MONASH University

REVOLUTION ANALYTICS

Rob J Hyndman

Forecasting using R

4. White noise and time series decomposition

OTexts.com/fpp/2/6

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Student award

- To students who make the most contribution to the class, as voted by their peers.
- Contributions can be on Piazza or during the webex online sessions.
- Contribute questions, answers, comments, code suggestions, etc.
- Looking for engaged learners, not experts.
- At end of course, all students to vote for best contributor.
- **$100 to the top voted student and $50 to the second student** (plus t-shirts).

Time zones

All sessions are at UTC 22:00 for the entire course.

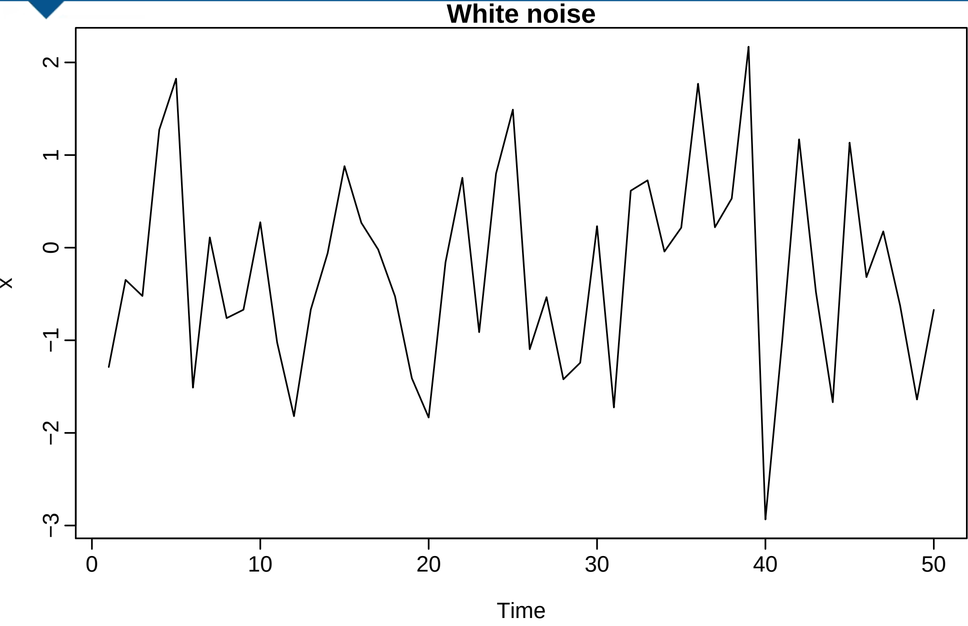
Be aware when ***your*** time zone changes.

- Most of Europe changed last Sunday. So classes are now one hour earlier for most European residents.
- Most of USA and Canada change next Sunday. So classes will be one hour earlier for most North American residents from next week.

Outline

1. **White noise**
2. Time series decomposition
3. Seasonal adjustment
4. Forecasting and decomposition

Example: White noise



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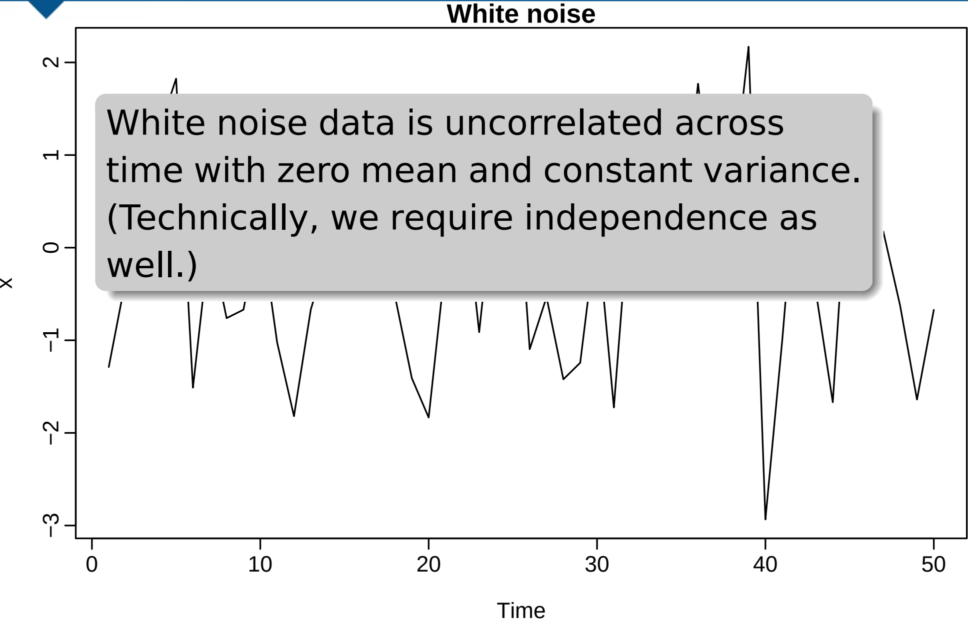

White noise data is uncorrelated across time with zero mean and constant variance.
(Technically, we require independence as well.)

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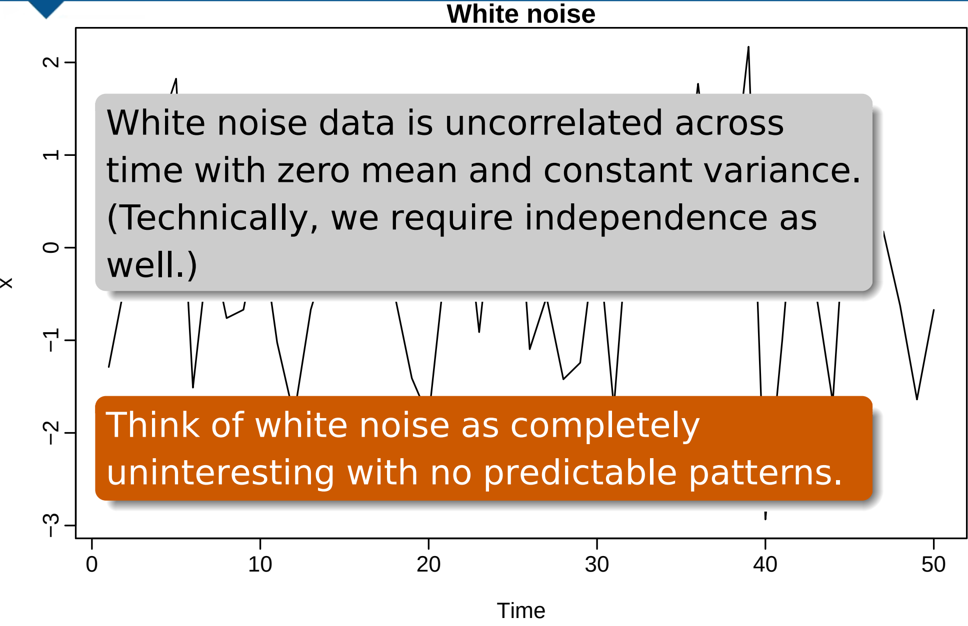

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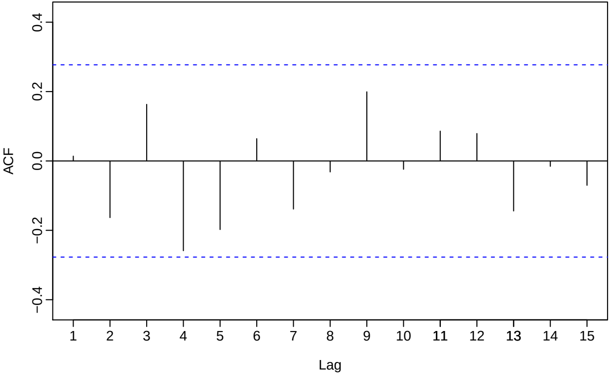
Think of white noise as completely uninteresting with no predictable patterns.

