculates root mean squared error
# between test data & naive data from train data
rms
```

1.4277309211939526

Simple Average Method

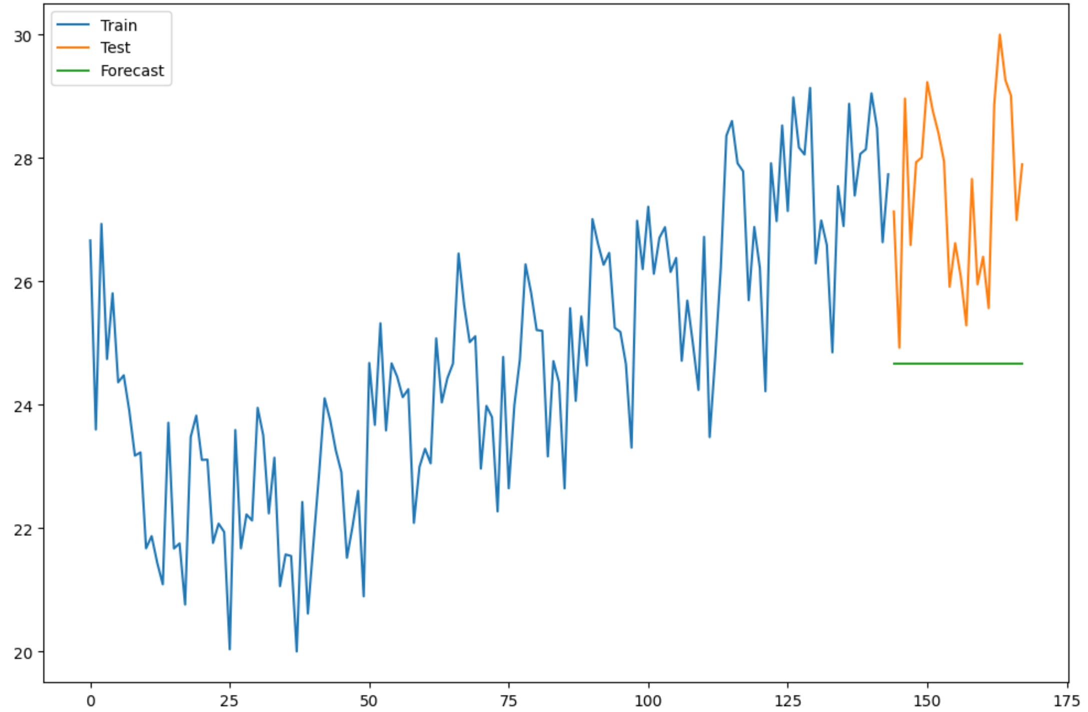
- assume that average of all the values will continue for the each month next years

```
y_hat_avg = df_test.copy()
y_hat_avg['MeanForecast'] = df_train['BirthRate'].mean()
y_hat_avg.head()
```

	BirthRate	MeanForecast
144	27.132	24.656833
145	24.924	24.656833
146	28.963	24.656833
147	26.589	24.656833
148	27.931	24.656833

```
plt.figure(figsize=(12, 8))
plt.plot(df_train.index, df_train.BirthRate, label='Train')
plt.plot(df_test.index, df_test.BirthRate, label='Test')
plt.plot(y_hat_avg.index, y_hat_avg.MeanForecast, label='Forecast')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f08bf629570>
```




```
rms = sqrt(mean_squared_error(df_test.BirthRate, y_hat_avg.MeanForecast))
# calculates root mean squared error
# between test data & MeanForecast data from train data
rms

# note that the RMS value in Simple Average method is lower due to
# dip in early values of training data
```

```
3.147657647627305
```

Moving Average

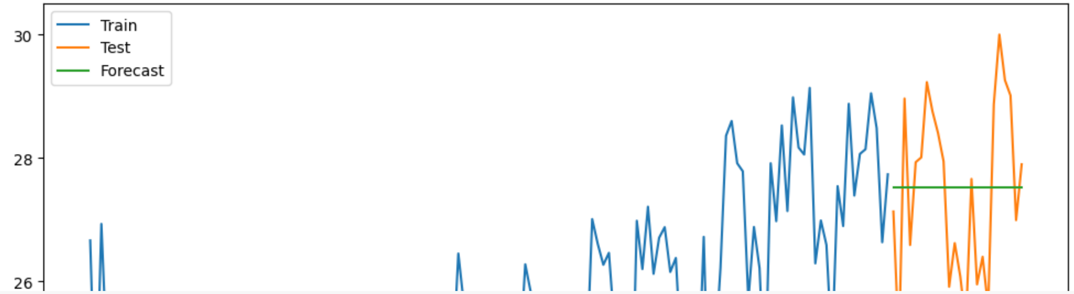
- used in stock market
- a series of averages, calculated from historic data
- assume that forecast .....
- take only the last values as per time period set, like last 3 months, 6 months, 12months etc.
- assume that the moving average of last time period in last cycle/year is the current forecast
- use the time period window based on which time period window gives you lowest RMSE

