MONASH University

MONASH BUSINESS SCHOOL

Forecasting: principles and practice

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2.2 Transformations

Outline

Variance stabilization

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Mathematical transformations for stabilizing variation

Square root	$w_t = \sqrt{y_t}$	$\downarrow$
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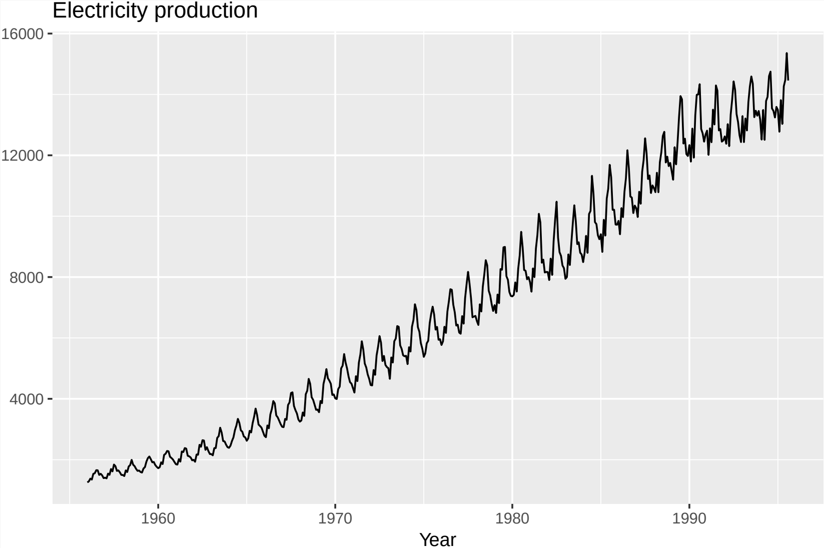
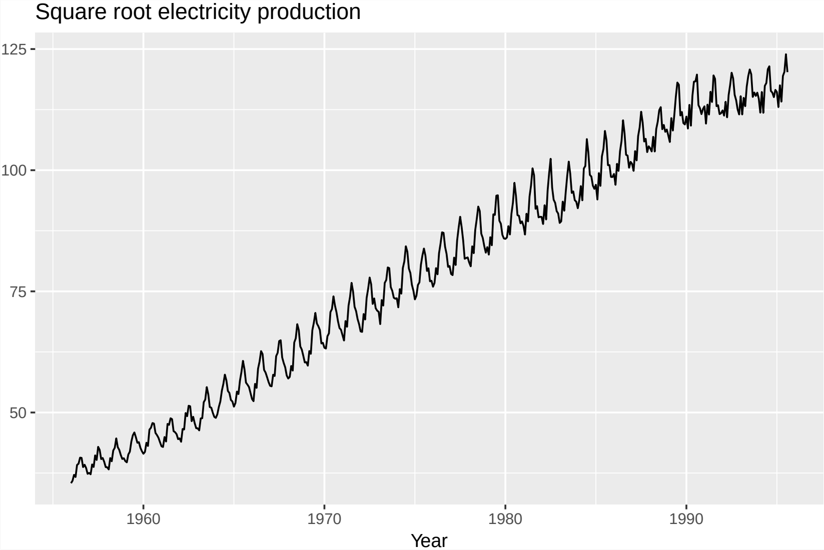
Logarithms, in particular, are useful because they are more interpretable: changes in a log value are

Variance stabilization



Variance stabilization



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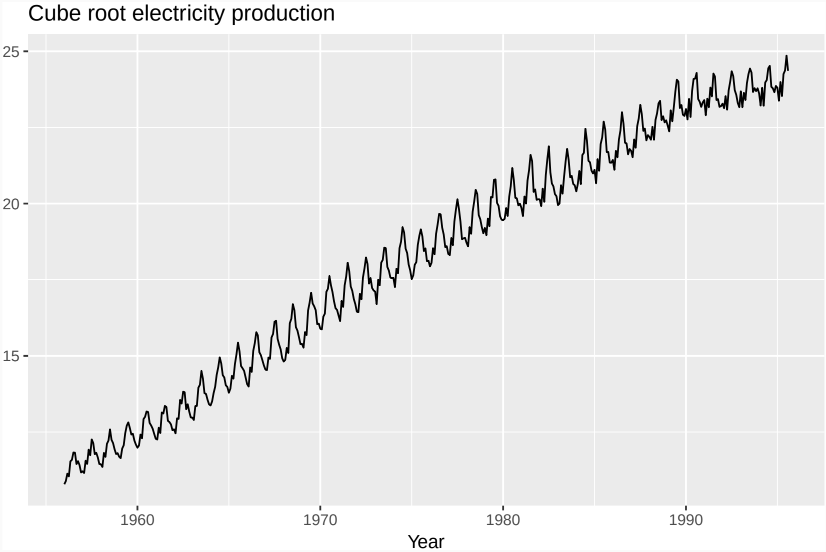

