Africast-Time Series Analysis & Forecasting Using R

https://workshop.f4sg.org/africast/

4. Transforming / adjusting time series

tsibble feasts fable

Outline

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Variance stabilization

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

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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

Variance stabilization

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Mathematical transformations for stabilizing variation

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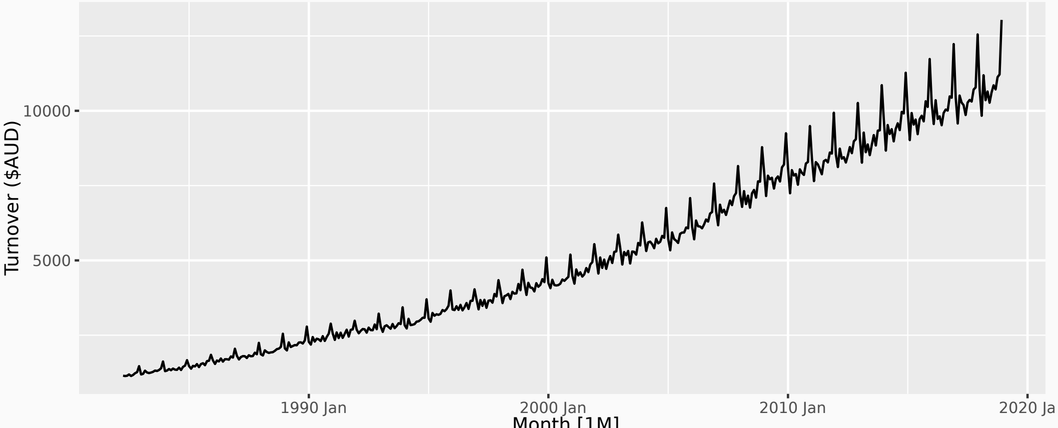
Cube root	$w_t = \sqrt[3]{y_t}$	Increasing
Logarithm	$w_t = \log(y_t)$	strength