```
# y_hat_avg = df_test.copy()
y_hat_avg['MovAvgForecast'] = df_train['BirthRate'].rolling(12).mean().iloc[-1]
y_hat_avg.head()
```

	BirthRate	MeanForecast	MovAvgForecast
144	27.132	24.656833	27.520917
145	24.924	24.656833	27.520917
146	28.963	24.656833	27.520917
147	26.589	24.656833	27.520917
148	27.931	24.656833	27.520917

```
plt.figure(figsize=(12, 8))
plt.plot(df_train.index, df_train.BirthRate, label='Train')
plt.plot(df_test.index, df_test.BirthRate, label='Test')
plt.plot(y_hat_avg.index, y_hat_avg.MovAvgForecast, label='Forecast')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f08bf6e6980>
```




```
rms = sqrt(mean_squared_error(df_test.BirthRate, y_hat_avg.MovAvgForecast))
# calculates root mean squared error
# between test data & MeanForecast data from train data
rms

# you need to change the rolling(12) value to 6, 3, etc. and
# see which window gives you the lowest RMSE, and proceed with that one only
```

```
1.4044810849760687
```

Weighted Moving Average

- works on weigted average
- suppose we have data of a year, then we have to assign weight to each month
- newest month will have highest weight
- oldest month will have lowest weight
- then calculate the weighted average for the last cycle/year, which will be the current forecast

```
x = df_train['BirthRate'].iloc[-12:]
```

```
wt_sum = 0
denom = 0
for ctr in range(len(x)):
    wt_sum = wt_sum + x.iloc[ctr]*(ctr+1)
    # sums up the product of weight & value
    denom = denom + ctr+1
    # sums up all the weights
wt_avg = wt_sum / denom
```

```
# y_hat_avg = df_test.copy()
y_hat_avg['WtMovAvgForecast'] = wt_avg
```

```
y_hat_avg.head()
```

	BirthRate	MeanForecast	MovAvgForecast	WtMovAvgForecast
144	27.132	24.656833	27.520917	27.806115
145	24.924	24.656833	27.520917	27.806115
146	28.963	24.656833	27.520917	27.806115
147	26.589	24.656833	27.520917	27.806115
148	27.931	24.656833	27.520917	27.806115

```
plt.figure(figsize=(12, 8))
plt.plot(df_train.index, df_train.BirthRate, label='Train')
plt.plot(df_test.index, df_test.BirthRate, label='Test')
plt.plot(y_hat_avg.index, y_hat_avg.WtMovAvgForecast, label='Forecast')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f08c1c23550>
```


```
rms = sqrt(mean_squared_error(df_test.BirthRate, y_hat_avg.MovAvgForecast))
# calculates root mean squared error
# between test data & MeanForecast data from train data
rms

```

```
1.4044810849760687
```

Exponential Smoothing

- to forecast univatiate time series data
- uses exponential window function