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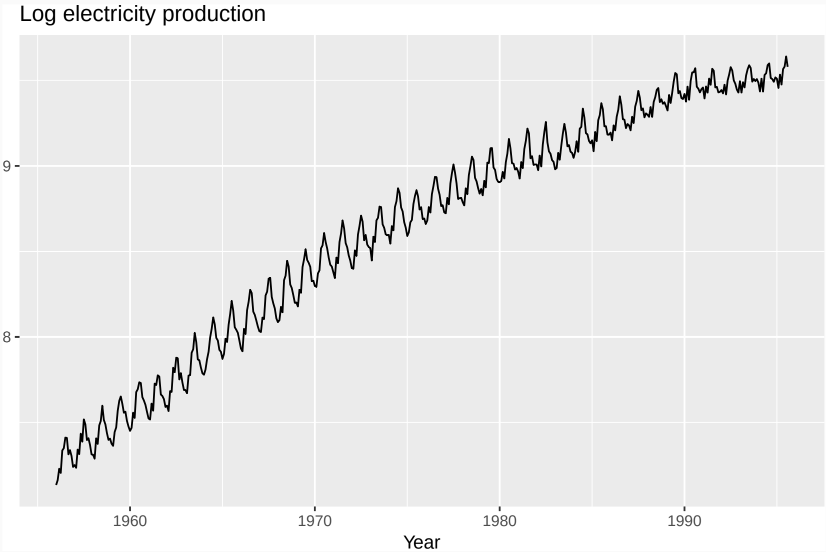

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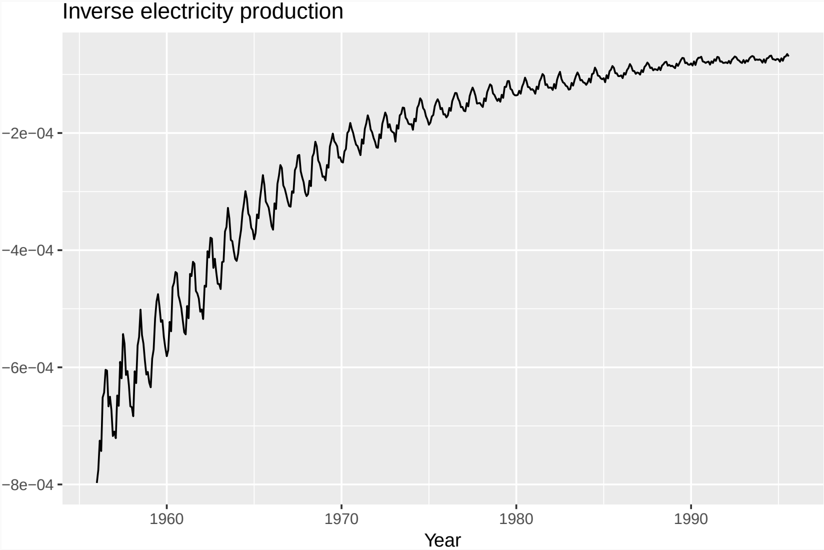

Outline

Box-Cox transformations

Each of these transformations is close to a member of the family of **Box-Cox transformations**:

$$w_t = \begin{cases} \log(y_t), & \lambda = 0; \\ (y_t^\lambda - 1)/\lambda, & \lambda \neq 0. \end{cases}$$

