

Tidy Time Series & Forecasting in R

7. Exponential smoothing

bit.ly/fable2020



Outline

- 1 Exponential smoothing
- 2 Trend methods
- 3 Lab Session 14
- 4 Seasonal methods
- 5 ETS taxonomy
- 6 Lab Session 15
- 7 Non-Gaussian forecast distributions

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Pharmaceutical Benefits Scheme



Pharmaceutical Benefits Scheme

The Pharmaceutical Benefits Scheme (PBS) is the Australian government drugs subsidy scheme.

- Many drugs bought from pharmacies are subsidised to allow more equitable access to modern drugs.
- The cost to government is determined by the number and types of drugs purchased. Currently nearly 1% of GDP.
- The total cost is budgeted based on forecasts of drug usage.

Pharmaceutical Benefits Scheme



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POLITICS

Opp demands drug price restriction after PBS budget blow-out

The Federal Opposition has called for tighter controls on drug prices after the Pharmaceutical Benefits Scheme (PBS) budget blew out by almost \$800 million.

The money was spent on two new drugs including the controversial anti-smoking aid Zyban, which dropped in price from \$220 to \$22 after it was listed on the PBS.



FEATURES



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SPECIALS

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Pharmaceutical Benefits Scheme

- In 2001: \$4.5 billion budget, under-forecasted by \$800 million.
- Thousands of products. Seasonal demand.
- Subject to covert marketing, volatile products, uncontrollable expenditure.
- Although monthly data available for 10 years, data are aggregated to annual values, and only the first three years are used in estimating the forecasts.
- All forecasts being done with the FORECAST function in MS-Excel!

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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Additively?

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

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

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Perhaps a mix of both?

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

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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

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")

ETS models

General notation

ETS : ExponenTial Smoothing



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

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

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

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

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

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

Holt's linear trend

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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
```

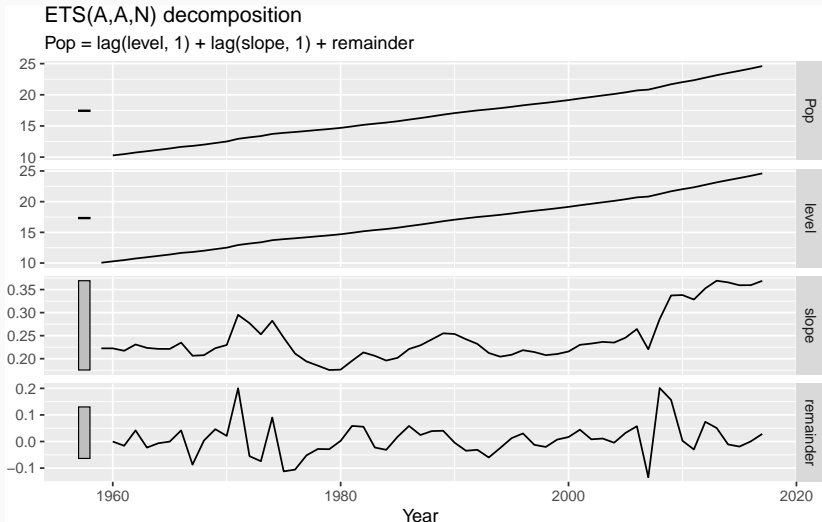

Example: Australian population

