bit.ly/etsa2022

Exploratory time series analysis using R

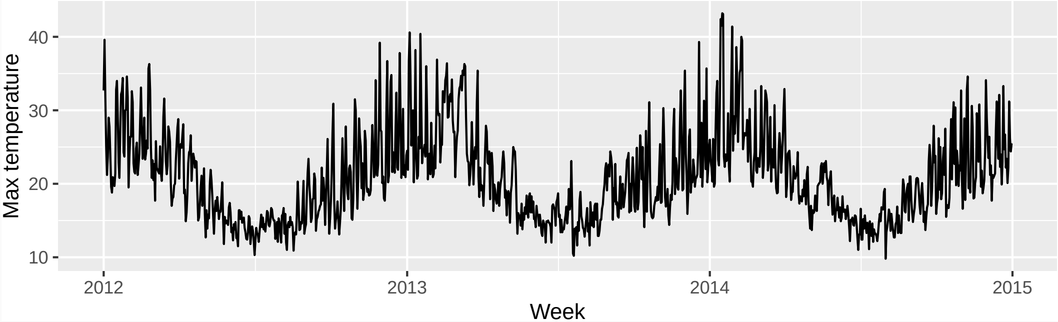
2. Visualising trend and seasonality

Outline

Outline

Time plots: autoplot( )

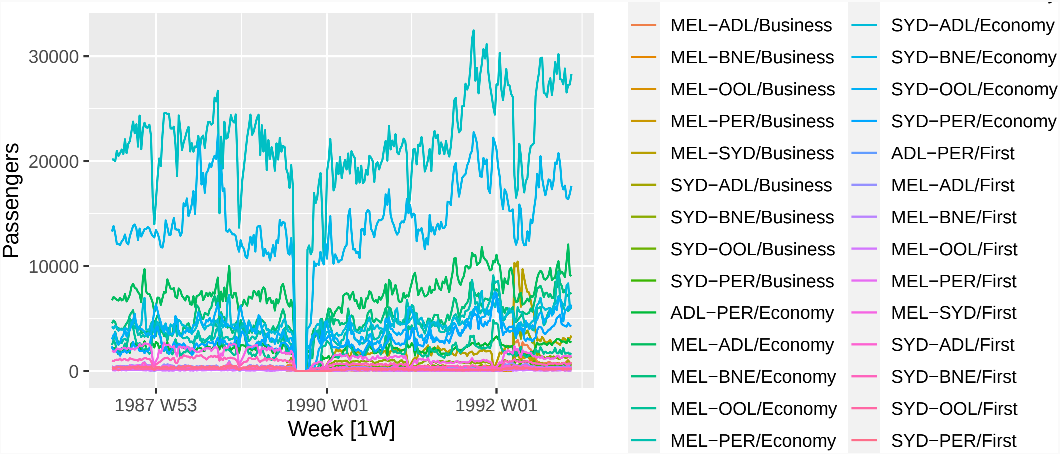
```
maxtemp <- vic_elec ▷
  index_by(Day = date(Time)) ▷
  summarise(Temperature = max(Temperature))
maxtemp ▷
  autoplot(Temperature) +
  labs(x = "Week", y = "Max temperature")
```



