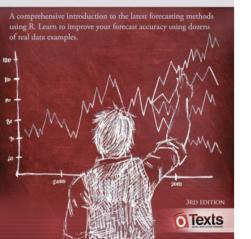
Rob J Hyndman George Athanasopoulos

# FORECASTING PRINCIPLES AND PRACTICE



## 8. Exponential smoothing

8.7 Forecasting with ETS models
OTexts.org/fpp3/

#### Forecasting with ETS models

**Traditional point forecasts:** iterate the equations for

$$t = T + 1, T + 2, \dots, T + h$$
 and set all  $\varepsilon_t = 0$  for  $t > T$ .

#### Forecasting with ETS models

#### **Traditional point forecasts:** iterate the equations for

$$t = T + 1, T + 2, \dots, T + h$$
 and set all  $\varepsilon_t = 0$  for  $t > T$ .

- Not the same as  $E(y_{t+h}|\mathbf{x}_t)$  unless seasonality is additive.
- fable uses  $E(y_{t+h}|\mathbf{x}_t)$ .
- Point forecasts for ETS(A,\*,\*) are identical to ETS(M,\*,\*) if the parameters are the same.

#### **Example: ETS(A,A,N)**

etc.

$$\begin{aligned} y_{T+1} &= \ell_T + b_T + \varepsilon_{T+1} \\ \hat{y}_{T+1|T} &= \ell_T + b_T \\ y_{T+2} &= \ell_{T+1} + b_{T+1} + \varepsilon_{T+2} \\ &= (\ell_T + b_T + \alpha \varepsilon_{T+1}) + (b_T + \beta \varepsilon_{T+1}) + \varepsilon_{T+2} \\ \hat{y}_{T+2|T} &= \ell_T + 2b_T \end{aligned}$$

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#### Example: ETS(M,A,N)

```
y_{T+1} = (\ell_T + b_T)(1 + \varepsilon_{T+1})
         \hat{\mathbf{y}}_{T+1|T} = \ell_T + \mathbf{b}_T.
            y_{T+2} = (\ell_{T+1} + b_{T+1})(1 + \varepsilon_{T+2})
                      = \{ (\ell_T + b_T)(1 + \alpha \varepsilon_{T+1}) + [b_T + \beta(\ell_T + b_T)\varepsilon_{T+1}] \} (1 + \varepsilon_{T+2})
         \hat{\mathbf{y}}_{T+2|T} = \ell_T + 2b_T
etc.
```

#### Forecasting with ETS models

Prediction intervals: can only be generated using the models.

- The prediction intervals will differ between models with additive and multiplicative errors.
- Exact formulae for some models.
- More general to simulate future sample paths, conditional on the last estimate of the states, and to obtain prediction intervals from the percentiles of these simulated future paths.

#### **Prediction intervals**

(A,N,A)

(A,A,A)

PI for most ETS models:  $\hat{y}_{T+h|T} \pm c\sigma_h$ , where c depends on coverage probability and  $\sigma_h$  is forecast standard deviation.

(A,N,N) 
$$\sigma_h = \sigma^2 \Big[ 1 + \alpha^2 (h-1) \Big]$$

A,N) 
$$\sigma_h = \sigma^2 \left[ 1 + (h-1) \left\{ \alpha^2 + \alpha \beta h + \frac{1}{6} \beta^2 h (2h-1) \right\} \right]$$

 $\sigma_h = \sigma^2 \left[ 1 + \alpha^2 (h - 1) + \gamma k (2\alpha + \gamma) \right]$ 

(A,A,N) 
$$\sigma_h = \sigma^2 \left[ 1 + \alpha \left( H - 1 \right) \right]$$
  
(A,A,N)  $\sigma_h = \sigma^2 \left[ 1 + (h - 1) \left\{ \alpha^2 + \alpha \beta h + \frac{1}{6} \beta^2 h (2h - 1) \right\} \right]$ 

A,N) 
$$\sigma_h = \sigma^2 \left[ 1 + (h-1) \{ \alpha^2 + \alpha \beta h + \frac{1}{6} \beta^2 h (2h-1) \} \right]$$

(A,A,N) 
$$\sigma_h = \sigma^2 \left[ 1 + (h-1) \left\{ \alpha^2 + \alpha \beta h + \frac{1}{6} \beta^2 h (2h-1) \right\} \right]$$
  
(A,A<sub>d</sub>,N)  $\sigma_h = \sigma^2 \left[ 1 + \alpha^2 (h-1) + \frac{\beta \phi h}{(1-\phi)^2} \left\{ 2\alpha (1-\phi) + \beta \phi \right\} - \frac{\beta \phi (1-\phi^h)}{(1-\phi)^2 (1-\phi^2)} \left\{ 2\alpha (1-\phi^2) + \beta \phi (1+2\phi-\phi^h) \right\} \right]$ 