Example: White noise

$$
\begin{aligned}
r_1 &= 0.013 \\
r_2 &= -0.163 \\
r_3 &= 0.163 \\
r_4 &= -0.259 \\
r_5 &= -0.198 \\
r_6 &= 0.064 \\
r_7 &= -0.139 \\
r_8 &= -0.032 \\
r_9 &= 0.199 \\
r_{10} &= -0.240
\end{aligned}
$$



Sample autocorrelations for white noise series.

For uncorrelated data, we would expect each autocorrelation to be close to zero.

Sampling distribution of autocorrelations

Sampling distribution of r_k for white noise data is asymptotically $\text{N}(0,1/T)$.

- 95% of all r_k for white noise must lie within $\pm 1.96/\sqrt{T}$.
- If this is not the case, the series is probably not WN.
- Common to plot lines at $\pm 1.96/\sqrt{T}$ when plotting ACF. These are the *critical values*.

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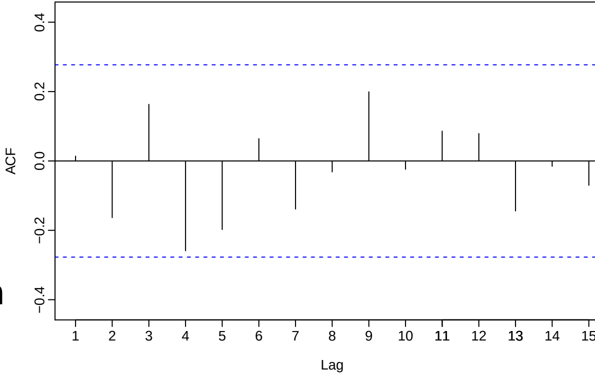
Autocorrelation

Example:

$T = 50$ and so critical values at $\pm 1.96/\sqrt{50} = \pm 0.28$.

All autocorrelation coefficients lie within these limits, confirming that the data are white noise.



(More precisely, the data cannot be distinguished from white noise.)

Example: Pigs slaughtered

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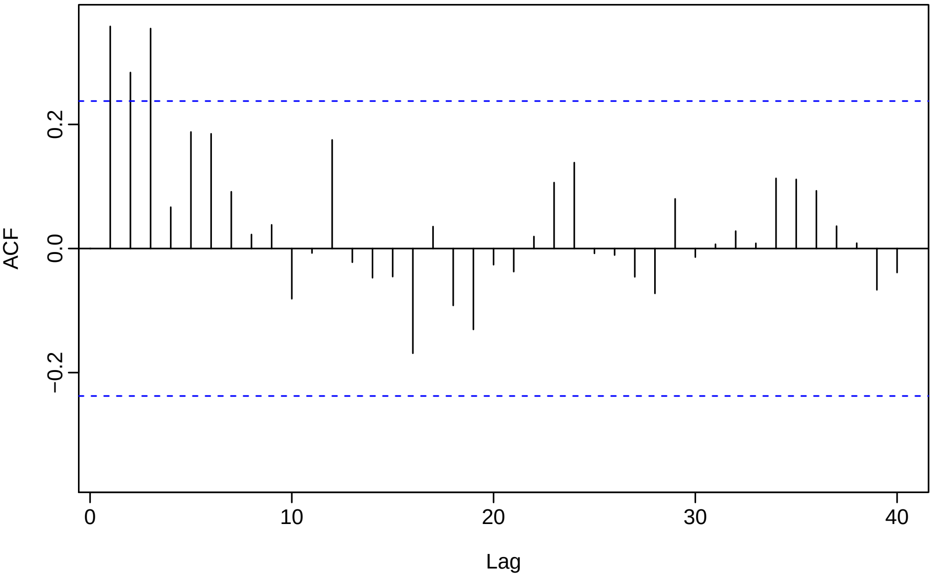

Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 1990 through August 1995. (Source: Australian Bureau of Statistics.)

- Difficult to detect pattern in time plot.
- ACF shows some significant autocorrelation at lags 1, 2, and 3.
- r_{12} relatively large although not significant. This may indicate some slight seasonality.

These show the series is **not a white noise series**.

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ACF of residuals

- We assume that the residuals are white noise (uncorrelated, mean zero, constant variance). If they aren't, then there is information left in the residuals that should be used in computing forecasts.
- So a standard residual diagnostic is to check the ACF of the residuals of a forecasting method.
- We *expect* these to look like white noise.

Dow-Jones naive forecasts revisited

$$\hat{y}_{t|t-1} = y_{t-1}$$
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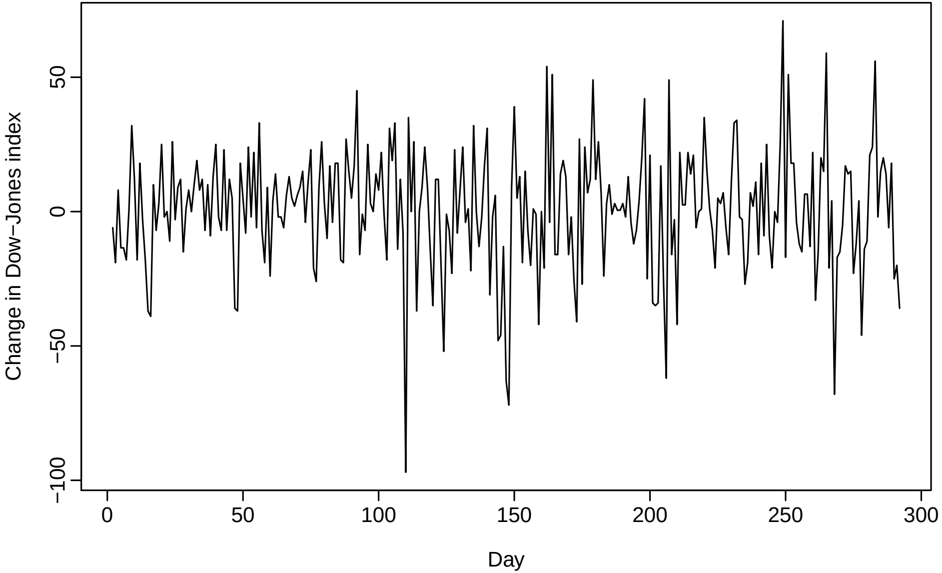
Forecasting Dow-Jones index