Ansett airlines

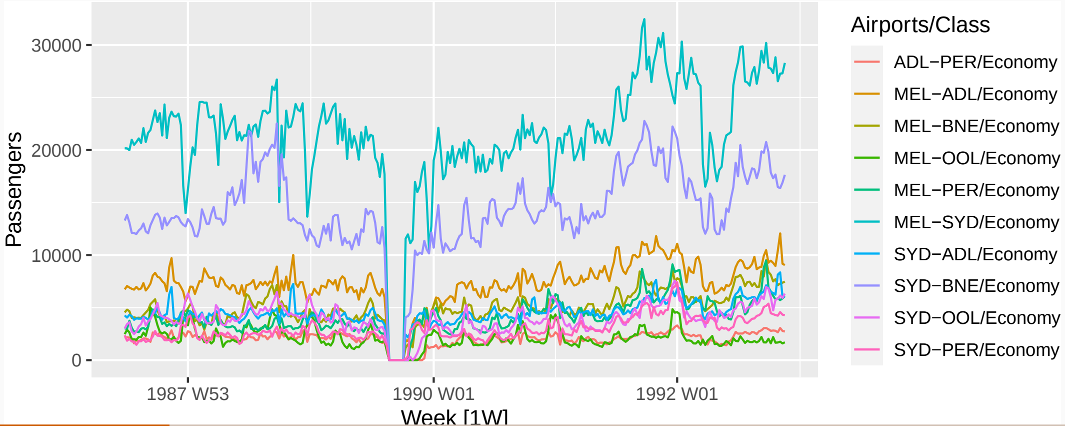
Ansett airlines

```
ansett |>
  autoplot(Passengers)
```



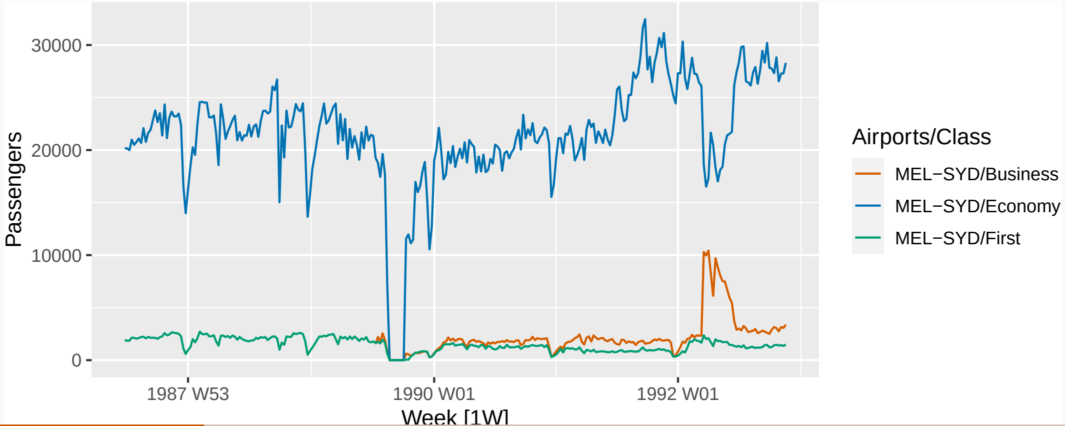
Ansett airlines

```
ansett |>
  filter(Class == "Economy") |>
  autoplot(Passengers)
```



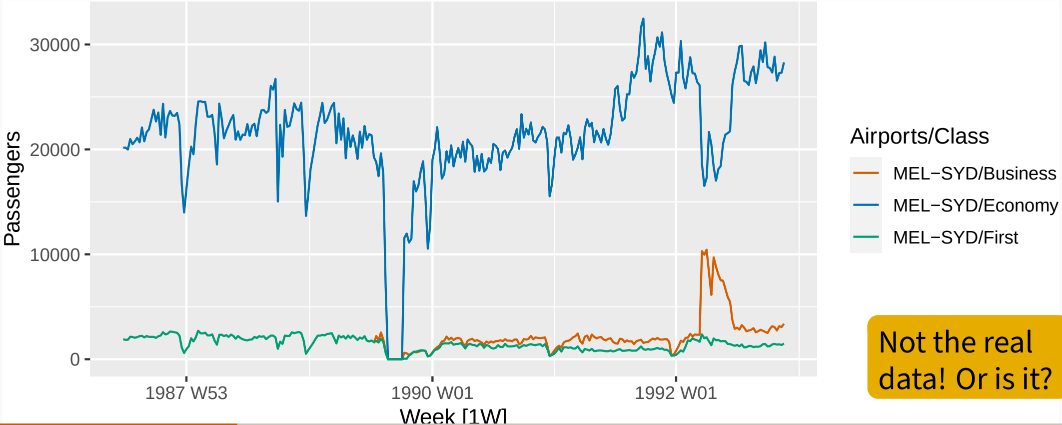
Ansett airlines

```r
ansett |>
  filter(Airports == "MEL-SYD") |>
  autoplot(Passengers)
```



Ansett airlines

```r
ansett |>
  filter(Airports == "MEL-SYD") |>
  autoplot(Passengers)
```



Not the real data! Or is it?

