MONASH University

MONASH BUSINESS SCHOOL

Forecasting using R

Rob J Hyndman

2.2 Transformations

Outline

Variance stabilization

If the data show different variation at different levels of the series, then a transformation can be useful.

Denote original observations as $y_1, \dots, y_n$ and transformed observations as $w_1, \dots, w_n$.

Mathematical transformations for stabilizing variation

Square root	$w_t = \sqrt{y_t}$	$\downarrow$
Cube root	$w_t = \sqrt[3]{y_t}$	Increasing
Logarithm	$w_t = \log(y_t)$	strength

Logarithms, in particular, are useful because they are more interpretable: changes in a log value are **relative (percent) changes on the original scale.**

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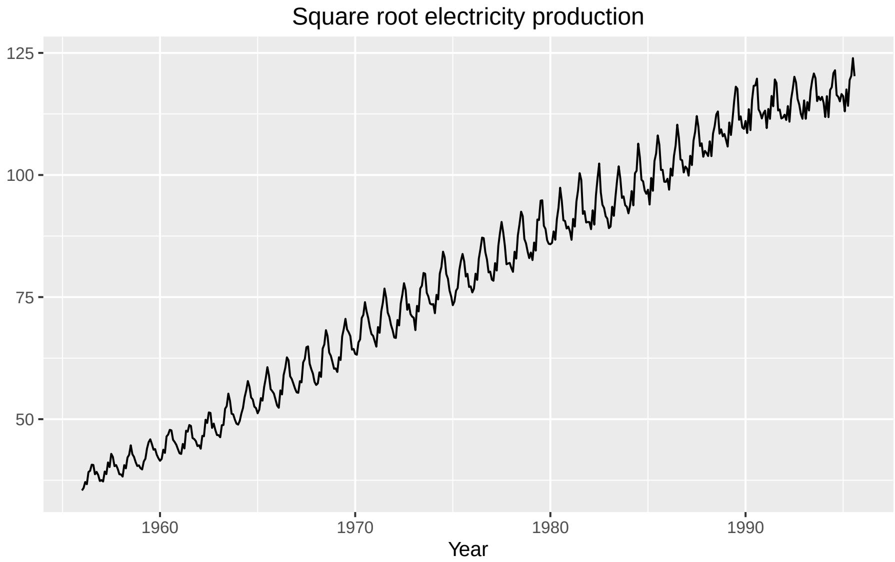
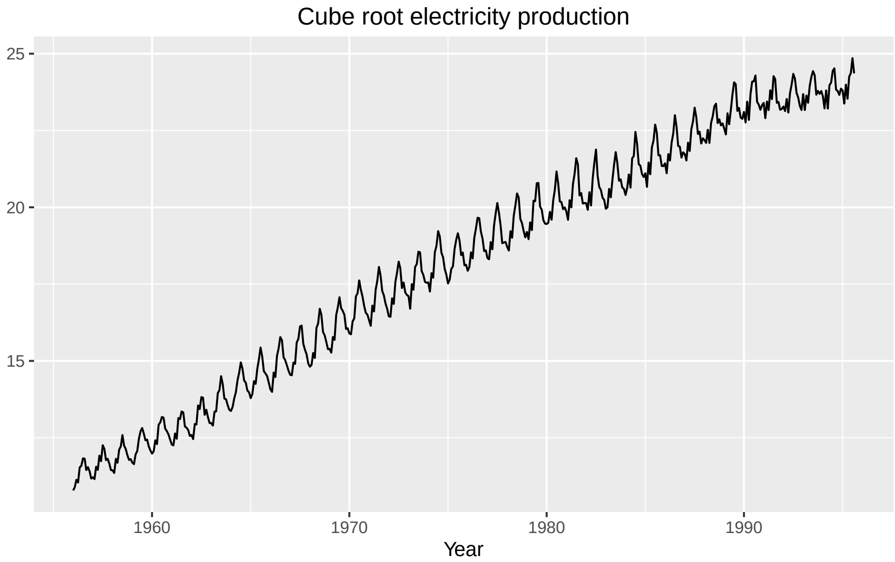
Variance stabilization



