Smoothing Forecasting Technique

Agenda

- Forecasting range
- Splitting time series data for training and testing
- Performance of time series model

Agenda

- Simple forecast
- Exponential smoothing
  - Simple exponential smoothing
  - Double exponential smoothing (Holt model)
  - Triple exponential smoothing (Holt-Winter model)

Building Forecasting Models

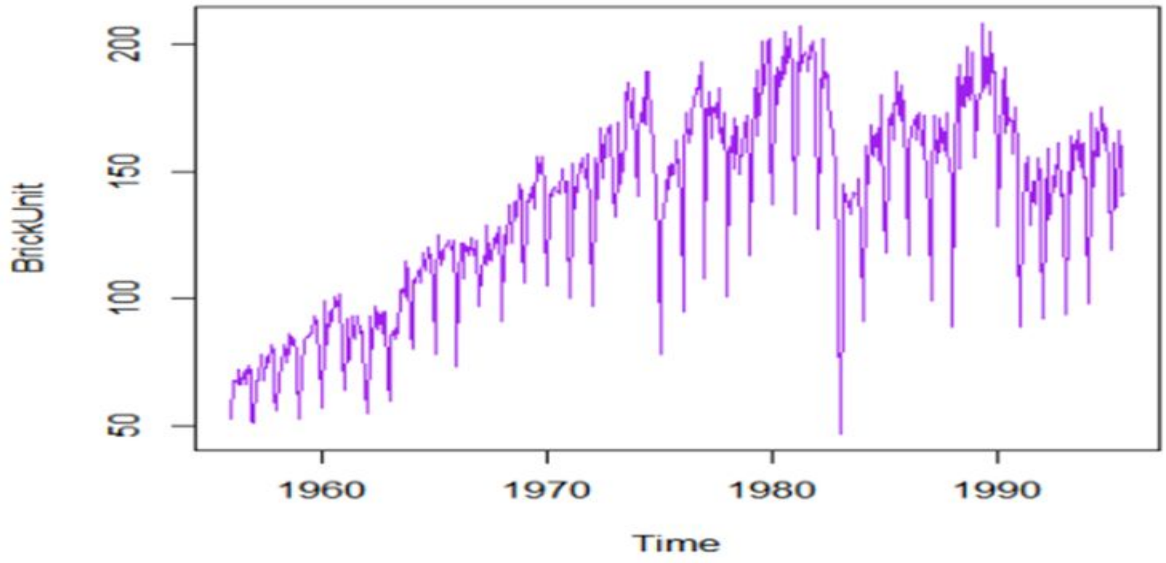
Gathering information

- Historical data is required to build the model for future prediction.
- If volume of data is limited, forecasts will not be reliable enough.
- If data is available for very long past, data may not be useful at all

Gathering information

Example: Clay Brick Production

Monthly production of clay bricks (in Millions)



To learn to forecast!

- Not all time series are equally easy or difficult to forecast. It depends on
  - How well the contributing factors are understood
  - How much data is available

Year	Quarter	Turnover
1982	Q3	13423.2
1982	Q4	13128.8
1983	Q1	15398.8
1983	Q2	12964.2
1983	Q3	13133.5
1983	Q4	13271.7
1984	Q1	15596.3
1984	Q2	13018
1984	Q3	13409.3
1984	Q4	13304.2

We should not try to forecast if the available is for a short duration

Will not provide reliable forecast for next 8 quarters

Might get a working forecast for the next 3-4 quarters

Forecast Range

- Different industry needs forecast for different range for different purpose with different accuracy.
- Based on the amount of data availability, one should not try to forecast more than a few periods ahead.
- Example: Airlines industry can be interested in passenger volume forecast for
    - Long-term forecast: 5-10 years :- Strategic decision making
    - Mid-term forecast: 2-5 years :- Manpower hiring / Route alteration
    - Short-term forecast: 2 weeks - 6 months :- Pilot / Cabin Crew rostering

Forecast Range

- Very long range forecasts do not work well!!

- Forecasts are done under the assumption that the market and other conditions in future are very much like the present.

- Not that there will be no change in the market, but the change is gradual and not a drastic change