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

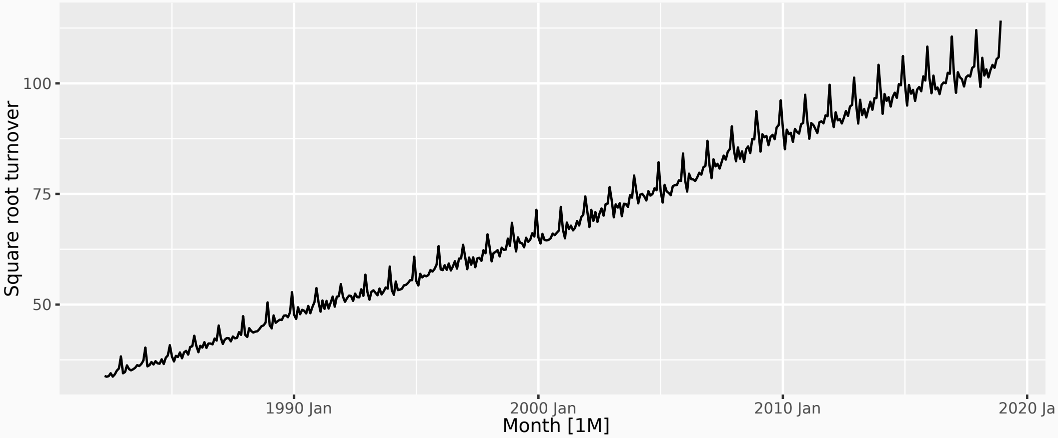
Variance stabilization

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



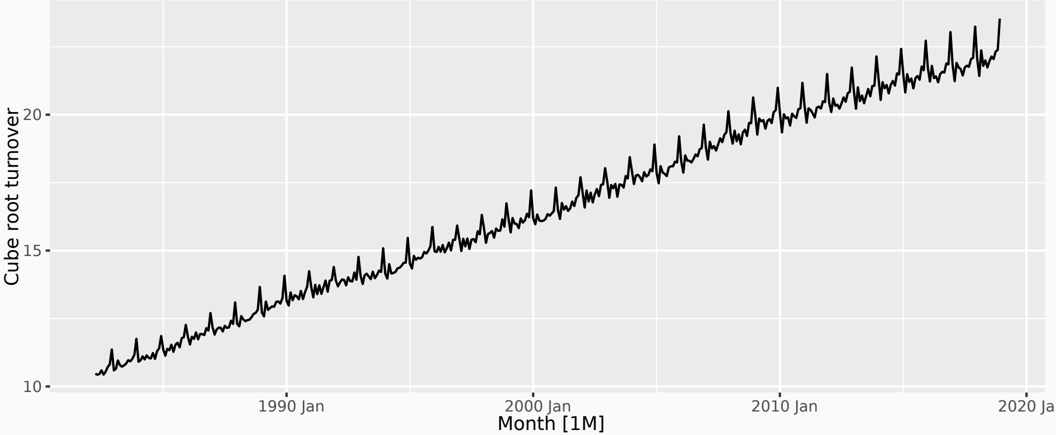
Variance stabilization

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



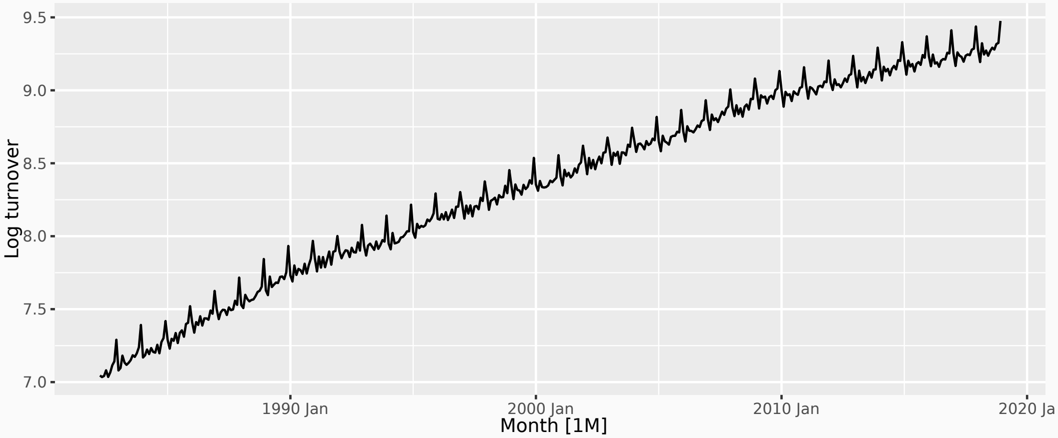
Variance stabilization

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



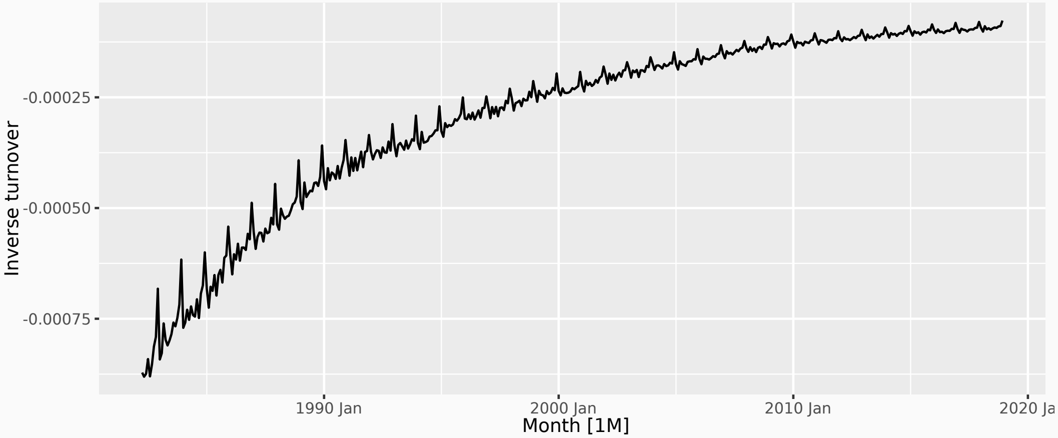
Variance stabilization

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



Variance stabilization

```r
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**:

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

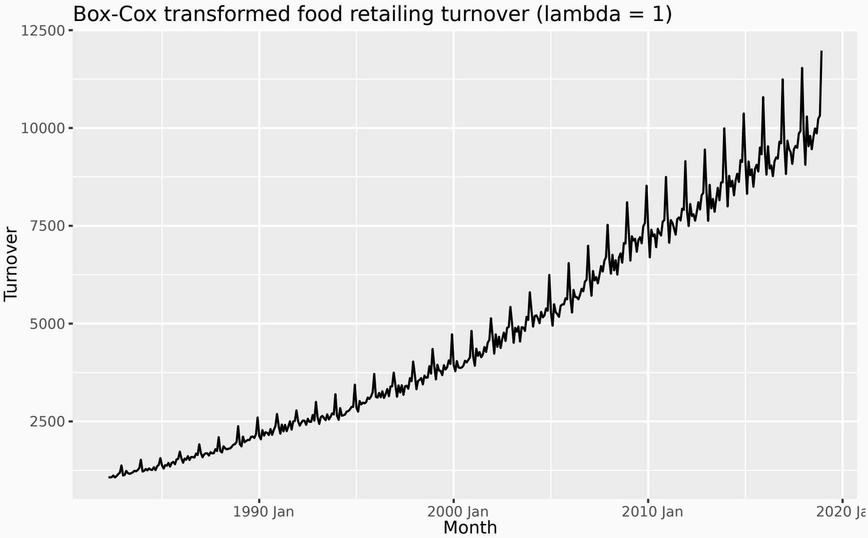
Box-Cox transformations

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

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

- 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          0.0895
```

Box-Cox transformations

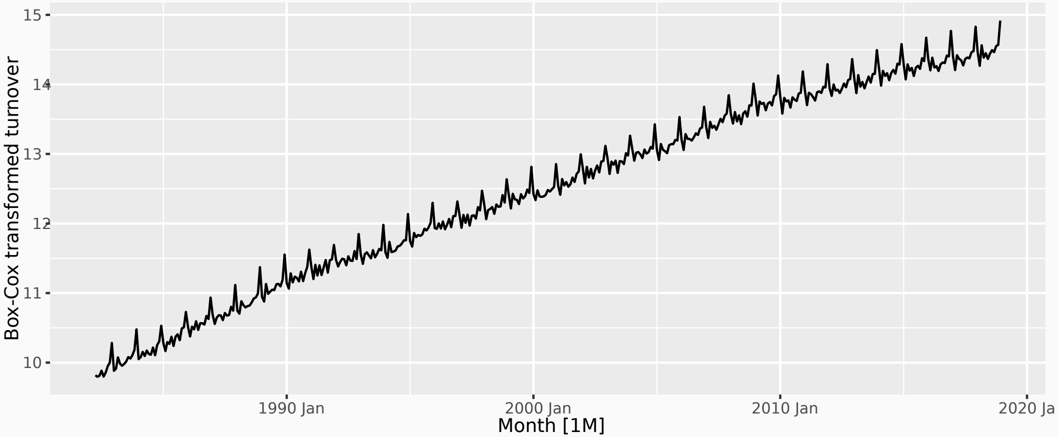
```
food |>
  features(Turnover, features = guerrero)
```

```
# A tibble: 1 x 1
  lambda_guerrero
            <dbl>
1          0.0895
```

- 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

```r
food |> autoplot(box_cox(Turnover, 0.0895)) +
  labs(y = "Box-Cox transformed turnover")
```



