bit.ly/fable2022

Tidy Time Series & Forecasting in R

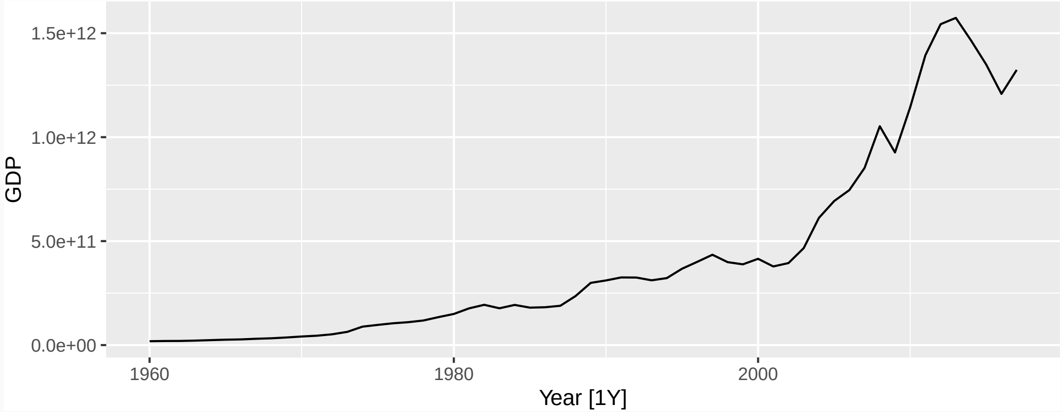
3. Transformations

Outline

Outline

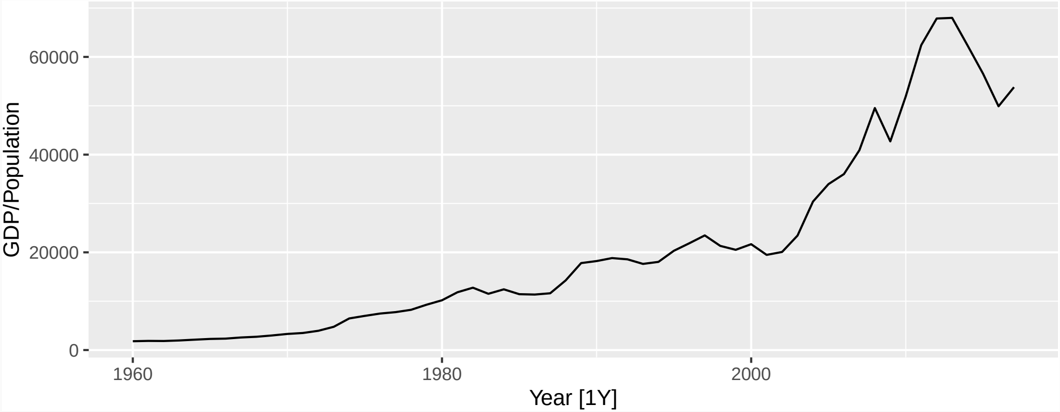
Per capita adjustments

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



Per capita adjustments

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



Outline

Lab Session 6

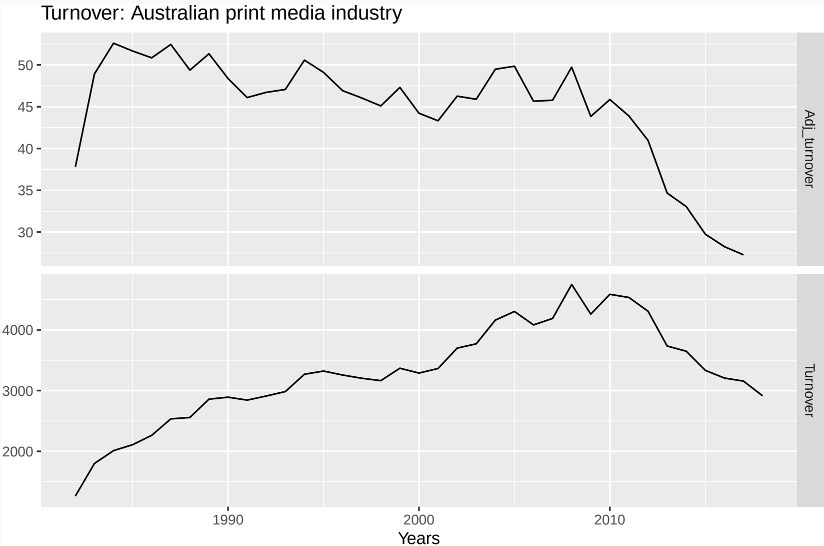
Consider the GDP information in `global_economy`. Plot the GDP per capita for each country over time. Which country has the highest GDP per capita? How has this changed over time?