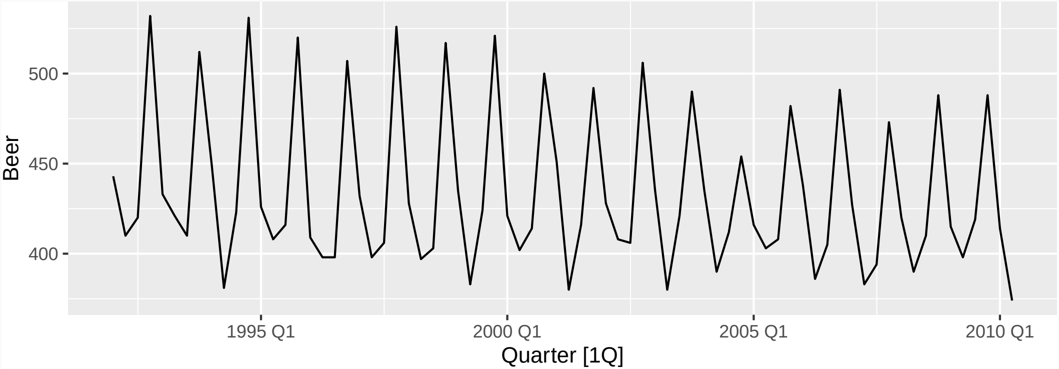
Outline

Seasonal plots: `gg_season()`

- Data plotted against the individual “seasons” in which the data were observed.
- Something like a time plot except that the data from each season are overlapped.
- Enables the underlying seasonal pattern to be seen more clearly, and also allows any substantial departures from the seasonal pattern to be easily identified.

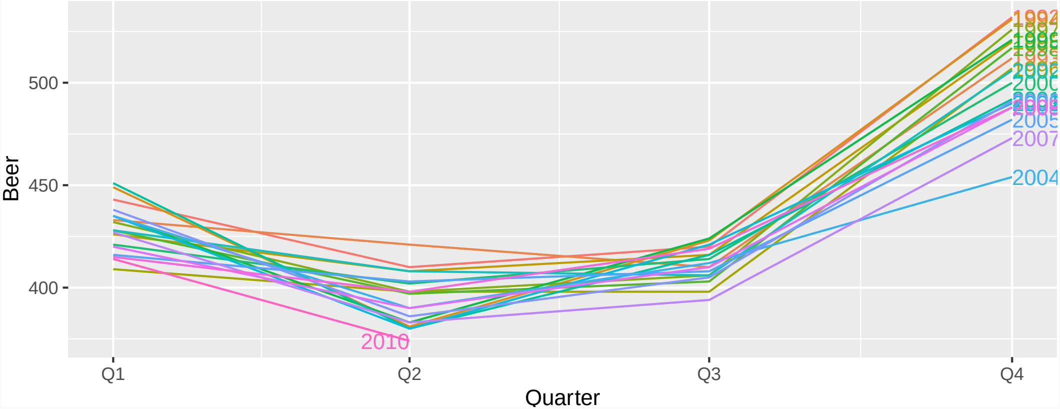
Quarterly Australian Beer Production

```r
beer <- aus_production |>
  select(Quarter, Beer) |>
  filter(year(Quarter) >= 1992)
beer |> autoplot(Beer)
```



Quarterly Australian Beer Production

```
beer |> gg_season(Beer, labels = "right")
```