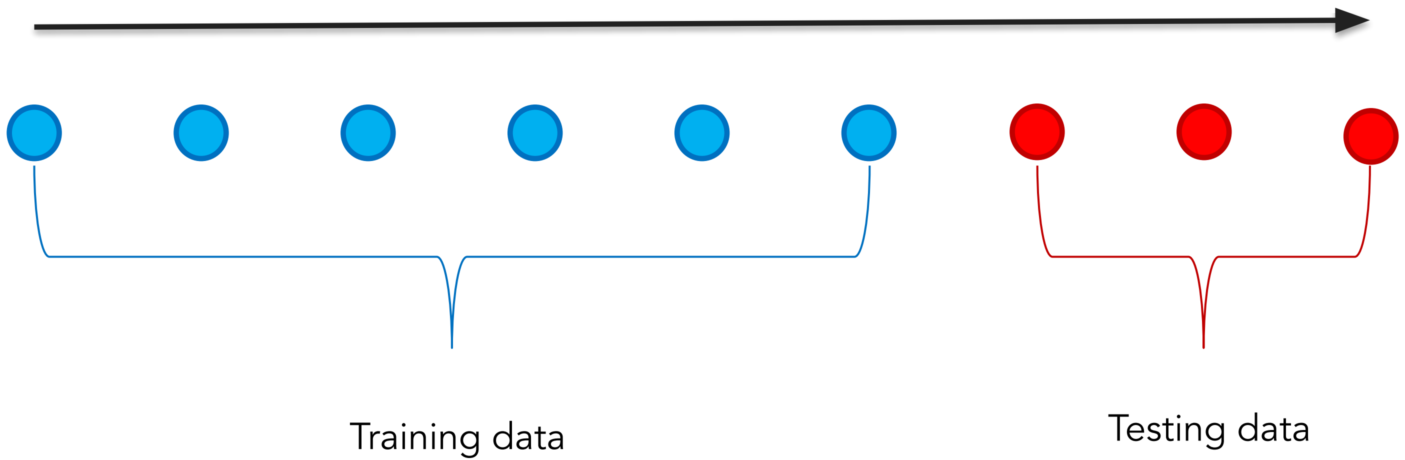
- Examples: Events like Demonetization or 2008 US financial crises or COVID-19 pandemic would throw the forecasts into disarray.

Model Validation

Splitting time series data

- For other predicting models hold-out sample is randomly chosen from the total sample usually in 80:20 ratio.

- For time series , the hold out data should be the most recent part of data.



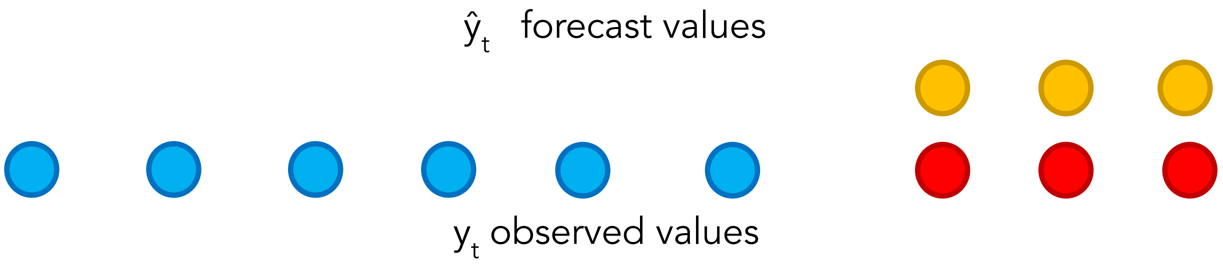
Splitting time series data

- If there is seasonality in the data, the at least one full season's data need to be held out for validation.

- Once a model is selected, held-out period must be incorporated into the sample for final forecasts for future

Measures of forecast accuracy

- Performance of forecast method is tested by comparing the forecast values with the test sample observations.
- Can compare the observed and forecast values through various statistical measures.



Measures of forecast accuracy

- Sum of squares of residuals

$$RSS = \sum (y_t - \hat{y}_t)^2$$

- Mean of squares of residuals

$$MSS = \frac{1}{T} \sum (y_t - \hat{y}_t)^2$$

- Mean absolute deviation

$$MAD = \frac{1}{T} \sum |y_t - \hat{y}_t|$$

- Mean absolute percent error

$$MAPE = \frac{1}{T} \sum [(|y_t - \hat{y}_t|) / y_t] \times 100$$

Simple Forecast

Simple forecast

- Examples of Simple forecast methods:
    - Naïve Forecast
    - Average Forecast
    - Moving Average Forecast

Naïve Forecast

- Naïve forecast is simplest forecasting method; uses the most recently observed value in the time series as the forecast for the next period.
- Prior observations are not considered.
- Example: for given time series, forecast for the next time period would be;

$$\hat{y}_{t+1} = y_t = 17342.3$$

Time period	y_1	y_2	y_3	y_4	………	Y_{t-1}	y_t
Quarter	1982-Q3	1982-Q4	1983-Q1	1983-Q2	……	1991-Q4	1992-Q1
Turnover	13432.2	13128.8	15398.8	12964.2	……	14914.3	17342.3

Average Forecast

- In this method, future forecast are developed by calculating average of all time series observations.
- Example: for given sample time series, forecast for the next time period would be;

$$\hat{y}_{t+1} = \frac{y_1 + y_2 + y_3 + y_4 + \ldots\ldots + y_{t-1} + y_t}{\text{no of observations}}$$

Time period	y_1	y_2	y_3	y_4	....	Y_{t-1}	y_t
Quarter	1982-Q3	1982-Q4	1983-Q1	1983-Q2	......	1991-Q4	1992-Q1
Turnover	13432.2	13128.8	15398.8	12964.2	......	14914.3	17342.3