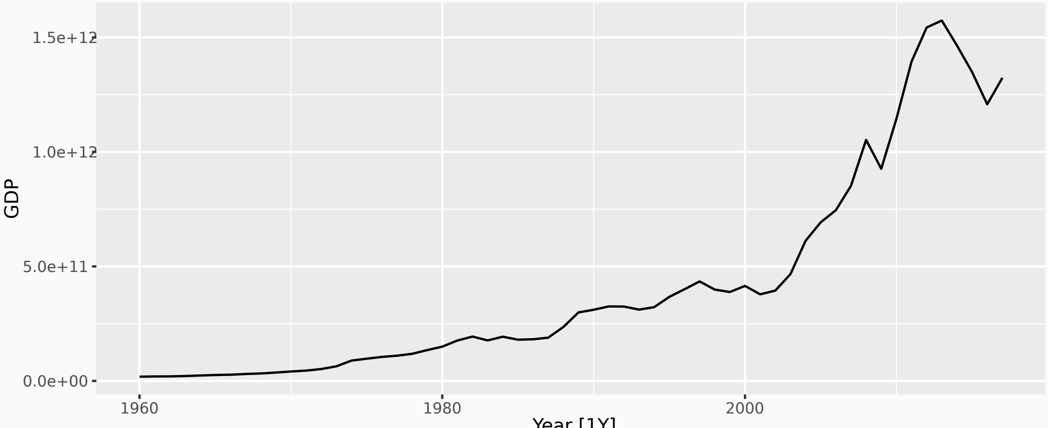
Transformations

- 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

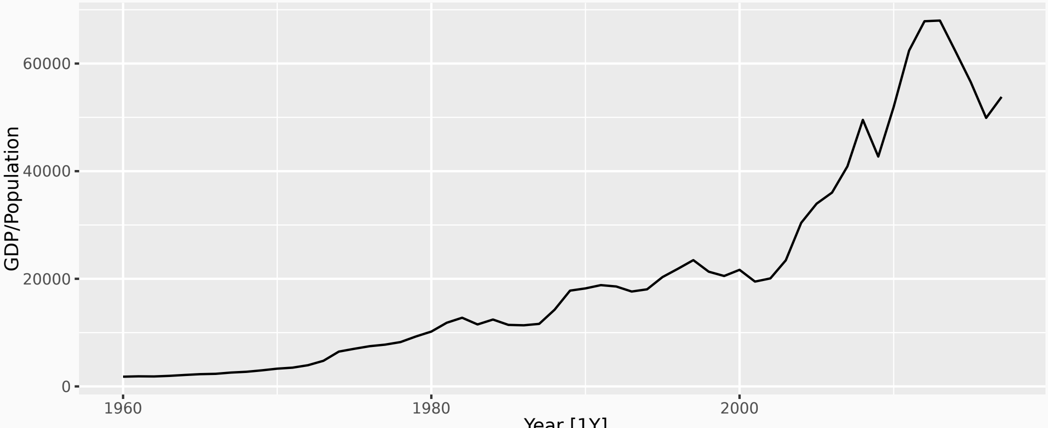
Per capita adjustments

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



Per capita adjustments

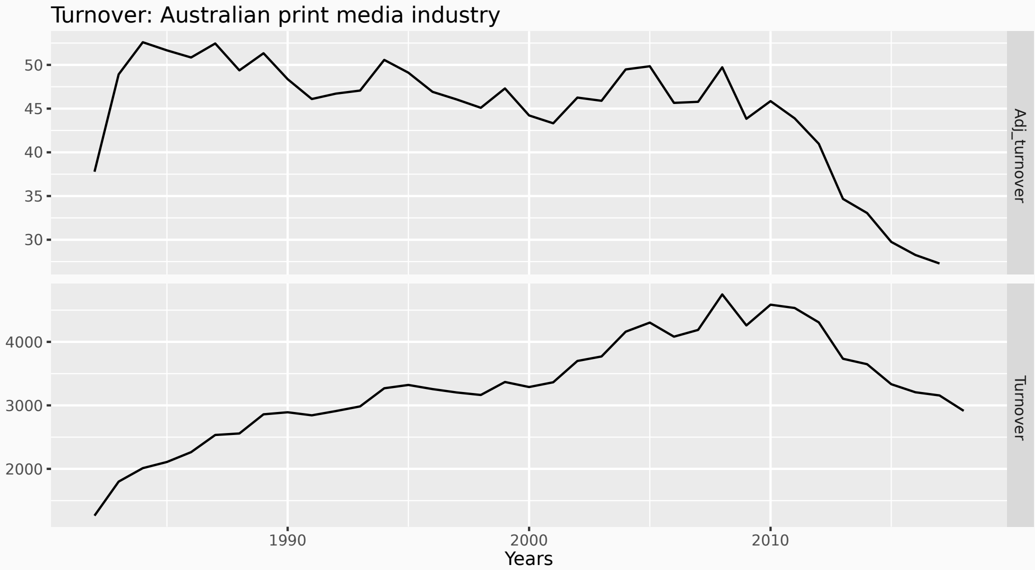
```r
global_economy |>
  filter(Country == "Australia") |>
  autoplot(GDP / Population)
```



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, Country == "Australia")
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") +
  labs(x = "Years", y = NULL,
       title = "Turnover: Australian print media industry")
```

Inflation adjustments



Outline

Time series decomposition

Trend-Cycle aperiodic changes in level over time.

Seasonal (almost) periodic changes in level due to seasonal factors (e.g., the quarter of the year, the month, or day of the week).

Additive decomposition

$$y_t = S_t + T_t + R_t$$

where
$$\begin{aligned} y_t &= \text{data at period } t \\ T_t &= \text{trend-cycle component at period } t \\ S_t &= \text{seasonal component at period } t \\ R_t &= \text{remainder component at period } t \end{aligned}$$

STL decomposition

- STL: “Seasonal and Trend decomposition using Loess”
- Very versatile and robust.
- Seasonal component allowed to change over time, and rate of change controlled by user.
- Smoothness of trend-cycle also controlled by user.
- Optionally robust to outliers
- No trading day or calendar adjustments.
- Only additive.
- Take logs to get multiplicative decomposition.
- Use Box-Cox transformations to get other decompositions.

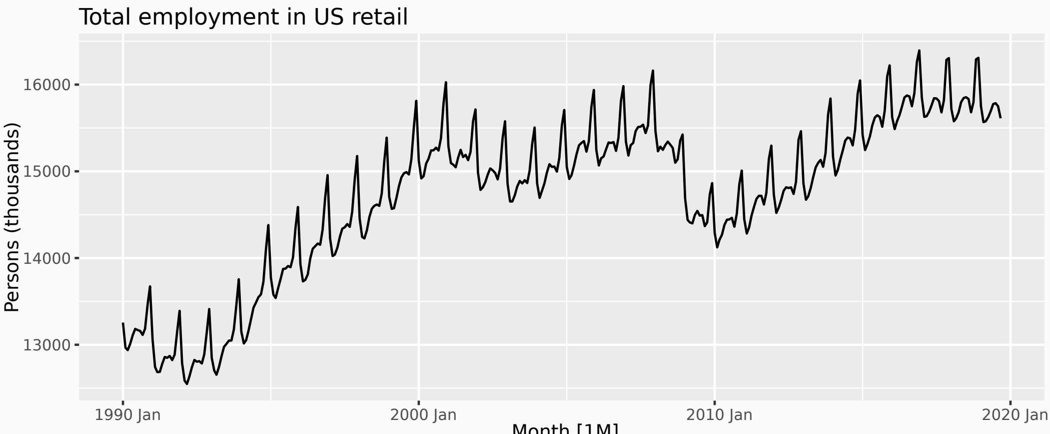
US Retail Employment

```r
us_retail_employment <- us_employment |>
  filter(year(Month) >= 1990, Title == "Retail Trade") |>
  select(-Series_ID)
us_retail_employment
```

```
# A tsibble: 357 x 3 [1M]
      Month Title        Employed
      <mth> <chr>           <dbl>
 1 1990 Jan Retail Trade   13256.
 2 1990 Feb Retail Trade   12966.
 3 1990 Mar Retail Trade   12938.
 4 1990 Apr Retail Trade   13012.
 5 1990 May Retail Trade   13108.
 6 1990 Jun Retail Trade   13183.
 7 1990 Jul Retail Trade   13170.
 8 1990 Aug Retail Trade   13160.
 9 1990 Sep Retail Trade   13113.
```

US Retail Employment

```
us_retail_employment |>
  autoplot(Employed) +
  labs(y = "Persons (thousands)", title = "Total employment in US retail")
```



US Retail Employment