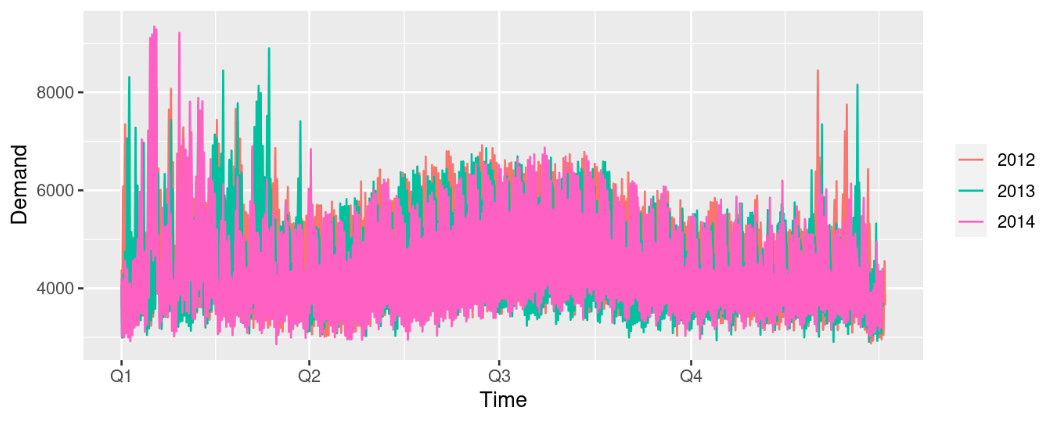
Multiple seasonal periods

```r
vic_elec
```

```
## # A tsibble: 52,608 x 5 [30m] <Australia/Melbourne>
##    Time                Demand Temperature Date       Holiday
##    <dttm>               <dbl>       <dbl> <date>     <lgl>
##  1 2012-01-01 00:00:00  4383.        21.4 2012-01-01 TRUE
##  2 2012-01-01 00:30:00  4263.        21.0 2012-01-01 TRUE
##  3 2012-01-01 01:00:00  4049.        20.7 2012-01-01 TRUE
##  4 2012-01-01 01:30:00  3878.        20.6 2012-01-01 TRUE
##  5 2012-01-01 02:00:00  4036.        20.4 2012-01-01 TRUE
##  6 2012-01-01 02:30:00  3866.        20.2 2012-01-01 TRUE
##  7 2012-01-01 03:00:00  3694.        20.1 2012-01-01 TRUE
##  8 2012-01-01 03:30:00  3562.        19.6 2012-01-01 TRUE
##  9 2012-01-01 04:00:00  3433.        19.1 2012-01-01 TRUE
## 10 2012-01-01 04:30:00  3359.        19.0 2012-01-01 TRUE
## # ... with 52,598 more rows
```

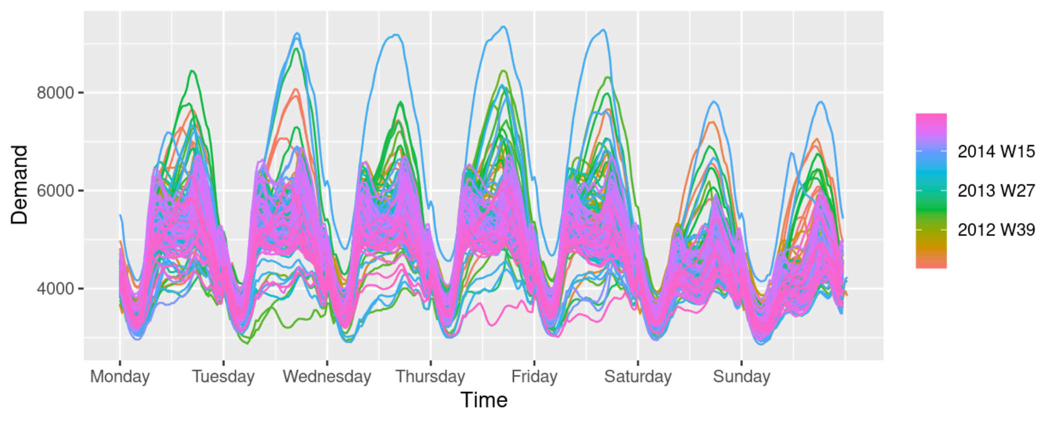
Multiple seasonal periods

```
vic_elec ▷ gg_season(Demand)
```