Moving average Forecast

- In this forecasts, all future values are equal to the moving average of the historical data
  - Take average over a window of certain width of the time series to forecast the future values.
  - Move the window to update the average value.
  - More the number of periods in the moving average, the greater the smoothing effect.
- Simple moving average formula can be written as;

$$\hat{y}_{t+1} = \frac{y_t + y_{t-1} + y_{t-2} + y_{t-3} + \ldots\ldots + y_{t-n+1}}{\text{no of observations}}$$

where, $\hat{y}_{t+1}$ = Forecast for the coming period

y_t = last observation of time series

n = window to calculate moving average

Limitations of moving average forecast

- Equal importance is given to each observation used in the moving average calculation, whereas most recent observations are more relevant to current conditions for predicting forecast.

- The moving average calculation does not consider data outside the window of average, therefore available data is not fully utilized.

- Moving average as a forecast can give misleading results when there is an underlying seasonality in time series.

Exponential Smoothing

Exponential smoothing

- The exponential smoothing technique is a weighted moving average procedure where exponential declining of weights happens as data become older.

- More weightage is given to the recent observations.

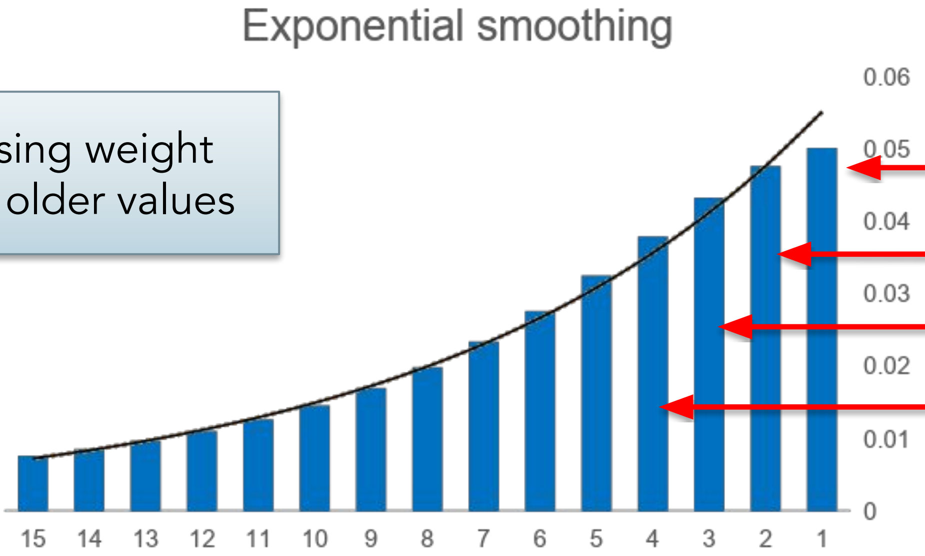
- One or more smoothing parameters control how fast the weights decay.

- These parameters have values between 0 and 1

Exponential smoothing

$0 < \alpha < 1$

Decreasing weight
given to older values



α

$\alpha(1 - \alpha)^1$

$\alpha(1 - \alpha)^2$

$\alpha(1 - \alpha)^3$

Characteristics of exponential smoothing

- Higher weights are given to more recent observations.
- All past data can be considered as there is no cut-off point as in case of moving averages.
- This technique adapts continually as new data becomes available.
- The basic model needs to be modified to cope up with trends and seasonality based on which exponential smoothing technique is used:
    - Simple exponential smoothing
    - Double exponential smoothing
    - Triple exponential smoothing

Simple exponential smoothing (SES)

- This technique can be used if the time series has neither a pronounced trend nor seasonality.
- Performance of the smoothing parameter α controls performance of the method.
- This method can be represented as;