```
from statsmodels.tsa.api import ExponentialSmoothing, SimpleExpSmoothing, Holt
```

Simple Exponential Smoothing

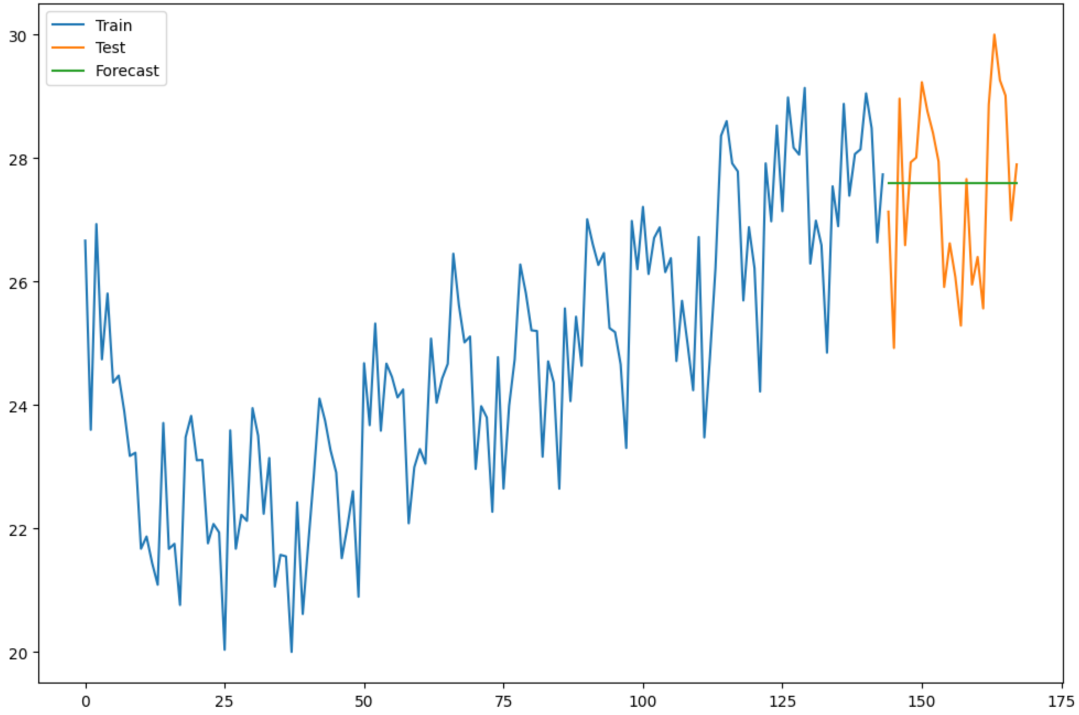
```
# Simple Exponential Smoothing
mod1 = SimpleExpSmoothing(np.asarray(df_train.BirthRate)).fit(smoothing_level=0.8)
```

```
y_hat_avg['SES'] = mod1.forecast(len(df_test))
y_hat_avg.head()
```

	BirthRate	MeanForecast	MovAvgForecast	WtMovAvgForecast	SES
144	27.132	24.656833	27.520917	27.806115	27.591807
145	24.924	24.656833	27.520917	27.806115	27.591807
146	28.963	24.656833	27.520917	27.806115	27.591807
147	26.589	24.656833	27.520917	27.806115	27.591807
148	27.931	24.656833	27.520917	27.806115	27.591807

```
plt.figure(figsize=(12, 8))
plt.plot(df_train.index, df_train.BirthRate, label='Train')
plt.plot(df_test.index, df_test.BirthRate, label='Test')
plt.plot(y_hat_avg.index, y_hat_avg.SES, label='Forecast')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f08bfaa41f0>
```




```
rms = sqrt(mean_squared_error(df_test.BirthRate, y_hat_avg.SES))
# calculates root mean squared error
# between test data & SES data from train data
```

```
rms

```

```
1.4086237555629835
```

Holt's Linear Trend Method

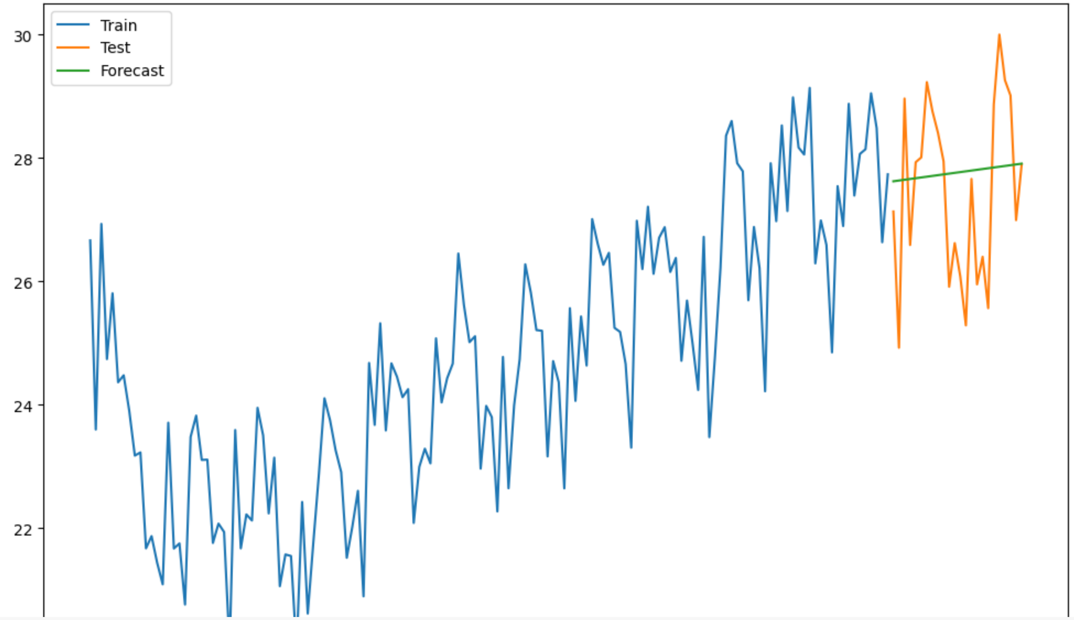
```
# Holt's Linear Trend Method
mod1 = Holt(np.asarray(df_train.BirthRate)).fit(smoothing_level=0.6)
```