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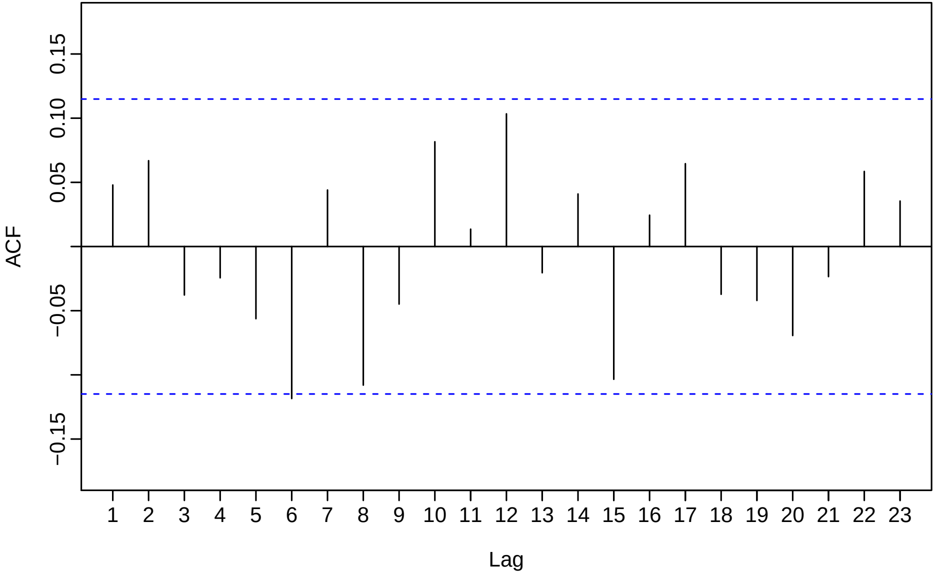
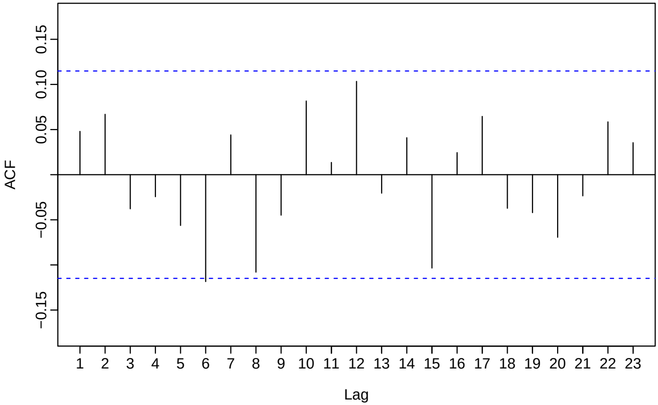


Example: Dow-Jones residuals



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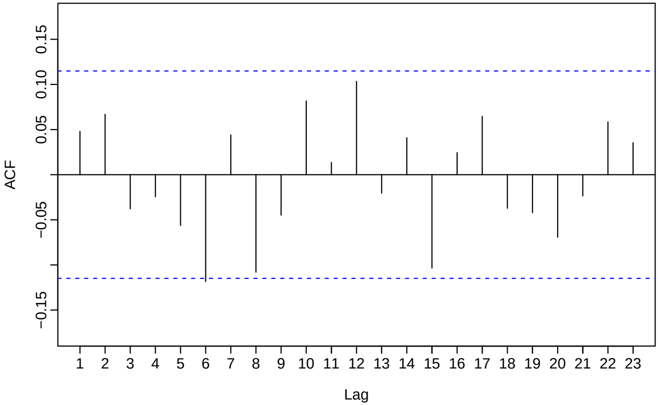

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Portmanteau tests

Consider a *whole set* of r_k values, and develop a test to see whether the set is significantly different from a zero set.

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Box-Pierce test

$$Q = T\sum_{k=1}^{h} r_k^2$$

where h is max lag being considered and T is number of observations.

- My preferences: $h = 10$ for non-seasonal data, $h = 2m$ for seasonal data.
- If each r_k close to zero, Q will be **small**.
- If some r_k values large (positive or negative), Q will be **large**.

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Ljung-Box test

$$Q^* = T(T+2)\sum_{k=1}^{h}(T-k)^{-1}r_k^2$$

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- My preferences: $h = 10$ for non-seasonal data, $h = 2m$ for seasonal data.
- Better performance, especially in small samples.

Portmanteau tests

- If data are WN, Q^* has χ^2 distribution with $(h - K)$ degrees of freedom where $K =$ no. parameters in model.
- When applied to raw data, set $K = 0$.
- For the Dow-Jones example,

```
res <- residuals(naive(dj))

# lag=h and fitdf=K
> Box.test(res, lag=10, fitdf=0)
Box-Pierce test
X-squared = 14.0451, df = 10, p-value = 0.1709
> Box.test(res, lag=10, fitdf=0, type="Lj")
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X-squared = 14.4615, df = 10, p-value = 0.153
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Exercise

1. Calculate the residuals from a seasonal naive forecast applied to the quarterly Australian beer production data from 1992.
2. Test if the residuals are white noise.

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```
beer <- window(ausbeer,start=1992)
fc <- snaive(beer)
res <- residuals(fc)
Acf(res)
Box.test(res, lag=8, fitdf=0, type="Lj")
```

Outline

Time series decomposition

$$Y_t = f(S_t, T_t, E_t)$$

where $Y_t =$ data at period t
$S_t =$ seasonal component at period t
$T_t =$ trend-cycle component at period t
$E_t =$ remainder (or irregular or error) component at period t

Additive decomposition: $Y_t = S_t + T_t + E_t$.
Multiplicative decomposition: $Y_t = S_t \times T_t \times E_t$.

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Time series decomposition

- Additive model appropriate if magnitude of seasonal fluctuations does not vary with level.
- If seasonal are proportional to level of series, then multiplicative model appropriate.
- Multiplicative decomposition more prevalent with economic series
- Logs turn multiplicative relationship into an additive relationship:

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History of time series decomposition

