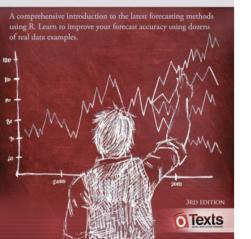
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FORECASTING PRINCIPLES AND PRACTICE



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

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

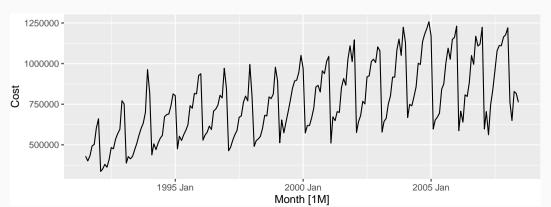
 $+ \gamma k(2\alpha + \gamma) + \frac{2\beta\gamma\phi}{(1-\phi)(1-\phi^m)} \left\{ k(1-\phi^m) - \phi^m(1-\phi^{mk}) \right\}$

(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()
```

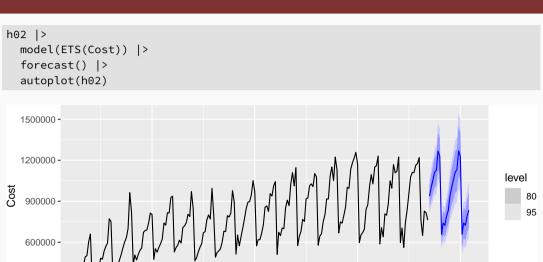
```
## Series: Cost
## Model: ETS(M,Ad,M)
     Smoothing parameters:
##
       alpha = 0.307
##
      beta = 0.000101
##
##
    gamma = 0.000101
##
       phi = 0.978
##
     Initial states:
     l[0] b[0] s[0] s[-1] s[-2] s[-3] s[-4] s[-5] s[-6] s[-7] s[-8] s[-9]
##
    417269 8206 0.872 0.826 0.756 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