```
y_hat_avg['HoltLinear'] = mod1.forecast(len(df_test))
y_hat_avg.head()
```

	BirthRate	MeanForecast	MovAvgForecast	WtMovAvgForecast	SES	HoltLinear
144	27.132	24.656833	27.520917	27.806115	27.591807	27.621742
145	24.924	24.656833	27.520917	27.806115	27.591807	27.634163
146	28.963	24.656833	27.520917	27.806115	27.591807	27.646583
147	26.589	24.656833	27.520917	27.806115	27.591807	27.659004
148	27.931	24.656833	27.520917	27.806115	27.591807	27.671424

```
plt.figure(figsize=(12, 8))
plt.plot(df_train.index, df_train.BirthRate, label='Train')
plt.plot(df_test.index, df_test.BirthRate, label='Test')
plt.plot(y_hat_avg.index, y_hat_avg.HoltLinear, label='Forecast')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f08bf6b4df0>
```




```
rms = sqrt(mean_squared_error(df_test.BirthRate, y_hat_avg.HoltLinear))
# calculates root mean squared error
# between test data & HoltLinear data from train data
rms
```

```
1.4238880670306986
```

Holt-Winter's method

```
mod3 = ExponentialSmoothing(np.asarray(df_train.BirthRate) , seasonal_periods=)
```

```
y_hat_avg['HoltWinter'] = mod1.forecast(len(df_test))
y_hat_avg.head()
```

```
plt.figure(figsize=(12, 8))
plt.plot(df_train.index, df_train.BirthRate, label='Train')
plt.plot(df_test.index, df_test.BirthRate, label='Test')
plt.plot(y_hat_avg.index, y_hat_avg.HoltWinter, label='Forecast')
plt.legend()
```

```
rms = sqrt(mean_squared_error(df_test.BirthRate, y_hat_avg.HoltWinter))
# calculates root mean squared error
# between test data & HoltWinter data from train data
rms
```

ARIMA Model

- ARIMA: Auto-Regressive Integrated Moving Average
- combination of weighted Moving average & ...
- input arguments are dataframe and p, d, q
- d: central value, level of differencing which converts a non-stationary Time-Series into a stationary Time-Series
- p:
- q:
- Stationary time series, mean doesn't change, but
- can be used only when data set is converted into stationary Time-Series
- Differencing

```
4, 8, 5, 9, 6, 8, 7  - actual values
 4, 3, 4, 3, 2, 1    - first level of differecning
   1, 1, 1, 1        - second level of differecning
```

-

AD Fuller test

- for finding the value of 'd' - level of differencing
- to check the stationarity of a time series
- H 0 : the time series is not stationary
- H a : the time series is stationary

```
from statsmodels.tsa.stattools import adfuller
```

```
adfuller(df_train)
# returns (TestStatistic, P-Value, lags, n_obs, critical values, res_store)
# here P-Value 0.972 > 0.05, so H 0 is not rejected
```