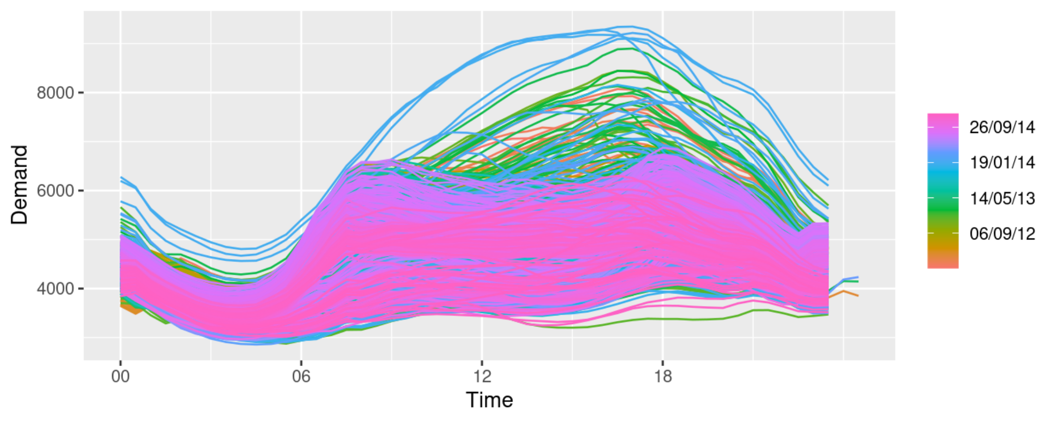
Multiple seasonal periods

```
vic_elec ▷ gg_season(Demand, period = "week")
```



Multiple seasonal periods

```
vic_elec ▷ gg_season(Demand, period = "day")
```

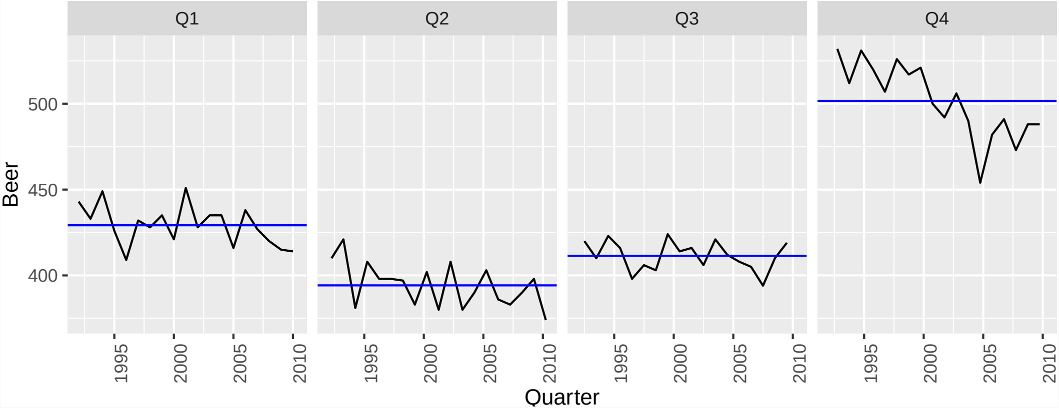


Seasonal subseries plots: `gg_subseries()`

- Data for each season collected together in time plot as separate time series.
- Enables the underlying seasonal pattern to be seen clearly, and changes in seasonality over time to be visualized.

Quarterly Australian Beer Production

```
beer |> gg_subseries(Beer)
```



Outline

Lab Session 2

Look at the quarterly tourism data for the Snowy Mountains

```r
snowy <- tourism |>
  filter(Region == "Snowy Mountains")
```

- Use `autoplot()`, `gg_season()` and `gg_subseries()` to explore the data.
- What do you learn?