- Classical method originated in 1920s.
  In R: `decompose()`.
- Census II method introduced in 1957.
  Basis for modern X-12-ARIMA method.
- STL method introduced in 1983. It only allows additive decomposition.
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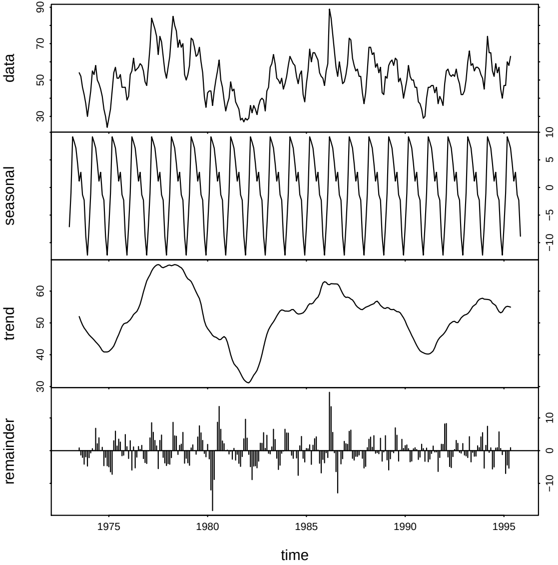
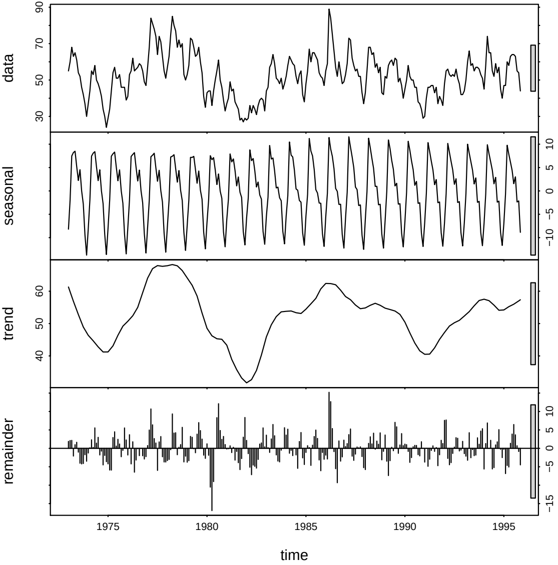
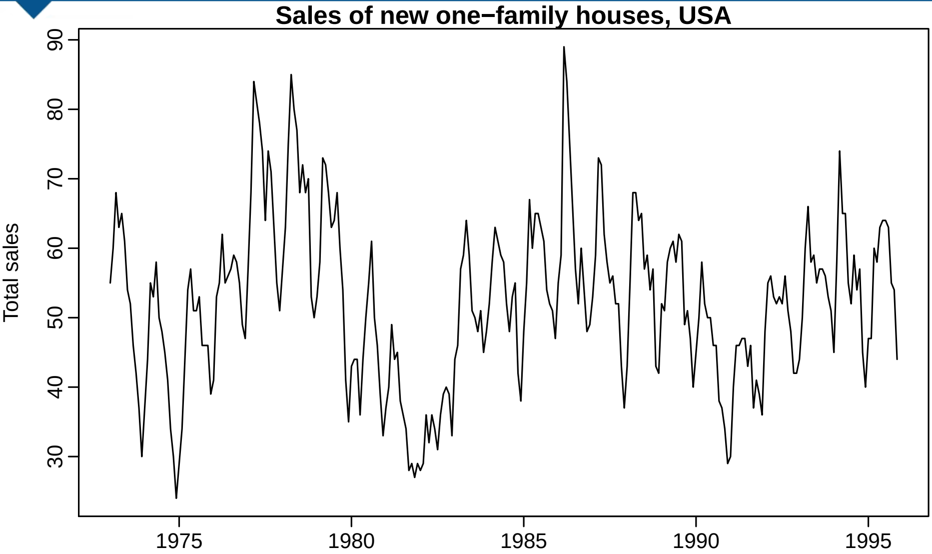
Classical decomposition



STL decomposition



Examples: US house sales



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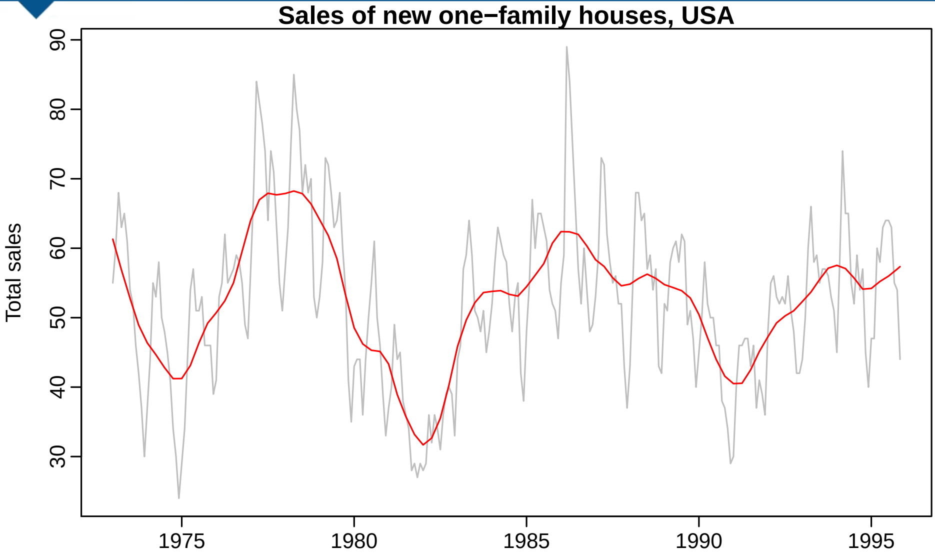

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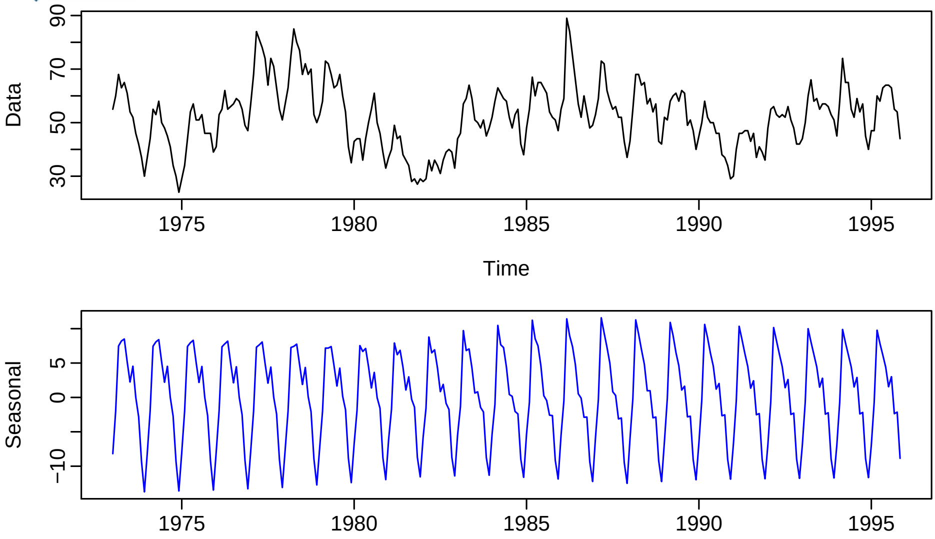