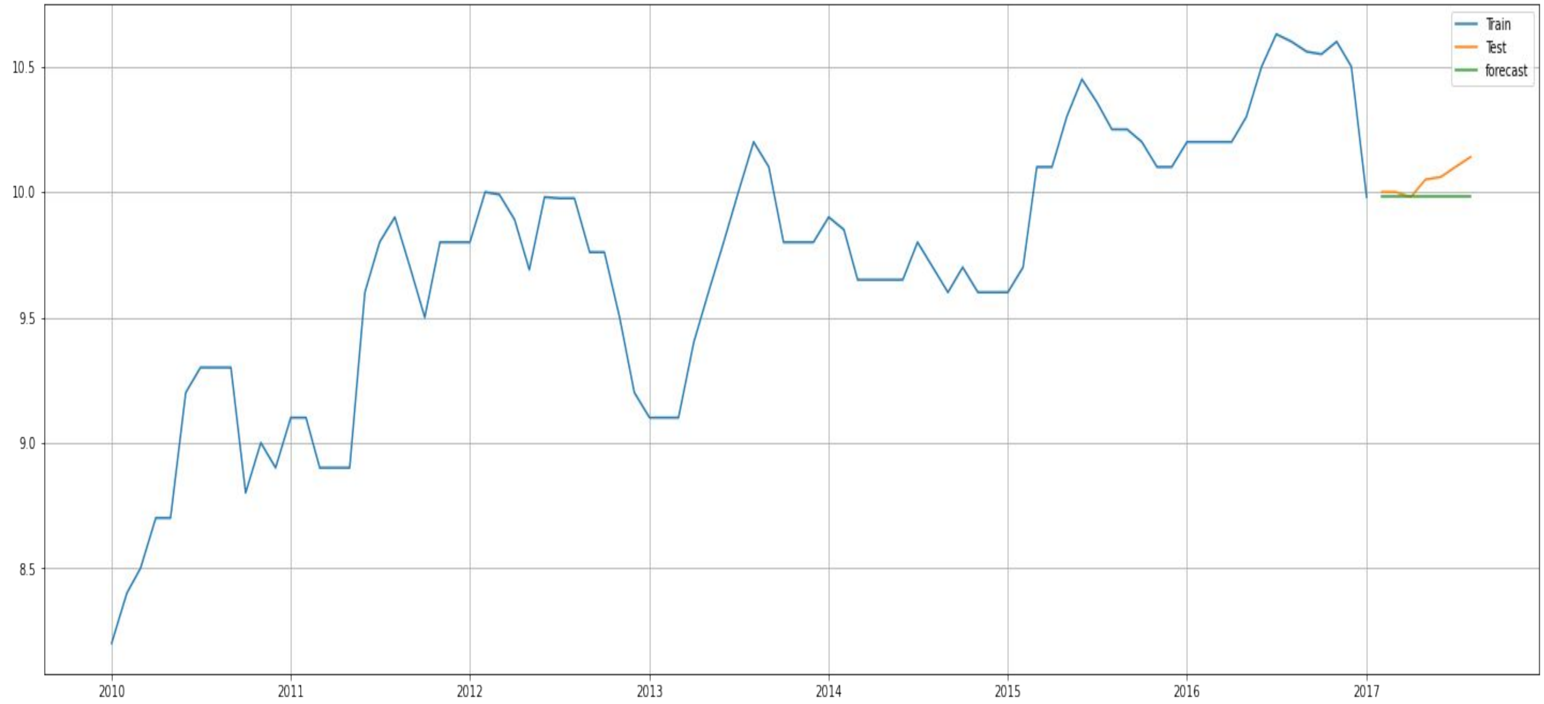
Next forecast = Latest forecast + α (Latest Observation – Latest Forecast)

$$\hat{y}_{t+1} = \hat{y}_t + \alpha (y_t - \hat{y}_t)$$

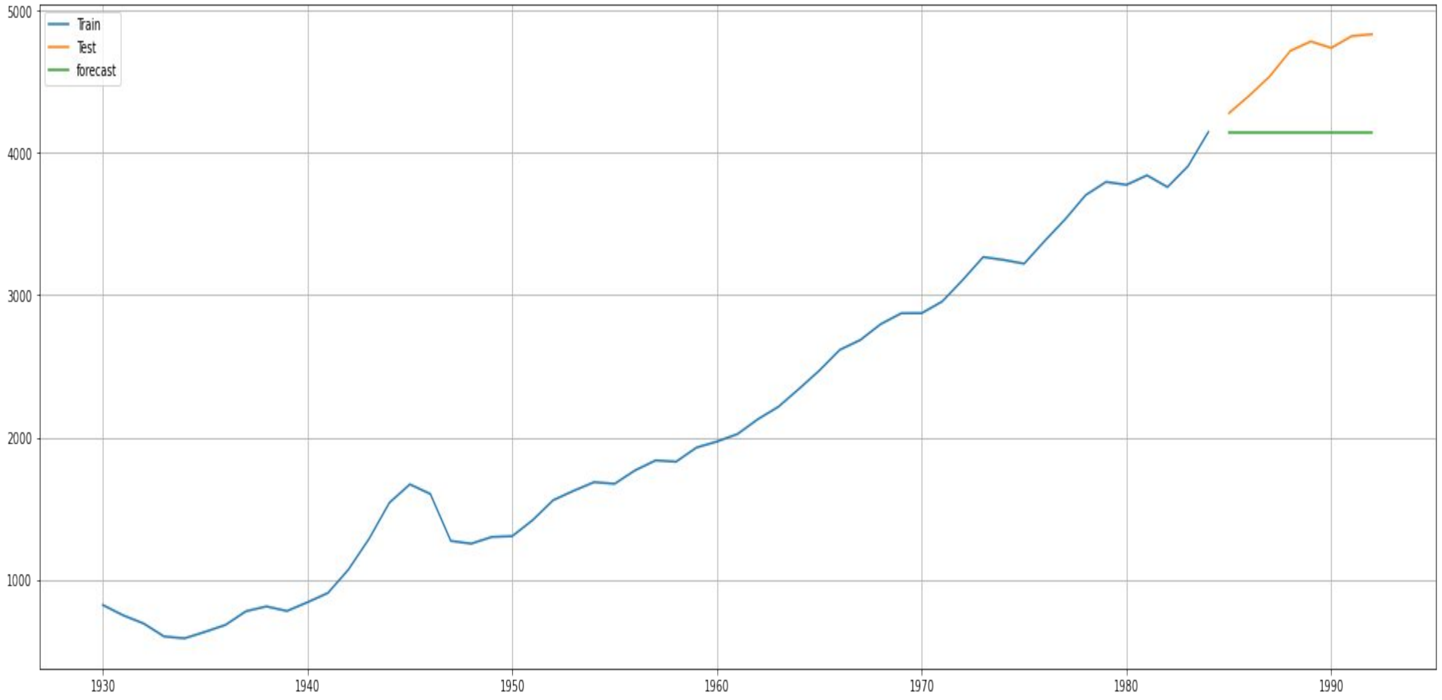
Simple exponential smoothing (SES)

