

Time Series Analysis & Forecasting Using R

7. Exponential smoothing



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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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



For a fresh perspective on the federal election, reach into ABC Online's campaign weblog, [The Poll Vault](#).

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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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Multiplicatively?

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

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

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

ETS models

General notation **E T S : Exponential Smoothing**



Error Trend Season

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

ETS models

General notation **E T S : Exponential Smoothing**



Error Trend Season

The diagram shows three arrows pointing from the words 'Error', 'Trend', and 'Season' below to the letters 'E', 'T', and 'S' respectively in the 'ETS' part of the notation above.

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

Trend: None ("N"), additive ("A"), multiplicative ("M"), or damped ("Ad" or "Md").

ETS models

General notation **E T S : ExponenTial Smoothing**



Error Trend Season

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

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

Measurement equation

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

State equation

$$l_t = l_{t-1} + \alpha \varepsilon_t$$

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 state(s) over time.

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

Forecast equation

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

Measurement equation

$$y_t = l_{t-1}(1 + \varepsilon_t)$$

State equation

$$l_t = l_{t-1}(1 + \alpha\varepsilon_t)$$

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

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

Forecast equation

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State equation

$$l_t = l_{t-1}(1 + \alpha\varepsilon_t)$$

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

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

Measurement equation

$$y_t = l_{t-1} + b_{t-1} + \varepsilon_t$$

State equations

$$l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t$$

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

Holt's linear trend

Additive errors: ETS(A,A,N)

Forecast equation

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

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

State equations

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

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

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

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

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

Example: Australian population

```
aus_economy <- global_economy |>
  filter(Country == "Australia") |>
  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[0] b[0]

10.1 0.222

sigma^2: 0.0041

AIC AICc BIC

-77.0 -75.8 -66.7

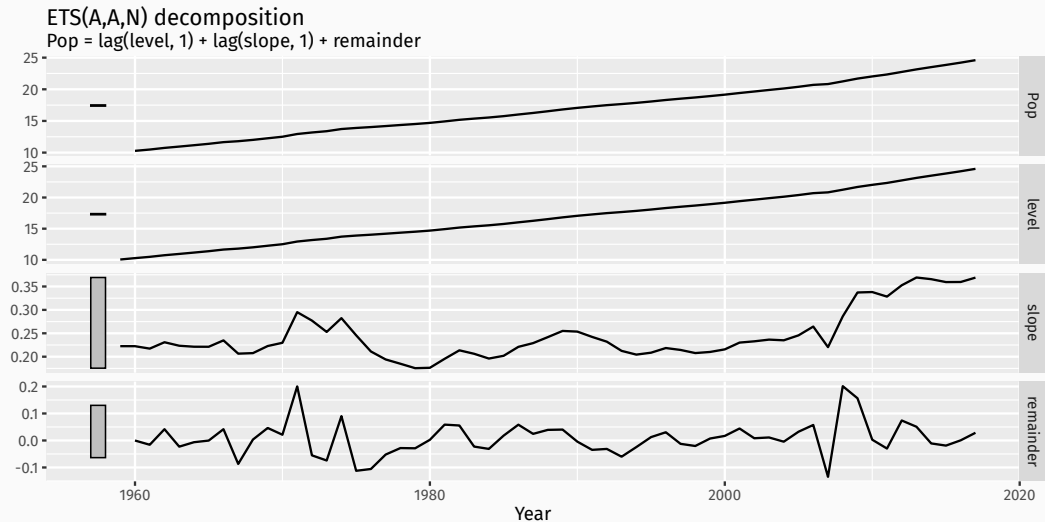
Example: Australian population

```
components(fit)
```

```
# A dable: 59 x 7 [1Y]
# Key:      Country, .model [1]
# :        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
```

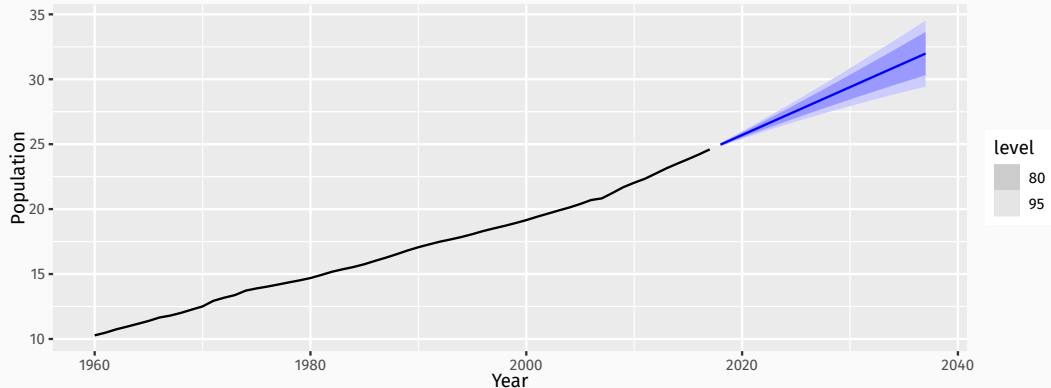
Example: Australian population