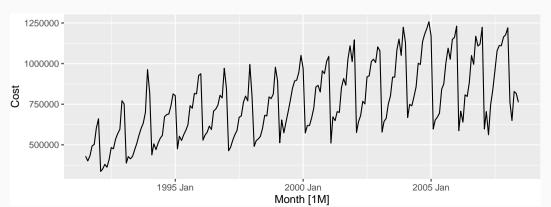
 $(\mathsf{A}, \mathsf{A}_d, \mathsf{A}) \quad \sigma_\mathsf{h} = \sigma^2 \Big[ 1 + \alpha^2 (\mathsf{h} - 1) + \frac{\beta \phi \mathsf{h}}{(1 - \phi)^2} \left\{ 2\alpha (1 - \phi) + \beta \phi \right\} - \frac{\beta \phi (1 - \phi^\mathsf{h})}{(1 - \phi)^2 (1 - \phi^2)} \left\{ 2\alpha (1 - \phi^2) + \beta \phi (1 + 2\phi - \phi^\mathsf{h}) \right\} \Big] \Big] + \alpha^2 (\mathsf{h} - 1) + \beta \phi (1 + 2\phi - \phi^\mathsf{h}) \Big\}$ 

 $+ \gamma k(2\alpha + \gamma) + \frac{2\beta\gamma\phi}{(1-\phi)(1-\phi^m)} \left\{ k(1-\phi^m) - \phi^m(1-\phi^{mk}) \right\}$ 

(A,N) 
$$\sigma_h = \sigma^2 \left[ 1 + \alpha^2 (h - 1) \right]$$
  
(A,N)  $\sigma_h = \sigma^2 \left[ 1 + (h - 1) \left\{ \alpha^2 + \alpha \beta h + \frac{1}{6} \beta^2 h (2h - 1) \right\} \right]$ 

 $\sigma_h = \sigma^2 \left[ 1 + (h-1) \left\{ \alpha^2 + \alpha \beta h + \frac{1}{6} \beta^2 h (2h-1) \right\} + \gamma k \left\{ 2\alpha + \gamma + \beta m (k+1) \right\} \right]$ 

```
h02 <- PBS |>
  filter(ATC2 == "H02") |>
  summarise(Cost = sum(Cost))
h02 |> autoplot(Cost)
```



```
h02 |>
model(ETS(Cost)) |>
report()
```

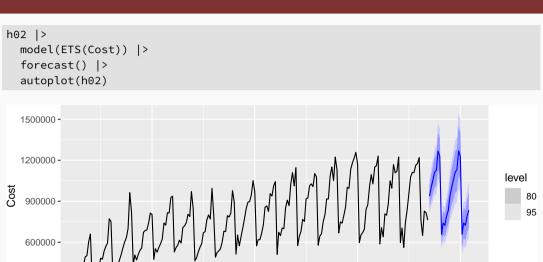
```
## Series: Cost
## Model: ETS(M,Ad,M)
     Smoothing parameters:
##
       alpha = 0.307
##
      beta = 0.000101
##
##
    gamma = 0.000101
##
       phi = 0.978
##
     Initial states:
     l[0] b[0] s[0] s[-1] s[-2] s[-3] s[-4] s[-5] s[-6] s[-7] s[-8] s[-9]
##
    417269 8206 0.872 0.826 0.756 0.773 0.687 1.28 1.32 1.18 1.16 1.1
##
    s[-10] s[-11]
     1.05 0.981
##
##
     sigma^2: 0.0046
##
##
   ATC ATCC BTC
## 5515 5519 5575
```

```
h02 |>
model(ETS(Cost ~ error("A") + trend("A") + season("A"))) |>
report()
```

```
## Series: Cost
## Model: ETS(A,A,A)
##
    Smoothing parameters:
##
   alpha = 0.17
## beta = 0.00631
##
    gamma = 0.455
##
##
    Initial states:
    l[0] b[0] s[0] s[-1] s[-2] s[-3] s[-4] s[-5] s[-6] s[-7]
##
   409706 9097 -99075 -136602 -191496 -174531 -241437 210644 244644 145368
    s[-8] s[-9] s[-10] s[-11]
   130570 84458 39132 -11674
##
##
    sigma^2: 3.5e+09
##
   ATC ATCC BTC
## 5585 5589 5642
```

1995 Jan

300000 -



2000 Jan

2005 Jan

2010 Jan

```
h02 |>
model(
  auto = ETS(Cost),
  AAA = ETS(Cost ~ error("A") + trend("A") + season("A"))
) |>
accuracy()
```

Model	MAE	RMSE	MAPE	MASE	RMSSE
auto	38649	51102	4.99	0.638	0.689
AAA	43378	56784	6.05	0.716	0.766