Outline

Inflation adjustments

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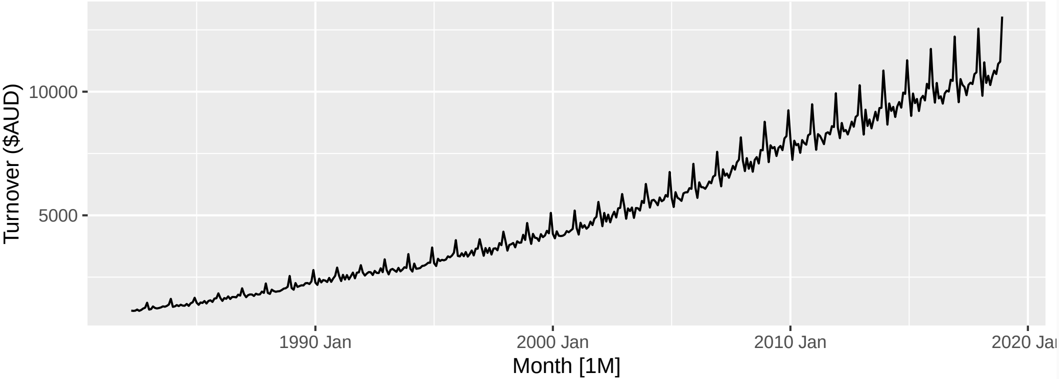
Logarithms, in particular, are useful because they are more interpretable: changes in a log value are **relative (percent) changes on the original**

