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# Tidy Time Series & Forecasting in R



## 3. Transformations

[robjhyndman.com/workshop2020](http://robjhyndman.com/workshop2020)

# Outline

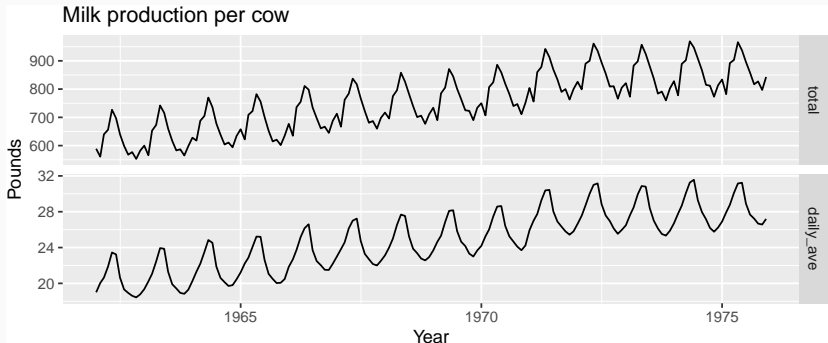
- 1 Calendar adjustments
- 2 Per capita adjustments
- 3 Inflation adjustments
- 4 Mathematical transformations
- 5 Lab Session 6

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# Calendar adjustments

```
as_tsibble(fma::milk) %>%  
  rename(total = value) %>%  
  mutate(daily_ave = total / days_in_month(as_date(index))) %>%  
  gather(key="Series", value="Milk", factor_key=TRUE) %>%  
  ggplot(aes(x=index, y=Milk)) + geom_line() +  
    facet_grid(Series ~ ., scales='free') + xlab("Year") +  
    ylab("Pounds") + ggtitle("Milk production per cow")
```

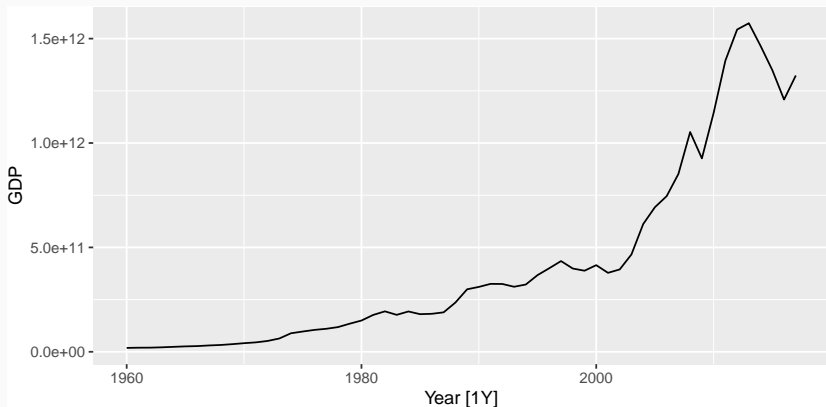


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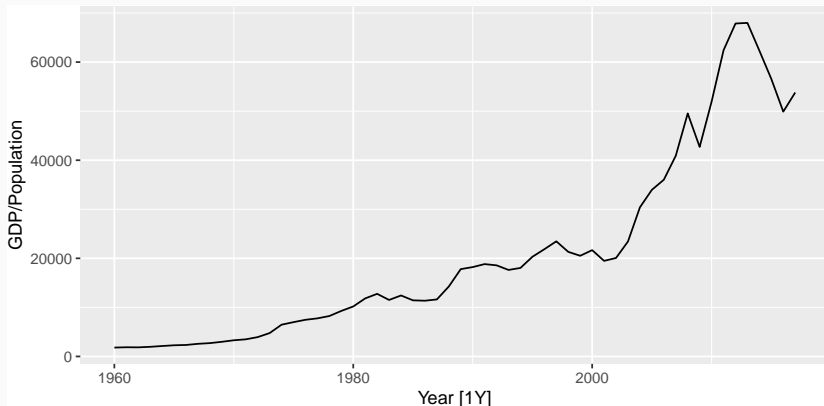
# Per capita adjustments

```
global_economy %>%  
  filter(Country == "Australia") %>%  
  autoplot(GDP)
```



# Per capita adjustments

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



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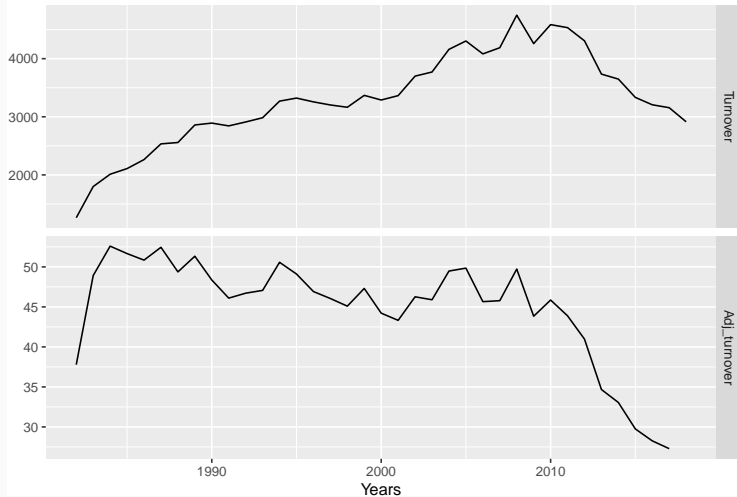