```
dcmp <- us_retail_employment |>
  model(stl = STL(Employed))
dcmp
```

```
# A mable: 1 x 1
      stl
  <model>
1   <STL>
```

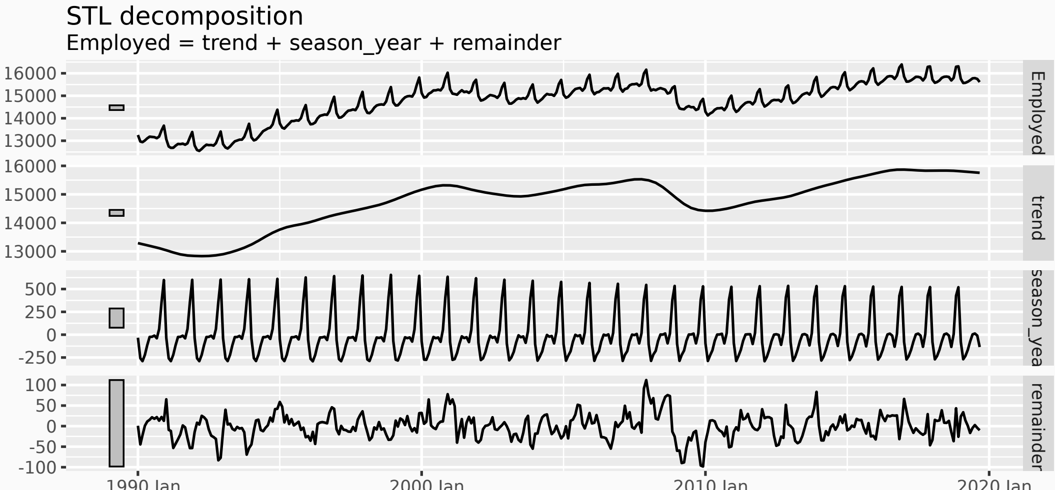
US Retail Employment

```
components(dcmp)
```

```
# A dable: 357 x 7 [1M]
# Key:      .model [1]
# :         Employed = trend + season_year + remainder
   .model    Month Employed  trend season_year remainder season_adjust
   <chr>     <mth>    <dbl>  <dbl>       <dbl>     <dbl>         <dbl>
 1 stl    1990 Jan   13256. 13288.      -33.0      0.836        13289.
 2 stl    1990 Feb   12966. 13269.     -258.     -44.6          13224.
 3 stl    1990 Mar   12938. 13250.     -290.     -22.1          13228.
 4 stl    1990 Apr   13012. 13231.     -220.       1.05         13232.
 5 stl    1990 May   13108. 13211.     -114.      11.3          13223.
 6 stl    1990 Jun   13183. 13192.      -24.3     15.5          13207.
 7 stl    1990 Jul   13170. 13172.      -23.2     21.6          13193.
 8 stl    1990 Aug   13160. 13151.       -9.52    17.8          13169.
 9 stl    1990 Sep   13113. 13131.      -39.5     22.0          13153.
10 stl    1990 Oct   13185. 13110.       61.6     13.2          13124.
```

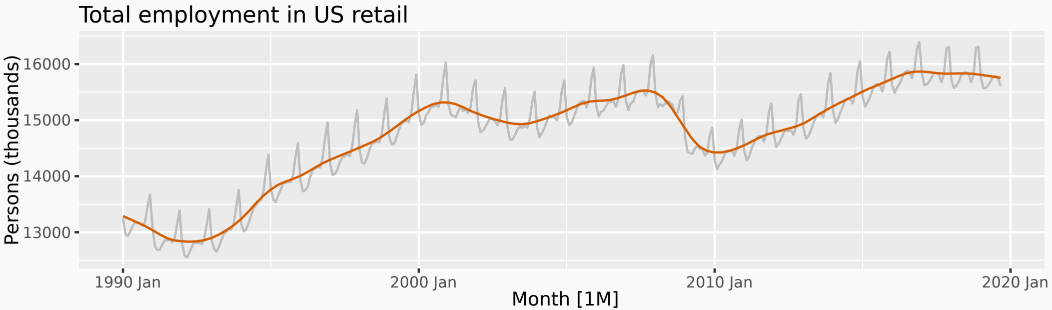
US Retail Employment

```
components(dcmp) |> autoplot()
```



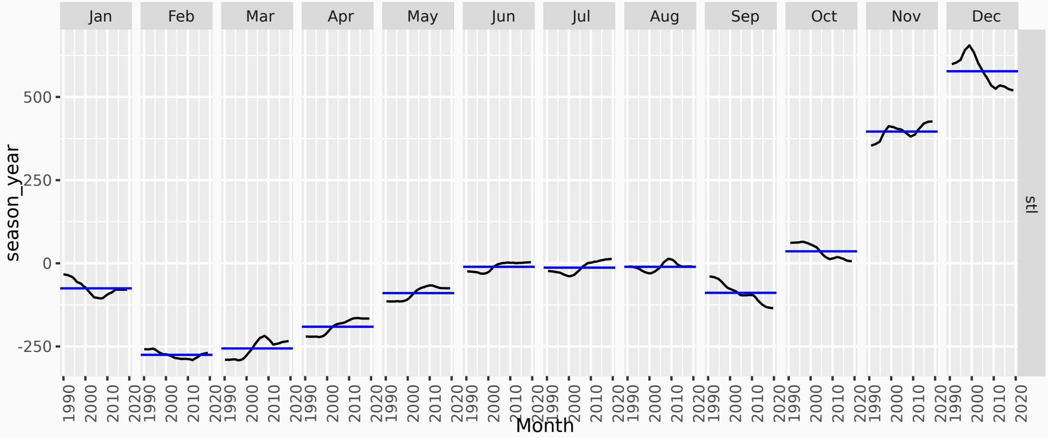
US Retail Employment

```r
us_retail_employment |>
  autoplot(Employed, color = "gray") +
  autolayer(components(dcmp), trend, color = "#D55E00") +
  labs(y = "Persons (thousands)", title = "Total employment in US retail")
```



US Retail Employment