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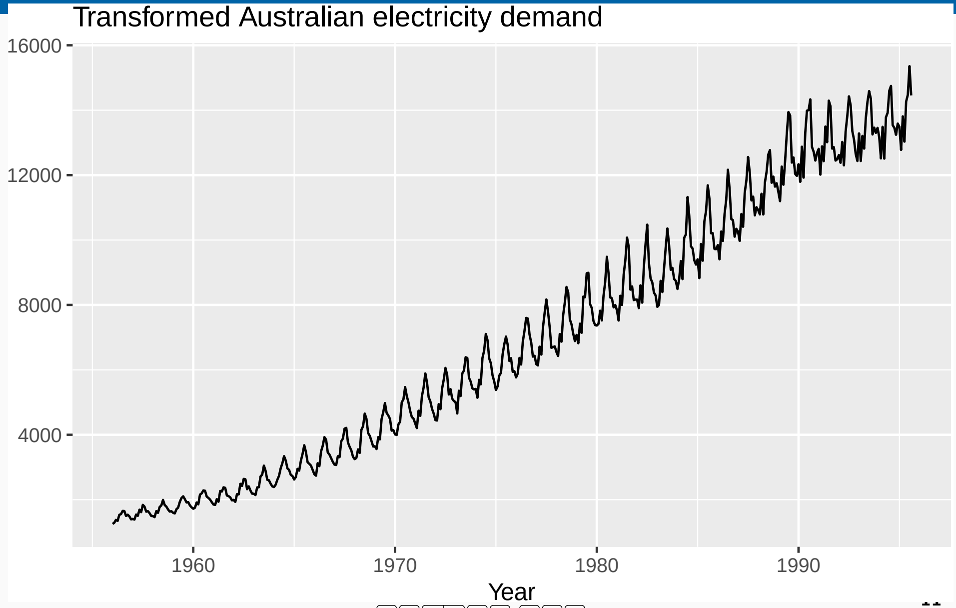
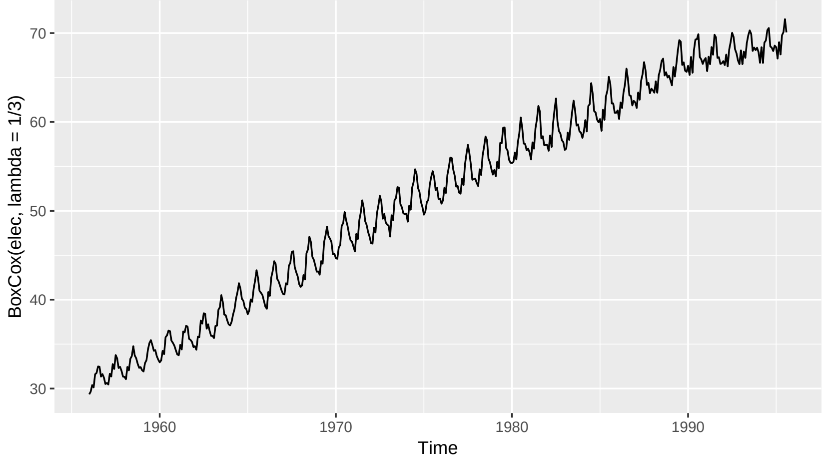
- $\lambda = 1$: (No substantive transformation)
- $\lambda = \frac{1}{2}$: (Square root plus linear transformation)
- $\lambda = 0$: (Natural logarithm)
- $\lambda = -1$: (Inverse plus 1)

Box-Cox transformations



Box-Cox transformations

```
autoplot(BoxCox(elec,lambda=1/3))
```



Box-Cox transformations

- y_t^λ for λ close to zero behaves like logs.
- If some $y_t = 0$, then must have $\lambda > 0$
- if some $y_t < 0$, no power transformation is possible unless all y_t adjusted by **adding a constant to all values**.
- Choose a simple value of λ. It makes explanation easier.
- Results are relatively insensitive to value of λ
- Often no transformation ($\lambda = 1$) needed.
- Transformation often makes little difference to forecasts but has large effect on PI.
- Choosing $\lambda = 0$ is a simple way to force forecasts

Automated Box-Cox transformations

```r
(BoxCox.lambda(elec))
```

```
## [1] 0.2654076
```

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- This attempts to balance the seasonal fluctuations and random variation across the series.
- Always check the results.
- A low value of λ can give extremely large prediction intervals.

