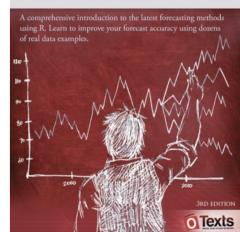
3. Time series decomposition

3.6 STL decomposition

OTexts.org/fpp3/

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FORECASTING PRINCIPLES AND PRACTICE



- STL: "Seasonal and Trend decomposition using Loess"
- Very versatile and robust.
- Unlike X-12-ARIMA, STL will handle any type of seasonality.
- Seasonal component allowed to change over time, and rate of change controlled by user.
- Smoothness of trend-cycle also controlled by user.
- Robust to outliers
- Not trading day or calendar adjustments.
- Only additive.
- Take logs to get multiplicative decomposition.
- Use Box-Cox transformations to get other decompositions.

```
us_retail_employment |>
  model(STL(Employed ~ season(window = 9), robust = TRUE)) |>
  components() |>
  autoplot() +
  labs(title = "STL decomposition: US retail employment")
```



```
us retail employment |>
  model(STL(Employed ~ season(window = 5))) |>
  components()
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.

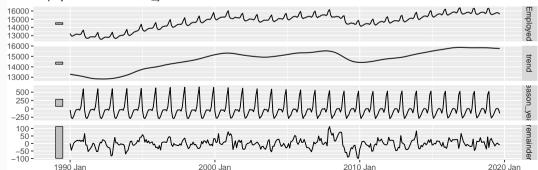
```
us_retail_employment |>
  model(STL(Employed)) |>
  components() |>
   autoplot()
     STL decomposition
     Employed = trend + season_year + remainder
16000 -
15000 -
14000 -
13000 -
16000 -
15000 -
14000 -
13000 -
 500 -
 250 -
 -250 -
 100 -
  50 -
 -50 -
-100 -
                                        2000 Jan
          1990 Jan
                                                                      2010 Jan
                                                                                                     2020 Jan
```

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

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

STL decomposition

Employed = trend + season_year + remainder



- 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.
- The trend window controls loess bandwidth applied to deasonalised values.
- The season window controls loess bandwidth applied to detrended subseries.
- Robustness weights based on remainder.
- Default season window = 13
- Default trend window = nextodd(

```
ceiling((1.5*period)/(1-(1.5/s.window)))
```