



Tidy Time Series & Forecasting in R



7. Exponential smoothing

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Outline

- 1 Exponential smoothing
- 2 Trend methods
- 3 Seasonal methods
- 4 ETS taxonomy
- 5 Lab Session 12

Outline

1 Exponential smoothing

2 Trend methods

3 Seasonal methods

4 ETS taxonomy

5 Lab Session 12

Historical perspective

- Developed in the 1950s and 1960s as methods (algorithms) to produce point forecasts.
- Combine a “level”, “trend” (slope) and “seasonal” component to describe a time series.
- The rate of change of the components are controlled by “smoothing parameters”: α , β and γ respectively.
- Need to choose best values for the smoothing parameters (and initial states).
- Equivalent ETS state space models developed in the 1990s and 2000s.

A model for levels, trends, and seasonalities

We want a model that captures the level (ℓ_t), trend (b_t) and seasonality (s_t).

How do we combine these elements?

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Perhaps a mix of both?

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How do the level, trend and seasonal components evolve over time?

ETS models

General notation

ETS : ExponenTial Smoothing

Error Trend Season

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

ETS models

General notation

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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").

ETS models

General notation

ETS : ExponenTial Smoothing



Error Trend Season

The diagram shows three arrows pointing upwards from the words 'Error', 'Trend', and 'Season' to the letters 'E', 'T', and 'S' respectively in the 'ETS' acronym.

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

Forecast equation

$$\hat{y}_{T+h|T} = \ell_T$$

Measurement equation

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

State equation

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

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

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

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

ETS(M,N,N): SES with multiplicative errors

Forecast equation	$\hat{y}_{T+h T} = \ell_T$
Measurement equation	$y_t = \ell_{t-1}(1 + \varepsilon_t)$
State equation	$\ell_t = \ell_{t-1}(1 + \alpha\varepsilon_t)$

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

ETS(M,N,N): SES with multiplicative errors

Forecast equation	$\hat{y}_{T+h T} = \ell_T$
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State equation	$\ell_t = \ell_{t-1}(1 + \alpha\varepsilon_t)$

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

- Models with additive and multiplicative errors with the same parameters generate the same point forecasts but different prediction intervals.

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Holt's linear trend

Additive errors: ETS(A,A,N)

Forecast equation $\hat{y}_{T+h|T} = \ell_T + hb_T$

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

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

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

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

Multiplicative errors: ETS(M,A,N)

Forecast equation $\hat{y}_{T+h|T} = \ell_T + hb_T$

Measurement equation $y_t = (\ell_{t-1} + b_{t-1})(1 + \varepsilon_t)$

State equations $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$

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

Example: Australian population

```
aus_economy <- global_economy %>% filter(Code == "AUS") %>%  
  mutate(Pop = Population/1e6)  
fit <- aus_economy %>% model(AAN = ETS(Pop))  
report(fit)
```

```
## Series: Pop  
## Model: ETS(A,A,N)  
## Smoothing parameters:  
##   alpha = 1  
##   beta  = 0.327  
##  
## Initial states:  
##   l      b  
## 10.1 0.222  
##  
## sigma^2: 0.0041  
##  
## AIC  AICc  BIC  
## -77.0 -75.8 -66.7
```

