

# Forecasting: principles and practice

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2.2 Seasonality and trends

# Outline

- 1 Time series components
- 2 STL decomposition
- 3 Lab session 12
- 4 Forecasting and decomposition
- 5 Lab session 13
- 6 Lab session 14

# 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  $t$

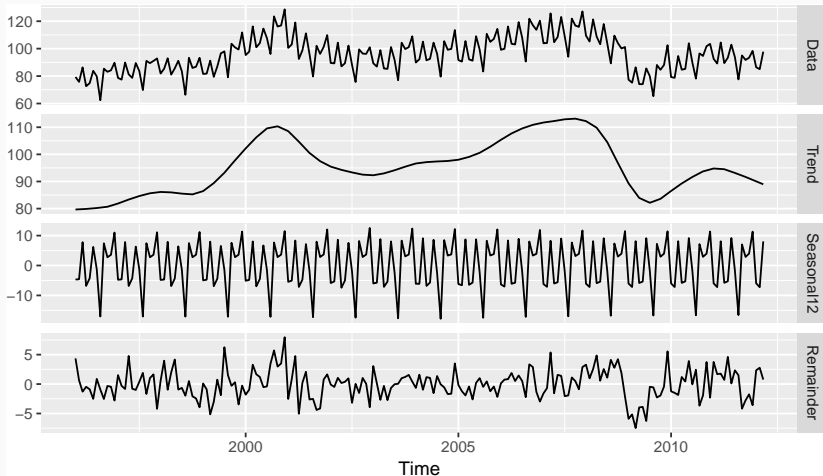
$T_t$  = trend-cycle component at period  $t$

$R_t$  = 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.

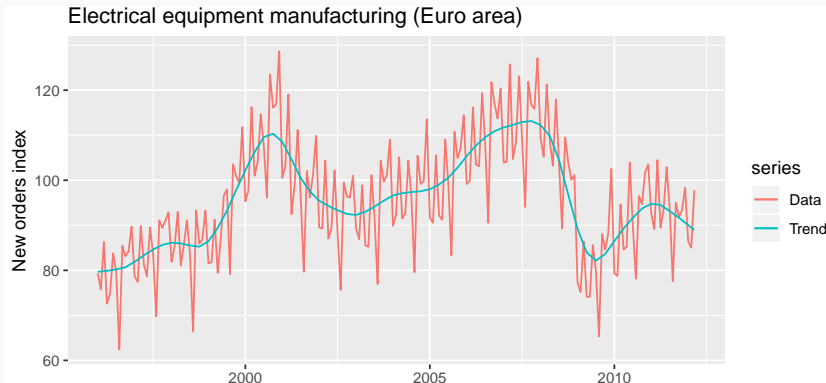
# Euro electrical equipment

```
fit <- mstl(elecequip)  
autoplot(fit)
```



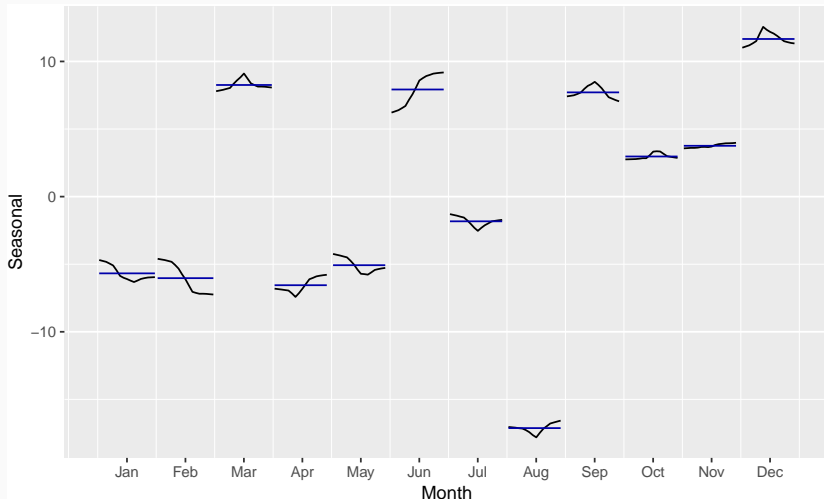
# Euro electrical equipment

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



# Euro electrical equipment

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

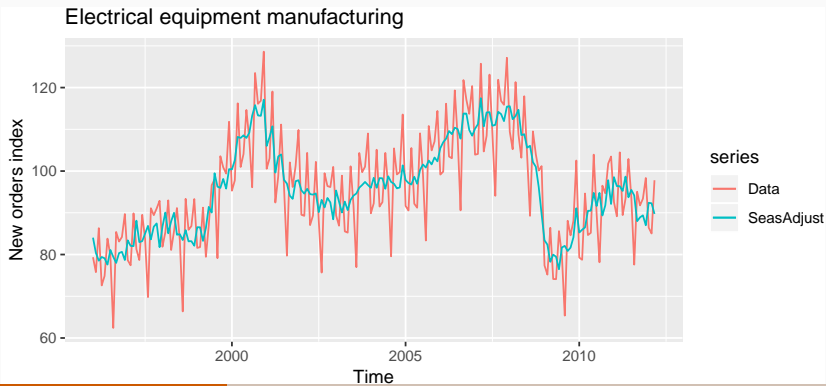




# Seasonal adjustment

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.