```
components(dcmp) |> gg_subseries(season_year)
```



Seasonal adjustment

- Useful by-product of decomposition: an easy way to calculate seasonally adjusted data.
- Additive decomposition: seasonally adjusted data given by

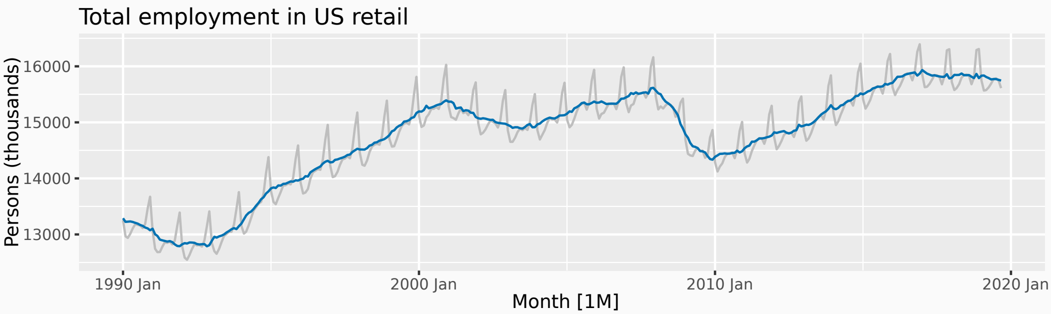
$$y_t - S_t = T_t + R_t$$

- Multiplicative decomposition: seasonally adjusted data given by

$$y_t / S_t = T_t \times R_t$$

US Retail Employment

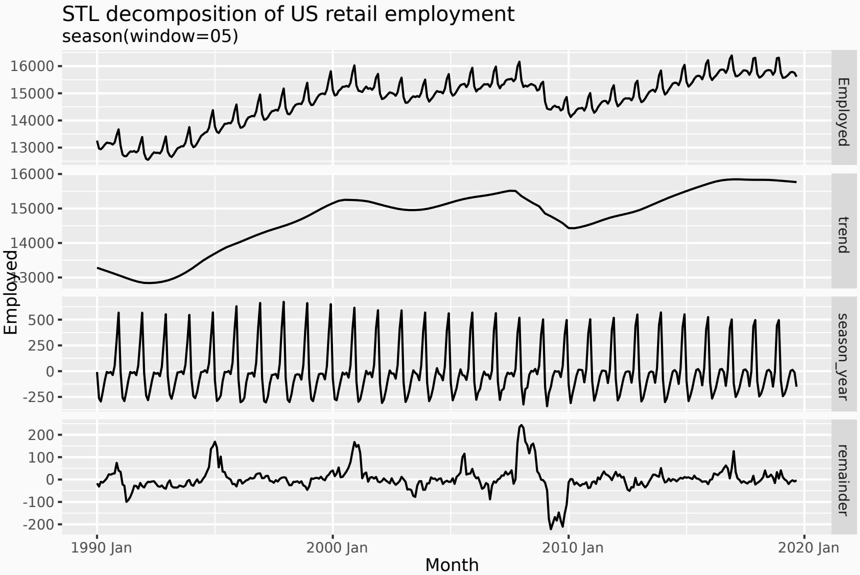
```
us_retail_employment |>
  autoplot(Employed, color = "gray") +
  autolayer(components(dcmp), season_adjust, color = "#0072B2") +
  labs(y = "Persons (thousands)", title = "Total employment in US retail")
```



Seasonal adjustment

- We use estimates of S based on past values to seasonally adjust a current value.
- Seasonally adjusted series reflect **remainders** as well as **trend**. Therefore they are not "smooth" and "downturns" or "upturns" can be misleading.
- It is better to use the trend-cycle component to look for turning points.

STL decomposition



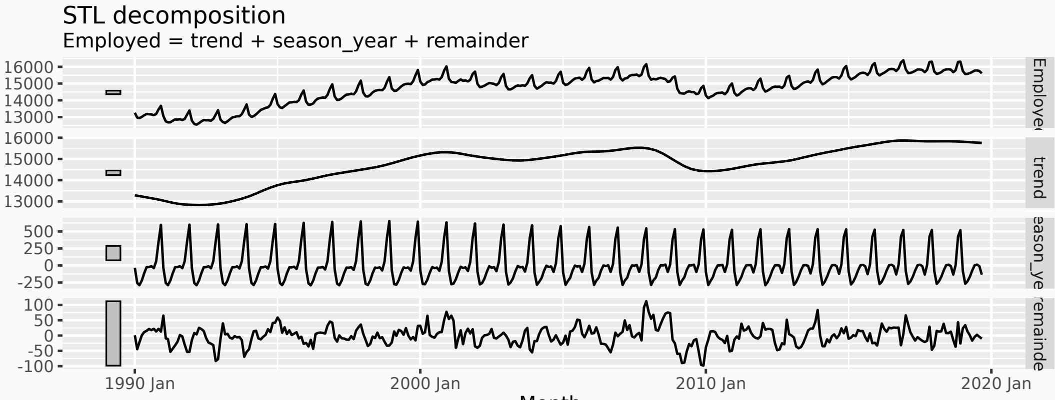
STL decomposition

```r
us_retail_employment |>
  model(STL(Employed ~ trend(window = 15) + season(window = "periodic"),
    robust = TRUE
  )) |>
  components()
```

- `trend(window = ?)` controls wiggliness of trend component.
- `season(window = ?)` controls variation on seasonal component.
- `season(window = 'periodic')` is equivalent to an infinite window.

STL decomposition

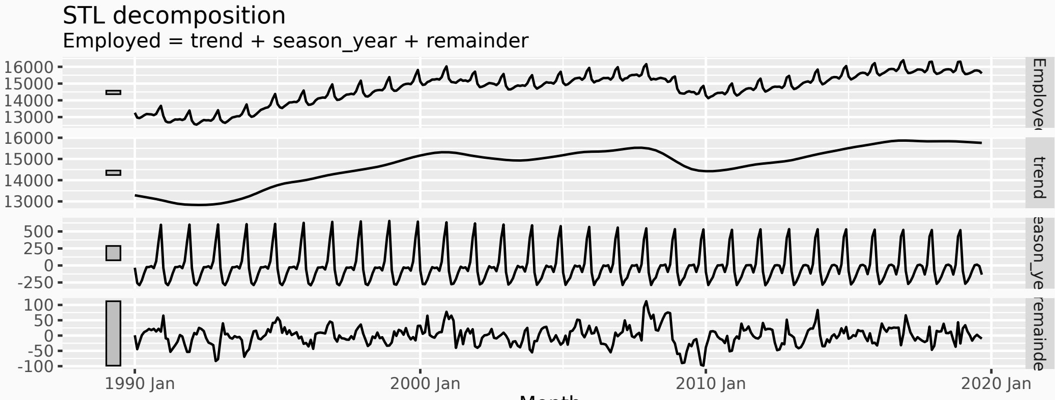
```
us_retail_employment |>
  model(STL(Employed)) |>
  components() |>
  autoplot()
```



STL decomposition

- `STL()` chooses `season(window=13)` by default
- Can include transformations.

```
us_retail_employment |>
  model(STL(Employed)) |>
  components() |>
  autoplot()
```



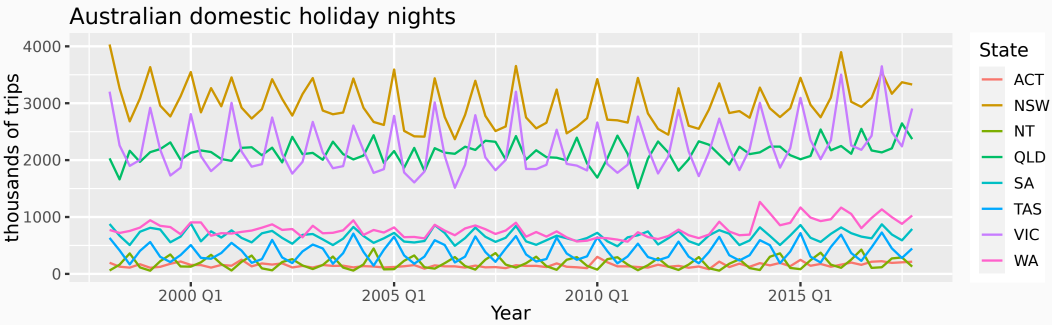
STL decomposition

- Algorithm that updates trend and seasonal components iteratively.
- Starts with $\hat{T}_t = 0$
- Uses a mixture of loess and moving averages to successively refine the trend and seasonal estimates.
- trend window controls loess bandwidth on deasonalised values.
- season window controls loess bandwidth on detrended subseries.
- Robustness weights based on remainder.
- Default season: `window = 13`
- Default trend:

`window =`

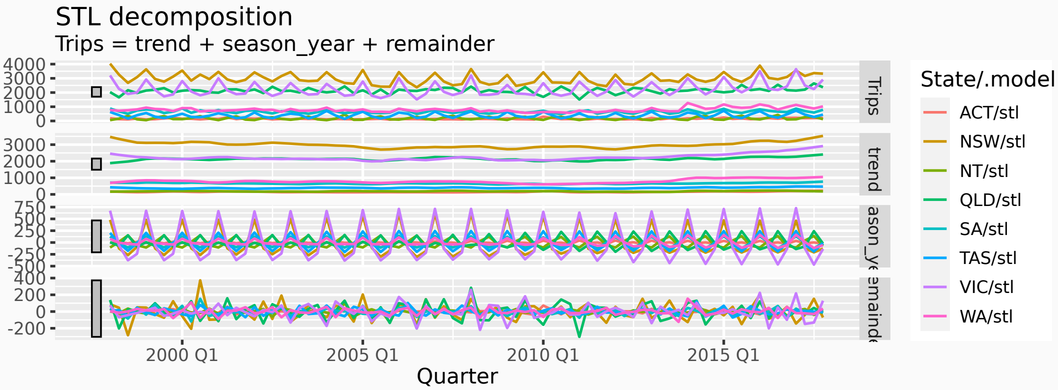
Australian holidays