- The higher is the value of α (i.e. the nearer to 1), the forecast becomes more sensitive to latest observations.
- The lower is the value of α (i.e. the nearer to 0), forecast will be less sensitively to latest observations.
- Simple exponential forecast technique can not cope up with trends and seasonality present is time series.

SES Forecast for oil production TS



SES Forecast for US-GDP TS



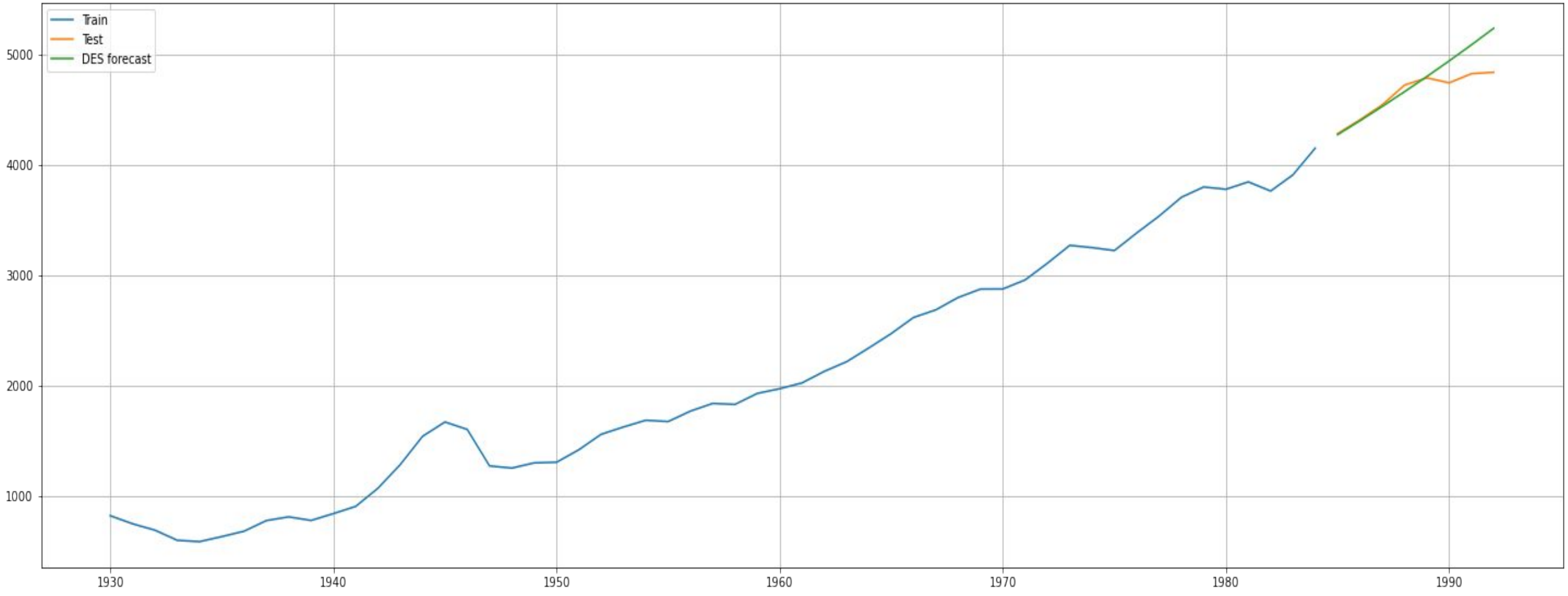
Double exponential smoothing (DES)

- This technique is the extension of Simple exponential smoothing (SES).
- Also called as Holt's linear trend method.
- Allow the forecasting of data with a trend.
- This technique considers two separate components:
    - Level : captures short term average value
    - Trend : captures the trend