Variance stabilization



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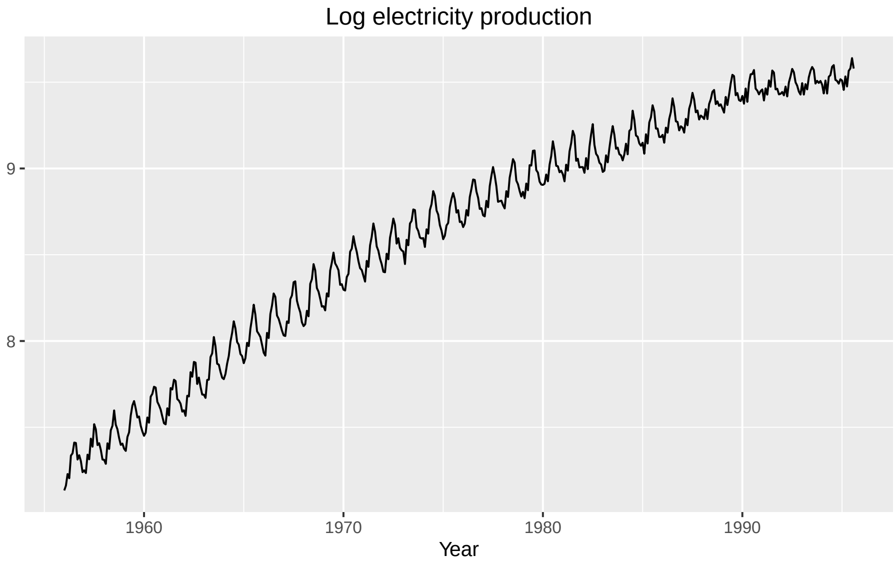

Variance stabilization

Outline

Box-Cox transformations

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

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

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

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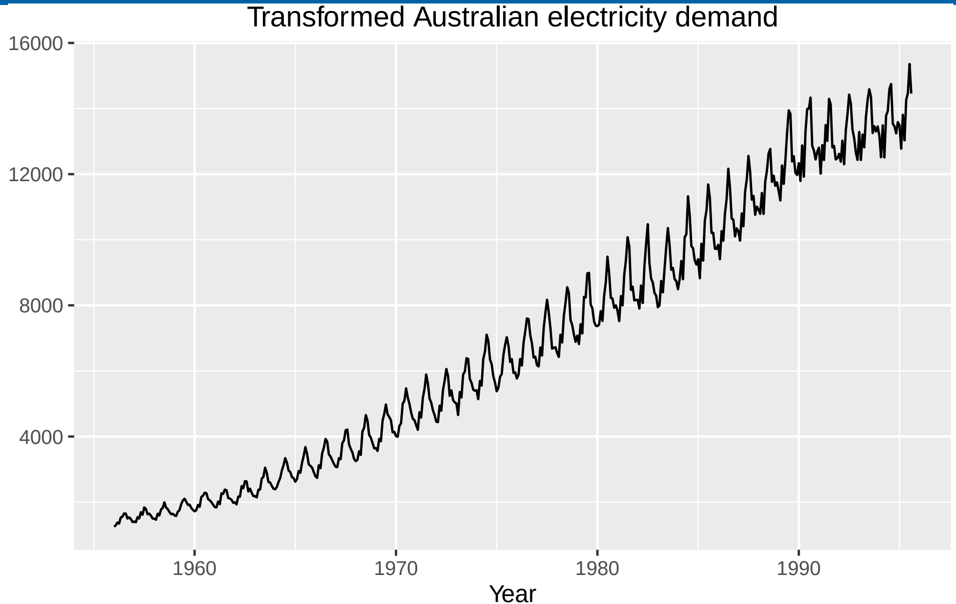
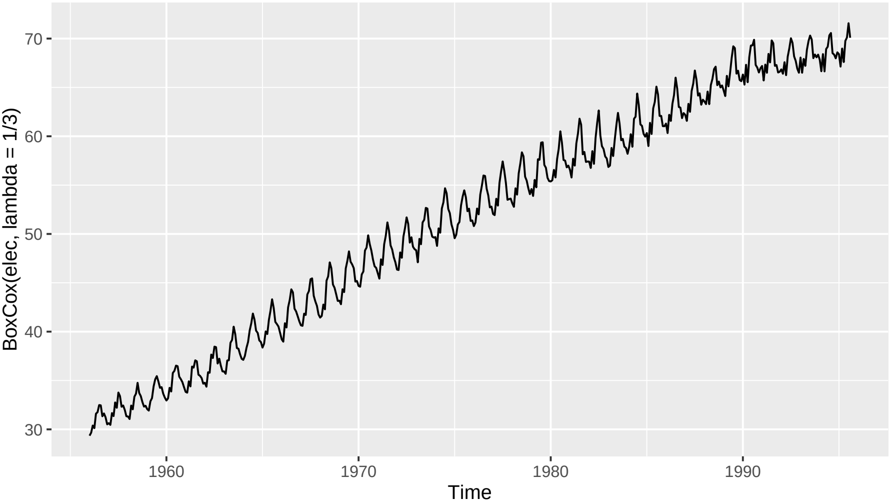
Box-Cox transformations