```
components(fit) |> autoplot()
```



Example: Australian population

```
fit |>  
  forecast(h = 20) |>  
  autoplot(aus_economy) +  
  labs(y = "Population", x = "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

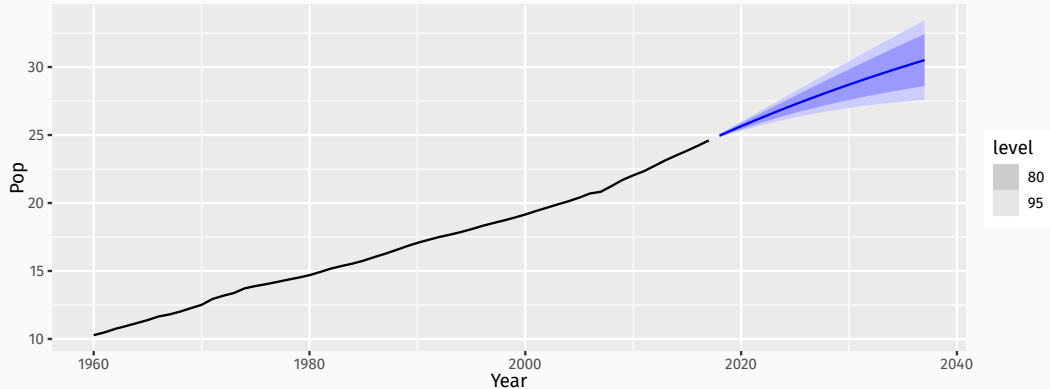
Additive errors

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)>

```
# i 253 more rows
```

Example: National populations

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

```
# A fable: 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  
# i 1,305 more rows
```


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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	SA	Holiday	<ETS(A,N,A)>
2	Adelaide Hills	SA	Holiday	<ETS(A,A,N)>
3	Alice Springs	NT	Holiday	<ETS(M,N,A)>
4	Ballarat	VIC	Holiday	<ETS(M,N,A)>
5	Barkly	NT	Holiday	<ETS(A,N,A)>
6	Barossa	SA	Holiday	<ETS(A,N,N)>
7	Bendigo Loddon	VIC	Holiday	<ETS(M,N,N)>
8	Blue Mountains	NSW	Holiday	<ETS(M,N,M)>
9	Brisbane	QLD	Holiday	<ETS(A,A,N)>
10	Bundaberg	QLD	Holiday	<ETS(A,N,A)>

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 dable: 84 x 9 [1Q]
```

```
# Key:      Region, State, Purpose, .model [1]
```

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

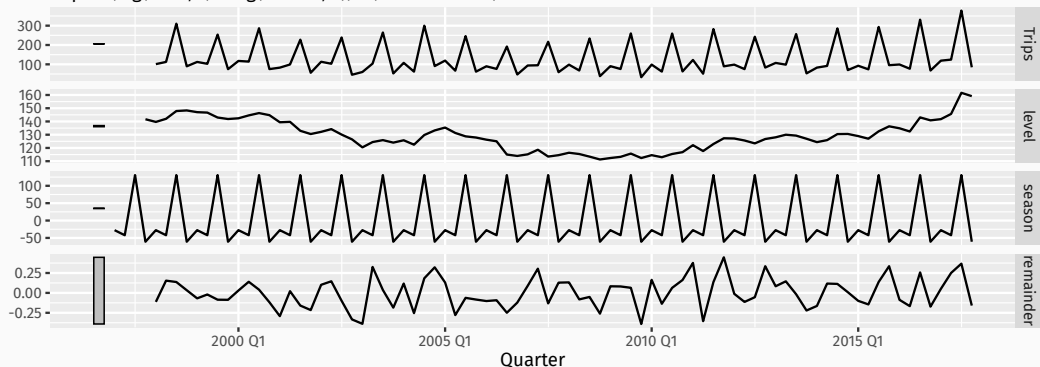
	Region <chr>	State <chr>	Purpose <chr>	.model <chr>	Quarter <qtr>	Trips <dbl>	level <dbl>	season <dbl>	remainder <dbl>
1	Snowy Mountains	NSW	Holiday	ets	1997 Q1	NA	NA	-27.7	NA
2	Snowy Mountains	NSW	Holiday	ets	1997 Q2	NA	NA	-42.2	NA
3	Snowy Mountains	NSW	Holiday	ets	1997 Q3	NA	NA	131.	NA
4	Snowy Mountains	NSW	Holiday	ets	1997 Q4	NA	142.	-61.0	NA
5	Snowy Mountains	NSW	Holiday	ets	1998 Q1	101.	140.	-27.7	-0.113
6	Snowy Mountains	NSW	Holiday	ets	1998 Q2	112.	142.	-42.2	0.154
7	Snowy Mountains	NSW	Holiday	ets	1998 Q3	310.	148.	131.	0.137
8	Snowy Mountains	NSW	Holiday	ets	1998 Q4	89.8	148.	-61.0	0.0335
9	Snowy Mountains	NSW	Holiday	ets	1999 Q1	112.	147.	-27.7	-0.0687
10	Snowy Mountains	NSW	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 fable: 608 x 7 [1Q]
```

