

Business Analytics using Data Mining & Forecasting

BU7143 & BU7144

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Overview of Forecasting Methods

- 1. Benchmark methods
 - 1. Naïve Forecast
 - 2. Seasonal Naïve Forecast
- 2. Regression
- 3. Smoothing
 - 1. Moving Average
 - 2. Arima
 - 3. Simple Exponential Smoothing
 - 4. Double Exponential
 - 5. Holt-Winters Smoothing

Profile	No Seasonality	Additive Seasonality	Multiplicative Seasonality
No Trend	AA****		
Additive Trend			
Multiplicative Trend	A STATE OF THE STA		

Simple exponential smoothing

Like MA, except use weighted average of all past values, instead of simple average in a window

Forecast at time t+1:

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

Equivalent to:

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

Smoothing parameter α

Simple exponential smoother corrects based on error

- If last period forecast was too high, next period is adjusted down
- If last period forecast was too low, next period is adjusted up

Amount of correction depends on value of α

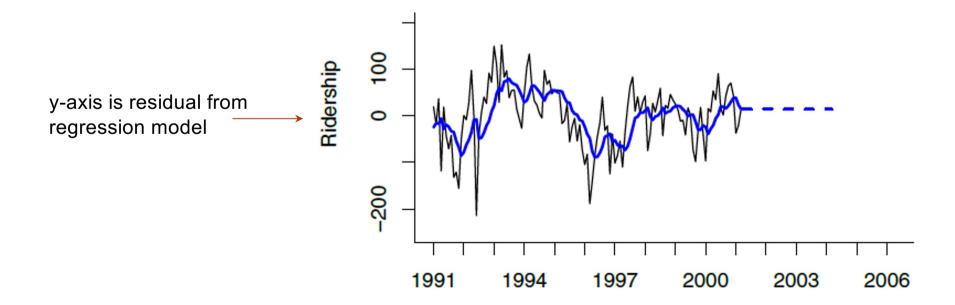
Value close to 1 > fast learning, close to 0 > low learning

Output for simple exponential smoothing applied to residuals from regression model:

```
# get residuals
residuals.ts <- train.lm.trend.season$residuals

# run simple exponential smoothing
# use ets() with model = "ANN" (additive error (A),
# no trend (N), no seasonality (N))
# and alpha = 0.2 to fit simple exponential smoothing.

ses <- ets(residuals.ts, model = "ANN", alpha = 0.2)
ses.pred <- forecast(ses, h = nValid, level = 0)</pre>
```



Moving average and simple exponential smoothing can be used only when there is no trend or seasonality. When those features are present:

- One solution is to remove those components via regression
- Another is to use advanced exponential smoothing, which can capture trend and seasonality
- Double-exponential smoothing used for series with a trend

Double exponential smoothing

Incorporates trend

K-step ahead forecast is derived from the level (L) and trend (T) estimates at time t

Additive:

$$F_{t+k} = L_t + kT_t$$

Multiplicative

$$F_{t+k} = L_t \times (T_t)^k$$

where

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + T_{t-1})$$

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

Holt Winters exponential smoothing

- Extension of double exponential smoothing
- Incorporate both trend and seasonality

Holt Winters forecast for time t+k

Adds seasonality to double exponential

For M seasons (e.g. M=7 for weekly), forecast is

$$F_{t+k} = (L_t + kT_t)S_{t+k-M}$$

Where L = level, T = trend, S = season

Updating L, T and S

Like eq. for double exponential, except for seasonal adjustment term

$$L_{t} = \underbrace{\frac{\alpha Y_{t}}{S_{t-M}}} + (1 - \alpha)(L_{t-1} + T_{t-1}),$$

Like double exponential equation

$$T_{t} = \beta (L_{t} - L_{t-1}) + (1 - \beta)T_{t-1},$$

Equation to update seasonal index

$$S_t = \frac{\gamma Y_t}{L_t} + (1 - \gamma) S_{t-M}$$

Holt Winters predictions:

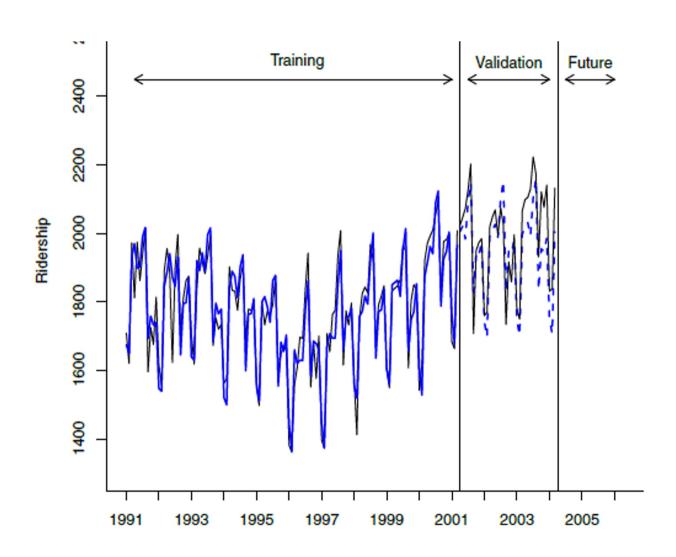
```
# run Holt-Winters exponential smoothing
# use ets() with option model = "MAA" to fit Holt-
# Winter's exponential smoothing
# with multiplicative error, additive trend, and
# additive seasonality.

hwin <- ets(train.ts, model = "MAA")

# create predictions

hwin.pred <- forecast(hwin, h = nValid, level = 0)</pre>
```

Holt-Winters Predictions



Summary

- Smoothing methods rely on local data, not mathematical structure
- Simple smoothing does not account for trend and seasonality, but can be combined with model-based forecasts to improve the forecast
- Holt-Winters smoothing incorporates seasonality and trend

Thanks for Attending

Q&A



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→ For support, email [address]