OM 252

- For Average, the first data point is absolutely referenced. Start from the 2nd data point.
- For SMA, we have a m called window size, starting from m+1th data point. No absolute reference.
- For WMA, same m as previous. Has an array of weights where weights are w1<= w1<=w3……<=wM and sum is 1, multiply the data points with corresponding w. Take sumproduct of the data points with weights(absolutely referenced)

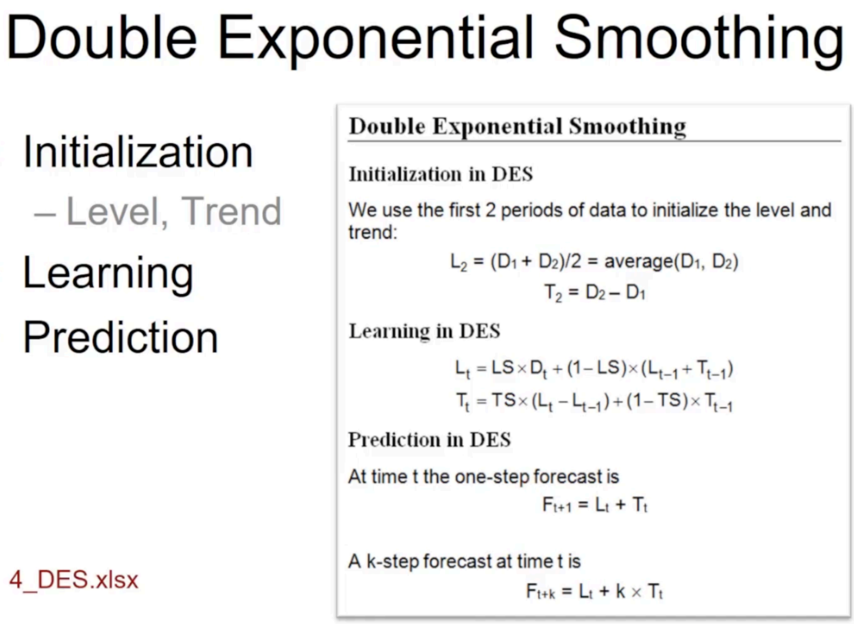
SES = Simple Exponential Smoothing

- Generalization of the WMA method
- Uses single parameter for weights: $0 \le LS \le 1$
- Three steps
  - Initialization … $F_2 = D_1$
  - Learning … $F_{t+1} = LS\ D_t + (1 - LS)\ F_t$
  - Prediction … same formula,
    if predicting one period into the future

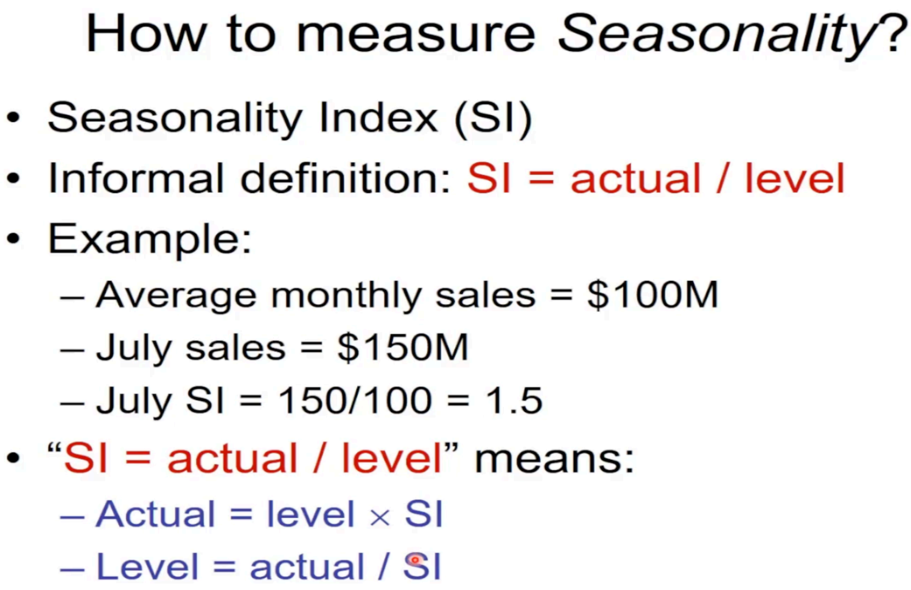
Interpretation:
Forecast = weighted average of Demand and Forecast from last period