Outline

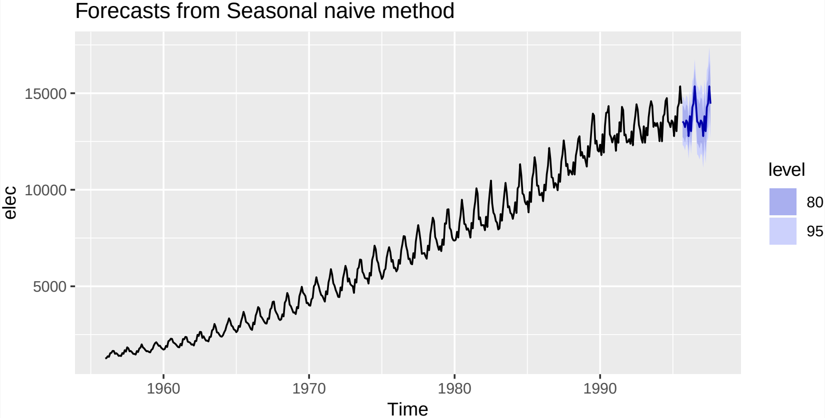
Back-transformation

We must reverse the transformation (or *back-transform*) to obtain forecasts on the original scale. The reverse Box-Cox transformations are given by

$$y_t = \begin{cases} \exp(w_t), & \lambda = 0; \\ (\lambda W_t + 1)^{1/\lambda}, & \lambda \neq 0. \end{cases}$$

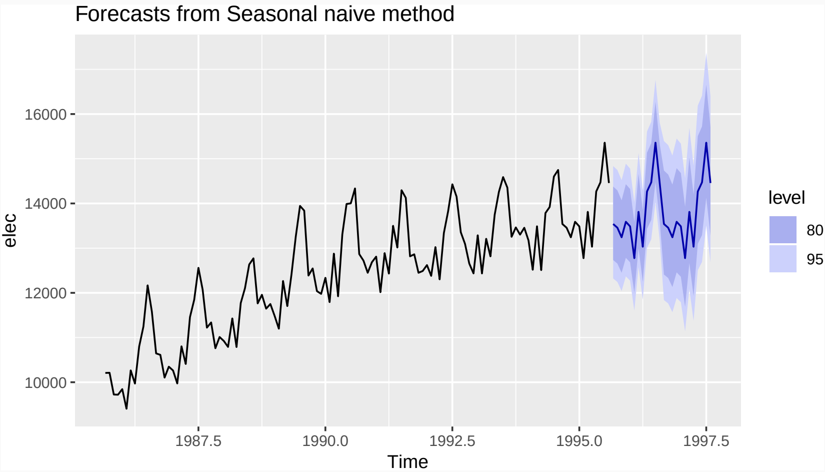
Back-transformation

```r
fit <- snaive(elec, lambda=1/3)
autoplot(fit)
```



Back-transformation

```
autoplot(fit, include=120)
```



Back transformation

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Back-transformed means

Let X be have mean μ and variance σ^2.

Let $f(x)$ be back-transformation function, and $Y = f(X)$.

$$\mathrm{E}[Y] = \mathrm{E}[f(X)] = f(\mu) + \tfrac{1}{2}\sigma^2[f''(\mu)]^2.$$

Back transformation

Box-Cox back-transformation:

$$y_t = \begin{cases} \exp(W_t) & \lambda = 0; \\ (\lambda W_t + 1)^{1/\lambda} & \lambda \neq 0. \end{cases}$$

$$f(x) = \begin{cases} e^x & \lambda = 0; \\ (\lambda x + 1)^{1/\lambda} & \lambda \neq 0. \end{cases}$$

$$f''(x) = \begin{cases} e^x & \lambda = 0; \\ (1 - \lambda)(\lambda x + 1)^{1/\lambda - 2} & \lambda \neq 0. \end{cases}$$

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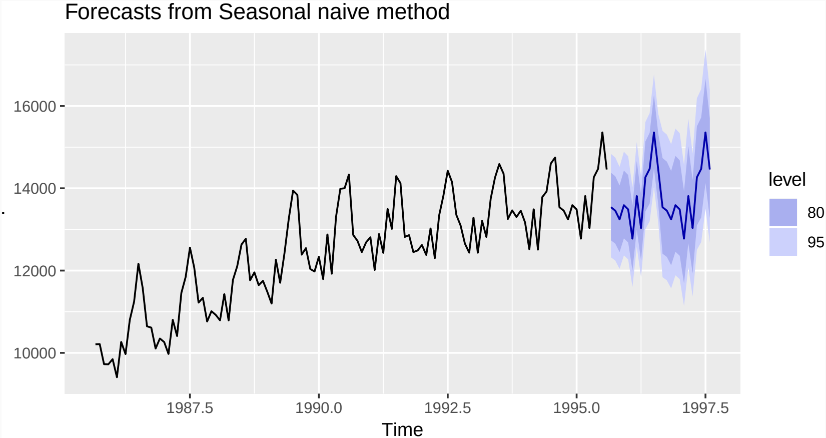
$$\mathrm{E}[Y] = \begin{cases} e^\mu \left[1 + \frac{\sigma^2}{2}\right] & \lambda = 0; \\ (\lambda\mu + 1)^{1/\lambda} \left[1 + \frac{\sigma^2(1-\lambda)}{2(\lambda\mu+1)^2}\right] & \lambda \neq 0. \end{cases}$$

