SCHOOL OF INFORMATION TECHNOLOGY AND ENGINEERING
ITA5007-Data Mining and Business Intelligence
MCA

Topic :
1. Time series models -- Simple Exponential Smoothing

Description:

What Is Exponential Smoothing?

Exponential smoothing is a time series forecasting method for univariate (data has only one variable) data. Time series methods like the Box-Jenkins ARIMA family of methods develop a model where the prediction is **a weighted linear sum of recent past observations or lags** (intervals).
Exponential smoothing forecasting methods are similar in that a prediction is a weighted sum of past observations, but the model explicitly uses an exponentially decreasing weight for past observations.

Collectively, the methods are sometimes referred to as ETS models, referring to the explicit modelling of Error, Trend and Seasonality.

Types of Exponential Smoothing

There are three main types of exponential smoothing time series forecasting methods.

Single Exponential Smoothing:

Single Exponential Smoothing, SES for short, also called Simple Exponential Smoothing, is a time series forecasting method for univariate data without a trend or seasonality. It requires a single parameter, called alpha (α), also called the smoothing factor or smoothing coefficient.

This parameter controls the rate at which the influence of the observations at prior time steps decay exponentially. Alpha is often set to a value between 0 and 1. Large values mean that the model pays attention mainly to the most recent past observations, whereas smaller values mean more of the history is taken into account when making a prediction.

α value close to 1 indicates fast learning (that is, only the most recent values influence the forecasts), whereas a value close to 0 indicates slow learning (past observations have a large influence on forecasts).
Hyperparameters:

Alpha: Smoothing factor for the level.

Double Exponential Smoothing:

Double Exponential Smoothing is an extension to Exponential Smoothing that explicitly adds support for trends in the univariate time series. In addition to the alpha parameter for controlling smoothing factor for the level, an additional smoothing factor is added to control the decay of the influence of the change in trend called beta (b). The method supports trends that change in different ways: an additive and a multiplicative, depending on whether the trend is linear or exponential respectively.

Double Exponential Smoothing with an additive trend is classically referred to as Holt's linear trend model, named for the developer of the method Charles Holt.

Additive Trend: Double Exponential Smoothing with a linear trend.

Multiplicative Trend: Double Exponential Smoothing with an exponential trend. For longer range (multi-step) forecasts, the trend may continue on unrealistically. As such, it can be useful to dampen the trend over time. Dampening means reducing the size of the trend over future time steps down to a straight line (no trend).

Hyperparameters:

Alpha: Smoothing factor for the level.
Beta: Smoothing factor for the trend.
Trend Type: Additive or multiplicative.
Dampen Type: Additive or multiplicative.
Phi: Damping coefficient.

Triple Exponential Smoothing:
Triple Exponential Smoothing is an extension of Exponential Smoothing that explicitly adds support for seasonality to the univariate time series. This method is sometimes called Holt-Winters Exponential Smoothing, named for two contributors to the method: Charles Holt and Peter Winters. In addition to the alpha and beta smoothing factors, a new parameter is added called gamma (g) that controls the influence on the seasonal component. Being an adaptive method, Holt-Winter's exponential smoothing allows the level, trend and seasonality patterns to change over time.

A popular forecasting method in business is exponential smoothing. Its popularity derives from its flexibility, ease of automation, cheap computation, and good performance. Simple exponential smoothing is similar to forecasting with a moving average, except that instead of taking a simple average over the w most recent values, we take a weighted average of all past values, such that the weights decrease exponentially into the past. The idea is to give more weight to recent information, yet not to completely ignore older information.

Like the moving average, simple exponential smoothing should only be used for forecasting series that have no trend or seasonality. As mentioned earlier, such series can be obtained by removing trend and/or seasonality from raw series, and then applying exponential smoothing to the series of residuals (which are assumed to contain no trend or seasonality).

The exponential smoother generates a forecast at time t + 1, (F_{t+1}) as follows:

$$F_{t+1} = \alpha Y_t + \alpha(1-\alpha)Y_{t-1} + \alpha(1-\alpha)^2 Y_{t-2} + \cdots,$$

where α is a constant between 0 and 1 called the *smoothing parameter*. The above formulation displays the exponential smoother as a weighted average of all past observations, with exponentially decaying weights. It turns out that we can write the exponential forecaster in another way, which is very useful in practice:

$$F_{t+1} = F_t + \alpha E_t,$$

where *Et* is the forecast error at time *t*. This formulation presents the exponential forecaster as an "active learner." It looks at the previous forecast (F_t) and how far it was from the actual value (E_t), and then corrects the next forecast based on that information. If last period the forecast was too high, the next period is adjusted down. The amount of correction depends on the value of the smoothing parameter α.

Example 1:
Demand: 25 32 24 28 26 27

$$F_{t+1}= \alpha D_t+(1- \alpha)F_t$$

F-Forecast
D-Demand
α - Smooting constant
F_{t+1}-forecast for period t+1
D_t =Demand in t
F_t=forecast at t

Question F_7:
$F_7= \alpha D_6+(1- \alpha)F_6$
$F_6= \alpha D_5+(1- \alpha)F_5$
.
.
.
$F_2= \alpha D_1+(1- \alpha)F_1$

Let α=0.2
Assume F_1=27 (simple average)
D_1=25
F_2=26.6
F_3=27.68
F_4=26.944
F_5=27.1552
F_6=26.92416
F_7=26.94

Solution =F_7=26.94

Courtesy :
1. https://machinelearningmastery.com/exponential-smoothing-for-time-series-forecasting-in-python/#:~:text=Exponential%20smoothing%20is%20a%20time%20series%20forecasting%20method%20for%20univariate%20data.&text=Exponential%20smoothing%20forecasting%20methods%20are,decreasing%20weight%20for%20past%20observations.
2. https://www.youtube.com/watch?v=k9dhcfIyOFc

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