```r
holidays |> autoplot(Trips) +
  labs(y = "thousands of trips", x = "Year",
       title = "Australian domestic holiday nights")
```



Australian holidays

```r
holidays |>
  model(stl = STL(Trips)) |>
  components() |>
  autoplot()
```



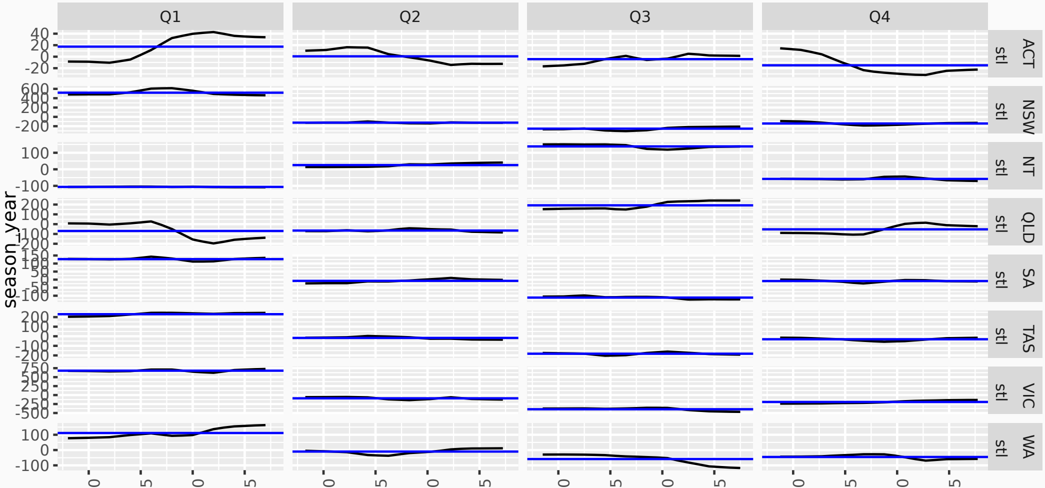
Holidays decomposition

```
dcmp <- holidays |>
  model(stl = STL(Trips)) |>
  components()
dcmp
```

```
# A dable: 640 x 8 [1Q]
# Key:     State, .model [8]
# :        Trips = trend + season_year + remainder
   State .model Quarter Trips trend season_year remainder season_adjust
   <chr> <chr>    <qtr> <dbl> <dbl>       <dbl>     <dbl>         <dbl>
 1 ACT   stl    1998 Q1  196.  172.       -8.48      32.6          205.
 2 ACT   stl    1998 Q2  127.  157.       10.3      -40.6          116.
 3 ACT   stl    1998 Q3  111.  142.      -16.8      -14.5          128.
 4 ACT   stl    1998 Q4  170.  130.       14.6       25.6          156.
 5 ACT   stl    1999 Q1  108.  135.       -8.63     -18.3          116.
 6 ACT   stl    1999 Q2  125.  148.       11.0      -34.6          114.
 7 ACT   stl    1999 Q3  178.  166.      -16.0       28.3          194.
 8 ACT   stl    1999 Q4  218.  177.       13.2       27.5          204.
```

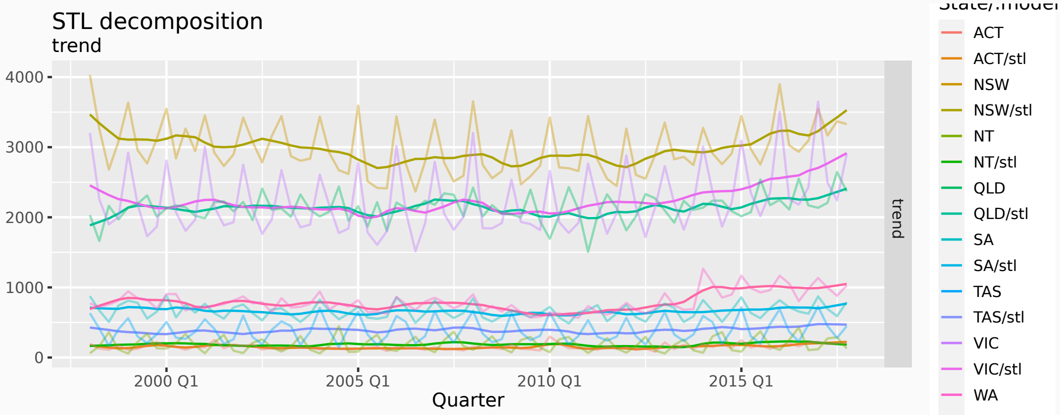
Holidays decomposition

```
dcmp |> gg_subseries(season_year)
```



Holidays decomposition

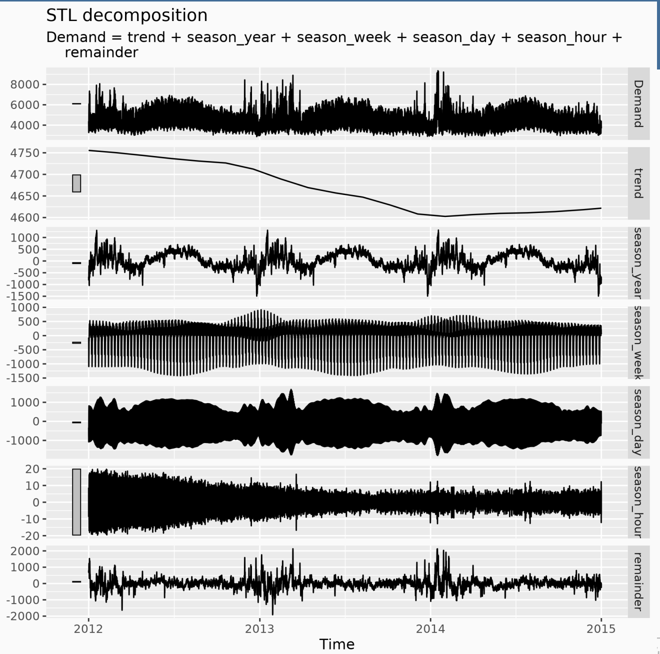
```r
autoplot(dcmp, trend, scale_bars = FALSE) +
  autolayer(holidays, alpha = 0.4)
```



Outline

Multiple seasonality