# Inflation adjustments

```
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) %>%  
  gather("Type", "Turnover", Turnover, Adj_turnover,  
         factor_key = TRUE) %>%  
  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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## Mathematical transformations for stabilizing variation

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

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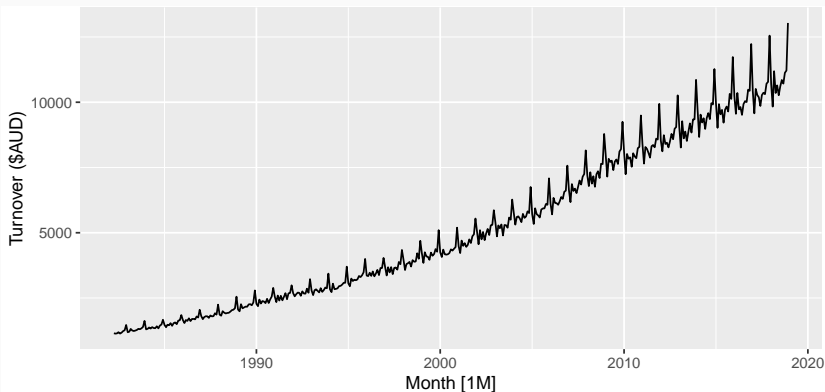
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Logarithms, in particular, are useful because they are more interpretable: changes in a log value are **relative (percent) changes on the original scale**.

# Variance stabilization

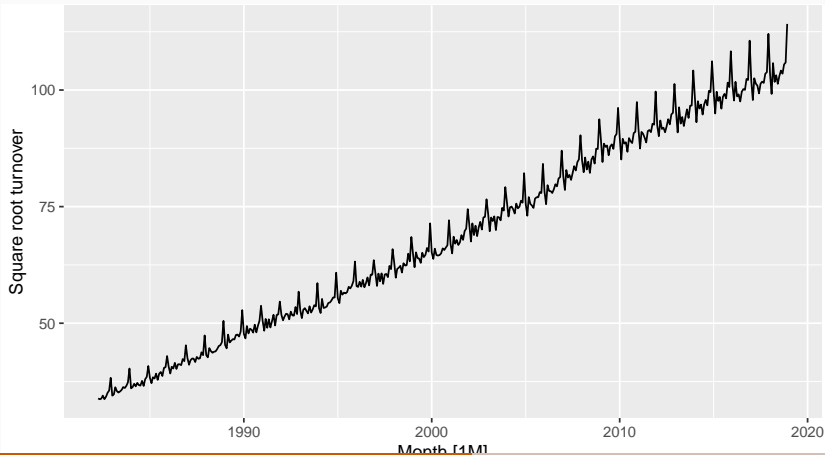
```
food <- aus_retail %>%  
  filter(Industry == "Food retailing") %>%  
  summarise(Turnover = sum(Turnover))
```





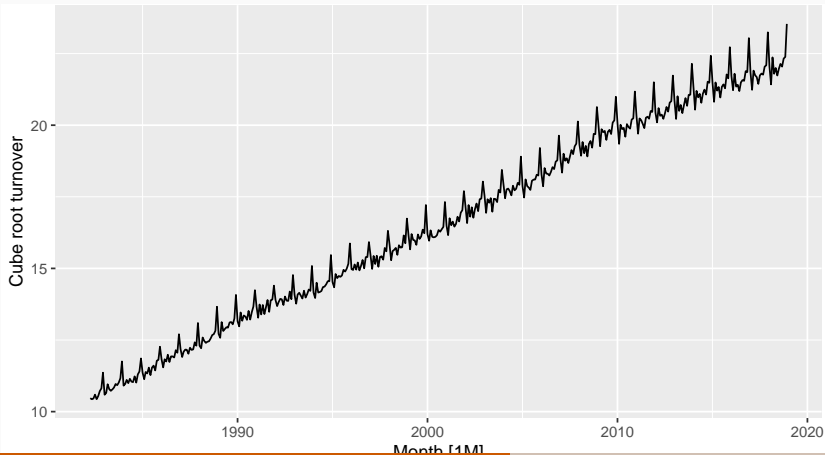
# Variance stabilization

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



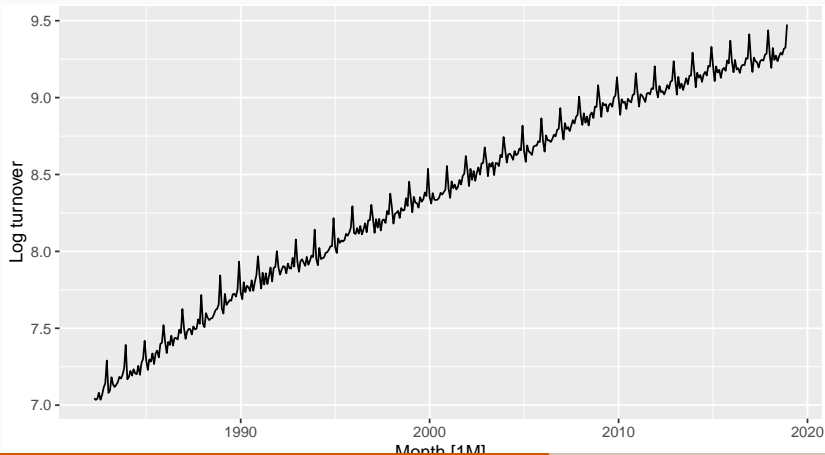
# Variance stabilization

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



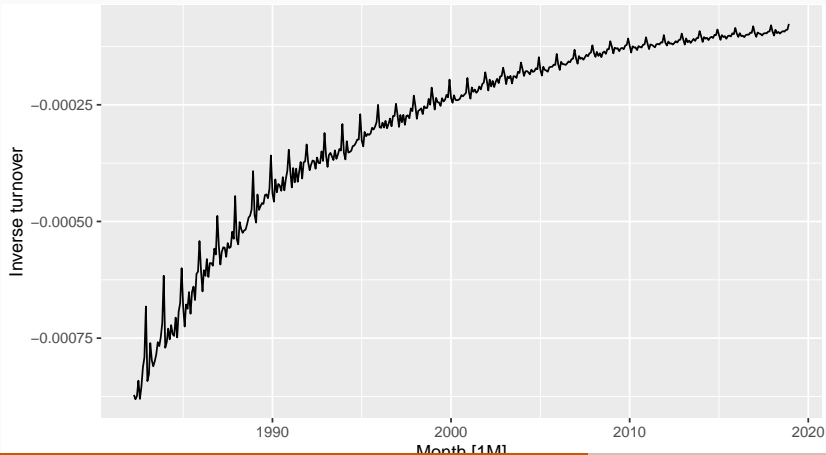
# Variance stabilization