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# STL decomposition

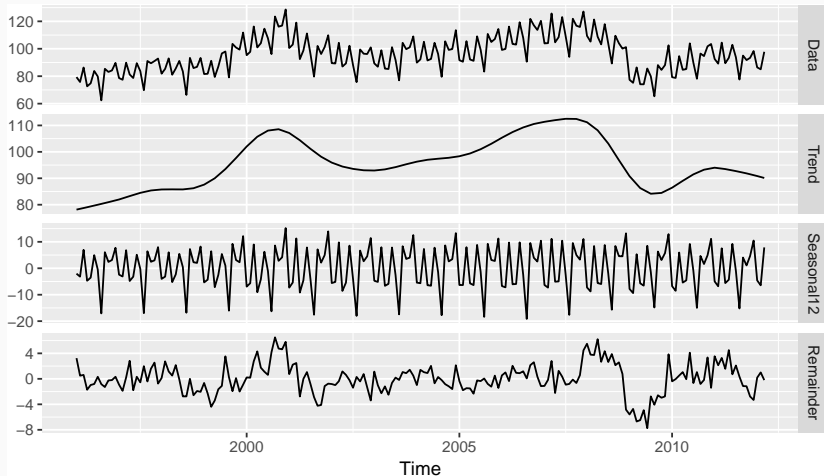
- STL: “Seasonal and Trend decomposition using Loess”,
- Very versatile and robust.
- Will handle any type of seasonality.
- Seasonal component allowed to change over time, and rate of change controlled by user.
- Smoothness of trend-cycle also controlled by user.
- Robust to outliers
- No trading day or calendar adjustments.
- Only additive.

# Euro electrical equipment

```
elecequip %>%
```

```
  mstl(s.window=5) %>%
```

```
  autoplot()
```

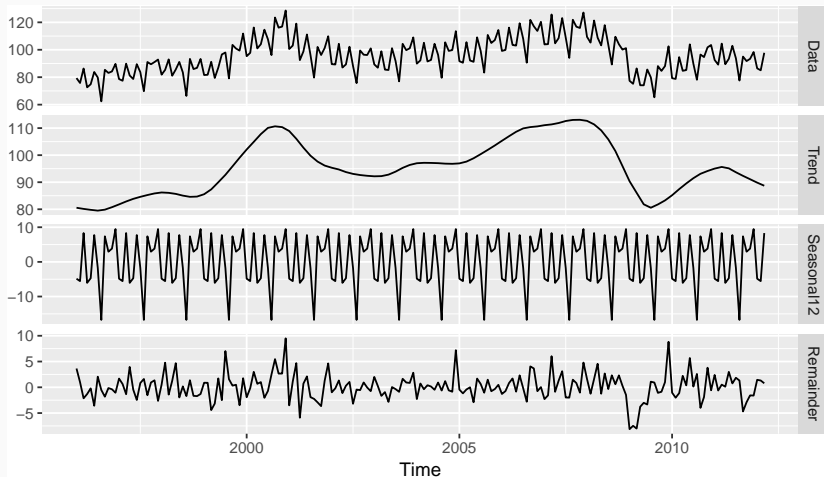


# Euro electrical equipment

```
elecequip %>%
```

```
  mstl(t.window=15, s.window='periodic', robust=TRUE) %>%
```

```
  autoplot()
```



# STL decomposition in R

- `t.window` controls wiggleness 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

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# Lab Session 12

# Outline

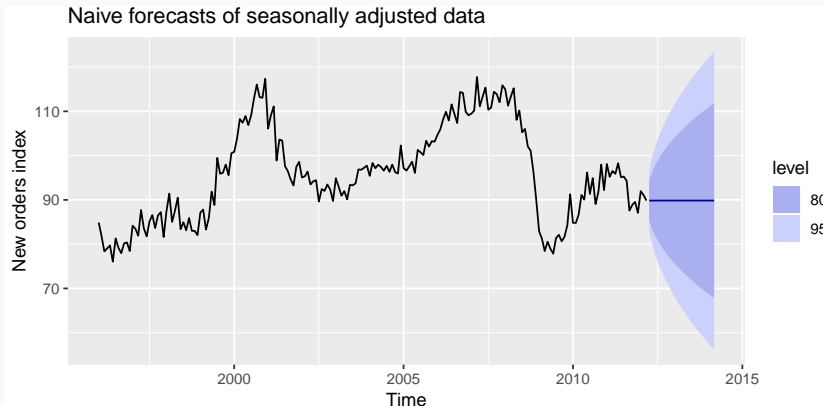
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# Forecasting and decomposition

- Forecast seasonal component by repeating the last year (naïve)
- 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.

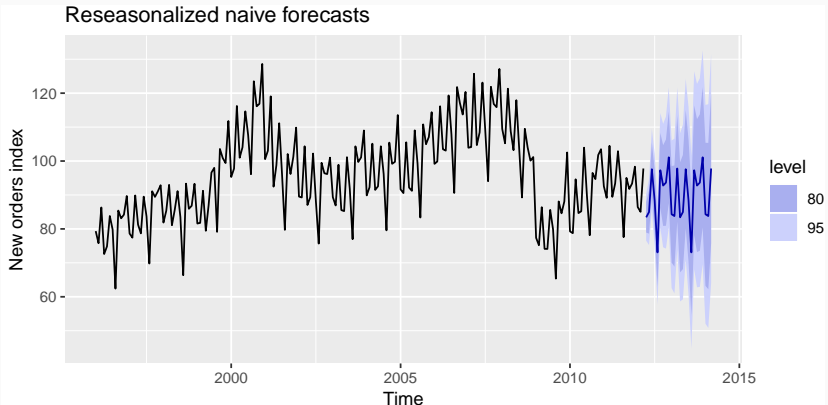
# Seas adj elec equipment

```
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)
```

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# Lab Session 13

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