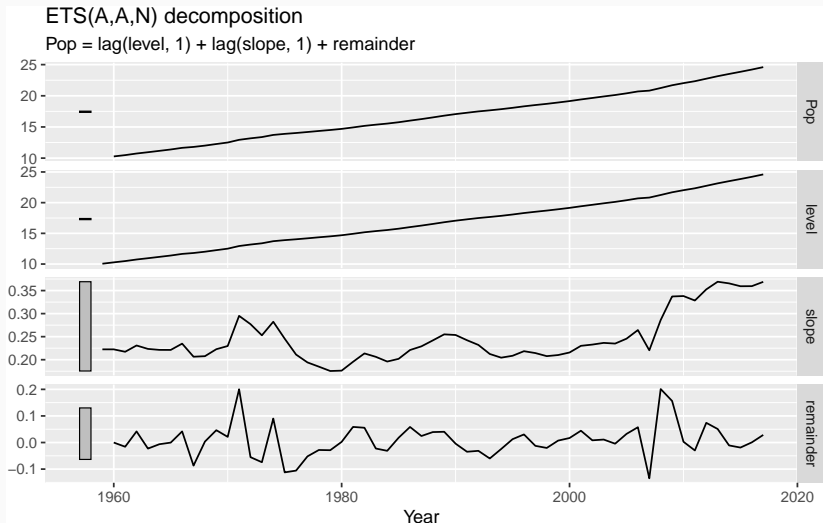
Example: Australian population

```
components(fit)
```

```
## # A dable:                59 x 7 [1Y]
## # Key:                    Country, .model [1]
## # ETS(A,A,N) Decomposition: Pop = lag(level, 1) + lag(slope, 1)
## #   remainder
##   Country   .model Year   Pop level slope remainder
##   <fct>     <chr>  <dbl> <dbl> <dbl> <dbl>      <dbl>
## 1 Australia AAN    1959  NA    10.1 0.222 NA
## 2 Australia AAN    1960  10.3 10.3 0.222 -0.000145
## 3 Australia AAN    1961  10.5 10.5 0.217 -0.0159
## 4 Australia AAN    1962  10.7 10.7 0.231  0.0418
## 5 Australia AAN    1963  11.0 11.0 0.223 -0.0229
## 6 Australia AAN    1964  11.2 11.2 0.221 -0.00641
## 7 Australia AAN    1965  11.4 11.4 0.221 -0.000314
## 8 Australia AAN    1966  11.7 11.7 0.235  0.0418
## 9 Australia AAN    1967  11.8 11.8 0.206 -0.0869
## 10 Australia AAN    1968  12.0 12.0 0.208  0.00350
```

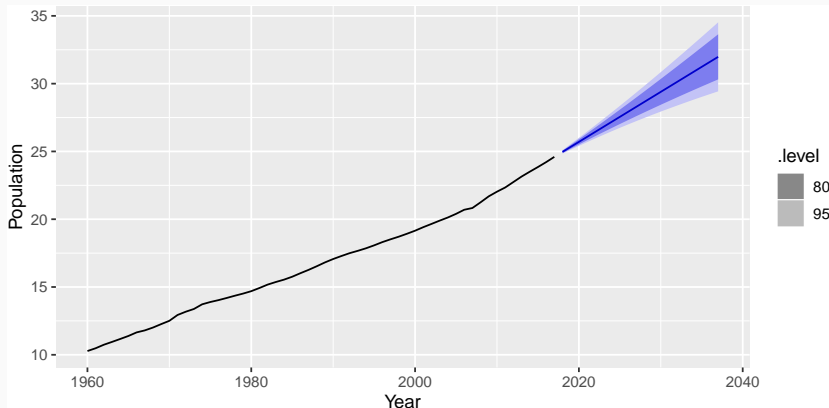
Example: Australian population

```
components(fit) %>% autoplot()
```



Example: Australian population

```
fit %>%  
  forecast(h = 20) %>%  
  autoplot(aus_economy) +  
  ylab("Population") + xlab("Year")
```



ETS(A,Ad,N): Damped trend method

Additive errors

Forecast equation $\hat{y}_{T+h|T} = \ell_T + (\phi + \dots + \phi^{h-1})b_T$

Measurement equation $y_t = (\ell_{t-1} + \phi b_{t-1}) + \varepsilon_t$

State equations $\ell_t = (\ell_{t-1} + \phi b_{t-1}) + \alpha \varepsilon_t$

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

ETS(A,Ad,N): Damped trend method

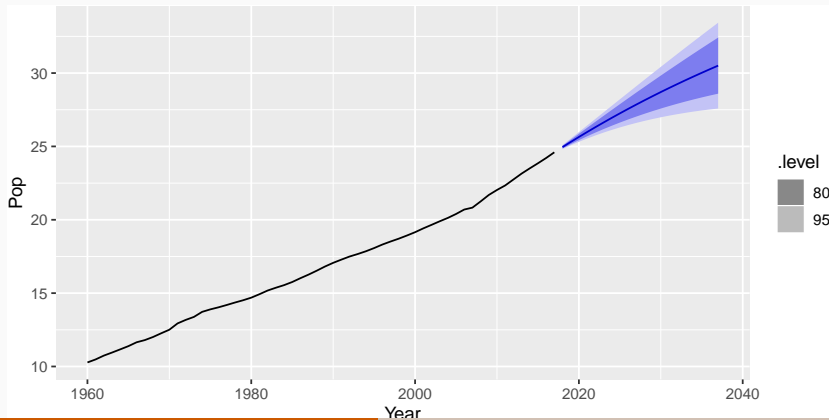
Additive errors

Forecast equation	$\hat{y}_{T+h T} = \ell_T + (\phi + \dots + \phi^{h-1})b_T$
Measurement equation	$y_t = (\ell_{t-1} + \phi b_{t-1}) + \varepsilon_t$
State equations	$\ell_t = (\ell_{t-1} + \phi b_{t-1}) + \alpha \varepsilon_t$ $b_t = \phi b_{t-1} + \beta \varepsilon_t$