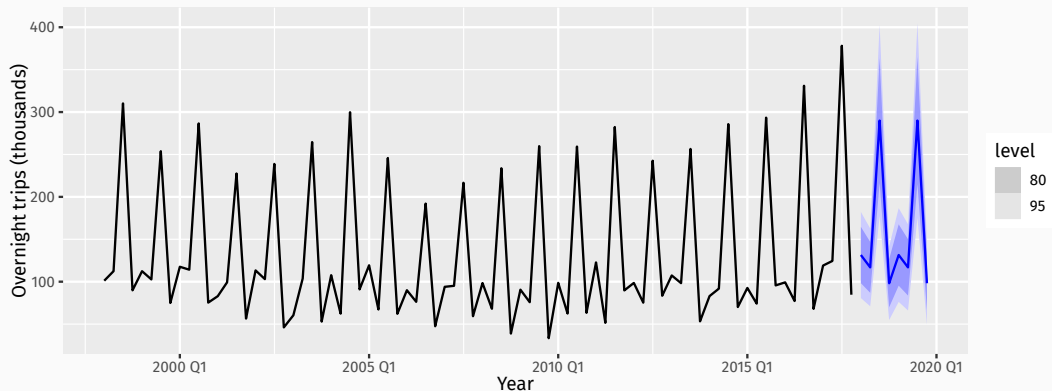
```
# Key:      Region, State, Purpose, .model [76]
```

	Region	State	Purpose	.model	Quarter	Trips	.mean
	<chr>	<chr>	<chr>	<chr>	<qtr>	<dist>	<dbl>
1	Adelaide	SA	Holiday	ets	2018 Q1	N(210, 457)	210.
2	Adelaide	SA	Holiday	ets	2018 Q2	N(173, 473)	173.
3	Adelaide	SA	Holiday	ets	2018 Q3	N(169, 489)	169.
4	Adelaide	SA	Holiday	ets	2018 Q4	N(186, 505)	186.
5	Adelaide	SA	Holiday	ets	2019 Q1	N(210, 521)	210.
6	Adelaide	SA	Holiday	ets	2019 Q2	N(173, 537)	173.
7	Adelaide	SA	Holiday	ets	2019 Q3	N(169, 553)	169.
8	Adelaide	SA	Holiday	ets	2019 Q4	N(186, 569)	186.
9	Adelaide Hills	SA	Holiday	ets	2018 Q1	N(19, 36)	19.4
10	Adelaide Hills	SA	Holiday	ets	2018 Q2	N(20, 36)	19.6

```
# i 598 more rows
```