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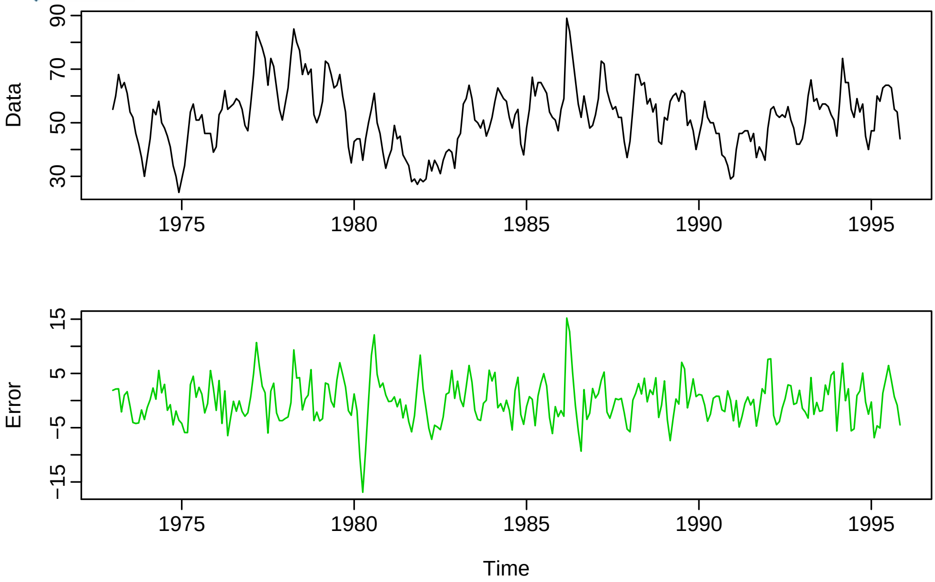

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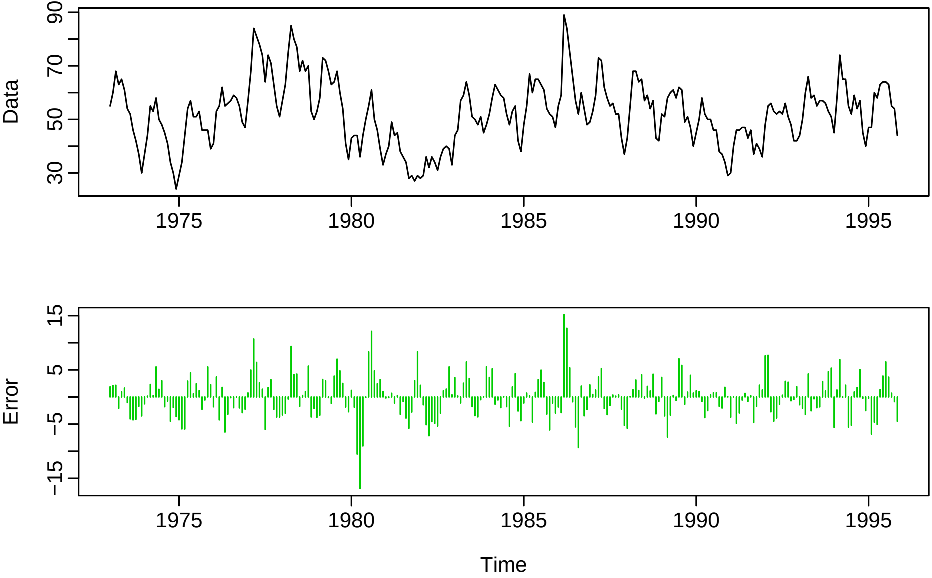

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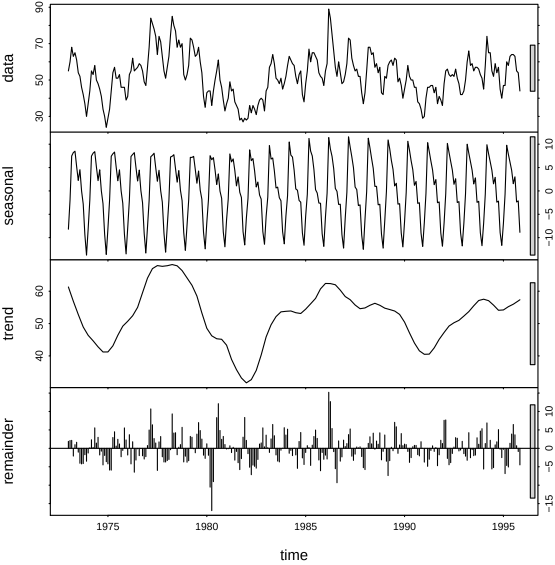
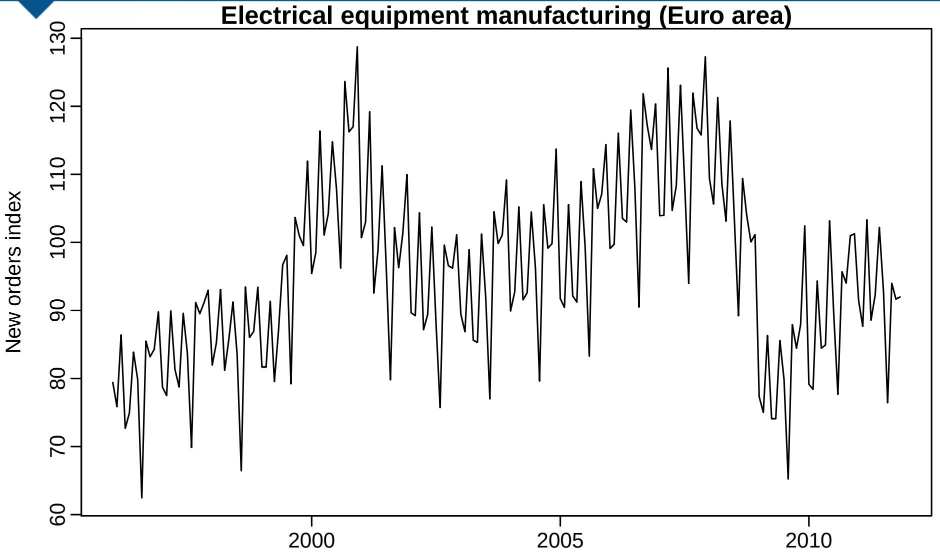


Time series decomposition in R

```
plot(decompose(hsales))
plot(stl(hsales,s.window="periodic"))
plot(stl(hsales,s.window=15))
```

Euro electrical equipment



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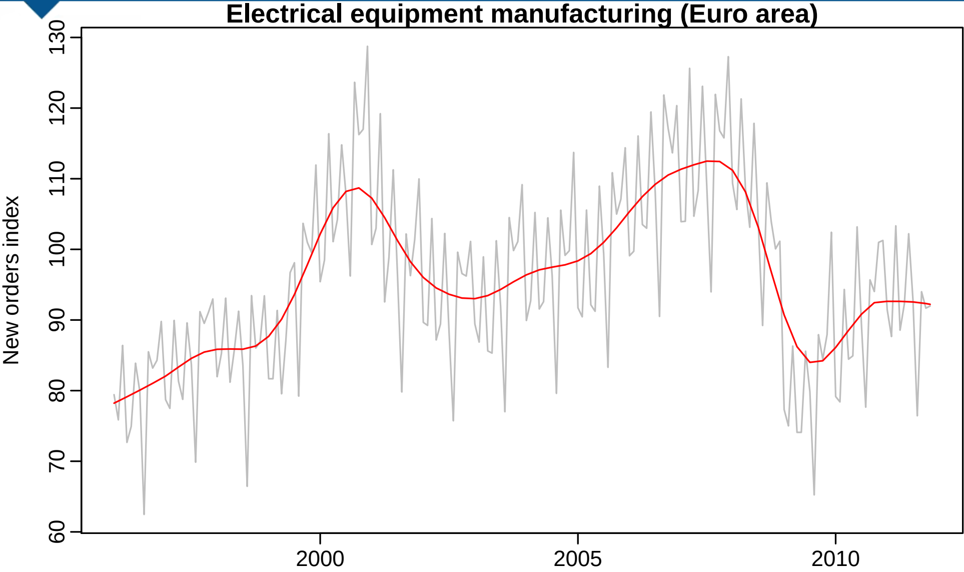

