greatlearningForecast 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, not a drastic change
- A financial crash like 2008 US market will send all forecasts into a tizzy
- Events like Demonetization would throw the forecasts into disarray

Based on the amount of data availability, one should not try to forecast more than a few periods ahead

Scope of Module Scope of Module

- Only univariate TS is explored
- No attempt made to forecast more than one interdependent TS
- The variable measured in TS is assumed to be continuous and have fairly decent volume
- Intermittent demand TS is not considered

Gathering Information

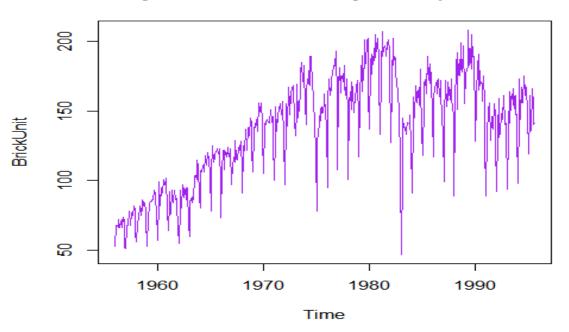
Historical data required for future prediction

If volume of data is limited, forecasts will not be reliable enough

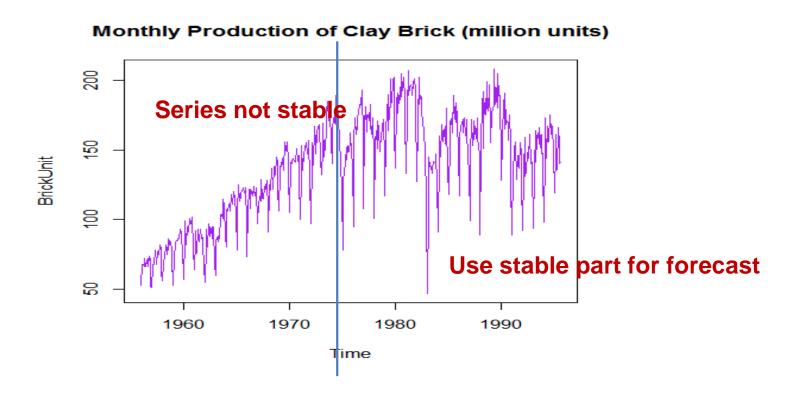
If data is available for very long past, data may not be useful at all

Example: Clay Brick Production

Monthly Production of Clay Brick (million units)



Example: Clay Brick Production



Forecast Range

Different industry needs forecast for different range for different purpose with different accuracy

Example: Airlines industry: Interested in passenger volume forecast

- 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
 - Dynamic pricing

Forecast

Simple Forecast

- Naïve Forecast: Use the last observed value
- Average Forecast:
- Moving Average Forecast:
 - Take average over a window of certain width
 - Move the window

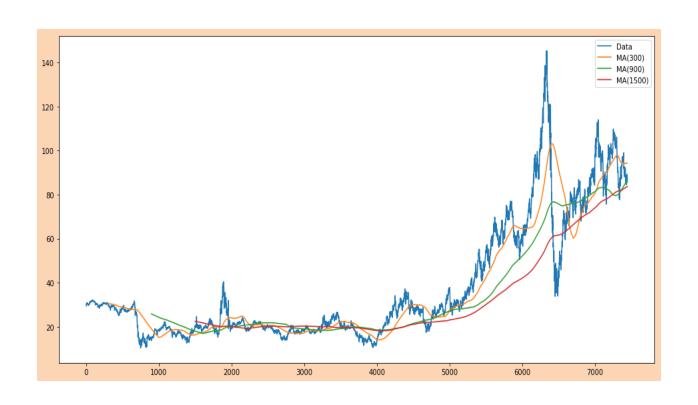
None of these work well even for the most regular series

greatlearningMoving Average

 One of the most popular and oftenused technical indicators to understand stock movement

 The moving average is easy to calculate and, once plotted on a chart, is a powerful visual trend-spotting tool.

