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FORECASTING

PRINCIPLES AND PRACTICE

A comprehensive introduction to the latest forecasting methods using R. Learn to improve your forecast accuracy using dozens of real data examples.



3RD EDITION

 **OTexts**
Open Texts Publishing

8. Exponential smoothing

8.6 Estimation and model selection

OTexts.org/fpp3/

Estimating ETS models

- Smoothing parameters α , β , γ and ϕ , and the initial states ℓ_0 , b_0 , s_0 , s_{-1} , \dots , s_{-m+1} are estimated by maximising the “likelihood” = the probability of the data arising from the specified model.
- For models with additive errors equivalent to minimising SSE.
- For models with multiplicative errors, **not** equivalent to minimising SSE.

Innovations state space models

Let $\mathbf{x}_t = (\ell_t, b_t, s_t, s_{t-1}, \dots, s_{t-m+1})$ and $\varepsilon_t \stackrel{\text{iid}}{\sim} N(0, \sigma^2)$.

$$y_t = \underbrace{h(\mathbf{x}_{t-1})}_{\mu_t} + \underbrace{k(\mathbf{x}_{t-1})\varepsilon_t}_{e_t}$$

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}) + g(\mathbf{x}_{t-1})\varepsilon_t$$

Additive errors

$$k(x) = 1. \quad y_t = \mu_t + \varepsilon_t.$$

Multiplicative errors

$$k(\mathbf{x}_{t-1}) = \mu_t. \quad y_t = \mu_t(1 + \varepsilon_t).$$

$\varepsilon_t = (y_t - \mu_t)/\mu_t$ is relative error.

Innovations state space models

Estimation

$$\begin{aligned} L^*(\boldsymbol{\theta}, \mathbf{x}_0) &= T \log \left(\sum_{t=1}^T \varepsilon_t^2 \right) + 2 \sum_{t=1}^T \log |k(\mathbf{x}_{t-1})| \\ &= -2 \log(\text{Likelihood}) + \text{constant} \end{aligned}$$

- Estimate parameters $\boldsymbol{\theta} = (\alpha, \beta, \gamma, \phi)$ and initial states $\mathbf{x}_0 = (\ell_0, b_0, s_0, s_{-1}, \dots, s_{-m+1})$ by minimizing L^* .

Parameter restrictions

Usual region

- Traditional restrictions in the methods $0 < \alpha, \beta^*, \gamma^*, \phi < 1$ (equations interpreted as weighted averages).
- In models we set $\beta = \alpha\beta^*$ and $\gamma = (1 - \alpha)\gamma^*$.
- Therefore $0 < \alpha < 1$, $0 < \beta < \alpha$ and $0 < \gamma < 1 - \alpha$.
- $0.8 < \phi < 0.98$ — to prevent numerical difficulties.

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- $0.8 < \phi < 0.98$ — to prevent numerical difficulties.

Admissible region

- To prevent observations in the distant past having a continuing effect on current forecasts.
- Usually (but not always) less restrictive than *traditional* region.
- For example for ETS(A,N,N):
traditional $0 < \alpha < 1$ while *admissible* $0 < \alpha < 2$.

Model selection

Akaike's Information Criterion

$$\text{AIC} = -2 \log(L) + 2k$$

where L is the likelihood and k is the number of parameters & initial states estimated in the model.

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Corrected AIC

$$\text{AIC}_c = \text{AIC} + \frac{2k(k+1)}{T-k-1}$$

which is the AIC corrected (for small sample bias).

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which is the AIC corrected (for small sample bias).

Bayesian Information Criterion

$$\text{BIC} = \text{AIC} + k[\log(T) - 2].$$

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.

Some unstable models

- Some of the combinations of (Error, Trend, Seasonal) can lead to numerical difficulties; see equations with division by a state.
- These are: $ETS(A,N,M)$, $ETS(A,A,M)$, $ETS(A,A_d,M)$.
- Models with multiplicative errors are useful for strictly positive data, but are not numerically stable with data containing zeros or negative values. In that case only the six fully additive models will be applied.

