Tidy Time Series & Forecasting in R

3. Transformations

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Outline

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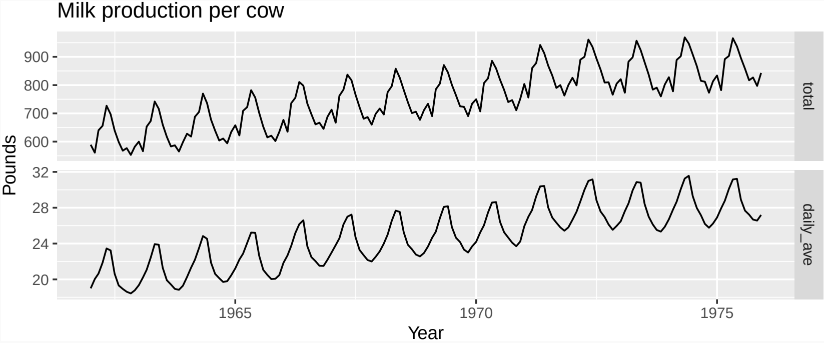
Calendar adjustments

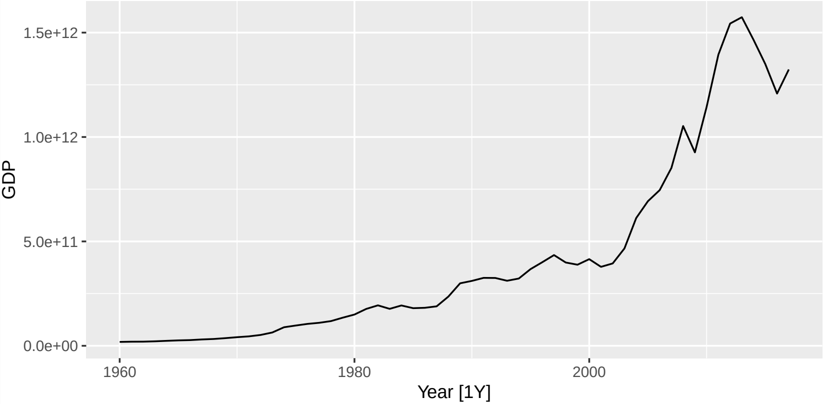
```r
as_tsibble(fma::milk) %>%
  rename(total = value) %>%
  mutate(daily_ave = total / days_in_month(as_date(index))) %>%
  pivot_longer(-index, names_to = "Series", values_to = "Milk") %>%
  mutate(Series = factor(Series, levels=c("total","daily_ave"))) %>%
  ggplot(aes(x=index, y=Milk)) + geom_line() +
    facet_grid(Series ~ ., scales='free') + xlab("Year") +
    ylab("Pounds") +  ggtitle("Milk production per cow")
```



Outline

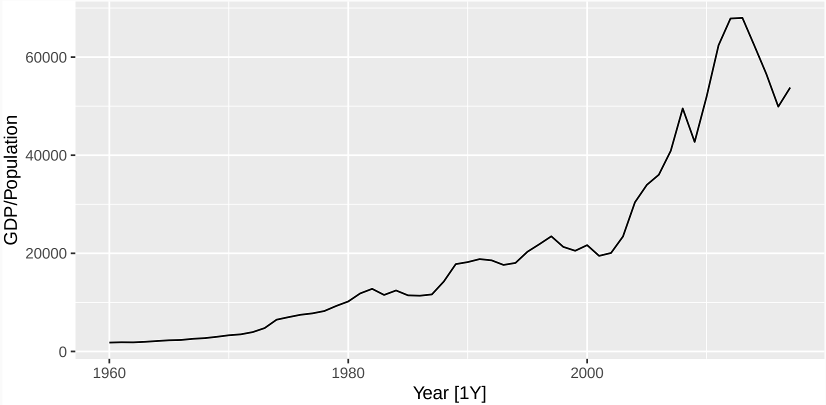
Per capita adjustments

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



Per capita adjustments

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



Outline

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?

