

Time Series Analysis & Forecasting Using R

3. Transformations



Outline

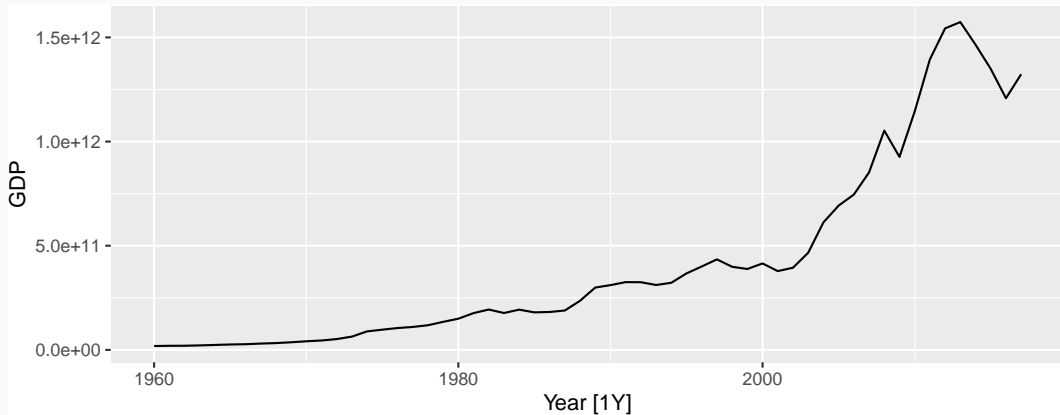
- 1 Per capita adjustments
- 2 Lab Session 6
- 3 Inflation adjustments
- 4 Mathematical transformations
- 5 Lab Session 7

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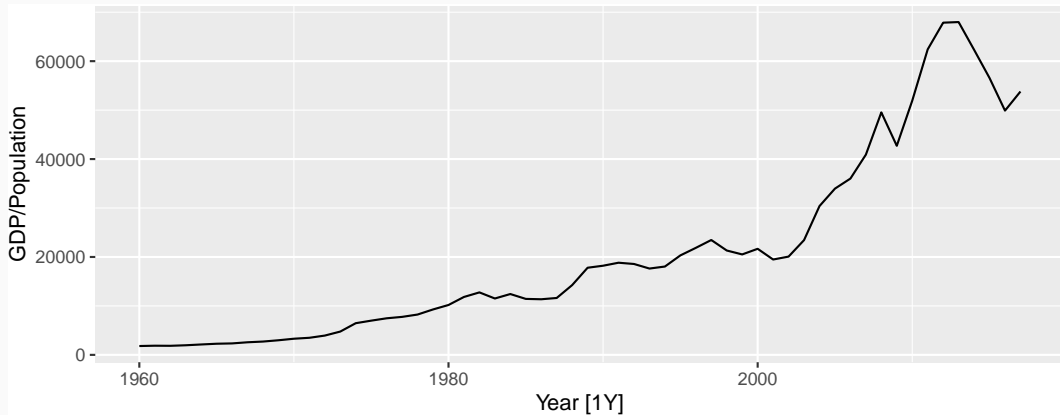
Per capita adjustments

```
global_economy ▷  
  filter(Country = "Australia") ▷  
  autoplot(GDP)
```



Per capita adjustments

```
global_economy ▷  
  filter(Country = "Australia") ▷  
  autoplot(GDP / Population)
```



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Lab Session 6

Consider the GDP information in `global_economy`. Plot the GDP per capita for each country over time. Which country has the highest GDP per capita? How has this changed over time?

