

Forecasting: principles and practice

Rob J Hyndman

2.2 Seasonality and trends

- 1 Time series components
- 2 STL decomposition
- 3 Lab session 12
- 4 Forecasting and decomposition
- 5 Lab session 13

Time series patterns

- **Trend** pattern exists when there is a long-term increase or decrease in the data.
- Seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).
 - **Cyclic** pattern exists when data exhibit rises and falls that are *not of fixed period* (duration usually of at least 2 years).

Time series decomposition

$$Y_t = S_t + T_t + R_t$$

where Y_t = data at period t

 S_t = seasonal component at period t

 T_t = trend-cycle component at period t

 R_t = remainder (or irregular or error) component at period t

Time series decomposition

$$Y_t = S_t + T_t + R_t$$

where Y_t = data at period t

 S_t = seasonal component at period t

 T_t = trend-cycle component at period t

 R_t = remainder (or irregular or error) component at period t

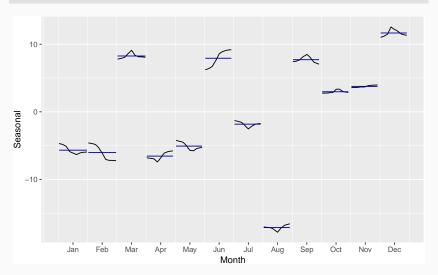
- Additive model appropriate if magnitude of seasonal fluctuations does not vary with level.
- If seasonal are proportional to level of series, use a Box-Cox transformation first.

fit <- mstl(elecequip)</pre> autoplot(fit) 120 -100 -80 -60 -110 -100 -90 -80 -10 -Seasonal12 0 --10 **-**Remainder 5 --5 **-**2005 2000 Time

```
autoplot(elecequip, series="Data") +
autolayer(trendcycle(fit), series="Trend") +
ylab("New orders index") + xlab("") +
ggtitle("Electrical equipment manufacturing (Euro area)")
```



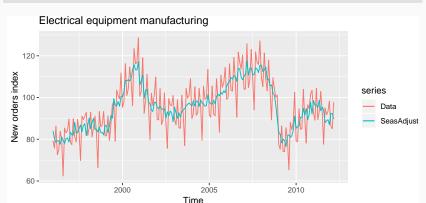
ggmonthplot(seasonal(fit)) + ylab("Seasonal")



Seasonal adjustment

Seasonally adjusted data given by $Y_t - S_t = T_t + E_t$

```
autoplot(elecequip, series="Data") +
  autolayer(seasadj(fit), series="SeasAdjust") +
  ylab("New orders index") +
  ggtitle("Electrical equipment manufacturing")
```



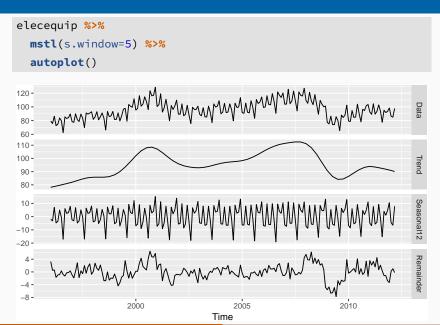
History of time series decomposition

- Classical method originated in 1920s.
- Census II method introduced in 1957. Basis for modern X-12-ARIMA method.
- STL method introduced in 1983
- TRAMO/SEATS introduced in 1990s.

- 1 Time series components
- 2 STL decomposition
- 3 Lab session 12
- 4 Forecasting and decomposition
- 5 Lab session 13

STL decomposition

- STL: "Seasonal and Trend decomposition using Loess",
- Very versatile and robust.
- 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
- No trading day or calendar adjustments.
- Only additive.



```
elecequip %>%
  mstl(t.window=15, s.window='periodic', robust=TRUE) %>%
   autoplot()
120 -
100 -
80 -
60 -
110 -
100 -
90 -
80 -
10 -
                                                                                          Seasonal12
 0 -
-10 -
10 -
                                                                                          Remainder
 5 -
-5 -
                                                                         2010
                         2000
                                                 2005
                                            Time
```

STL decomposition in R

- t.window controls wiggliness of trend component.
- s.window controls variation on seasonal component.
- seasonal() extracts seasonal component
- trendcycle() extracts trend component
- remainder() extracts remainder component
- seasadj() computes seasonally adjusted data

- **1** Time series components
- 2 STL decomposition
- 3 Lab session 12
- 4 Forecasting and decomposition
- 5 Lab session 13

Lab Session 12

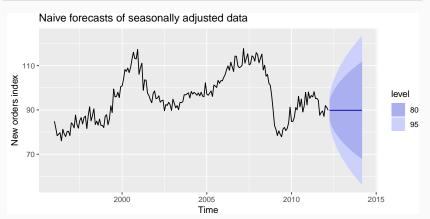
- 1 Time series components
- 2 STL decomposition
- 3 Lab session 12
- 4 Forecasting and decomposition
- 5 Lab session 13

Forecasting and decomposition

- Forecast seasonal component by repeating the last year (snaive)
- Forecast seasonally adjusted data using non-seasonal time series method. E.g.,
 - Holt's method
 - Random walk with drift model
- Combine forecasts of seasonal component with forecasts of seasonally adjusted data to get forecasts of original data.
- Sometimes a decomposition is useful just for understanding the data before building a separate forecasting model.

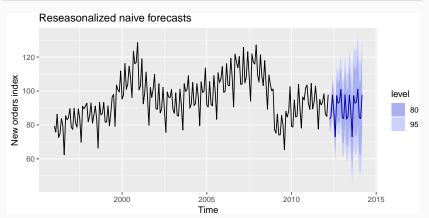
Seas adj elec equipment

```
mstl(elecequip, t.window=15, s.window="periodic") %>%
  seasadj() %>% naive(h=24) %>%
  autoplot() + ylab("New orders index") +
  ggtitle("Naive forecasts of seasonally adjusted data")
```



Seas adj elec equipment

```
mstl(elecequip, t.window=15, s.window="periodic") %>%
  forecast(method="naive", h=24) %>%
  autoplot() + ylab("New orders index") +
  ggtitle("Reseasonalized naive forecasts")
```



Decomposition and prediction intervals

- It is common to take the prediction intervals from the seasonally adjusted forecasts and modify them with the seasonal component.
- This ignores the uncertainty in the seasonal component estimate.
- It also ignores the uncertainty in the future seasonal pattern.

Some more R functions

```
fcast <- stlf(elecequip, method='naive')

fcast <- stlf(elecequip, method='naive',
   h=36, s.window=11, robust=TRUE)</pre>
```

- 1 Time series components
- 2 STL decomposition
- 3 Lab session 12
- 4 Forecasting and decomposition
- 5 Lab session 13

Lab Session 13