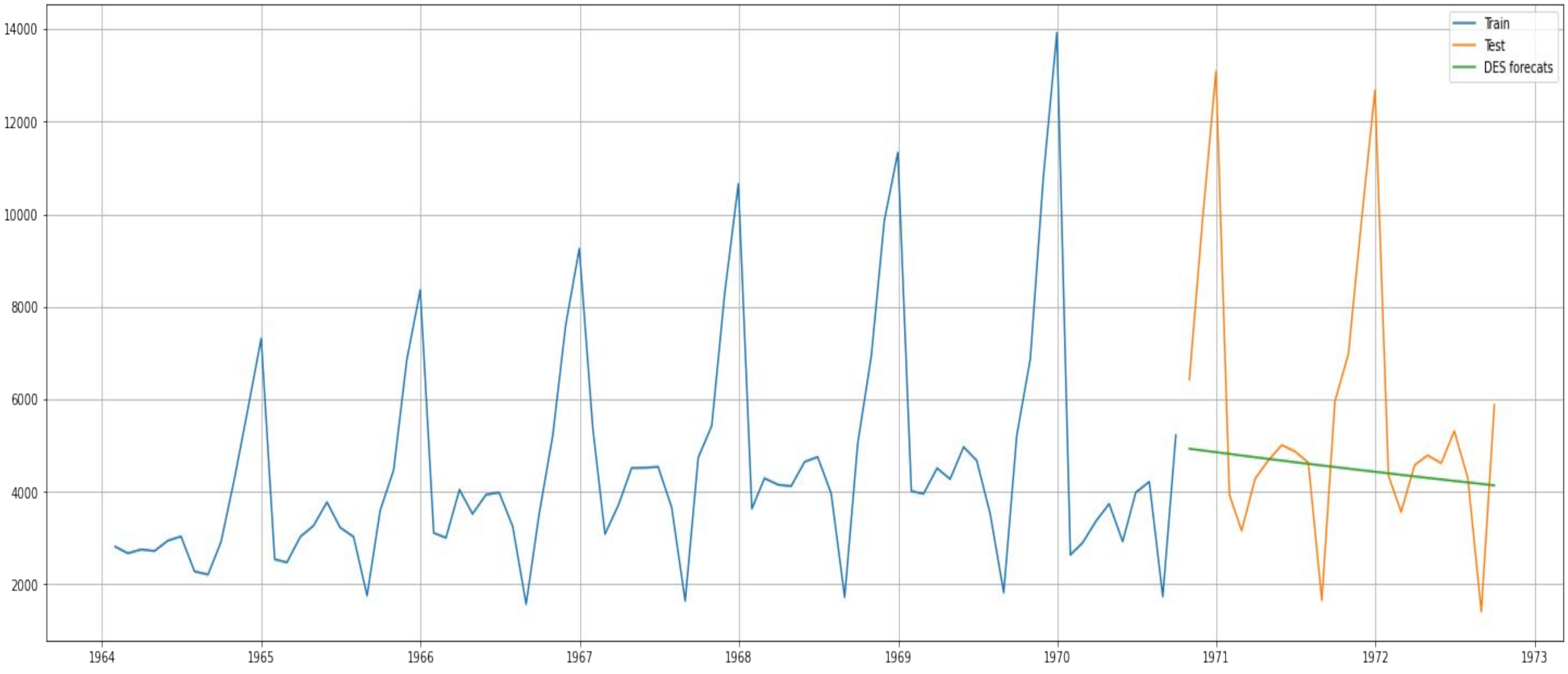
Double exponential smoothing (DES)

- First smoothing parameter α corresponds to the level series.
- Second smoothing parameter β corresponds to the trend series.