```
(0.2017160479163269,
 0.9723576777571017,
 13,
 130,
 {'1%': -3.4816817173418295,
  '5%': -2.8840418343195267,
  '10%': -2.578770059171598},
 322.55907506392055)
```

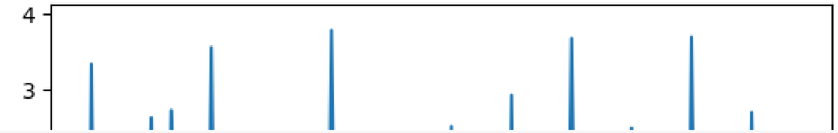
-

```
# after first level of differencing
# d = 1
adfuller(df_train.diff().dropna())
# returns (TestStatistic, P-Value, lags, n_obs, critical values, res_store)
# here P-Value 0.0005 < 0.05, so H 0 is rejected
# so time series is now stationary
```

```
(-4.253904918858687,
 0.0005333378978881231,
 14,
 128,
 {'1%': -3.4825006939887997,
  '5%': -2.884397984161377,
  '10%': -2.578960197753906},
 314.64706729275866)
```

```
plt.plot(df_train.diff())
```

```
[<matplotlib.lines.Line2D at 0x7f08bf877a90>]
```

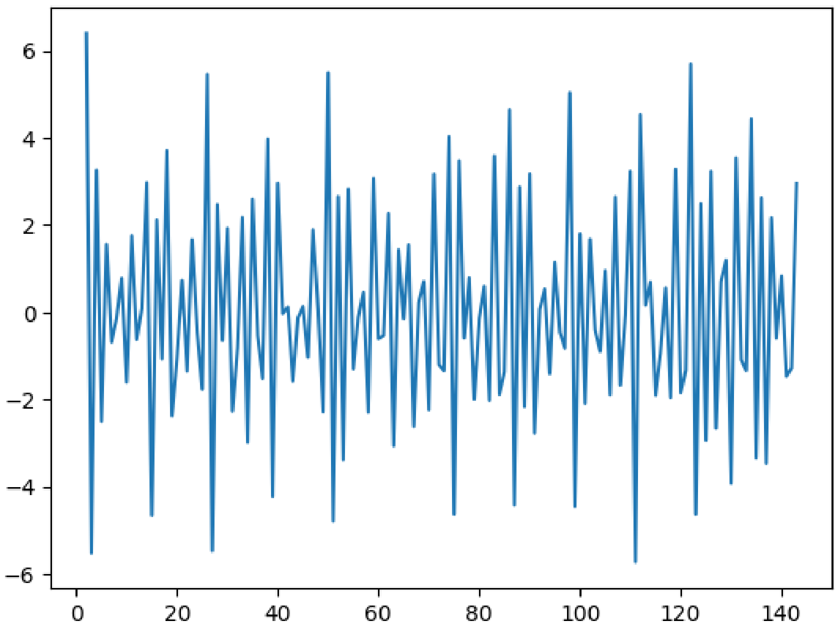



```
# after Second level of differencing
# d = 2 , for double checking if Time-Series is stationary
adfuller(df_train.diff().diff().dropna())
# returns (TestStatistic, P-Value, lags, n_obs, critical values, res_store)
# here P-Value is almost zero < 0.05, so H 0 is rejected
# so time series is now stationary
```

```
(-7.414679804135267,
 6.985733866859221e-11,
 14,
 127,
 {'1%': -3.482920063655088,
  '5%': -2.884580323367261,
  '10%': -2.5790575441750883},
 329.7642316985588)
```