- Damping parameter $0 < \phi < 1$.
- If $\phi = 1$, identical to Holt's linear trend.
- As $h \rightarrow \infty$, $\hat{y}_{T+h|T} \rightarrow \ell_T + \phi b_T / (1 - \phi)$.
- Short-run forecasts trended, long-run forecasts constant.

Example: Australian population

```
aus_economy %>%  
  model(holt = ETS(Pop ~ trend("Ad"))) %>%  
  forecast(h = 20) %>%  
  autoplot(aus_economy)
```



Example: National populations

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

```
## # A mable: 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)>  
## # ... with 253 more rows
```

Example: National populations

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

```
## # A tibble: 1,315 x 5 [1Y]  
## # Key:      Country, .model [263]  
##   Country      .model Year   Pop .distribution  
##   <fct>        <chr>   <dbl> <dbl> <dist>  
## 1 Afghanistan ets      2018  36.4 N(36, 0.012)  
## 2 Afghanistan ets      2019  37.3 N(37, 0.059)  
## 3 Afghanistan ets      2020  38.2 N(38, 0.164)  
## 4 Afghanistan ets      2021  39.0 N(39, 0.351)  
## 5 Afghanistan ets      2022  39.9 N(40, 0.644)  
## 6 Albania     ets      2018   2.87 N(2.9, 0.00012)  
## 7 Albania     ets      2019   2.87 N(2.9, 0.00060)  
## 8 Albania     ets      2020   2.87 N(2.9, 0.00169)  
## 9 Albania     ets      2021   2.86 N(2.9, 0.00362)
```

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ETS(A,A,A): Holt-Winters additive method

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

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

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

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

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

- $k = \text{integer part of } (h - 1)/m$.
- $\sum_i s_i \approx 0$.
- Parameters: $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$, $0 \leq \gamma \leq 1 - \alpha$ and $m = \text{period of seasonality (e.g. } m = 4 \text{ for quarterly data)}$.

ETS(M,A,M): Holt-Winters multiplicative method

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

Observation equation $y_t = (\ell_{t-1} + b_{t-1})s_{t-m}(1 + \varepsilon_t)$

State equations $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$

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

$$s_t = s_{t-m}(1 + \gamma\varepsilon_t)$$

- k is integer part of $(h - 1)/m$.
- $\sum_i s_i \approx m$.
- Parameters: $0 \leq \alpha \leq 1$, $0 \leq \beta^* \leq 1$, $0 \leq \gamma \leq 1 - \alpha$ and $m =$ period of seasonality (e.g. $m = 4$ for quarterly data).