DSE for US GDP TS



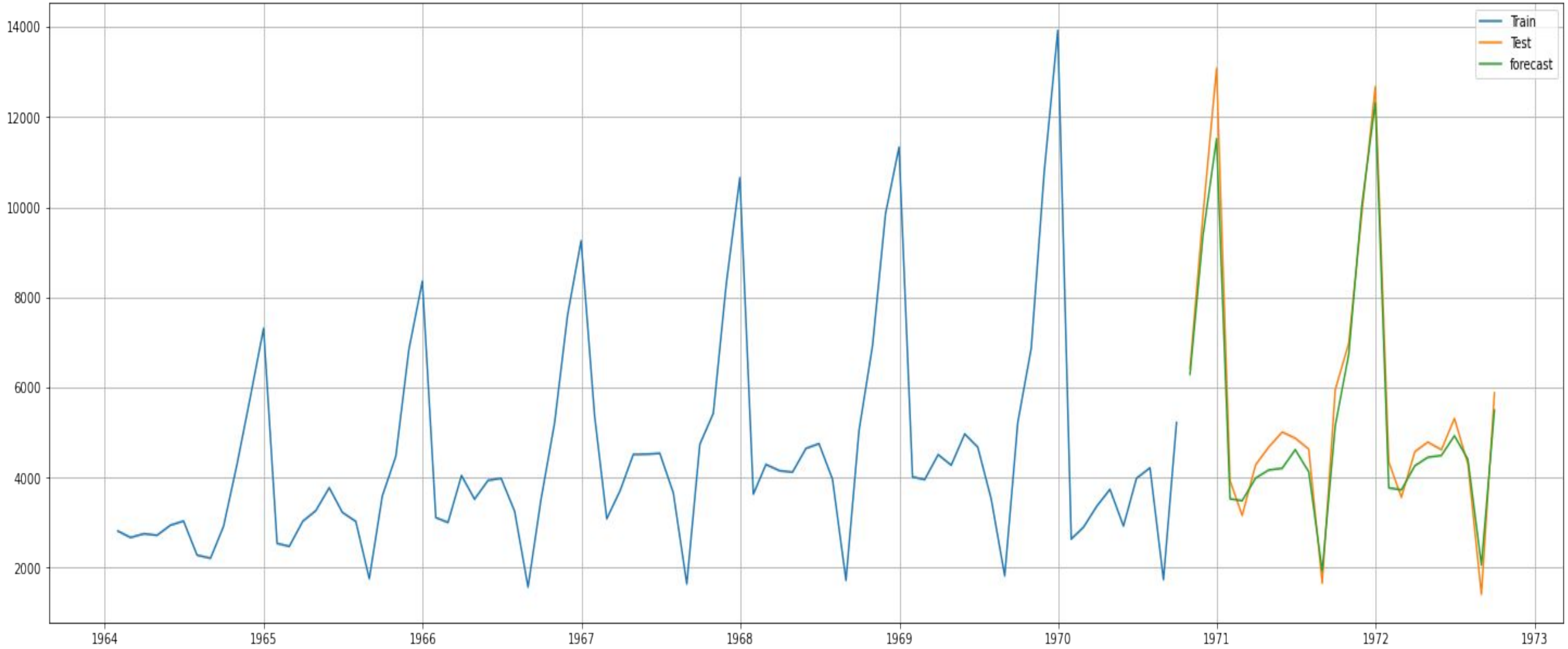
DSE forecast for Champagne TS



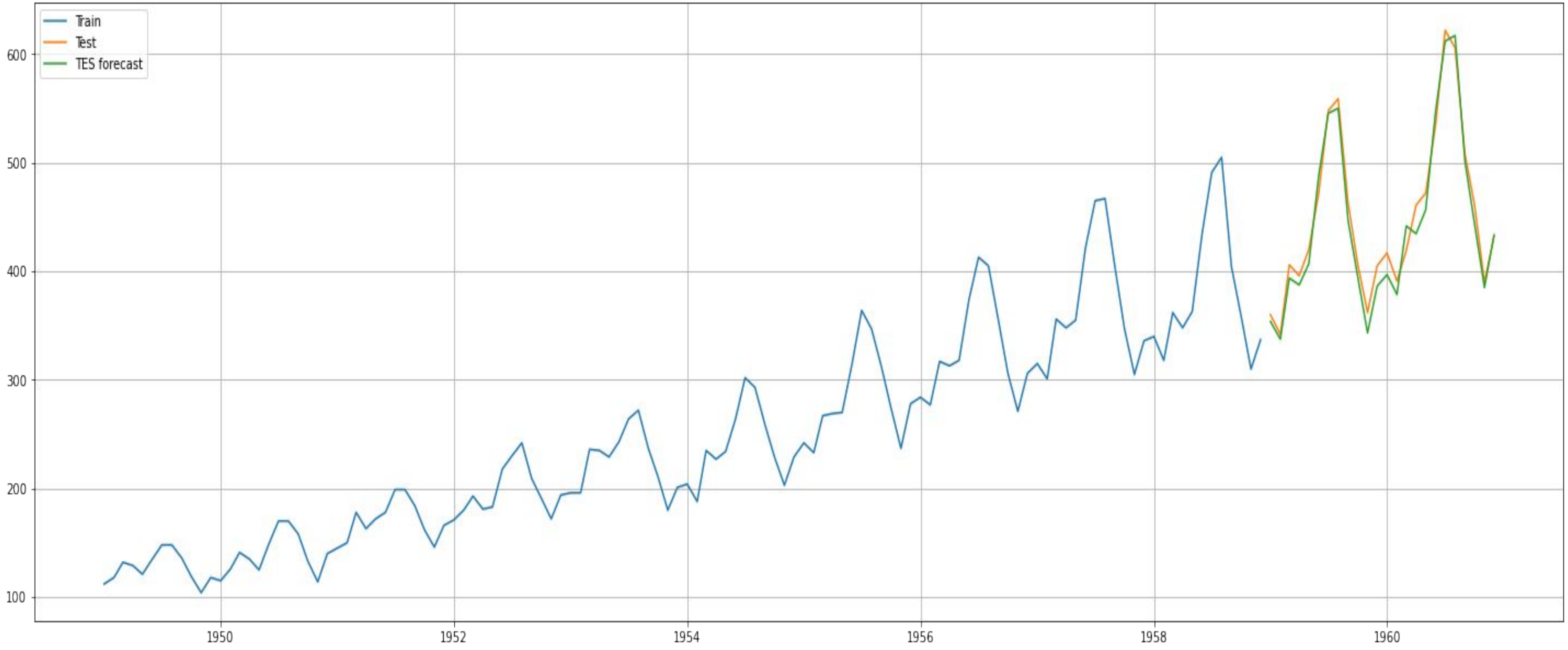
Triple Exponential Smoothing

- Also called as Holt-Winter's model.
- This model helps to capture seasonality associated with the time series data.
- As seasonality can be additive or multiplicative, Holt-Winter's model can also be additive or multiplicative.
- This method comprises of three components:
    - Level components (L_t)
    - Trend components (T_t)
    - Seasonal component (S_t)