Example: National populations

```
fit <- global_economy |>
  mutate(Pop = Population / 1e6) |>
  model(ets = ETS(Pop))
fit
```

```
## # A tibble: 263 x 2
## # Key:   Country [263]
##   Country                ets
##   <fct>                  <model>
## 1 Afghanistan    <ETS(A,A,N)>
## 2 Albania        <ETS(M,A,N)>
## 3 Algeria        <ETS(M,A,N)>
## 4 American Samoa <ETS(M,A,N)>
## 5 Andorra        <ETS(M,A,N)>
## 6 Angola         <ETS(M,A,N)>
## 7 Antigua and Barbuda <ETS(M,A,N)>
## 8 Arab World     <ETS(M,A,N)>
## 9 Argentina     <ETS(A,A,N)>
## 10 Armenia       <ETS(M,A,N)>
```

Example: National populations

```
fit |>  
  forecast(h = 5)
```

```
## # A tibble: 1,315 x 5 [1Y]  
## # Key:      Country, .model [263]  
##   Country      .model Year      Pop .mean  
##   <fct>        <chr>  <dbl>      <dist> <dbl>  
## 1 Afghanistan ets     2018    N(36, 0.012) 36.4  
## 2 Afghanistan ets     2019    N(37, 0.059) 37.3  
## 3 Afghanistan ets     2020    N(38, 0.16) 38.2  
## 4 Afghanistan ets     2021    N(39, 0.35) 39.0  
## 5 Afghanistan ets     2022    N(40, 0.64) 39.9  
## 6 Albania     ets     2018    N(2.9, 0.00012) 2.87  
## 7 Albania     ets     2019    N(2.9, 6e-04) 2.87  
## 8 Albania     ets     2020    N(2.9, 0.0017) 2.87  
## 9 Albania     ets     2021    N(2.9, 0.0036) 2.86  
## 10 Albania    ets     2022    N(2.9, 0.0066) 2.86  
## # ... with 1,305 more rows
```

Example: Australian holiday tourism

```
holidays <- tourism |>
  filter(Purpose == "Holiday")
fit <- holidays |> model(ets = ETS(Trips))
fit
```

```
## # A mable: 76 x 4
```

```
## # Key:      Region, State, Purpose [76]
```

##	Region	State	Purpose	ets
##	<chr>	<chr>	<chr>	<model>
## 1	Adelaide	South Australia	Holiday	<ETS(A,N,A)>
## 2	Adelaide Hills	South Australia	Holiday	<ETS(A,A,N)>
## 3	Alice Springs	Northern Territory	Holiday	<ETS(M,N,A)>
## 4	Australia's Coral Coast	Western Australia	Holiday	<ETS(M,N,A)>
## 5	Australia's Golden Outback	Western Australia	Holiday	<ETS(M,N,M)>
## 6	Australia's North West	Western Australia	Holiday	<ETS(A,N,A)>
## 7	Australia's South West	Western Australia	Holiday	<ETS(M,N,M)>
## 8	Ballarat	Victoria	Holiday	<ETS(M,N,A)>
## 9	Barkly	Northern Territory	Holiday	<ETS(A,N,A)>
## 10	Barossa	South Australia	Holiday	<ETS(A,N,N)>

Example: Australian holiday tourism

```
fit |>  
  filter(Region == "Snowy Mountains") |>  
  report()
```

```
## Series: Trips  
## Model: ETS(M,N,A)  
##   Smoothing parameters:  
##     alpha = 0.157  
##     gamma = 1e-04  
##  
##   Initial states:  
##   l[0] s[0] s[-1] s[-2] s[-3]  
##   142  -61   131 -42.2 -27.7  
##  
##   sigma^2:  0.0388  
##  
##   AIC AICc  BIC  
##   852  854  869
```


Example: Australian holiday tourism

```
fit |>
  filter(Region == "Snowy Mountains") |>
  components(fit)
```

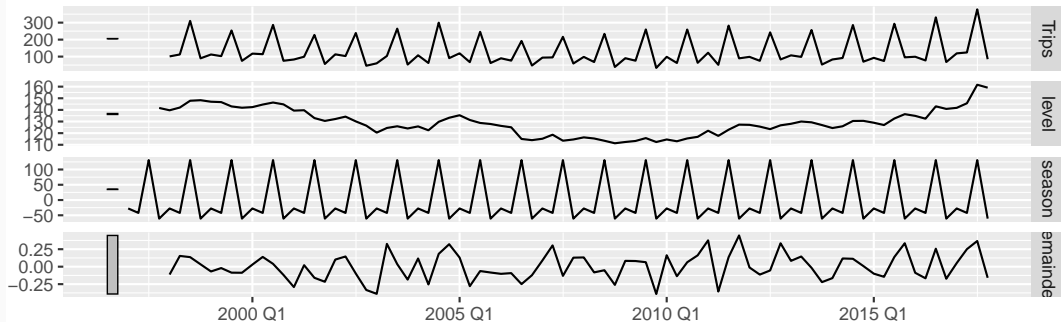
```
## # A dtable: 84 x 9 [1Q]
## # Key:      Region, State, Purpose, .model [1]
## # :        Trips = (lag(level, 1) + lag(season, 4)) * (1 + remainder)
##   Region      State Purpose .model Quarter Trips level season remain~1
##   <chr>        <chr>  <chr>  <chr>    <qtr>  <dbl>  <dbl>  <dbl>  <dbl>
## 1 Snowy Mountains New S~ Holiday ets     1997 Q1  NA      NA    -27.7  NA
## 2 Snowy Mountains New S~ Holiday ets     1997 Q2  NA      NA    -42.2  NA
## 3 Snowy Mountains New S~ Holiday ets     1997 Q3  NA      NA    131.   NA
## 4 Snowy Mountains New S~ Holiday ets     1997 Q4  NA     142.  -61.0  NA
## 5 Snowy Mountains New S~ Holiday ets     1998 Q1 101.    140.  -27.7  -0.113
## 6 Snowy Mountains New S~ Holiday ets     1998 Q2 112.    142.  -42.2   0.154
## 7 Snowy Mountains New S~ Holiday ets     1998 Q3 310.    148.  131.   0.137
## 8 Snowy Mountains New S~ Holiday ets     1998 Q4  89.8   148.  -61.0   0.0335
## 9 Snowy Mountains New S~ Holiday ets     1999 Q1 112.    147.  -27.7  -0.0687
## 10 Snowy Mountains New S~ Holiday ets     1999 Q2 103.    147.  -42.2  -0.0199
```

