

MONASH BUSINESS SCHOOL

ETC3550/ETC5550 Applied forecasting

Ch8. Exponential smoothing OTexts.org/fpp3/



General notation ETS: ExponenTial Smoothing

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Error Trend Season

Error: Additive ("A") or multiplicative ("M")

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Trend: None ("N"), additive ("A"), multiplicative ("M"), or damped ("Ad" or "Md").

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General notation ETS: ExponenTial Smoothing

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Error Trend Season
```

Error: Additive ("A") or multiplicative ("M")

Trend: None ("N"), additive ("A"), multiplicative ("M"), or damped ("Ad" or "Md").

Seasonality: None ("N"), additive ("A") or multiplicative ("M")

ETS(A,N,N): SES with additive errors

ETS(A,N,N) model

Observation equation $y_t = \ell_{t-1} + \varepsilon_t$

State equation $\ell_t = \ell_{t-1} + \alpha \varepsilon_t$

where $\varepsilon_t \sim \text{NID}(0, \sigma^2)$.

- "innovations" or "single source of error" because equations have the same error process, ε_t .
- Measurement equation: relationship between observations and states.
 - State equation(s): evolution of the state(s) through time.

ETS(A,A,N)

Holt's methods method with additive errors.

Forecast equation
Observation equation
State equations

$$\begin{aligned} \hat{y}_{t+h|t} &= \ell_t + hb_t \\ y_t &= \ell_{t-1} + b_{t-1} + \varepsilon_t \\ \ell_t &= \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t \\ b_t &= b_{t-1} + \beta \varepsilon_t \end{aligned}$$

Forecast errors: $\varepsilon_t = y_t - \hat{y}_{t|t-1}$

ETS(A,A,A)

Holt-Winters additive method with additive errors.

Forecast equation
Observation equation
State equations

$$\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m(k+1)}$$

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$$

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t$$

$$b_t = b_{t-1} + \beta \varepsilon_t$$

$$s_t = s_{t-m} + \gamma \varepsilon_t$$

- Forecast errors: $\varepsilon_t = y_t \hat{y}_{t|t-1}$
- \blacksquare *k* is integer part of (h-1)/m.

ETS(M,A,M)

Holt-Winters multiplicative method with multiplicative errors.

Forecast equation
Observation equation
State equations

$$\begin{split} \hat{y}_{t+h|t} &= (\ell_t + hb_t) s_{t+h-m(k+1)} \\ y_t &= (\ell_{t-1} + b_{t-1}) s_{t-m} (1 + \varepsilon_t) \\ \ell_t &= (\ell_{t-1} + b_{t-1}) (1 + \alpha \varepsilon_t) \\ b_t &= b_{t-1} + \beta (\ell_{t-1} + b_{t-1}) \varepsilon_t \\ s_t &= s_{t-m} (1 + \gamma \varepsilon_t) \end{split}$$

- Forecast errors: $\varepsilon_t = (y_t \hat{y}_{t|t-1})/\hat{y}_{t|t-1}$
- \blacksquare *k* is integer part of (h-1)/m.

ETS model specification

```
ETS(y ~ error("A") + trend("N") + season("N"))
```

By default, optimal values for α , β , γ , and the states at time 0 are used.

The values for α , β and γ can be specified:

```
trend("A", alpha = 0.5, beta = 0.2)
trend("A", alpha_range = c(0.2, 0.8), beta_range = c(0.1, 0.4))
season("M", gamma = 0.04)
season("M", gamma_range = c(0, 0.3))
```

Exponential smoothing methods

		Seasonal Component			
	Trend	N	Α	M	
	Component	(None)	(Additive)	(Multiplicative)	
N	(None)	(N,N)	(N,A)	(N,M)	
Α	(Additive)	(A,N)	(A,A)	(A,M)	
A_{d}	(Additive damped)	(A _d ,N)	(A_d,A)	(A_d,M)	

(N,N): Simple exponential smoothing

(A,N): Holt's linear method

(A_d,N): Additive damped trend method (A,A): Additive Holt-Winters' method

(A,M): Multiplicative Holt-Winters' method

(A_d,M): Damped multiplicative Holt-Winters' method

Exponential smoothing methods

		Seasonal Component			
	Trend	N	Α	M	
	Component	(None)	(Additive)	(Multiplicative)	
N	(None)	(N,N)	(N,A)	(N,M)	
Α	(Additive)	(A,N)	(A,A)	(A,M)	
A_d	(Additive damped)	(A _d ,N)	(A_d,A)	(A_d,M)	

(N,N): Simple exponential smoothing

(A,N): Holt's linear method

(A_d,N): Additive damped trend method

(A,A): Additive Holt-Winters' method

(A,M): Multiplicative Holt-Winters' method

(A_d,M): Damped multiplicative Holt-Winters'

There are also multiplicative trend methods (not recommended).

Additive Error		Seasonal Component			
Trend		N	Α	M	
	Component	(None)	(Additive)	(Multiplicative)	
N	(None)	A,N,N	A,N,A	A,N,M	
Α	(Additive)	A,A,N	A,A,A	A,A,M	
A_d	(Additive damped)	A,A _d ,N	A,A_d,A	A,A _d ,M	

Multiplicative Error		Seasonal Component			
	Trend	N	Α	М	
	Component	(None)	(Additive)	(Multiplicative)	
N	(None)	M,N,N	M,N,A	M,N,M	
Α	(Additive)	M,A,N	M,A,A	M,A,M	
A_d	(Additive damped)	M,A _d ,N	M,A _d ,A	M,A_d,M	

Additive Error		Seasonal Component			
Trend		N	Α	M	
	Component	(None)	(Additive)	(Multiplicative)	
N	(None)	A,N,N	A,N,A	<u> </u>	
Α	(Additive)	A,A,N	A,A,A	<u>^,^,M</u>	
A_d	(Additive damped)	A,A _d ,N	A,A_d,A	<mark>^, ∆, </mark> ^	

Multiplicative Error		Seasonal Component			
	Trend	N	Α	М	
	Component	(None)	(Additive)	(Multiplicative)	
N	(None)	M,N,N	M,N,A	M,N,M	
Α	(Additive)	M,A,N	M,A,A	M,A,M	
A_d	(Additive damped)	M,A _d ,N	M,A _d ,A	M,A_d,M	

AIC and cross-validation

Minimizing the AIC assuming Gaussian residuals is asymptotically equivalent to minimizing one-step time series cross validation MSE.

Automatic forecasting

From Hyndman et al. (IJF, 2002):

- Apply each model that is appropriate to the data. Optimize parameters and initial values using MLE (or some other criterion).
- Select best method using AICc:
- Produce forecasts using best method.
- Obtain forecast intervals using underlying state space model.

Method performed very well in M3 competition.

Residuals

Response residuals

$$\hat{\boldsymbol{e}}_t = \boldsymbol{y}_t - \hat{\boldsymbol{y}}_{t|t-1}$$

Innovation residuals

Additive error model:

$$\hat{\varepsilon}_t$$
 = $y_t - \hat{y}_{t|t-1}$

Multiplicative error model:

$$\hat{\varepsilon}_t = \frac{y_t - \hat{y}_{t|t-1}}{\hat{y}_{t|t-1}}$$