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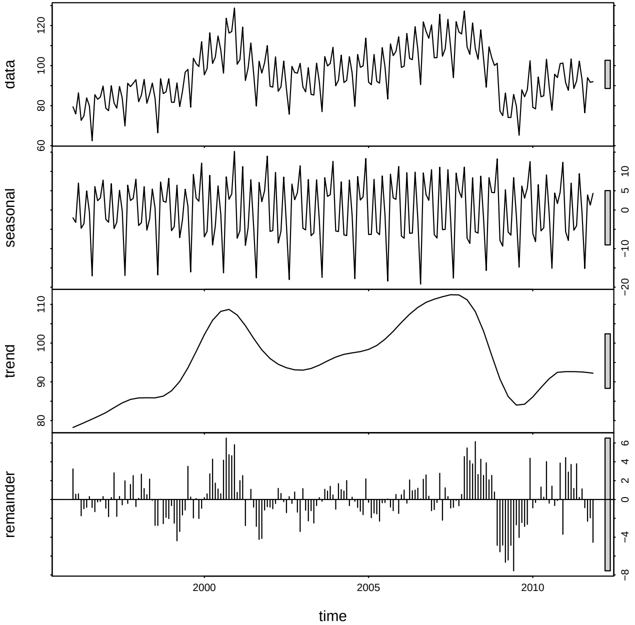
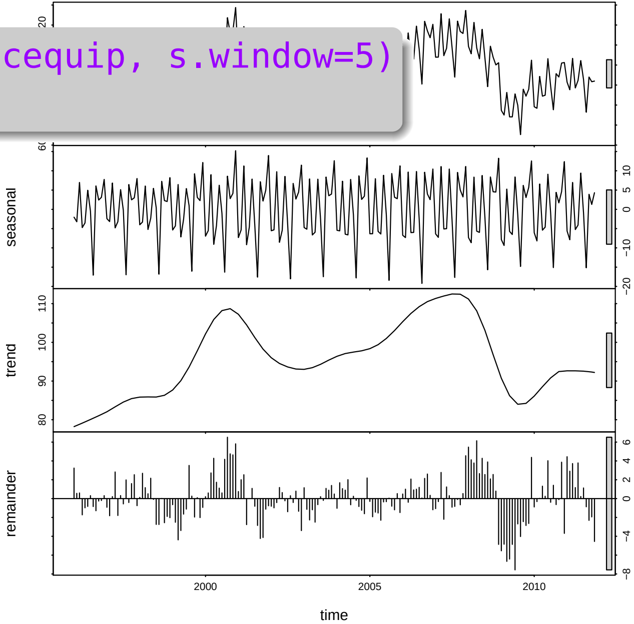


Euro electrical equipment

```r
fit <- stl(elecequip, s.window=5)
plot(fit)
```



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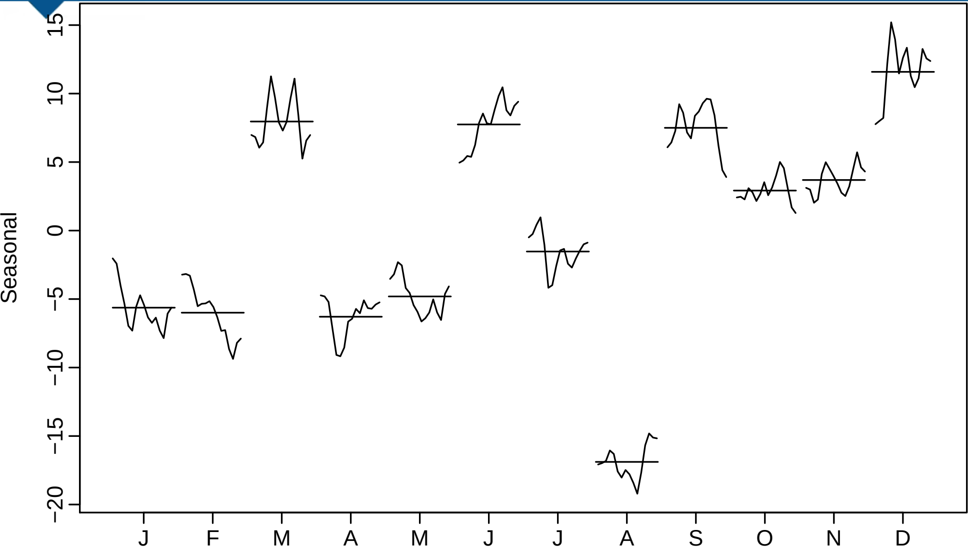
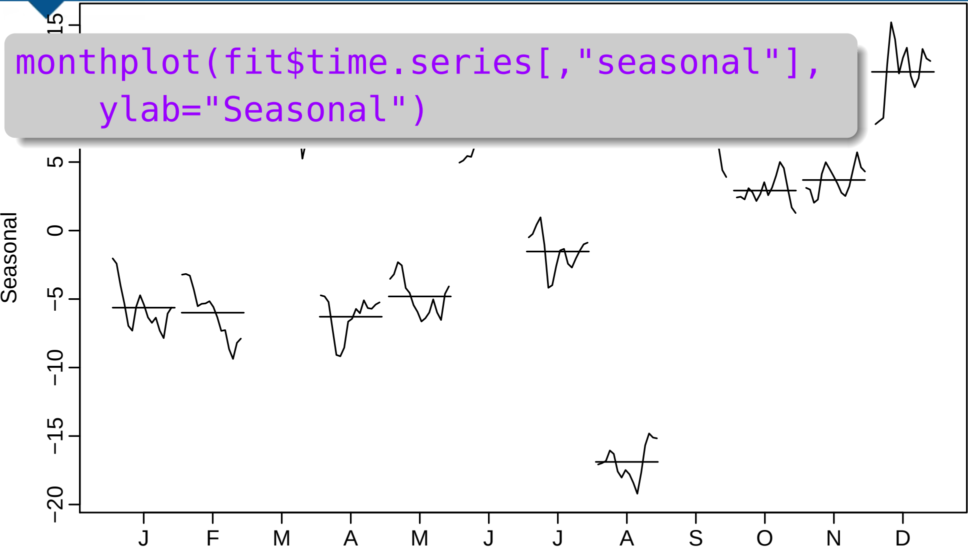