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
$y_t =$ data at period t
$T_t =$ trend-cycle component at period t
$S_t =$ seasonal component at period t
$R_t =$ remainder component at period t

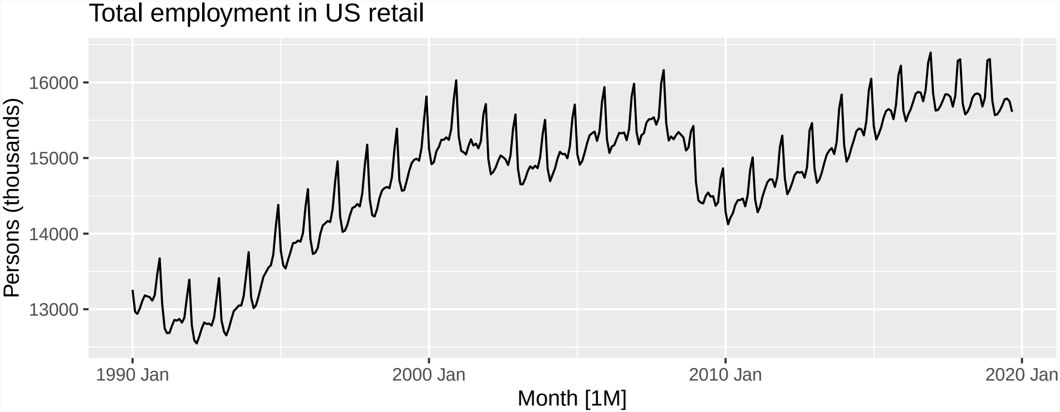
US Retail Employment

```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

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

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

US Retail Employment

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

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

- STL: “Seasonal and Trend decomposition using Loess”

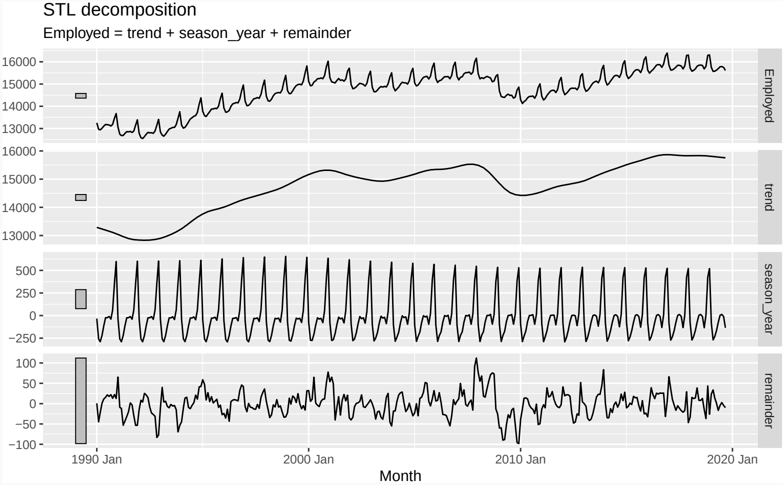
US Retail Employment