Box-Cox transformations

```r
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 to be positive

Automated Box-Cox transformations

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

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

- 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.

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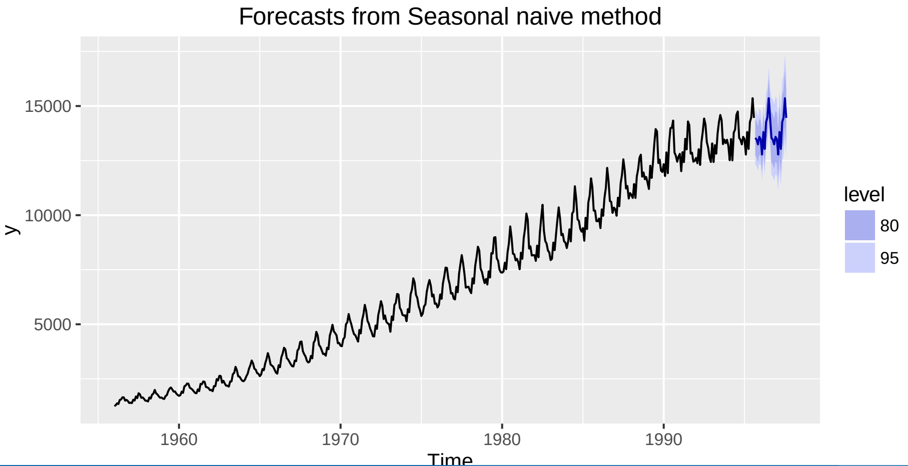
Back-transformation

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

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

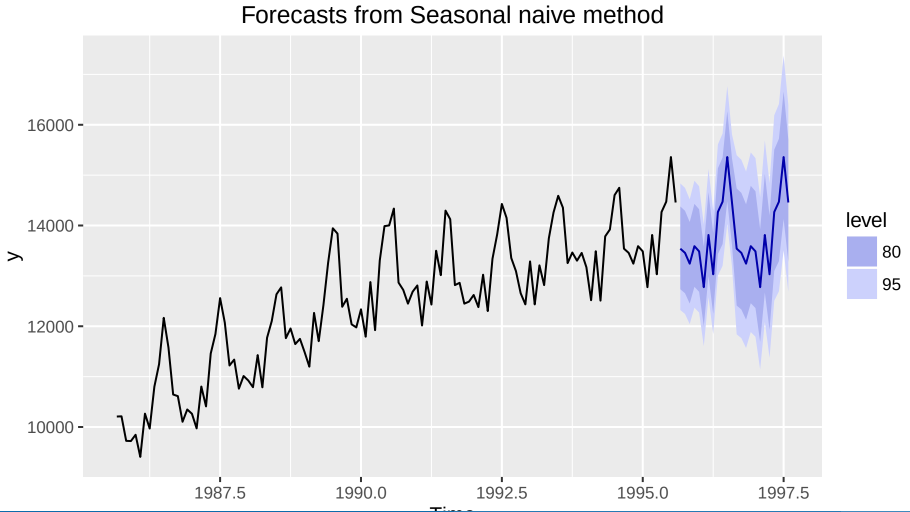
Back-transformation

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



Back-transformation

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



ETS and transformations

- A Box-Cox transformation followed by an additive ETS model is often better than an ETS model without transformation.
- It makes no sense to use a Box-Cox transformation and a *non-additive* ETS model.

Outline

Lab Session 9