```
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
```

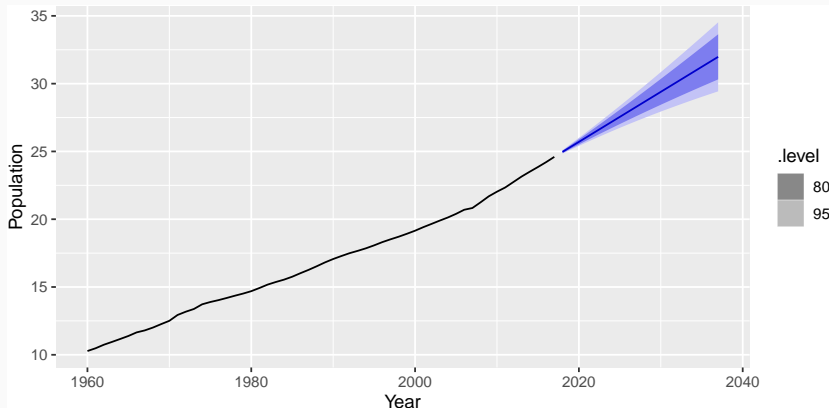
Example: Australian population

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

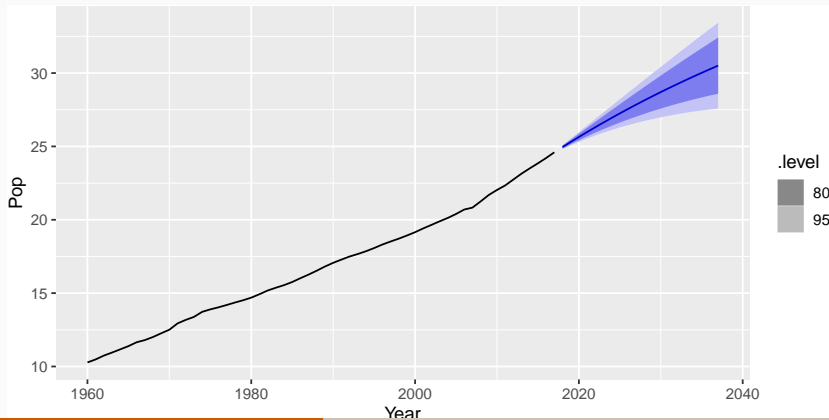
State equations $\ell_t = (\ell_{t-1} + \phi b_{t-1}) + \alpha \varepsilon_t$

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

- 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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Lab Session 14

Try forecasting the Chinese GDP from the `global_economy` data set using an ETS model.

Experiment with the various options in the `ETS()` function to see how much the forecasts change with damped trend, or with a Box-Cox transformation. Try to develop an intuition of what each is doing to the forecasts.

[Hint: use `h=20` when forecasting, so you can clearly see the differences between the various options when plotting the forecasts.]

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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)
```

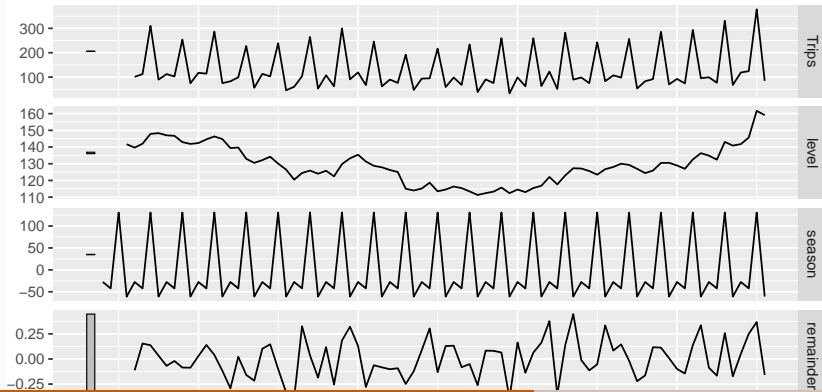
```
## # A dable:                84 x 9 [1Q]  
## # Key:                    Region, State, Purpose, .model [1]  
## # ETS(M,N,A) Decomposition: Trips = (lag(level, 1) + lag(season,  
## #   4)) * (1 + remainder)  
##   Region State Purpose .model   Quarter Trips level season  
##   <chr>  <chr> <chr>  <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
```