Back-transformation

```
elec %>% snaive(lambda=1/3, biasadj=FALSE) %>%
  autoplot(include=120)
```



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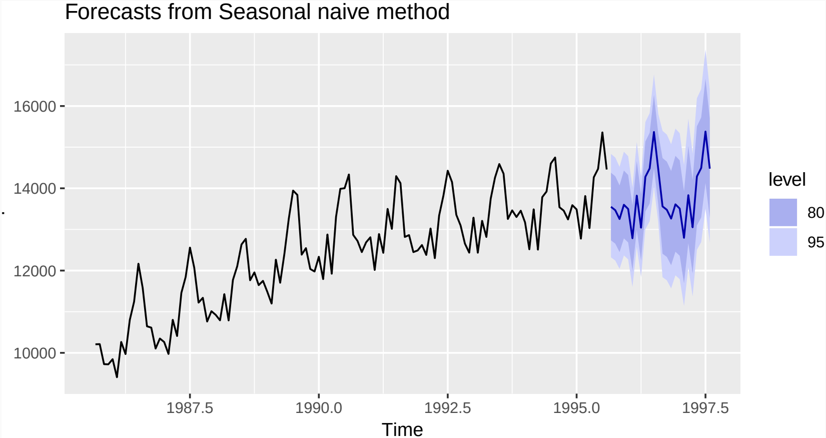

Back-transformation

```
eggs %>% ses(lambda=1/3, biasadj=FALSE) %>%
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```

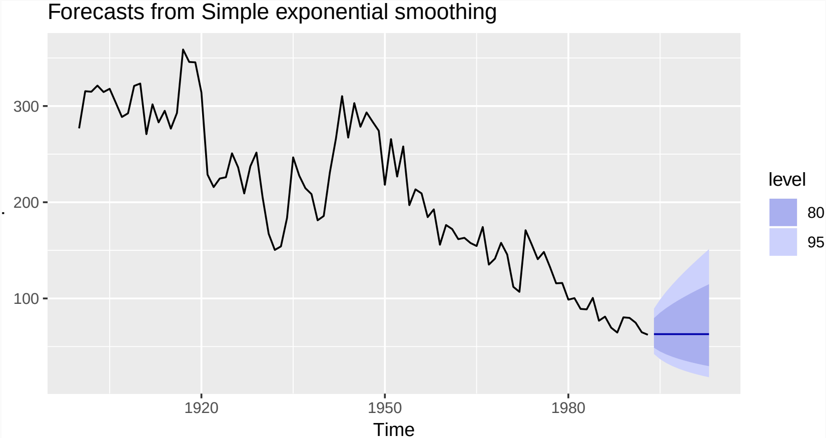

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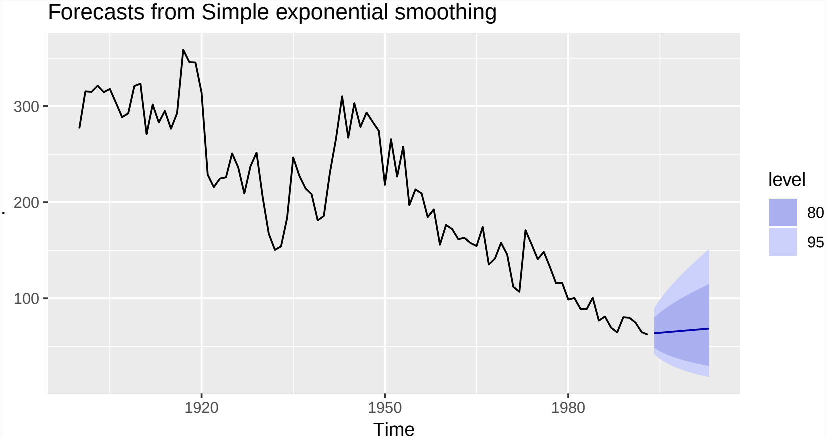

Outline

Lab Session 9