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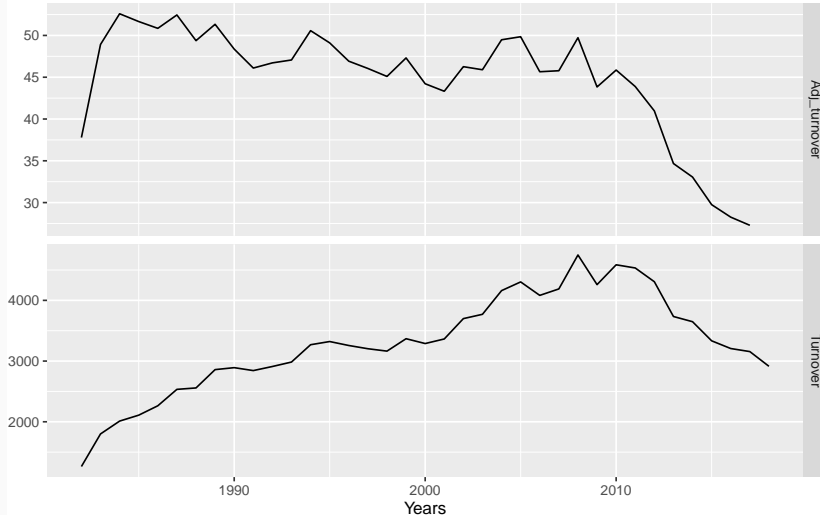
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Inflation adjustments

```
print_retail <- aus_retail ▷  
  filter(Industry = "Newspaper and book retailing") ▷  
  group_by(Industry) ▷  
  index_by(Year = year(Month)) ▷  
  summarise(Turnover = sum(Turnover))  
aus_economy <- filter(global_economy, Code = "AUS")  
print_retail ▷  
  left_join(aus_economy, by = "Year") ▷  
  mutate(Adj_turnover = Turnover / CPI) ▷  
  pivot_longer(c(Turnover, Adj_turnover),  
    names_to = "Type", values_to = "Turnover"  
  ) ▷  
  ggplot(aes(x = Year, y = Turnover)) +  
  geom_line() +  
  facet_grid(vars(Type), scales = "free_y") +  
  xlab("Years") + ylab(NULL) +  
  ggtitle("Turnover: Australian print media industry")
```

Inflation adjustments

Turnover: Australian print media industry



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Variance stabilization

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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

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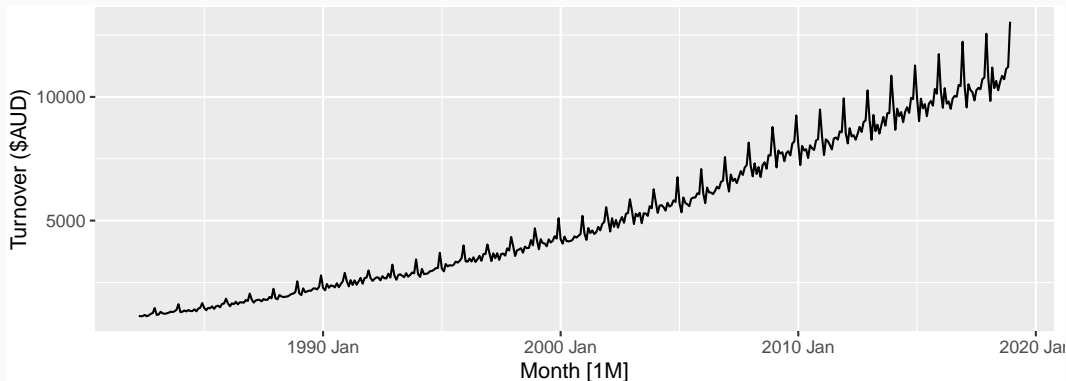
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Logarithms, in particular, are useful because they are more interpretable: changes in a log value are **relative (percent) changes on the original**

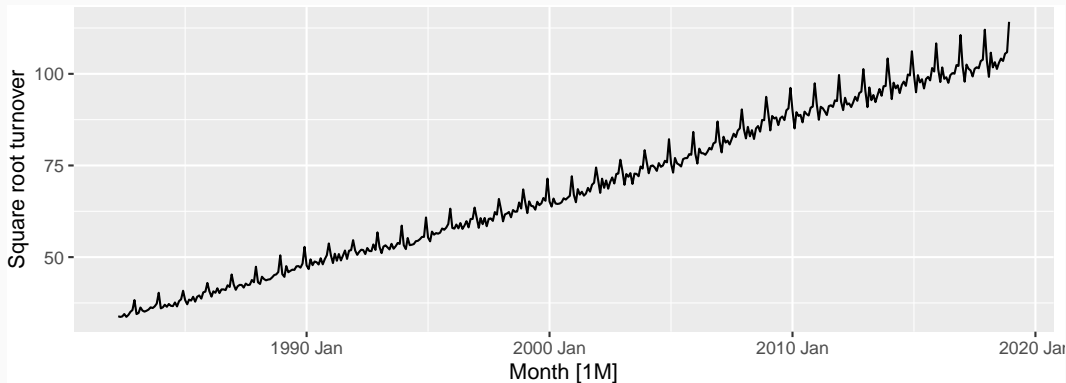
Variance stabilization

```
food <- aus_retail ▷  
  filter(Industry = "Food retailing") ▷  
  summarise(Turnover = sum(Turnover))
```