```
plt.plot(df_train.diff().diff())
```

```
[<matplotlib.lines.Line2D at 0x7f08c1b235b0>]
```



```

```

Lag

- Y t : actual values [4, 8, 5, 9, 6, 8, 7] - 0th lag
- Y t+1 : 1st lag
- Y t+2 : 2nd lag
- `Y t` and `Y t+1` have direct relation, `Y t+1` and `Y t+2` have direct relation, so `Y t` and `Y t+2` have indirect relation
-

PACF plot

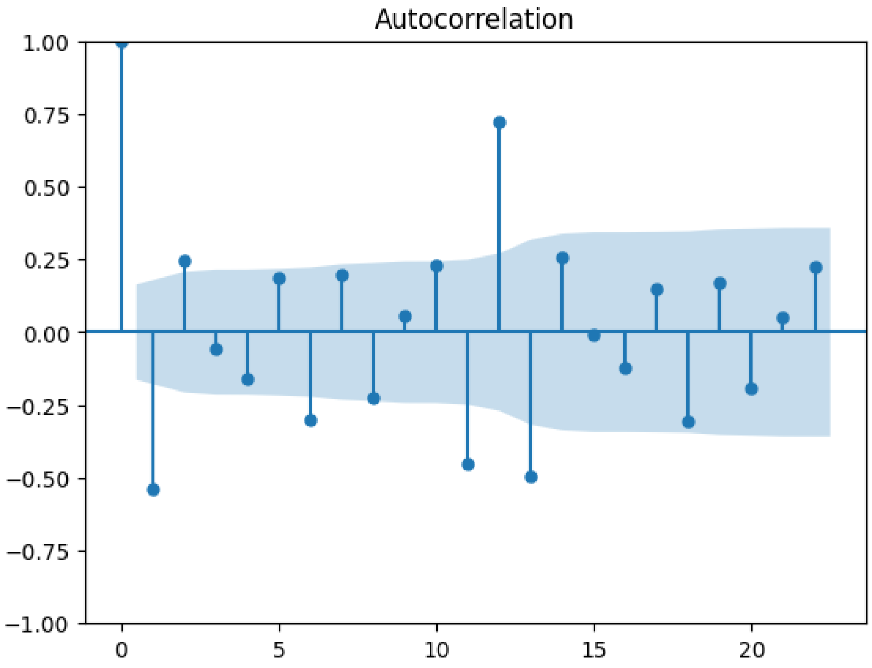
- Partial Auto-Correlation Factor Plot
- gives value of 'p'
- shows only direct correlation

ACF plot

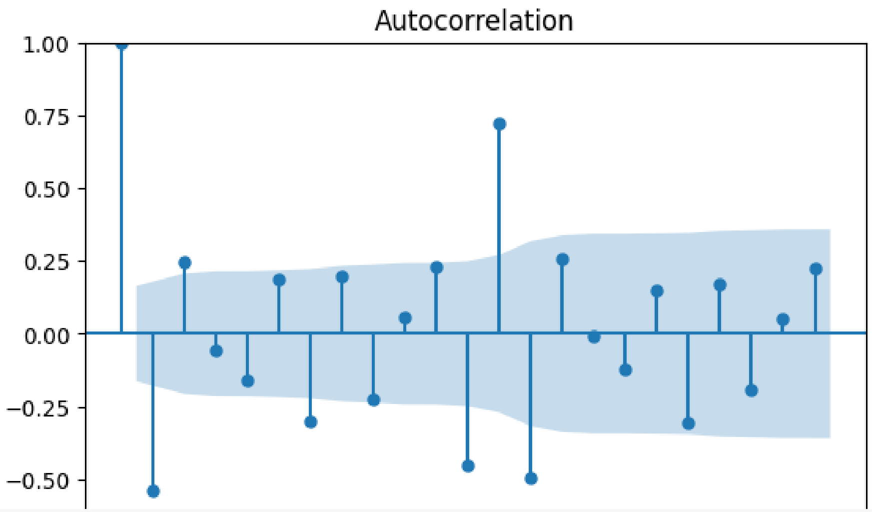
- Auto-Correlation Factor Plot
- gives value of 'q'
- when lag becomes insignnificant, that lag is value of 'q'
- shows direct & indirect correlation

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