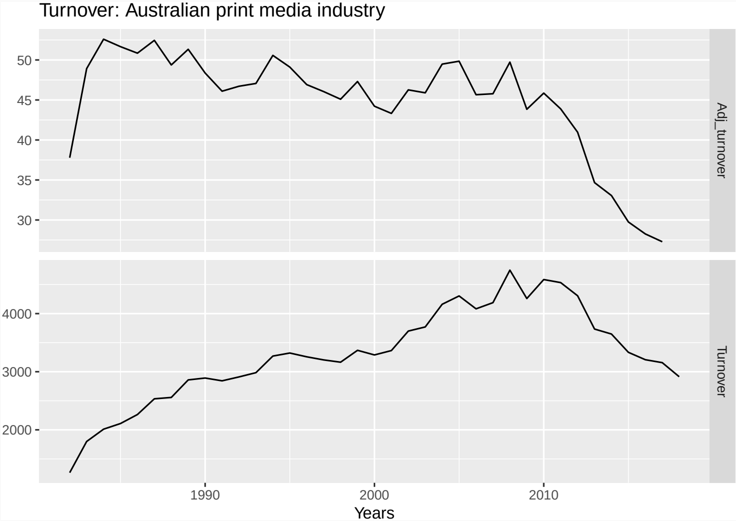
Outline

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

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



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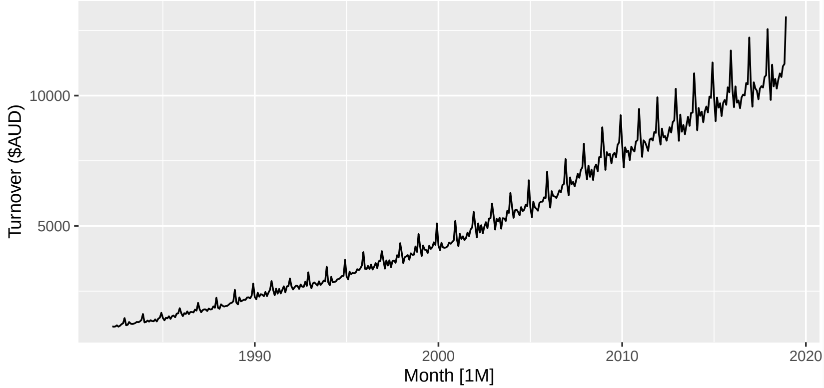
Logarithms, in particular, are useful because they are more interpretable: changes in a log value are **relative (percent) changes on the original scale**.