```
vic_elec |>
  model(STL(Demand)) |>
  components() |>
  autoplot()
```



Outline

The ABS stuff-up

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Treasurer Joe Hockey calls for answers over Australian Bureau of Statistics jobs data

By Michael Vincent and Simon Frazer

Updated 9 Oct 2014, 12:17pm

Federal Treasurer Joe Hockey says he wants answers to the problems the Australian Bureau of Statistics (ABS) has had with unemployment figures.

Mr Hockey, who is in the US to discuss Australia's G20 agenda, said last month's unemployment figures were "extraordinary".

The rate was 6.1 per cent after jumping to a 12-year high of 6.4 per cent the previous month.

The ABS has now taken the rare step of abandoning seasonal adjustment for its latest employment data.

PHOTO: Joe Hockey says he is unhappy with the volatility of ABS unemployment figures. (AAP: Alan Porritt)

RELATED STORY: ABS abandons seasonal adjustment for

The ABS stuff-up

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ABS abandons seasonal adjustment for latest jobs data

By business reporter Michael Janda

Updated 8 Oct 2014, 4:19pm

The Australian Bureau of Statistics is taking the rare step of abandoning seasonal adjustment for its latest employment data.

The ABS uses seasonal adjustment, based on historical experience, to account for the normal variation between hiring and firing patterns between different months.

However, after a winter where the seasonally adjusted unemployment rate swung wildly from 6.1 to 6.4 and back to 6.1 per cent, the bureau released a statement saying it will not adjust the original figure for September for seasonal factors.

It will also reset the seasonal adjustment for July and August to one, meaning that these months will also reflect the original figures

Sorry, this video has expired

VIDEO: Westpac chief economist Bill Evans discusses the ABS jobs data changes (ABC News)

RELATED STORY: Doubt the record breaking jobs figures? So does the ABS

RELATED STORY: Jobs increase record sees unemployment slashed

RELATED STORY: Unemployment surges to 12-year high at 6.4 pc

MAP: Australia

The ABS stuff-up

ABS jobs and unemployment figures – key questions answered by an expert

A professor of statistics at Monash University explains exactly what is seasonal adjustment, why it matters and what went wrong in the July and August figures

School leavers come on to the jobs market at the same time, causing a seasonal fluctuation. Photograph: Brian Snyder/Reuters

The Australian Bureau of Statistics has retracted its seasonally adjusted employment data for July and August, which recorded huge swings in the jobless rate. The ABS is also planning to review the methods it uses for seasonal adjustment to ensure its figures are as accurate as possible. Rob Hyndman, a professor of statistics at Monash University and member of the bureau's methodology advisory board, answers our questions:

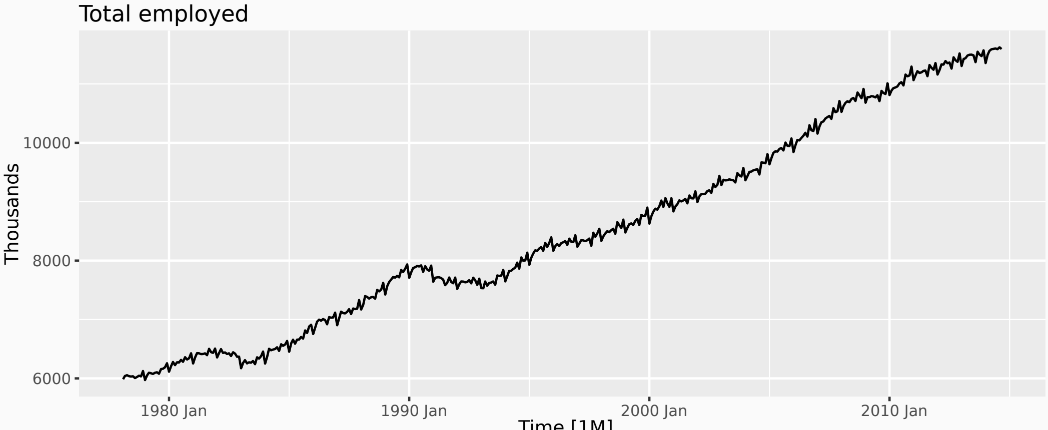
The ABS stuff-up

```r
employed
```

```
# A tsibble: 440 x 4 [1M]
       Time Month  Year Employed
      <mth> <ord> <dbl>    <dbl>
 1 1978 Feb Feb    1978    5986.
 2 1978 Mar Mar    1978    6041.
 3 1978 Apr Apr    1978    6054.
 4 1978 May May    1978    6038.
 5 1978 Jun Jun    1978    6031.
 6 1978 Jul Jul    1978    6036.
 7 1978 Aug Aug    1978    6005.
 8 1978 Sep Sep    1978    6024.
 9 1978 Oct Oct    1978    6046.
10 1978 Nov Nov    1978    6034.
# ℹ 430 more rows
```

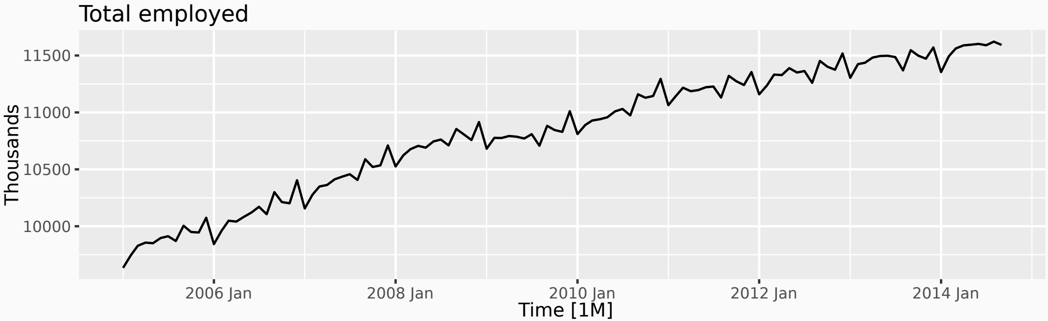
The ABS stuff-up