- In SES, the forecast for tomorrow is equal to today's forecast + today's error. By increasing LS, more weight is put on the most recent data.
- If LS is 1, then SES turns to the last point method. If LS is 0, then all the data points are equal to the first datapoint.
- For checking C3 not empty, use C3<>""
- Performance measures -
  - BIAS = Bias
  - MAD = Mean Absolute Deviation
  - MAPE = Mean Absolute Percent Error
  - MSE = Mean Squared Error
  - RMSE = Root Mean Squared Error
- Bias is the average of the errors, MAD is the average of absolute value of errors. Use ABS for absolute. MAPE is the average of absolute value of errors in terms of percentage. ABS(Et/Dt), put in % in 2 decimal places.

- MSE is the sum of squared errors divided by n-1. SUMXMY2(data points, forecast)/(count(any)-1). RMSE sqrt of MSE.
- Components of a time series: Level, trend, seasonality



- DES:
- Level and trend start at 2nd step(initialize), prediction starts at 3rd.



- TES:

Initialization in TES

We use the first (p + 1) periods of past data: D_1, D_2, ..., D_{p+1} for initialization (p is the number of "seasons" – 12 months, 4 quarters, 7 days, 24 hours, ...).

Let A be the average of the data over the first p periods. Seasonality is initialized by:

$$S_i = \frac{D_i}{A} \text{ for } i = 1, 2, \ldots, p.$$

For example, $S_i = 1.25$ suggests that the corresponding season is 25% "higher" than average.

The trend is initialized by:

$$T_p = \frac{D_{p+1} - D_1}{p}$$

which is an estimate of the per period growth over the first p + 1 observations.

The level is initialized by:

- $$L_p = A$$

At the end of period t (i.e., when D_t, the actual value of the forecasted series, becomes known), the estimates of the three components of the time series are updated as follows. (LS, TS, and SS are the smoothing constants for **L**evel, **T**rend, and **S**easonality respectively; all three are between 0 and 1.)

1. Update the level:

$$L_t = LS\frac{D_t}{S_{t-p}} + (1 - LS)(L_{t-1} + T_{t-1})$$

2. Update the trend:

$$T_t = TS(L_t - L_{t-1}) + (1 - TS)T_{t-1}$$

3. Update the seasonality:

$$S_t = SS\frac{D_t}{L_t} + (1 - SS)S_{t-p}$$

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Prediction in TES

At time t the one-step forecast is

$$F_{t+1} = (L_t + T_t)\, S_{t+1-p}$$

Suppose we have monthly data and it is the end of April. Then this formula means:

"To get the May forecast, take the April level (L_t), add the April trend (T_t), and multiply the sum with the seasonality from last May (S_{t+1-p})"

A k-step forecast at time t is

- $$F_{t+k} = (L_t + k\, T_t)\, S_{t+k-p} \quad (\text{for } k \le p)$$

- 95% prediction interval = point forecast +- 2*RMSE
- Control + ~ to see all the formulas
- MONTE CARLO SIMULATION:
    - Complete formula: MAX(ROUND(NORM.INV(RAND(),mean,stdev),0),0)
-
- Probability of profit greater than zero would be
  countif(profits, “>0”)/count(profits)
- To calculate the 95th percentile, we’ll use PERCENTILE.INC(data, 0.95)
- Carlson’s curve - technological forecast