Long Term Movement



EXPONENTIAL SMOOTHING FORECAST

Model Validation

Predictive power of a model is estimated by comparing its forecasting performance on a Test Data

A part of sample data is used to train (develop) the model: Training Data

A part of sample is withheld from estimation process: Test Data

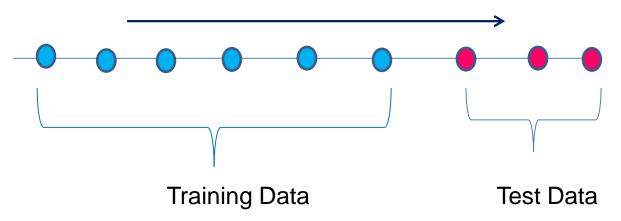
The model which gives smallest measure of error between forecast and actual series is the 'best'

greatlearningModel Validation

- Training Data is used to identify a few working models
- The forecasts for training data are called fitted values
- Each of the models is tested against the observed values of the series for hold-out period
- The model is selected to be the best where observed and forecasted values are the closest

Model Validation

- For other predicting models hold-out sample is randomly chosen from the total sample
- Usually in 80:20 ratio
- For time series hold-out sample has to be the most recent period because of the ordered nature of the data

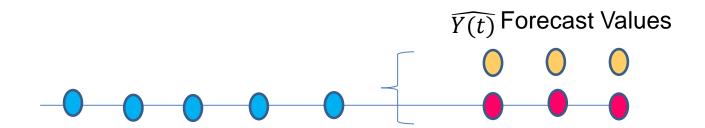


Model Validation

- 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



Y(t)Observed Values

Compare the observed and forecast values through various methods

Measures of Forecast Accuracy

Residual sum of squares

$$RSS = \sum (Y(t) - \widehat{Y(t)})^{2}$$

Mean sum of squares

$$MSS = \frac{1}{T} \sum (Y(t) - \widehat{Y(t)})^{2}$$

Mean absolute deviation

$$MAD = \frac{1}{T} \sum (|Y(t) - \widehat{Y(t)}|)$$

Mean absolute percent error

MAPE =
$$\frac{1}{T} \sum \left[\left(|Y(t) - \widehat{Y(t)}| \right) / Y(t) \right] \times 100$$

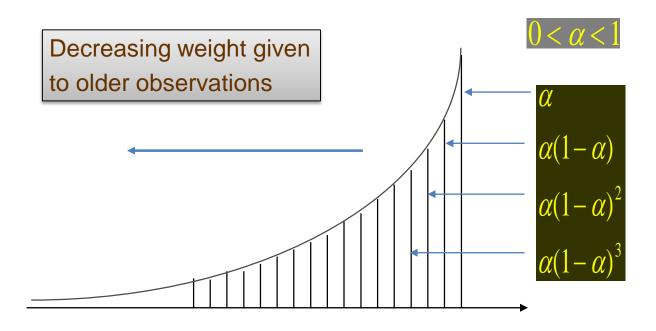
Forecast by Average

- Using mean of all past observations easiest, intuitive, naïve
- Naturally does not work well!!
- Can this scheme be modified to get useful forecasts?

greatlearningExponential Smoothing

- Weighted averages of past observations
- Weights decaying as observations get older
- Practically speaking, only the recent observations matter
- One or more parameters control how fast the weights decay
- These parameters have values between 0 and 1

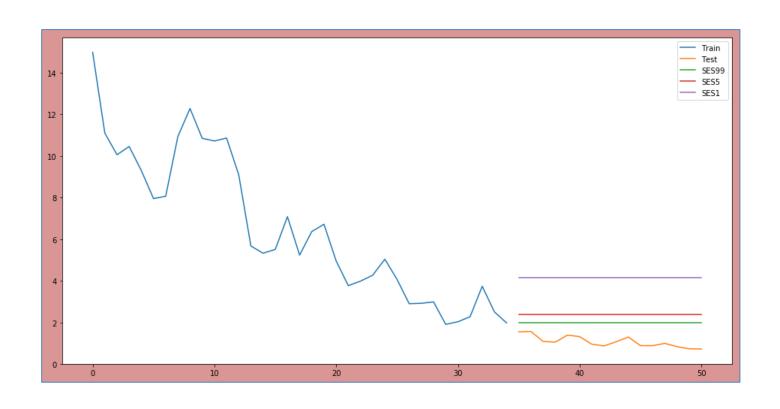
Exponential Smoothing



Simple Exponential (SES)

If the time series neither has a pronounced trend nor seasonality: Almost non-available!