```r
employed |>
  autoplot(Employed) +
  labs(title = "Total employed", y = "Thousands")
```



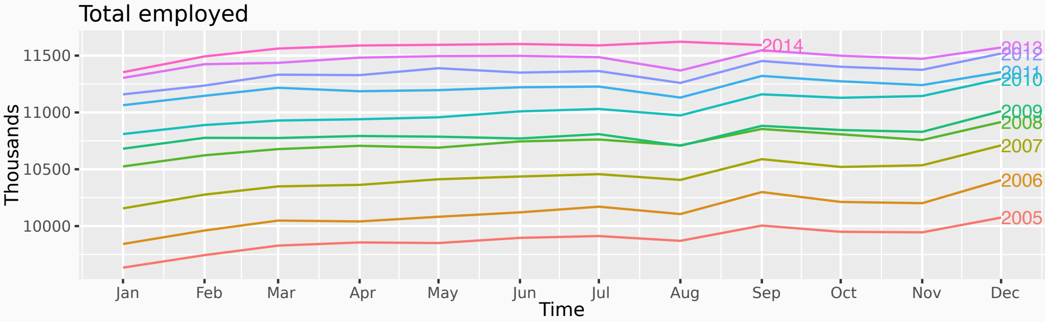
The ABS stuff-up

```r
employed |>
  filter(Year >= 2005) |>
  autoplot(Employed) +
  labs(title = "Total employed", y = "Thousands")
```



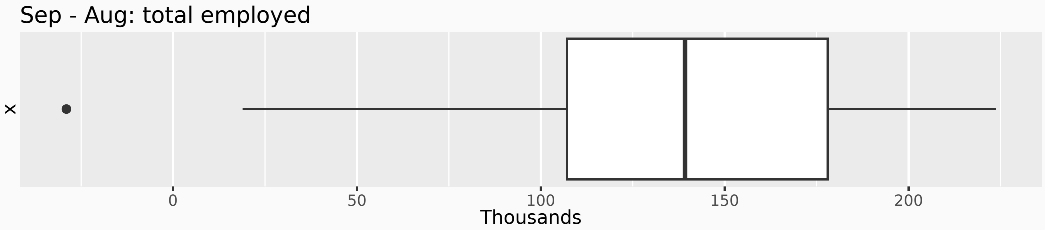
The ABS stuff-up

```
employed |>
  filter(Year >= 2005) |>
  gg_season(Employed, labels = "right") +
  labs(title = "Total employed", y = "Thousands")
```



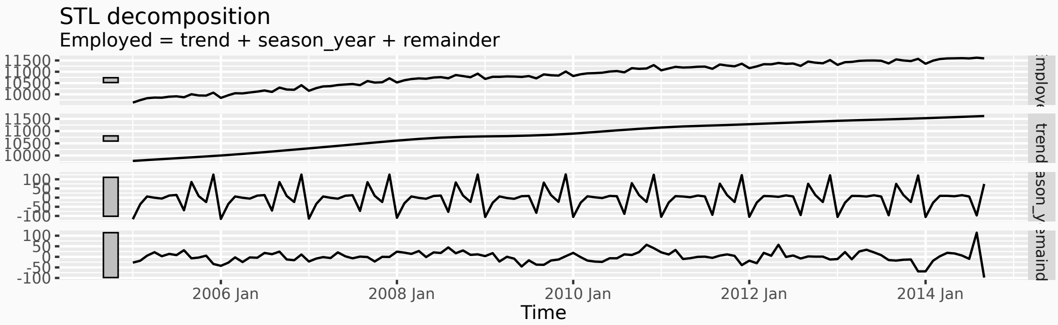
The ABS stuff-up

```r
employed |>
  mutate(diff = difference(Employed)) |>
  filter(Month == "Sep") |>
  ggplot(aes(y = diff, x = 1)) +
  geom_boxplot() +
  coord_flip() +
  labs(title = "Sep - Aug: total employed", y = "Thousands") +
  scale_x_continuous(breaks = NULL, labels = NULL)
```



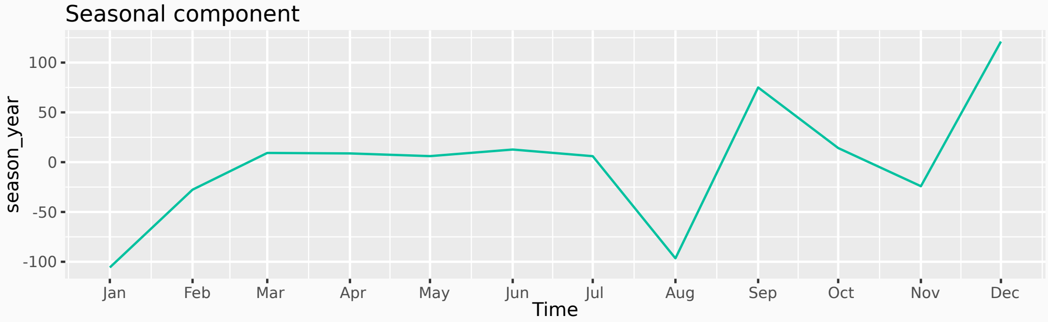
The ABS stuff-up

```r
dcmp <- employed |>
  filter(Year >= 2005) |>
  model(stl = STL(Employed ~ season(window = 11), robust = TRUE))
components(dcmp) |> autoplot()
```



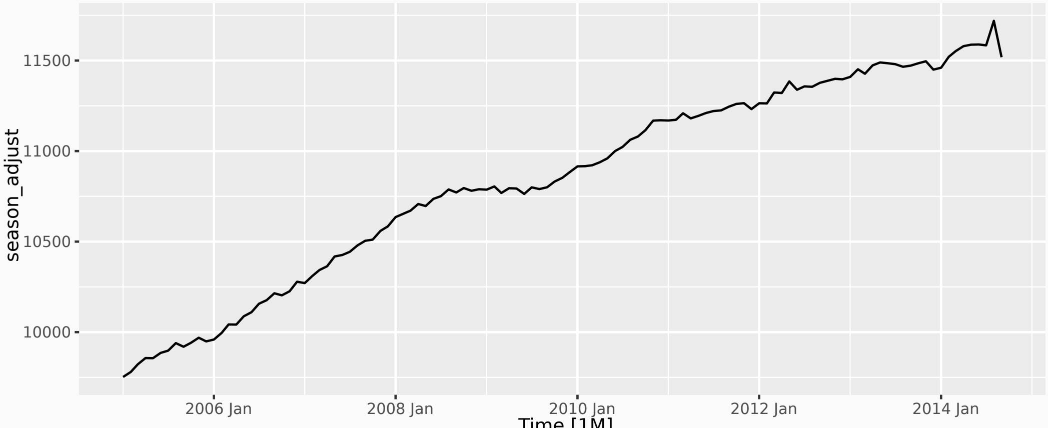
The ABS stuff-up

```
components(dcmp) |>
  filter(year(Time) == 2013) |>
  gg_season(season_year) +
  labs(title = "Seasonal component") + guides(colour = "none")
```



The ABS stuff-up

```r
components(dcmp) |>
  as_tsibble() |>
  autoplot(season_adjust)
```



The ABS stuff-up

- August 2014 employment numbers higher than expected.
- Supplementary survey usually conducted in August for employed people.
- Most likely, some employed people were claiming to be unemployed in August to avoid supplementary questions.
- Supplementary survey not run in 2014, so no motivation to lie about employment.
- In previous years, seasonal adjustment fixed the problem.
- The ABS has now adopted a new method to avoid the bias.