```
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**:

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

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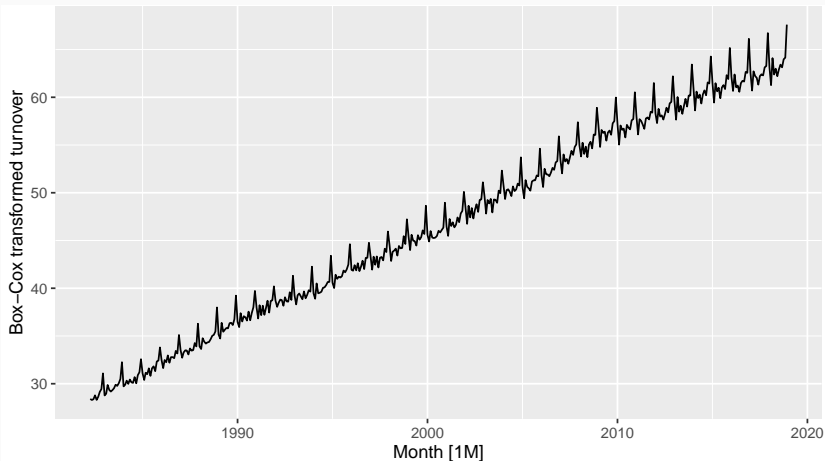
$$w_t = \begin{cases} \log(y_t), & \lambda = 0; \\ (y_t^\lambda - 1)/\lambda, & \lambda \neq 0. \end{cases}$$

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

# Box-Cox transformations

# Box-Cox transformations

```
food %>% autoplot(box_cox(Turnover, 1/3)) +  
  labs(y = "Box-Cox transformed turnover")
```





# Box-Cox transformations

- $y_t^\lambda$  for  $\lambda$  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**.
- Simple values of  $\lambda$  are easier to explain.
- Results are relatively insensitive to  $\lambda$ .
- Often no transformation ( $\lambda = 1$ ) needed.
- Transformation can have very large effect on PI.
- Choosing  $\lambda = 0$  is a simple way to force forecasts to be positive

# 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)
```

```
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```

```
##   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  $\lambda$  can give extremely large prediction intervals.

# 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

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

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# Lab Session 6

- 1 For the following series, find an appropriate Box-Cox transformation in order to stabilise the variance.
  - ▶ United States GDP from `global_economy`
  - ▶ Slaughter of Victorian “Bulls, bullocks and steers” in `aus_livestock`
  - ▶ Gas production from `aus_production`
- 2 Why is a Box-Cox transformation unhelpful for the `expsmooth::cangas` data?
- 3 For each of the following series, make a graph of the data. If transforming seems appropriate, do so and describe the effect. Tobacco from `aus_production`, Economy class passengers between Melbourne and Sydney from `ansett`, and Victorian Electricity Demand from `vic_elec`.