Petrol Consumption



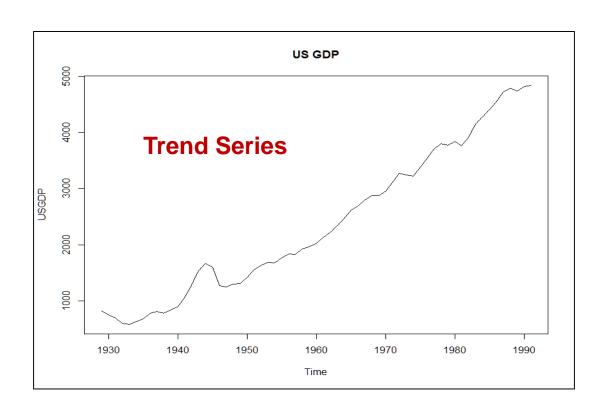
greatlearning Exponential Smoothing

- Performance of the smoothing parameter α controls performance of the method
- If α is closer to 1, forecasts follow the actual observations more closely
- If α is closer to 0, forecasts are farther from the actual observations and the line is smooth

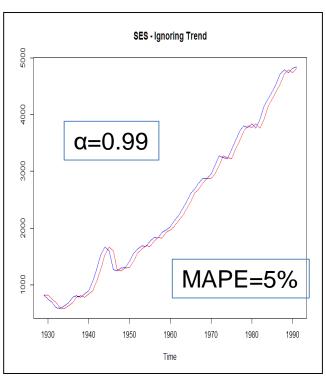
Double Exponential

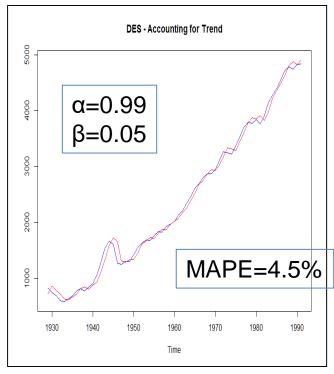
- Applicable when data has Trend but no seasonality
- An extension of SES
- Two separate components are considered: Level and Trend
- Level is the local mean
- One smoothing parameter α corresponds to the level series
- A second smoothing parameter β corresponds to the trend series
- Also known as Holt model

Caselet V: US GDP

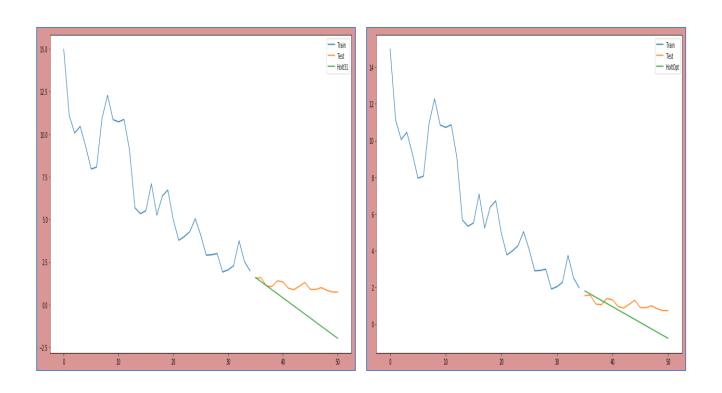


Caselet V: US GDP

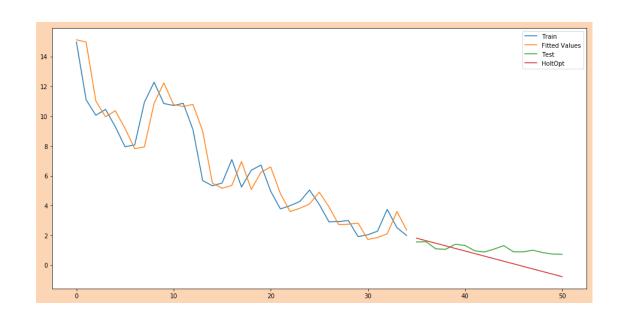




Petrol Consumption



Petrol Consumption



Exponential Smoothing with Seasonality: Holt-Winters' Model

- Because Seasonality can be additive or multiplicative, HW model can be additive or multiplicative
- Simultaneously smooths the level, trend and seasonality
- Three separate smoothing parameters