Seasonal sub-series plot of the seasonal component

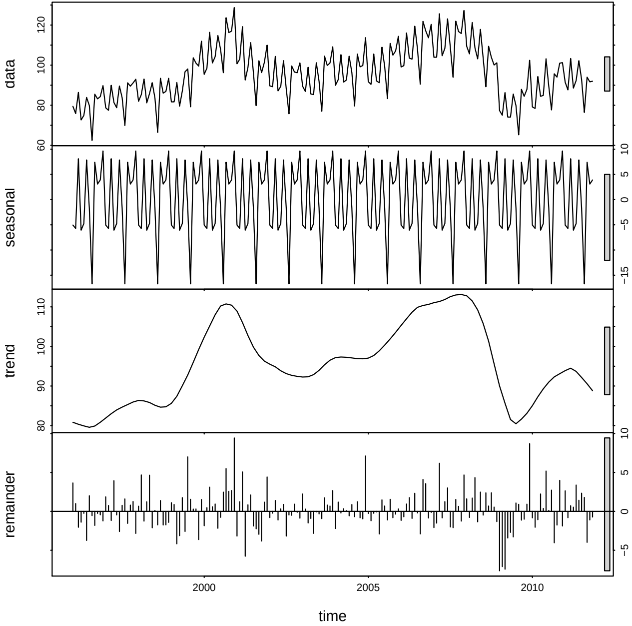
Euro electrical equipment




```
monthplot(fit$time.series[,"seasonal"],
    ylab="Seasonal")
```

Seasonal sub-series plot of the seasonal component

Euro electrical equipment



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```r
fit <- stl(elecequip, t.window=15,
  s.window="periodic", robust=TRUE)
plot(fit)
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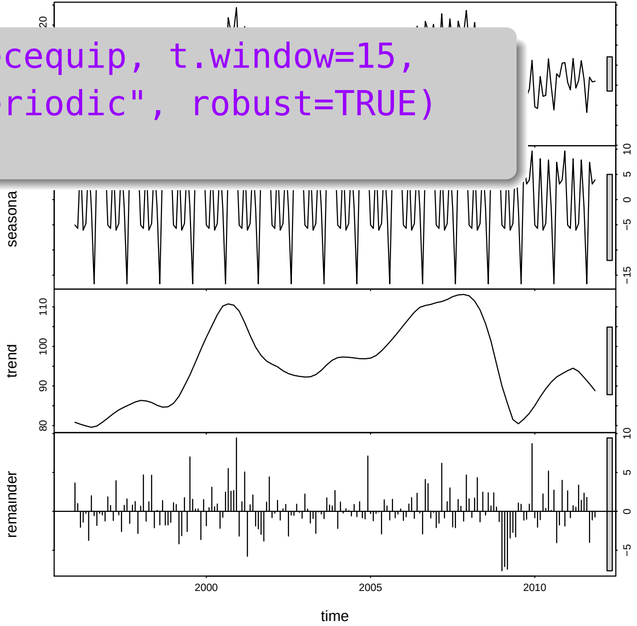

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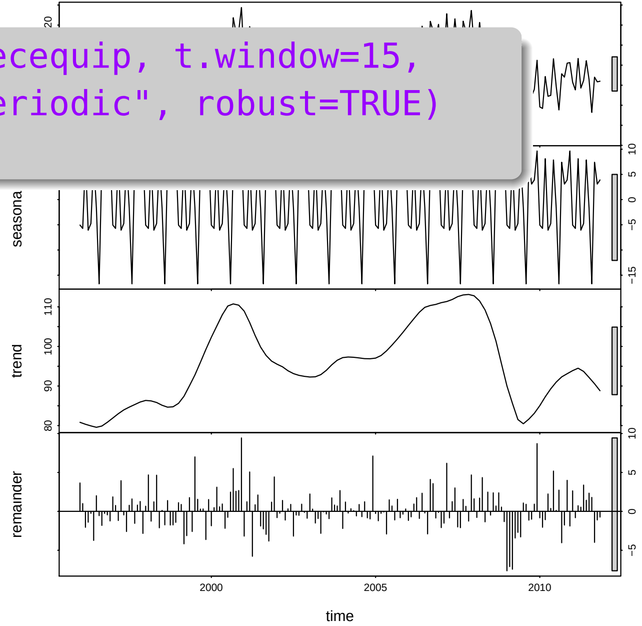

- `t.window` controls wiggliness of trend component.
- `s.window` controls variation in seasonal component.

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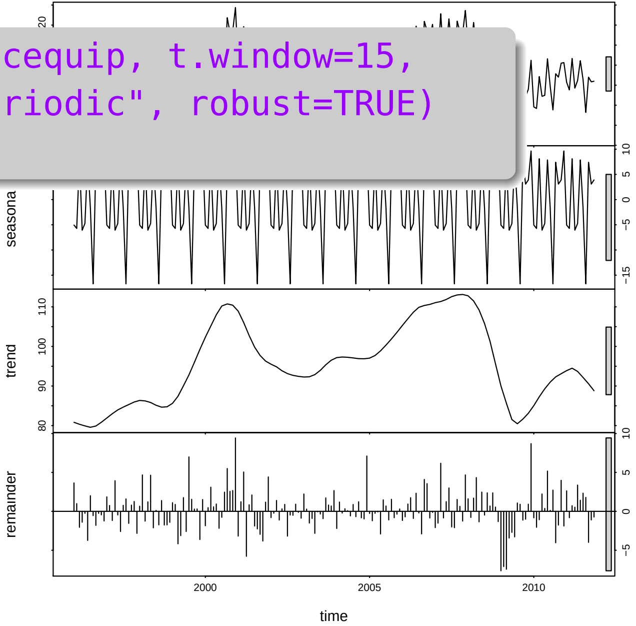

Outline

Seasonal adjustment

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

$$Y_t - S_t = T_t + E_t$$

- Multiplicative decomposition: seasonally adjusted data given by

$$Y_t / S_t = T_t \times E_t$$

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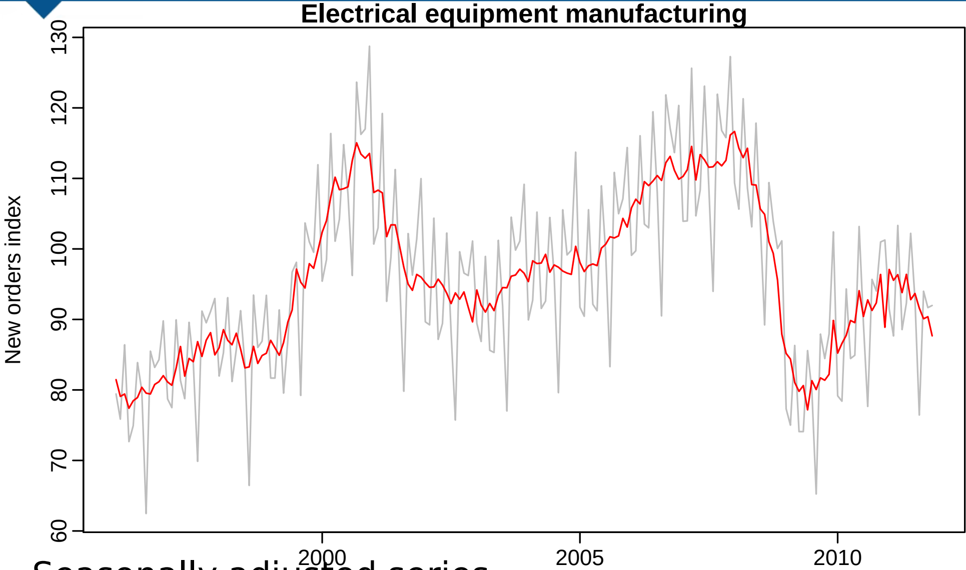

Seasonally adjusted series

Seasonal adjustment in R

`seasadj(obj)`

where `obj` is the output from `stl()` or `decompose()`.