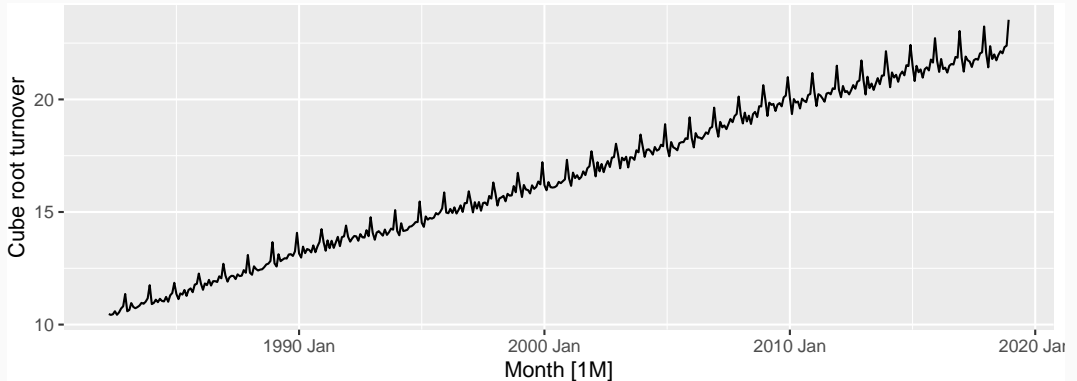
Variance stabilization

```
food > autoplot(sqrt(Turnover)) +  
  labs(y = "Square root turnover")
```



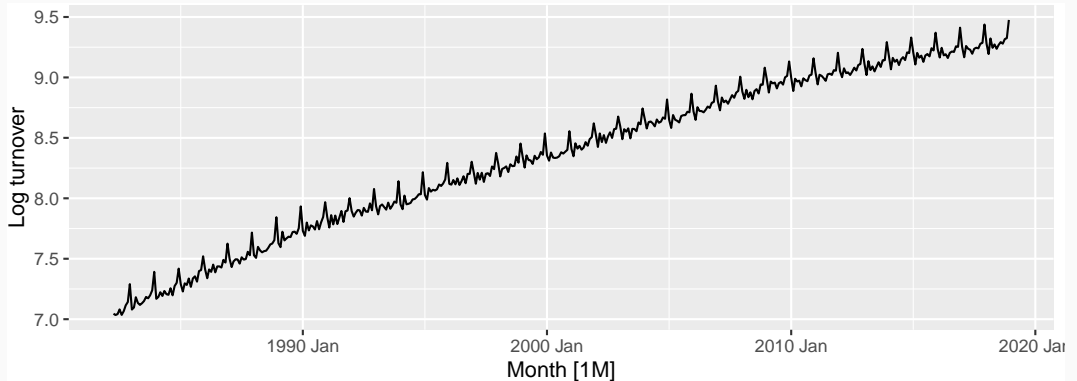
Variance stabilization

```
food > autoplot(Turnover^(1 / 3)) +  
  labs(y = "Cube root turnover")
```