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• \alpha: Smooths level; 0 < \alpha < 1
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• β : Smooths trend; $0 < \beta < 1$

γ: Smooths seasonality; 0 < γ < 1

Champagne Sales

Model Estimates

Smoothing parameters:

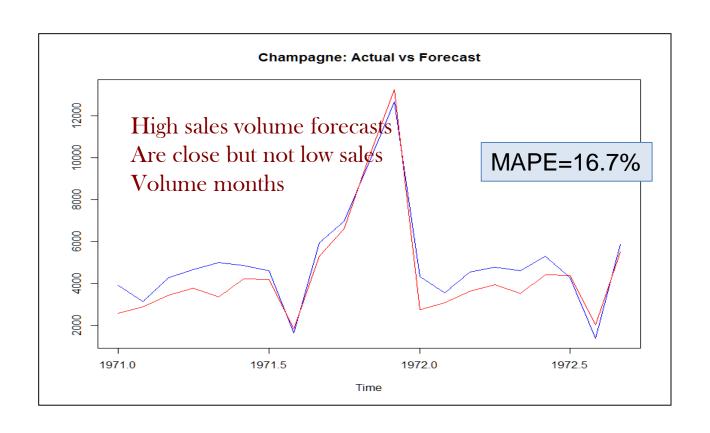
alpha = 0.0842

beta = 1e-04

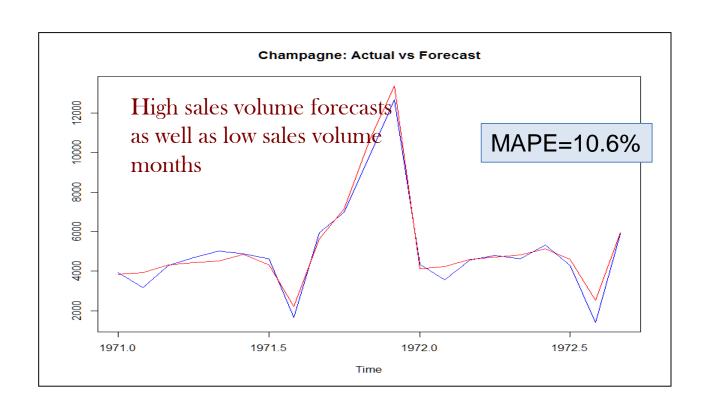
gamma = 0.7608

- Smoothing parameter for trend (β) almost 0 corroborates well with insignificant YOY movement
- Smoothing parameter for seasonality(γ) fairly high that almost all fluctuations are due to seasonality

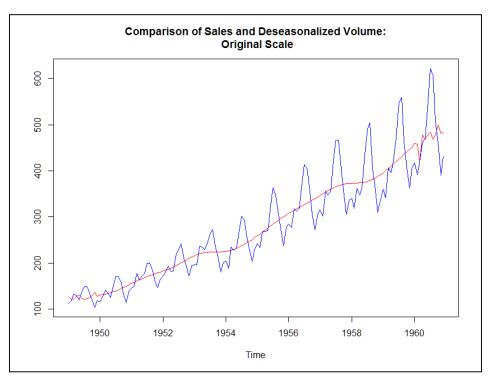
Champagne Sales



Champagne Sales



Passenger Volume



Significant trend and seasonality both

Passenger Volume

Model Estimates

Smoothing parameters:

alpha = 0.3515

beta = 0.0147

gamma = 0.6481

- Smoothing parameter for trend (β) small compared to other parameters
- Indicates almost a straight line trend
- Smoothing parameter for seasonality(γ) fairly high

Passenger Volume

Passenger Volume: Actual vs Forecast