Example: Australian holiday tourism

```
fit |>  
  forecast() |>  
  filter(Region == "Snowy Mountains") |>  
  autoplot(holidays) +  
  labs(x = "Year", y = "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 $\ell_0, b_0, s_0, s_{-1}, \dots, s_{-m+1}$ 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

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

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

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

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 15

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

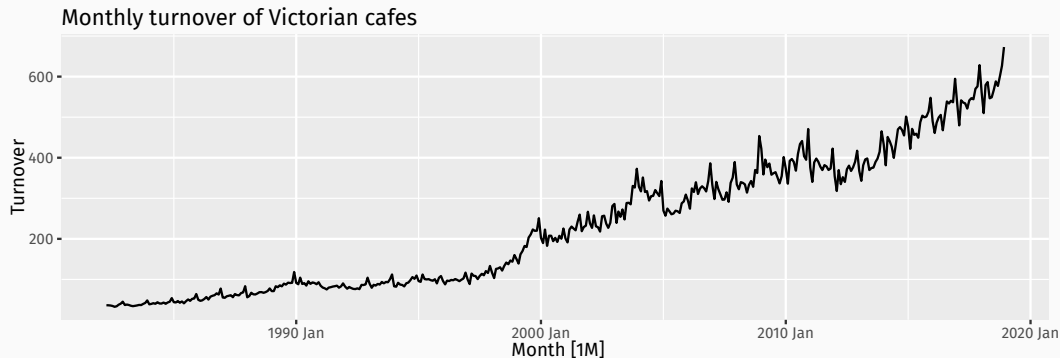
- Why is multiplicative seasonality necessary here?
- Experiment with making the trend damped. Does it improve the forecasts?

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

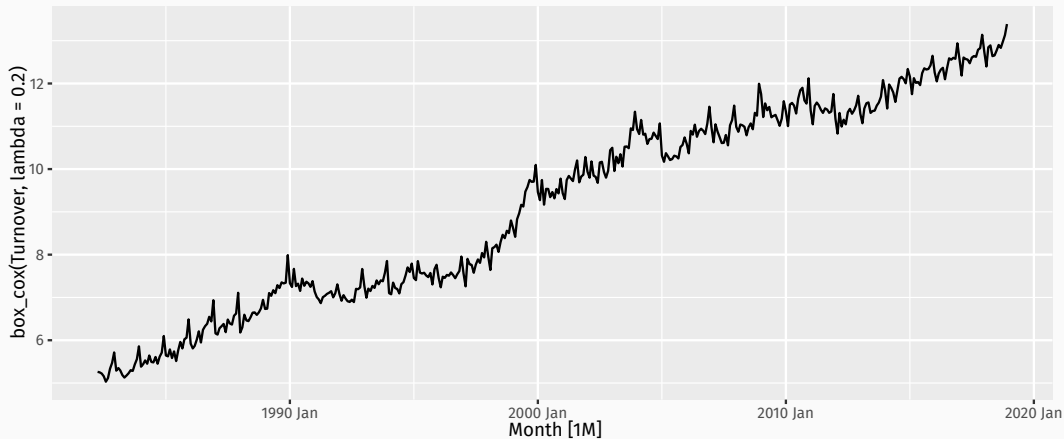
Non-Gaussian forecast distributions

```
vic_cafe <- tsibbledata::aus_retail |>
  filter(State == "Victoria",
         Industry == "Cafes, restaurants and catering services") |>
  select(Month, Turnover)
vic_cafe |>
  autoplot(Turnover) + labs(title = "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)>
```

```
(fc <- fit |> forecast(h = "3 years"))
```

```
# A fable: 36 x 4 [1M]  
# Key:      .model [1]  
  .model    Month      Turnover .mean  
  <chr>     <mth>      <dist> <dbl>  
1 ets      2019 Jan  t(N(13, 0.02)) 608.  
2 ets      2019 Feb  t(N(13, 0.028)) 563.  
3 ets      2019 Mar  t(N(13, 0.036)) 629.  
4 ets      2019 Apr  t(N(13, 0.044)) 615.  
5 ets      2019 May  t(N(13, 0.052)) 613.  
6 ets      2019 Jun  t(N(13, 0.061)) 593.
```

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)>
```