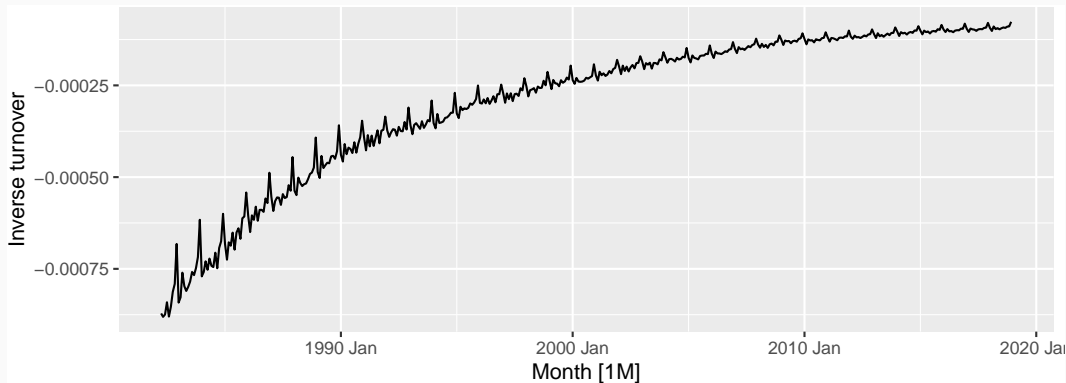
Variance stabilization

```
food > autoplot(log(Turnover)) +  
  labs(y = "Log turnover")
```



Variance stabilization

```
food > autoplot(-1 / Turnover) +  
  labs(y = "Inverse turnover")
```



Box-Cox transformations

Each of these transformations is close to a member of the family of

Box-Cox transformations:

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

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- Actually the Bickel-Doksum transformation (allowing for $y_t < 0$)
- $\lambda = 1$: (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

```
food ▷  
  features(Turnover, features = guerrero)
```

```
## # A tibble: 1 x 1  
##   lambda_guerrero  
##             <dbl>  
## 1             0.0524
```


Box-Cox transformations

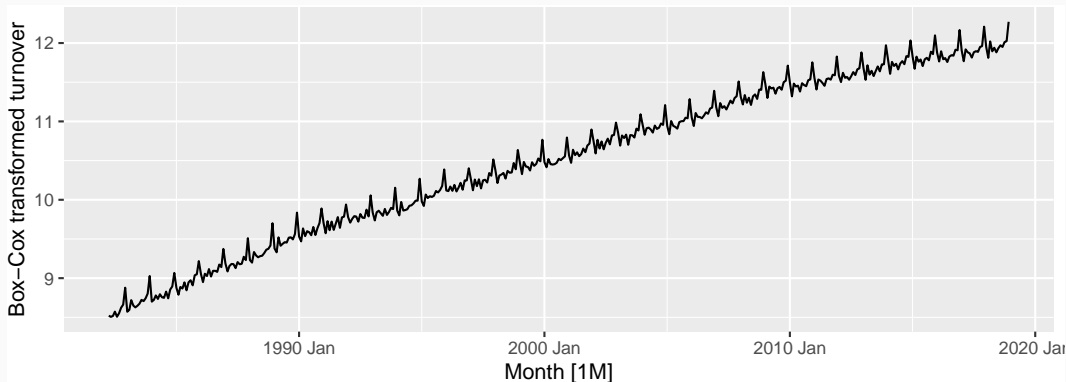
```
food >
  features(Turnover, features = guerrero)
```

```
## # A tibble: 1 x 1
##   lambda_guerrero
##             <dbl>
## 1             0.0524
```

- 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.

Box-Cox transformations

```
food > autoplot(box_cox(Turnover, 0.0524)) +  
  labs(y = "Box-Cox transformed turnover")
```



Transformations

- Often no transformation needed.
- Simple transformations are easier to explain and work well enough.
- Transformations can have very large effect on PI.
- If some data are zero or negative, then use $\lambda > 0$.
- $\log_{1p}()$ can also be useful for data with zeros.
- Choosing logs is a simple way to force forecasts to be positive
- Transformations must be reversed to obtain forecasts on the original scale. (Handled automatically by fable.)

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Lab Session 7

- 1 For the following series, find an appropriate transformation in order to stabilise the variance.
 - ▶ United States GDP from `global_economy`
 - ▶ Slaughter of Victorian “Bulls, bullocks and steers” in `aus_livestock`
 - ▶ Victorian Electricity Demand from `vic_elec`.
 - ▶ Gas production from `aus_production`
- 2 Why is a Box-Cox transformation unhelpful for the `canadian_gas` data?