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]
```

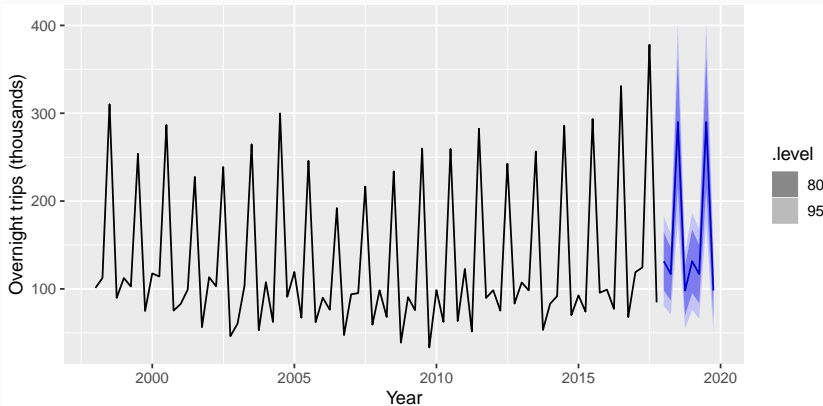
```
## # Key:      Region, State, Purpose, .model [76]
```

##	Region	State	Purpose	.model	Quarter	Trips	.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

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).

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

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

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 15

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

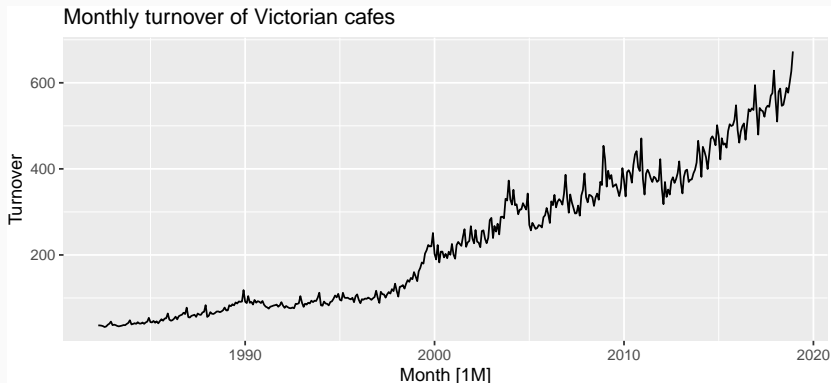
- Why is multiplicative seasonality necessary here?
- Experiment with making the trend damped.
Does it improve the forecasts?

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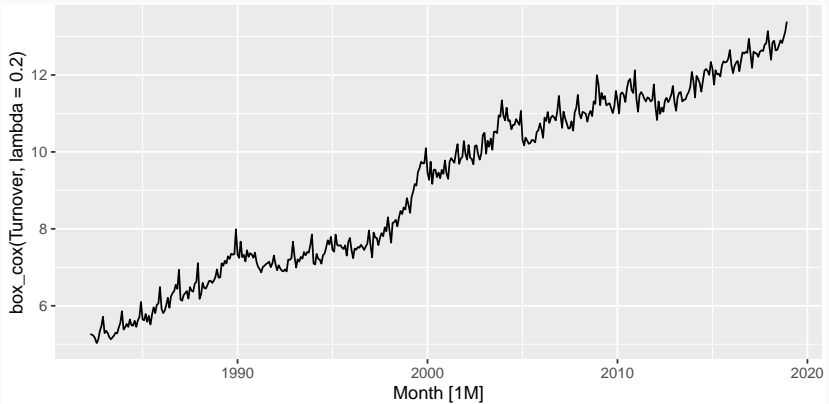
Non-Gaussian forecast distributions

```
vic_cafe <- tsibbledata::aus_retail %>%  
  filter(State == "Victoria",  
         Industry == "Cafes, restaurants and catering services") %>%  
  select(Month, Turnover)  
vic_cafe %>%  
  autoplot(Turnover) + ggtitle("Monthly turnover of Victorian cafes")
```



Forecasting with transformations

```
vic_cafe %>% autoplot(box_cox(Turnover, lambda = 0.2))
```



Forecasting with transformations

```
fit <- vic_cafe %>%  
  model(ets = ETS(box_cox(Turnover, 0.2)))  
fit
```

```
## # A mable: 1 x 1  
##   ets  
##   <model>  
## 1 <ETS(A,A,A)>
```

```
fit %>% forecast(h = "3 years")
```

```
## # A fable: 36 x 4 [1M]  
## # Key:      .model [1]  
##   .model      Month Turnover .distribution  
##   <chr>       <mth>      <dbl> <dist>  
## 1 ets        2019 Jan      608. t(N(13, 0.020))  
## 2 ets        2019 Feb      563. t(N(13, 0.028))  
## 3 ets        2019 Mar      629. t(N(13, 0.036))  
## 4 ets        2019 Apr      615. t(N(13, 0.044))  
## 5 ets        2019 May      613. t(N(13, 0.052))  
## 6 ets        2019 Jun      593. t(N(13, 0.061))
```

Forecasting with transformations

```
fit <- vic_cafe %>%  
  model(ets = ETS(box_cox(Turnover, 0.2)))  
fit
```

```
## # A mable: 1 x 1  
##   ets  
##   <model>  
## 1 <ETS(A,A,A)>
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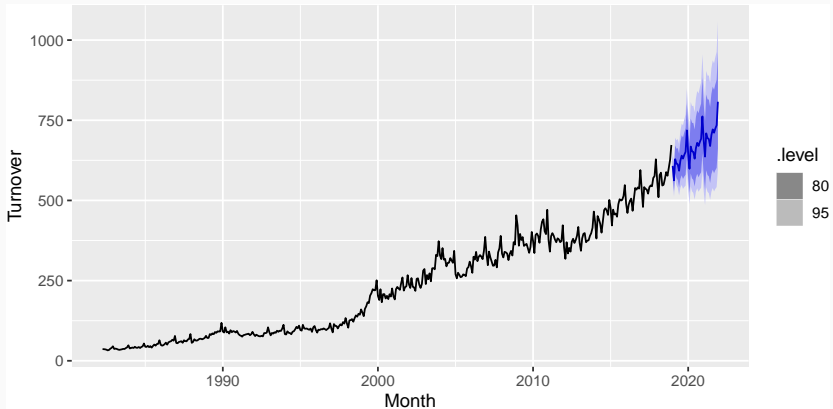
```
fit %>% forecast(h = "3 years")
```

```
## # A fable: 36 x 4 [1M]  
## # Key:      .model [1]  
##   .model      Month Turnover .distribution  
##   <chr>       <mth>      <dbl> <dist>  
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## 6 ets        2019 Jun      593. t(N(13, 0.061))
```