Example

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plot(hsales,col="gray")
fit <- stl(hsales,s.window=15)
hsales.sa <- seasadj(fit)
lines(hsales.sa, col="red")
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Forecasting and decomposition

- Forecast seasonal component by repeating the last year
- Forecast seasonally adjusted data using non-seasonal time series method. E.g.,
  - Holt's method — next topic
  - 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.

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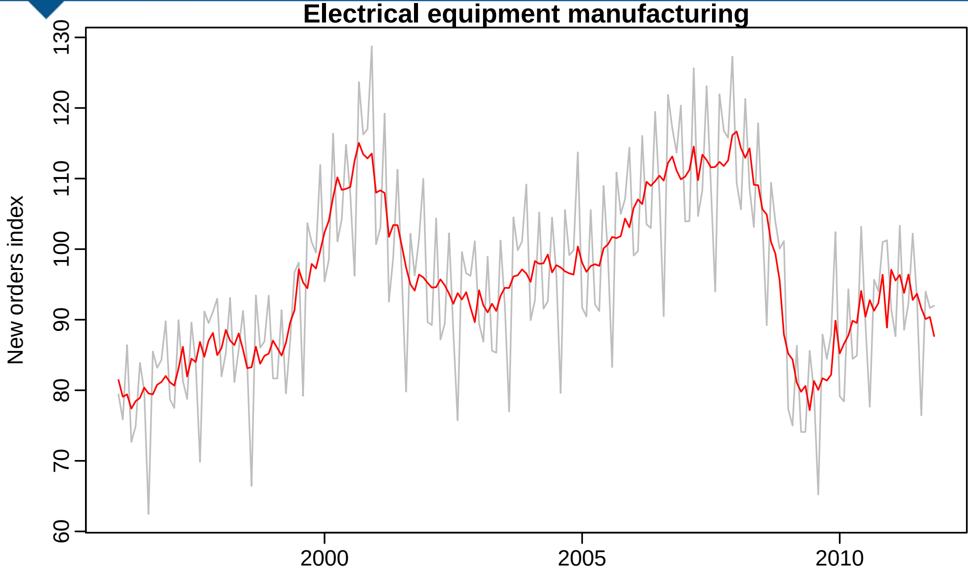

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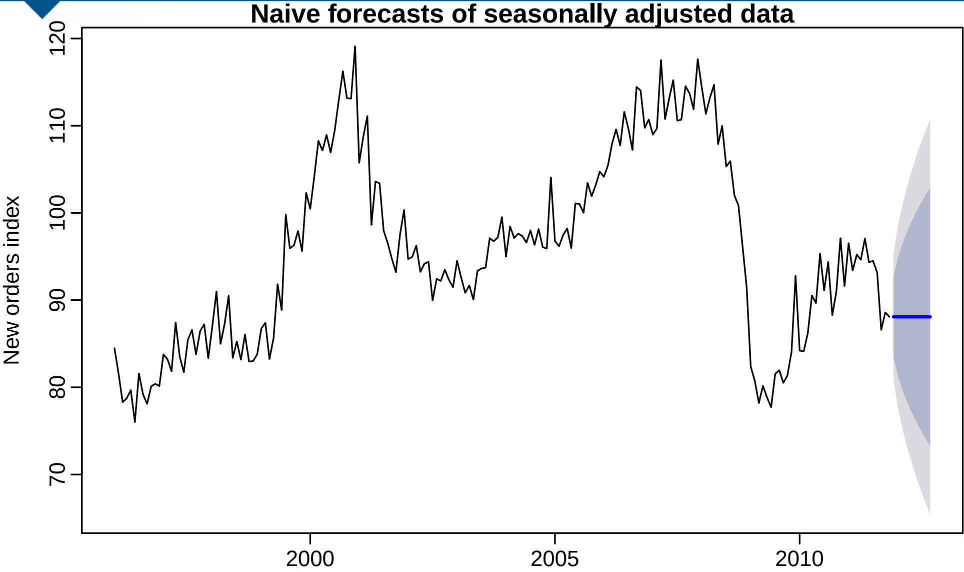

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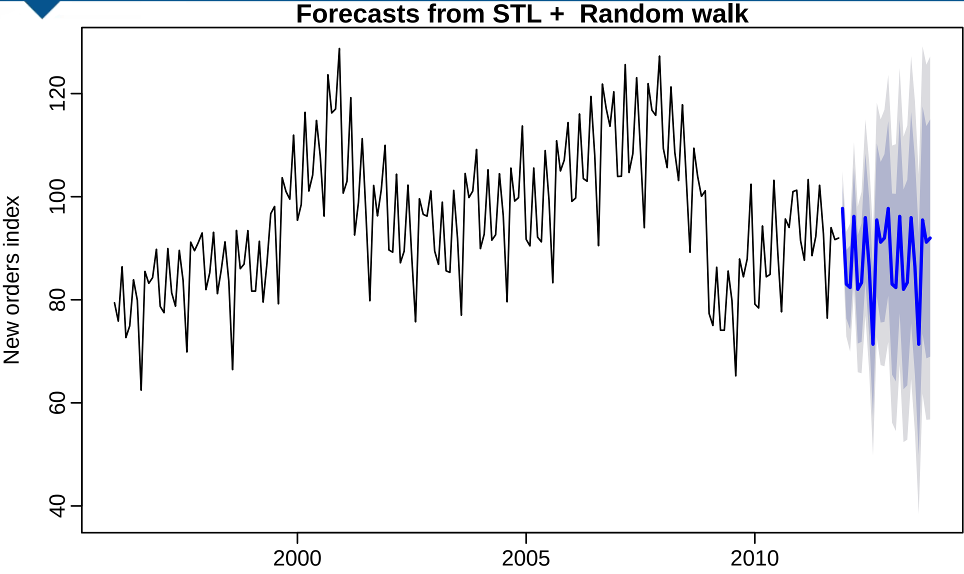

How to do this in R

```
fit <- stl(elecequip, t.window=15,
  s.window="periodic", robust=TRUE)

eeadj <- seasadj(fit)
plot(naive(eeadj), xlab="New orders index")

fcast <- forecast(fit, method="naive")
plot(fcast, ylab="New orders index")
```

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.
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