Example: Australian holiday tourism

```
fit |>  
  filter(Region == "Snowy Mountains") |>  
  components(fit) |>  
  autoplot()
```

ETS(M,N,A) decomposition

$\text{Trips} = (\text{lag}(\text{level}, 1) + \text{lag}(\text{season}, 4)) * (1 + \text{remainder})$



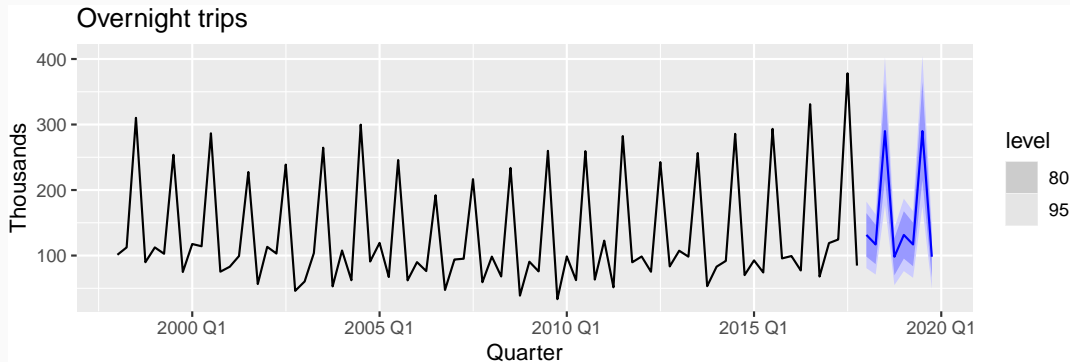
Example: Australian holiday tourism

```
fit |> forecast()
```

```
## # A tibble: 608 x 7 [1Q]
## # Key:   Region, State, Purpose, .model [76]
##   Region      State      Purpose .model Quarter      Trips .mean
##   <chr>      <chr>      <chr>  <chr>    <qtr>      <dist> <dbl>
## 1 Adelaide    South Australia Holiday ets    2018 Q1 N(210, 457) 210.
## 2 Adelaide    South Australia Holiday ets    2018 Q2 N(173, 473) 173.
## 3 Adelaide    South Australia Holiday ets    2018 Q3 N(169, 489) 169.
## 4 Adelaide    South Australia Holiday ets    2018 Q4 N(186, 505) 186.
## 5 Adelaide    South Australia Holiday ets    2019 Q1 N(210, 521) 210.
## 6 Adelaide    South Australia Holiday ets    2019 Q2 N(173, 537) 173.
## 7 Adelaide    South Australia Holiday ets    2019 Q3 N(169, 553) 169.
## 8 Adelaide    South Australia Holiday ets    2019 Q4 N(186, 569) 186.
## 9 Adelaide Hills South Australia Holiday ets    2018 Q1   N(19, 36)  19.4
## 10 Adelaide Hills South Australia Holiday ets    2018 Q2   N(20, 36)  19.6
## # ... with 598 more rows
```

Example: Australian holiday tourism

```
fit |>  
  forecast() |>  
  filter(Region == "Snowy Mountains") |>  
  autoplot(holidays) +  
  labs(y = "Thousands", title = "Overnight trips")
```



Residuals

Response residuals

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

Innovation residuals

Additive error model:

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

Multiplicative error model:

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

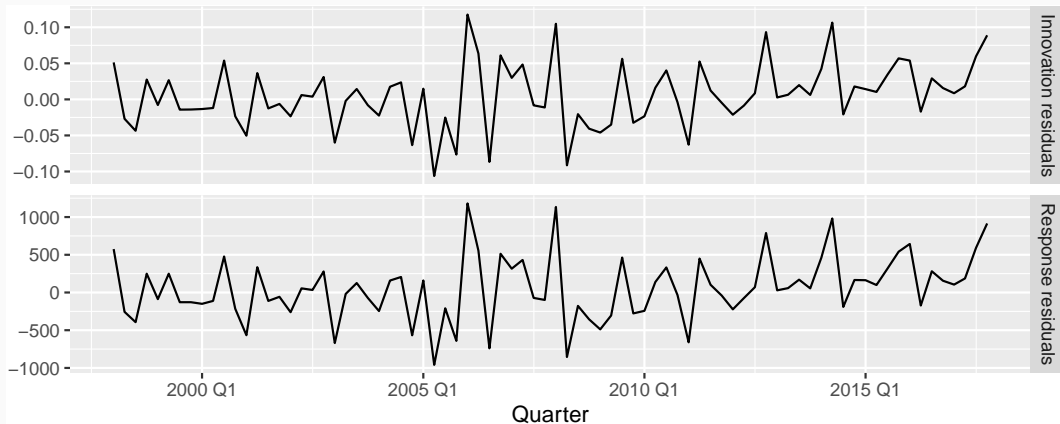
Example: Australian holiday tourism

```
aus_holidays <- tourism |>
  filter(Purpose == "Holiday") |>
  summarise(Trips = sum(Trips))
fit <- aus_holidays |>
  model(ets = ETS(Trips)) |>
  report()
```

```
## Series: Trips
## Model: ETS(M,N,M)
## Smoothing parameters:
##   alpha = 0.358
##   gamma = 0.000969
##
## Initial states:
## l[0] s[0] s[-1] s[-2] s[-3]
## 9667 0.943 0.927 0.968 1.16
##
## sigma^2: 0.0022
##
## AIC AICc BIC
## 1331 1333 1348
```

Example: Australian holiday tourism

```
residuals(fit)  
residuals(fit, type = "response")
```



Example: Australian holiday tourism

```
fit |>  
  augment()
```

```
## # A tsibble: 80 x 6 [1Q]  
## # Key:           .model [1]  
##   .model Quarter Trips .fitted .resid .innov  
##   <chr>      <qtr>  <dbl>  <dbl>  <dbl>  <dbl>  
## 1 ets      1998 Q1 11806. 11230.  576.   0.0513  
## 2 ets      1998 Q2  9276.  9532. -257.  -0.0269  
## 3 ets      1998 Q3  8642.  9036. -393.  -0.0435  
## 4 ets      1998 Q4  9300.  9050.  249.   0.0275  
## 5 ets      1999 Q1 11172. 11260. -88.0 -0.00781  
## 6 ets      1999 Q2  9608.  9358.  249.   0.0266  
## 7 ets      1999 Q3  8914.  9042. -129.  -0.0142  
## 8 ets      1999 Q4  9026.  9154. -129.  -0.0140  
## 9 ets      2000 Q1 11071. 11221. -150.  -0.0134  
## 10 ets     2000 Q2  9196.  9308. -111.  -0.0120  
## # ... with 70 more rows
```


Example: Australian holiday tourism

```
fit |>
  augment()
```

Innovation residuals (`.innov`) are given by $\hat{\varepsilon}_t$ while regular residuals (`.resid`) are $y_t - \hat{y}_{t-1}$. They are different when the model has multiplicative errors.

```
## # A tsibble: 80 x 6 [1Q]
## # Key:           .model [1]
##   .model Quarter  Trips .fitted .resid  .innov
##   <chr>    <qtr>   <dbl>   <dbl> <dbl>   <dbl>
## 1 ets      1998 Q1  11806.  11230.  576.    0.0513
## 2 ets      1998 Q2   9276.   9532. -257.   -0.0269
## 3 ets      1998 Q3   8642.   9036. -393.   -0.0435
## 4 ets      1998 Q4   9300.   9050.  249.    0.0275
## 5 ets      1999 Q1  11172.  11260.  -88.0  -0.00781
## 6 ets      1999 Q2   9608.   9358.  249.    0.0266
## 7 ets      1999 Q3   8914.   9042. -129.   -0.0142
## 8 ets      1999 Q4   9026.   9154. -129.   -0.0140
## 9 ets      2000 Q1  11071.  11221. -150.   -0.0134
## 10 ets     2000 Q2   9196.   9308. -111.   -0.0120
## # ... with 70 more rows
```