- $t(N)$ denotes a transformed normal distribution.
- back-transformation and bias adjustment is done automatically.

Forecasting with transformations

```
fc %>% autoplot(vic_cafe)
```



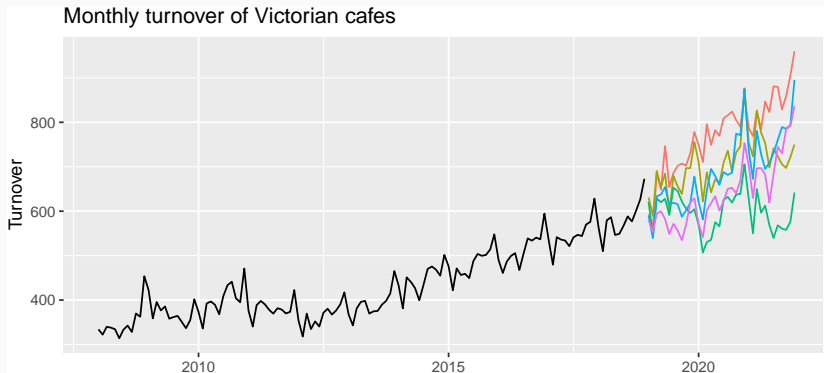
Bootstrapped forecast distributions

```
sim <- fit %>% generate(h = "3 years", times = 5, bootstrap = TRUE)
sim
```

```
## # A tsibble: 180 x 4 [1M]
## # Key:           .model, .rep [5]
##   .model  .rep    Month .sim
##   <chr>   <int>   <mth> <dbl>
## 1 ets      1 2019 Jan  593.
## 2 ets      1 2019 Feb  564.
## 3 ets      1 2019 Mar  684.
## 4 ets      1 2019 Apr  649.
## 5 ets      1 2019 May  747.
## 6 ets      1 2019 Jun  654.
## 7 ets      1 2019 Jul  686.
## 8 ets      1 2019 Aug  702.
## 9 ets      1 2019 Sep  707.
## 10 ets     1 2019 Oct  703.
## # ... with 170 more rows
```

Bootstrapped forecast distributions

```
vic_cafe %>%  
  filter(year(Month) >= 2008) %>%  
  ggplot(aes(x = Month)) +  
  geom_line(aes(y = Turnover)) +  
  geom_line(aes(y = .sim, colour = as.factor(.rep)), data = sim) +  
  ggtitle("Monthly turnover of Victorian cafes") +  
  guides(col = FALSE)
```



Bootstrapped forecast distributions

```
fc <- fit %>% forecast(h = "3 years", bootstrap = TRUE)
fc
```

```
## # A tibble: 36 x 4 [1M]
## # Key:   .model [1]
##   .model      Month Turnover .distribution
##   <chr>      <mth>      <dbl> <dist>
## 1 ets       2019 Jan       608. t(sim(=dbl[5000]))
## 2 ets       2019 Feb       563. t(sim(=dbl[5000]))
## 3 ets       2019 Mar       629. t(sim(=dbl[5000]))
## 4 ets       2019 Apr       615. t(sim(=dbl[5000]))
## 5 ets       2019 May       613. t(sim(=dbl[5000]))
## 6 ets       2019 Jun       593. t(sim(=dbl[5000]))
## 7 ets       2019 Jul       624. t(sim(=dbl[5000]))
## 8 ets       2019 Aug       640. t(sim(=dbl[5000]))
## 9 ets       2019 Sep       630. t(sim(=dbl[5000]))
## 10 ets      2019 Oct       642. t(sim(=dbl[5000]))
## # ... with 26 more rows
```

Bootstrapped forecast distributions

```
fc %>% autoplot(vic_cafe) +  
  ggtitle("Monthly turnover of Victorian cafes")
```