TES-forecast for Champagne TS



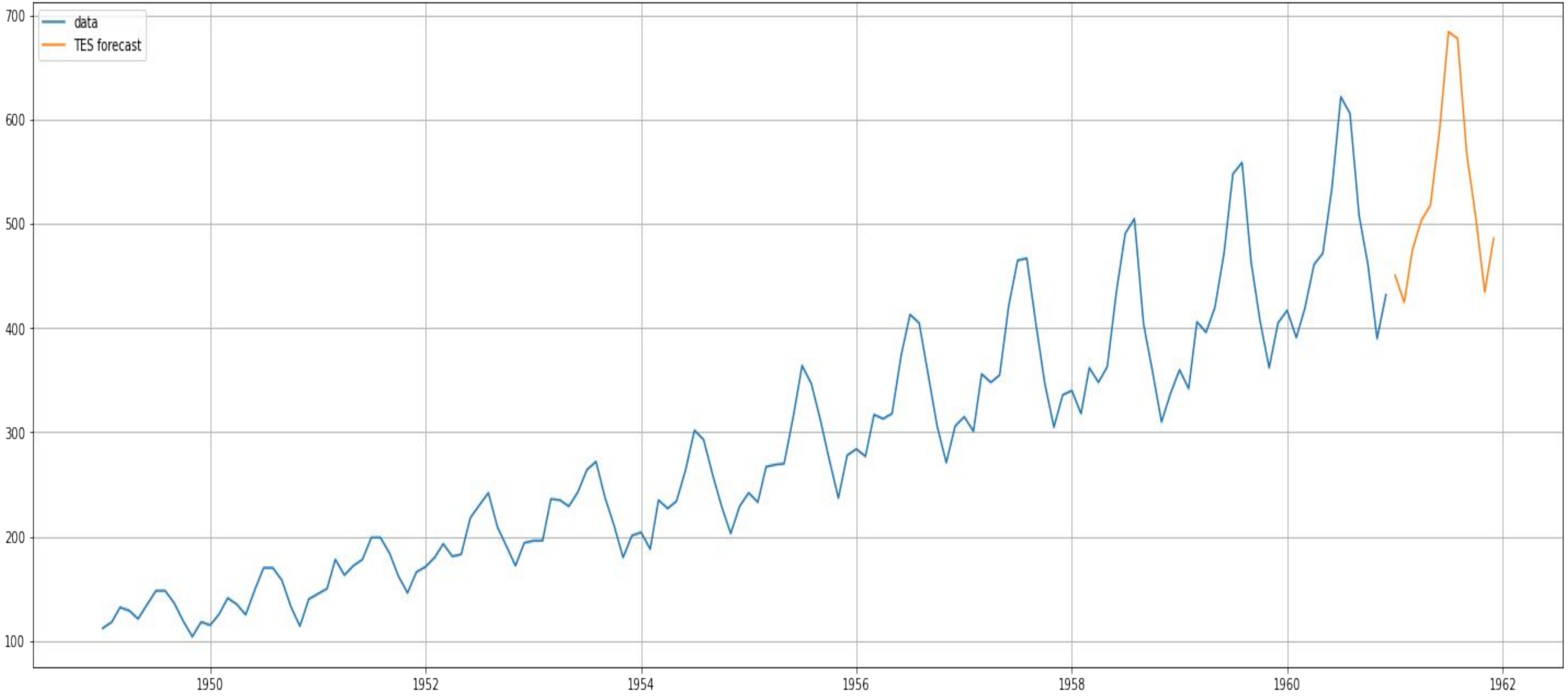
TES-multiplicative forecast for Air Passenger TS



Model Performance

Time Series	Forecasting technique	RMSE	MAPE
Oil Production	Simple ES	0.086	0.66
US GDP	Double ES	183.92	2.51
Champagne consumption	Holt-Winter_ADD	519.85	9.32
Air Passenger	Holt-Winter_MUL	13.87	2.81

Actual Forecast



Summary

- Forecasting range
- Splitting time series data
- Forecasting technique performance evaluation
- Simple forecasting technique
- Exponential forecasting technique

Thank You