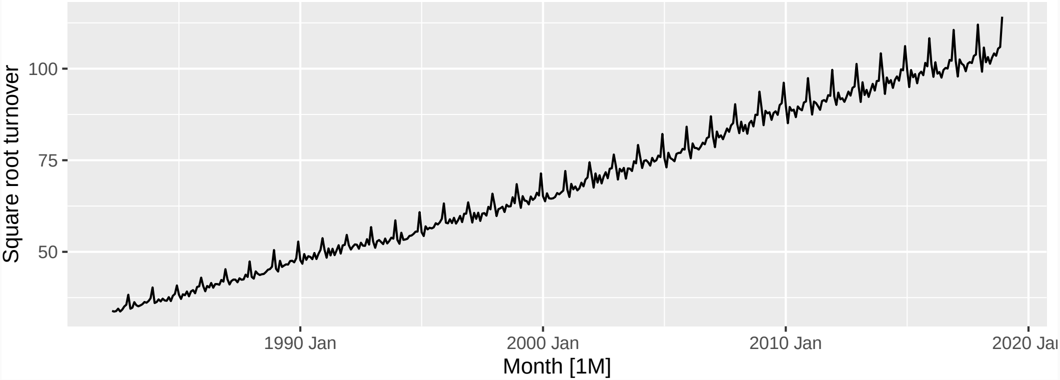
Variance stabilization

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



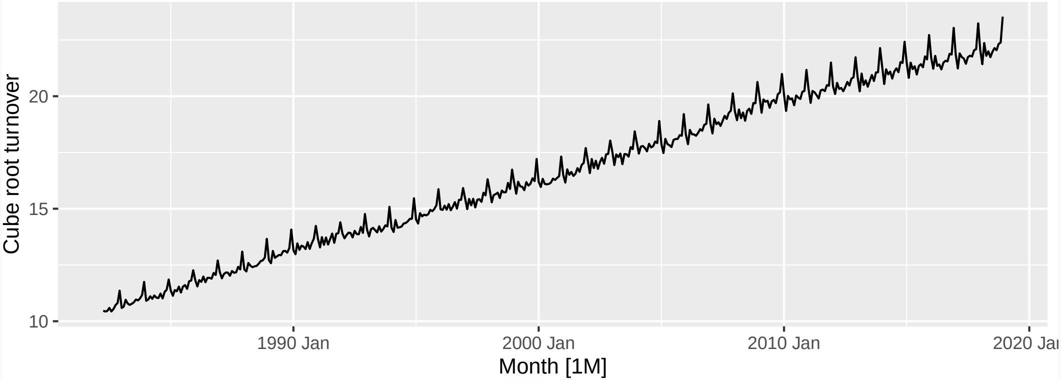
Variance stabilization

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



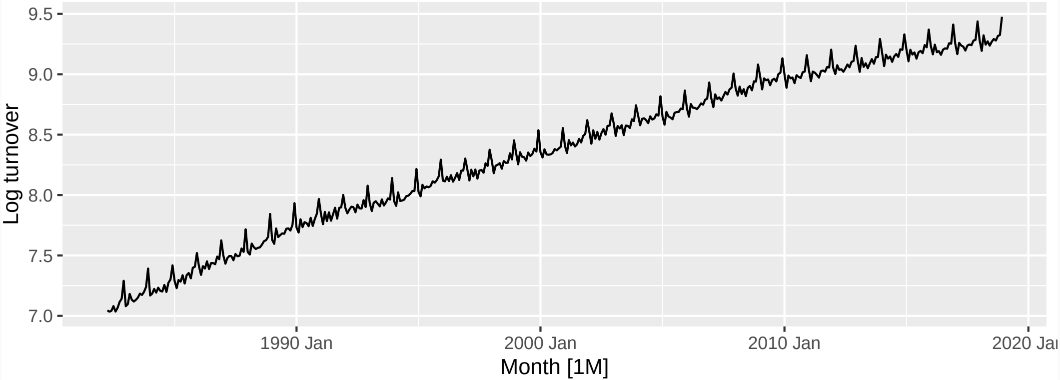
Variance stabilization

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



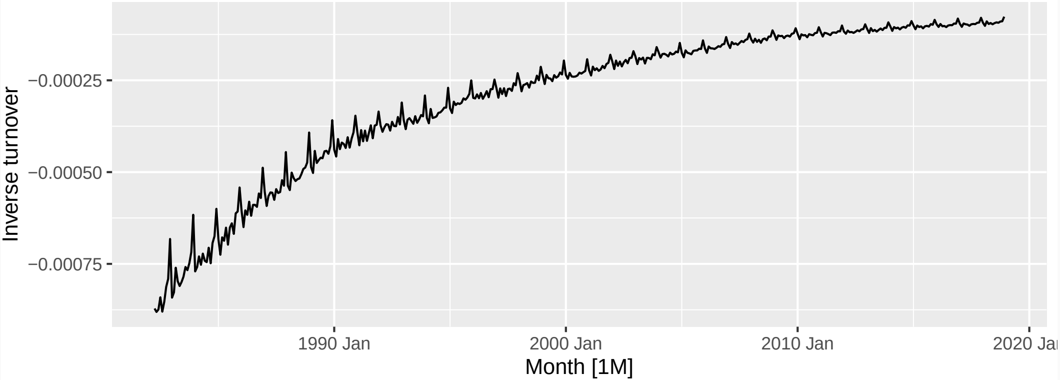
Variance stabilization

```
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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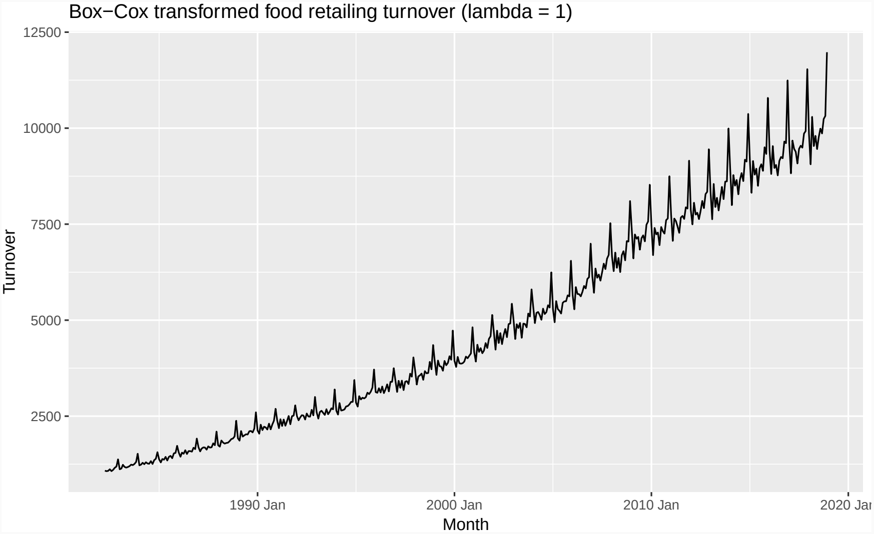
- Actually the Bickel-Doksum transformation (allowing for $y_t < 0$)
- $\lambda = 1$: (No substantive transformation)
- $\lambda = \frac{1}{2}$: (Square root plus linear transformation)
- $\lambda = 0$: (Natural logarithm)
- $\lambda = -1$: (Inverse plus 1)

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

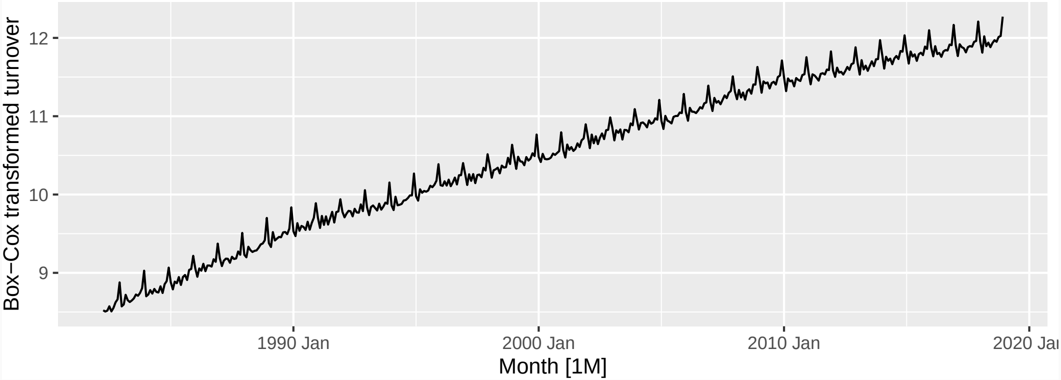
```
food |>
  features(Turnover, features = guerrero)
```

```
## # 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 $\lambda > 0$.
- `log1p()` 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`.)

Outline

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

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?