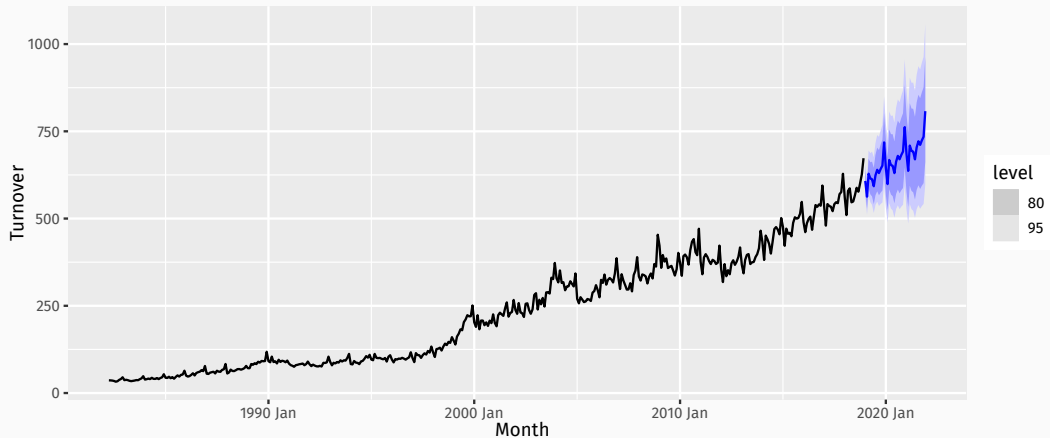
```
(fc <- fit |> forecast(h = "3 years"))
```

```
# A fable: 36 x 4 [1M]  
# Key:      .model [1]  
  .model    Month      Turnover .mean  
  <chr>     <mth>      <dist> <dbl>  
1 ets      2019 Jan  t(N(13, 0.02)) 608.  
2 ets      2019 Feb  t(N(13, 0.028)) 563.  
3 ets      2019 Mar  t(N(13, 0.036)) 629.  
4 ets      2019 Apr  t(N(13, 0.044)) 615.  
5 ets      2019 May  t(N(13, 0.052)) 613.  
6 ets      2019 Jun  t(N(13, 0.061)) 593.
```

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

Forecasting with transformations

```
fc |> autoplot(vic_cafe)
```



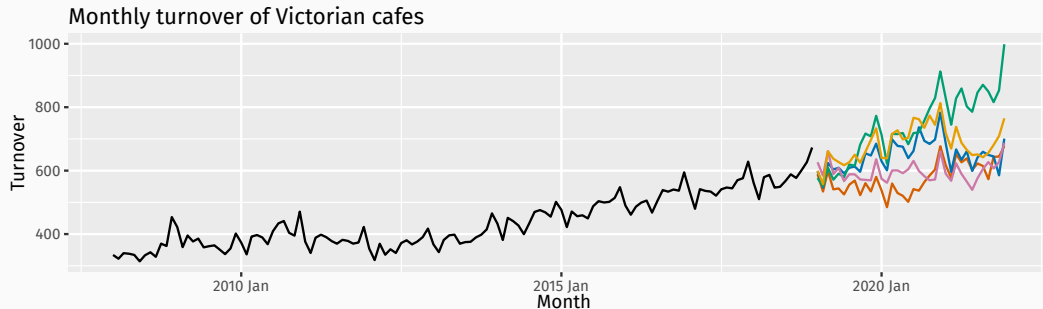
Bootstrapped forecast distributions

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

```
# A tsibble: 180 x 5 [1M]
# Key:           .model, .rep [5]
  .model .rep   Month   .innov .sim
  <chr>  <chr>   <mth>    <dbl> <dbl>
1 ets    1      2019 Jan -0.114  588.
2 ets    1      2019 Feb -0.108  534.
3 ets    1      2019 Mar -0.0309  599.
4 ets    1      2019 Apr -0.291  541.
5 ets    1      2019 May -0.0740  544.
6 ets    1      2019 Jun -0.0313  525.
7 ets    1      2019 Jul  0.00552  556.
8 ets    1      2019 Aug -0.00674  569.
9 ets    1      2019 Sep -0.245   523.
10 ets   1      2019 Oct  0.0891  560.
# i 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) +  
  labs(title = "Monthly turnover of Victorian cafes") +  
  guides(col = FALSE)
```



Bootstrapped forecast distributions

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

```
# A fable: 36 x 4 [1M]
# Key:      .model [1]
  .model      Month      Turnover .mean
  <chr>      <mth>      <dist> <dbl>
1 ets       2019 Jan sample[5000] 608.
2 ets       2019 Feb sample[5000] 562.
3 ets       2019 Mar sample[5000] 628.
4 ets       2019 Apr sample[5000] 615.
5 ets       2019 May sample[5000] 612.
6 ets       2019 Jun sample[5000] 592.
7 ets       2019 Jul sample[5000] 623.
8 ets       2019 Aug sample[5000] 639.
9 ets       2019 Sep sample[5000] 629.
10 ets      2019 Oct sample[5000] 641.
# i 26 more rows
```

Bootstrapped forecast distributions

```
fc |> autoplot(vic_cafe) +  
  labs(title = "Monthly turnover of Victorian cafes")
```