```
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.
```

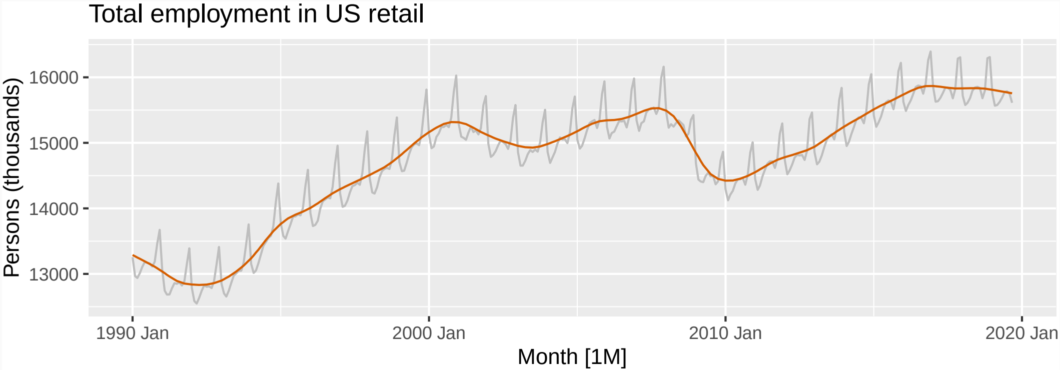
US Retail Employment

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



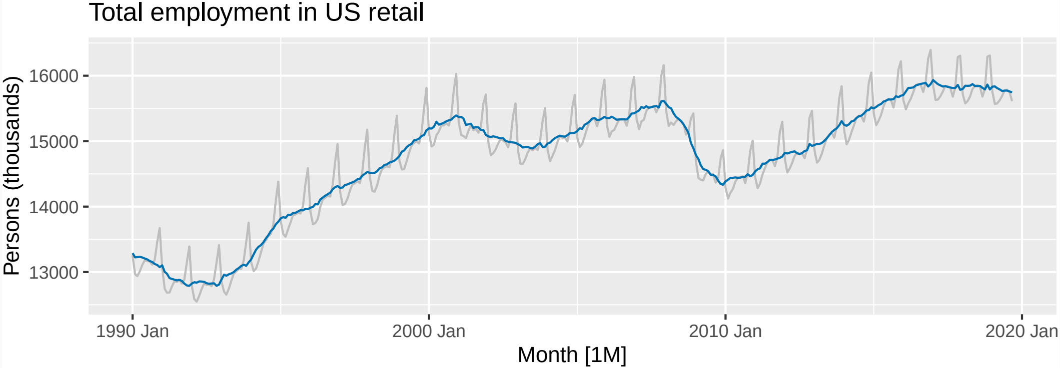
US Retail Employment

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



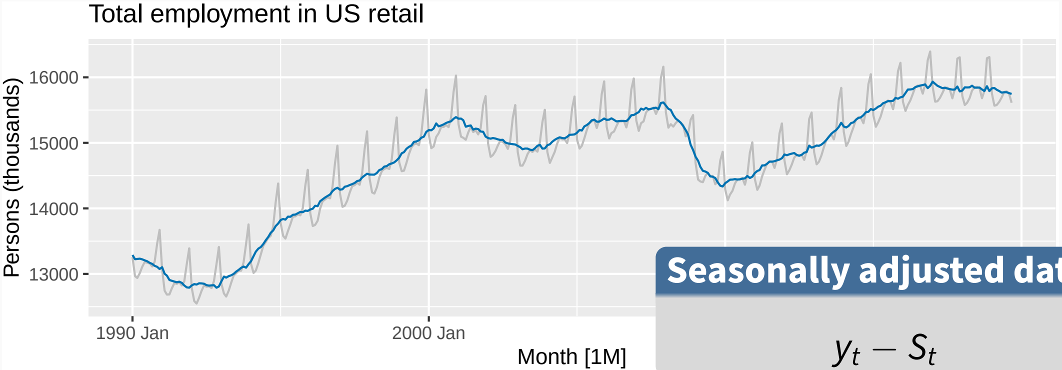
US Retail Employment

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



US Retail Employment

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



Seasonally adjusted data

$$y_t - S_t$$

STL decomposition

STL decomposition

```
us_retail_employment ▷
  model(STL(Employed ~ trend(window = 21) + season(window = 13),
    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

- 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 =`
  `nextodd(ceiling((1.5*period)/(1-(1.5/s.window)))`
- `window` values should be odd numbers for symmetry.

Outline

Lab Session 3

1. Produce an STL decomposition of the Snowy Mountains data.
2. Experiment with different values of the two `window` arguments.
3. Plot the seasonally adjusted series.