```
plt.figure(figsize=(12, 8))
plot_acf(df_train.diff().dropna())
# at zeroth lag, acf value is 1
# you can ignore the acf values
# which are not significant, which lie outside blue area
```

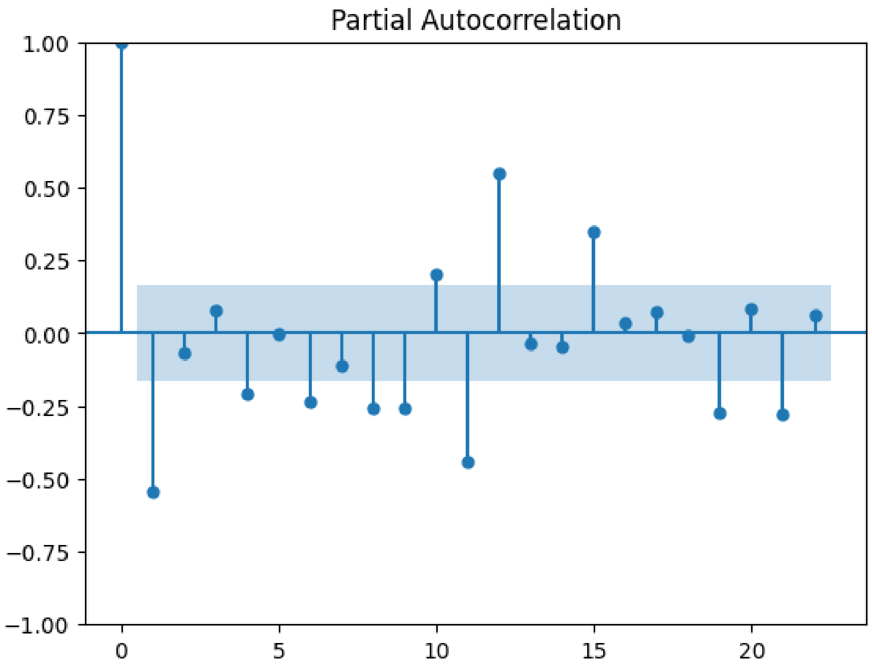


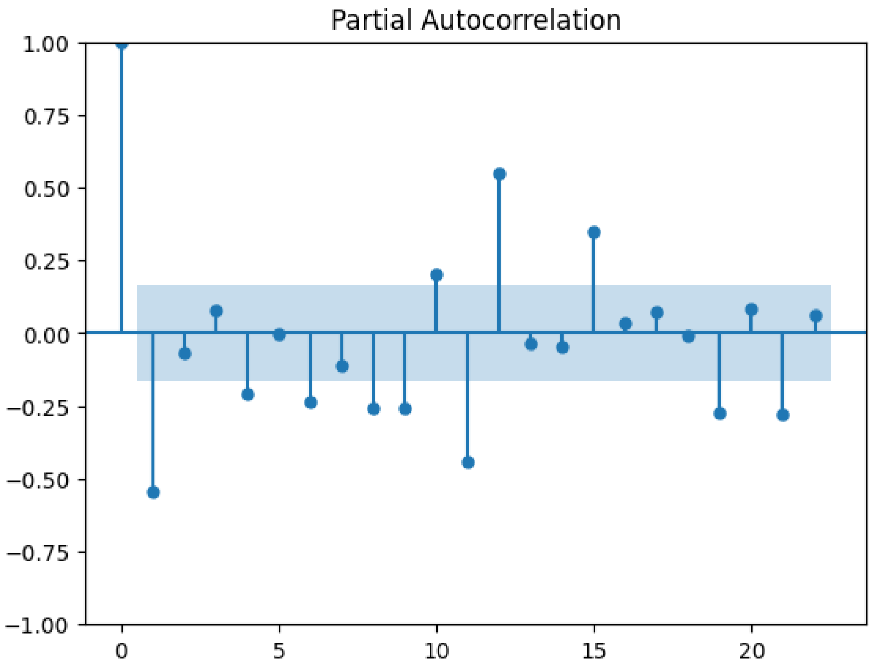

```
<Figure size 1200x800 with 0 Axes>
```




```
plot_pacf(df_train.diff().dropna())
# at zeroth lag, acf value is 1
# you can ignore the acf values
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/graphics/tsaplots.py:348: FutureWarnin
  warnings.warn(
```





- d = 1 [level of differencing]
- p = 1 [from PACF graph]
- q = 2 [from ACF graph]

ARIMA

```
from statsmodels.tsa.arima.model import ARIMA
```

```
mod4 = ARIMA(df_train, order=(1, 1, 2)).fit()
#ARIMA(df_train, order=(d, p, q)).fit()
```

```
pred = mod4.predict(len(df_test))
```

```
rms = sqrt(mean_squared_error(df_test.BirthRate, pred))
# calculates root mean squared error
# between test data & pred data  generated using train data into ARIMA
rms

```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-86-6f72ff0494ed> in <cell line: 1>()
----> 1 rms = sqrt(mean_squared_error(df_test.BirthRate, pred))
      2 # calculates root mean squared error
      3 # between test data & pred data  generated using train data into ARIMA
      4 rms

2 frames

/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py in
check_consistent_length(*arrays)
    395     uniques = np.unique(lengths)
    396     if len(uniques) > 1:
--> 397         raise ValueError(
    398             "Found input variables with inconsistent numbers of samples: %r"
    399             % [int(l) for l in lengths]

ValueError: Found input variables with inconsistent numbers of samples: [24, 120]
```

SEARCH STACK OVERFLOW