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 Territo~ Holiday <ETS(M,N,A~  
## 4 Australia's Coral Coast Western Australia Holiday <ETS(M,N,A~  
## 5 Australia's Golden Outba~ 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 Territo~ 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  s1  s2    s3    s4
## 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)
```

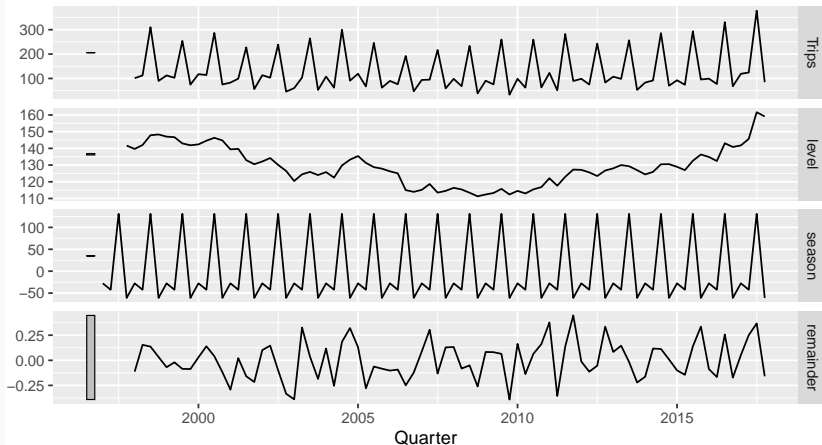
```
## # A dable:                84 x 9 [1Q]
## # Key:                    Region, State, Purpose, .model [1]
## # ETS(M,N,A) Decomposition: Trips = (lag(level, 1) + lag(season,
## #   4)) * (1 + remainder)
##   Region State Purpose .model   Quarter Trips level season
##   <chr>  <chr> <chr>  <chr>      <qtr>  <dbl>  <dbl>  <dbl>
## 1 Snowy~ New ~ Holiday ets      1997 Q1   NA      NA    -27.7
## 2 Snowy~ New ~ Holiday ets      1997 Q2   NA      NA    -42.2
## 3 Snowy~ New ~ Holiday ets      1997 Q3   NA      NA    131.
## 4 Snowy~ New ~ Holiday ets      1997 Q4   NA     142.   -61.0
## 5 Snowy~ New ~ Holiday ets      1998 Q1  101.    140.   -27.7
## 6 Snowy~ New ~ Holiday ets      1998 Q2  112.    142.   -42.2
## 7 Snowy~ New ~ Holiday ets      1998 Q3  310.    148.    131.
## 8 Snowy~ New ~ Holiday ets      1998 Q4   89.8   148.   -61.0
## 9 Snowy~ New ~ Holiday ets      1999 Q1  112.    147.   -27.7
## 10 Snowy~ New ~ Holiday ets      1999 Q2  103.    147.   -42.2
## # ...with 74 more rows, and 1 more variable: remainder <dbl>
```

Example: Australian holiday tourism

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

ETS(M,N,A) decomposition

Trips = (lag(level, 1) + lag(season, 4)) * (1 + remainder)



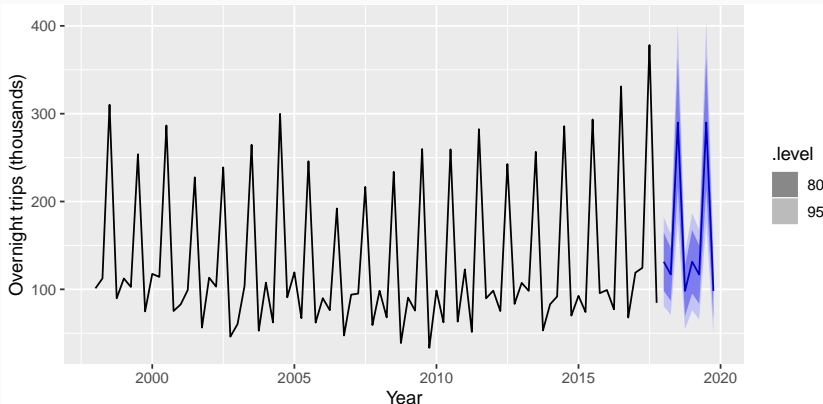
Example: Australian holiday tourism

```
fit %>% forecast()
```

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

Example: Australian holiday tourism

```
fit %>% forecast() %>%  
  filter(Region=="Snowy Mountains") %>%  
  autoplot(holidays) +  
    xlab("Year") + ylab("Overnight trips (thousands)")
```



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Exponential smoothing models

Additive Error

		Seasonal Component		
		N (None)	A (Additive)	M (Multiplicative)
Trend Component	N (None)	A,N,N	A,N,A	A,N,M
	A (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		
		N (None)	A (Additive)	M (Multiplicative)
Trend Component	N (None)	M,N,N	M,N,A	M,N,M
	A (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

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.

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.

Model selection

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Corrected AIC

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

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

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.

Corrected AIC

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

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):

- 1 Apply each model that is appropriate to the data. Optimize parameters and initial values using MLE.
 - 2 Select best method using AICc.
 - 3 Produce forecasts using best method.
 - 4 Obtain forecast intervals using underlying state space model.
- Method performed very well in M3 competition.
 - Used as a benchmark in the M4 competition.

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Lab Session 12

Find an ETS model for the Gas data from `aus_production`.

- Why is multiplicative seasonality necessary here?
- Experiment with making the trend damped.