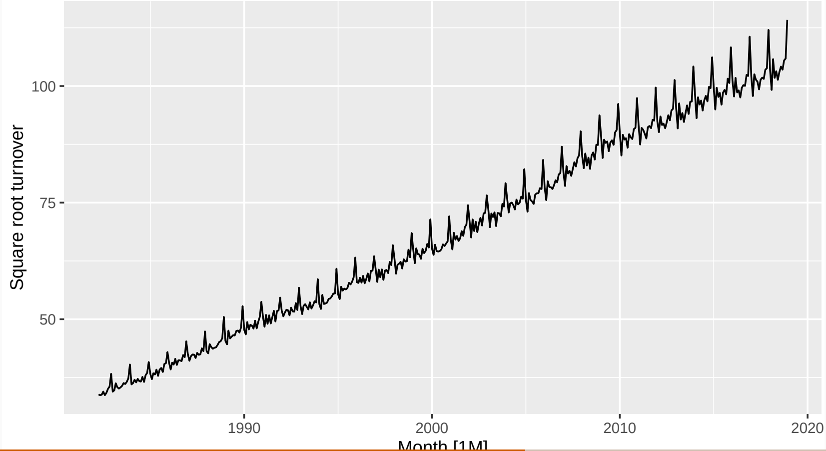
Variance stabilization

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



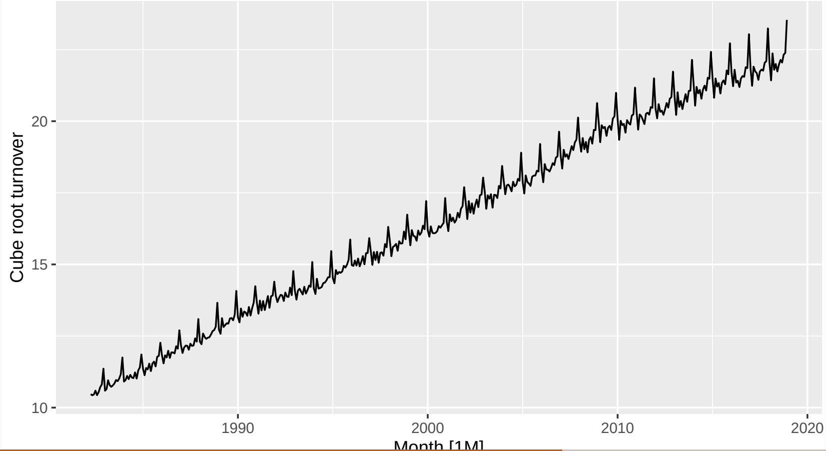
Variance stabilization

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



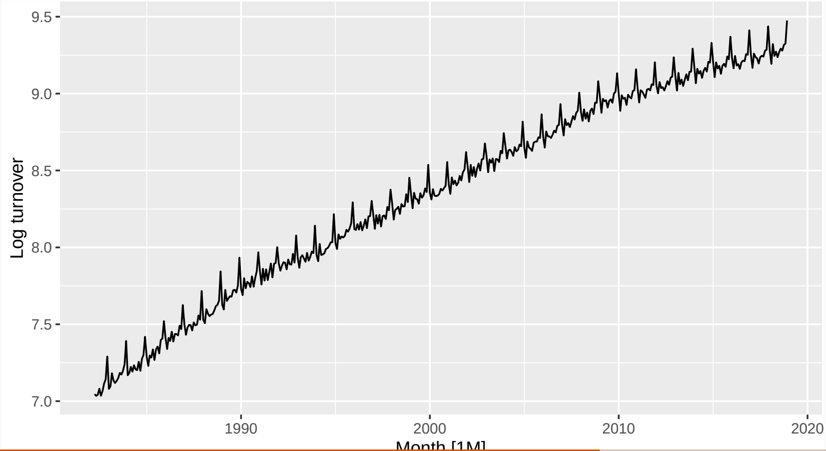
Variance stabilization

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



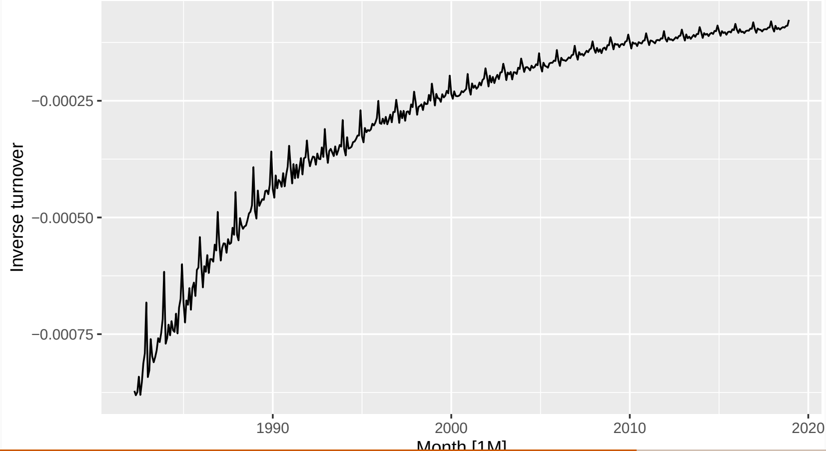
Variance stabilization

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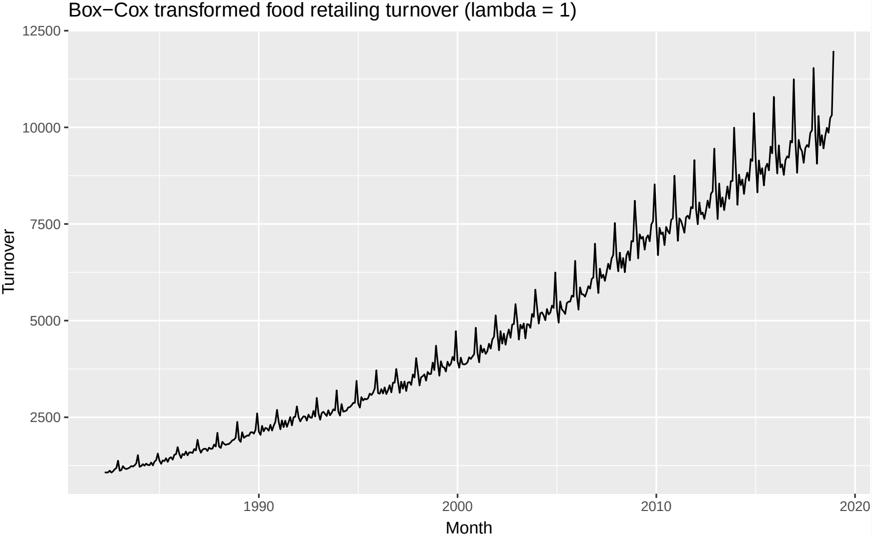
- $\lambda = 1$: (No substantive transformation)
- $\lambda = \frac{1}{2}$: (Square root plus linear transformation)
- $\lambda = 0$: (Natural logarithm)
- $\lambda = -1$: (Inverse plus 1)

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

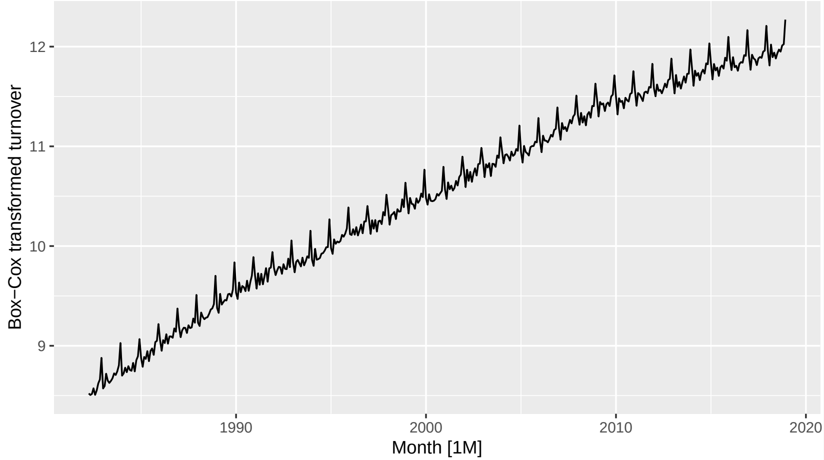
```
food %>%
  features(Turnover, features = guerrero)
```

```
## # 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 the data contains zeros, then don’t take logs.
- `logp1()` can be useful for data with zeros.
- If some data are negative, no power transformation is possible unless a constant is added to all values.
- 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`.)

Outline

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?