

ArDec: Autoregressive-based time series decomposition in R

Susana Barbosa

Universidade do Porto, Portugal





Time series decomposition

Approaches:

- non-parametric: filtering / smoothing (eg STL, discrete wavelet transform, ...)
- ▶ model-based: regression, structural models, ...

Goals:

- remove "known" (non-stationary) components
- describe components of interest (seasonal, trend, ...)





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Trend & seasonality

"The essential idea of trend is that it is smooth."

• "A trend is a consistent pattern over time.

"A trend is a long-term movement in time series data after other components have been accounted for. "

"A trend is a trend, is a trend, is a trend, ..."





Trend & seasonality

- "the characteristics of a time series giving rise to spectral peaks at seasonal frequencies" [Nerlove 1964]
- "the intra-year pattern of variation which is repeated constantly or in an evolving fashion from year to year" [Shiskin et al. 1967]
- "periodic fluctuations that recur with about the same intensity each year" [Hillmer and Tiao 1982].





How to retrieve physically-relevant components?







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M. West 1997 (Time series decomposition. Biometrika 84)

Basic concept:

$$X_t = \sum_{j=1}^{p} \phi_j X_{t-j} + \varepsilon_t \Longrightarrow X_t = \sum_{j=1}^{p} \gamma_t^j$$





Introduction	Method	Application	Summary

State-space representation of AR(p) process

$$\begin{aligned} X_t &= F^T Z_t \\ Z_t &= G Z_{t-1} + \varepsilon_t \end{aligned}$$

with

$$F^{T} = [1 \ 0 \dots 0]$$

$$Z_{t}^{T} = [X_{t} \ X_{t-1} \dots X_{t-p+1}]$$

$$G = \begin{bmatrix} \phi_{1} \ \phi_{2} \ \dots \ \phi_{p} \\ 1 \ 0 \ \dots \ 0 \\ \vdots \ 1 \ \ddots \ \vdots \\ 0 \end{bmatrix}$$





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State-space representation of AR(p) process

$$\begin{aligned} X_t &= F^T Z_t \\ Z_t &= G Z_{t-1} + \varepsilon \end{aligned}$$

 $G = EAE^{-1} \longrightarrow r_j e^{\pm iw_j}$ $a = E^T F, b_t = E^{-1} Z_t$ $X_t = \sum_{j=1}^p \gamma_t^j, \gamma_t^j = a^j b_t^j$

$$\begin{split} \mathbf{w}_{j} &= \mathbf{0} \longrightarrow \gamma_{t}^{j} = \mathbf{r}_{j} \gamma_{t-j} + \nu_{t} \\ \mathbf{w}_{j} &\neq \mathbf{0} \longrightarrow \gamma_{t}^{j} = 2\mathbf{r}_{j} \cos(\mathbf{w}_{j}) \gamma_{t-1}^{j} + \mathbf{r}_{j}^{2} \gamma_{t-2}^{j} + \eta_{t} \end{split}$$











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> library(ArDec)

> coef=ardec.lm(dat)\$coefficients

> coef

X1 X2 XЗ Χ4 Χ5 X 6 0 386186446 0 050007536 0 088643459 0 002730004 0 045915250 -0 009539645 X7 Χ8 X 9 X10 X11 X12 0.058137588 0.032015897 -0.075378709 0.064847440 0.117705959 0.169322783 X13 X14 X15 X16 X17 X18 0.060288889 -0.077621640 -0.074880590 -0.012911223 0.010869043 -0.009742732 X19 X20 X 21 X 22 X 23 X 24 -0.048499636 -0.002643505 -0.044422722 0.054698372 0.052529147 0.139849769 X25 X26 0.072803836 -0.081687104





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> ardec(dat,coef)

period		damping	
1	"trend"	"0.996"	
2	"12.089"	"0.986"	
3	"6.000"	"0.982"	





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```
> str(ardec.components(ardec.out))
```

```
List of 2

$ periodcomps:List of 2

..$ periods: num [1:2] 12.1 6.0

..$ comps : mts [1:936, 1:2] NA ...

....attr(*, "dimnames")=List of 2

.....$ : NULL

.....$ : NULL

.....$ : chr [1:2] "Series 1" "Series 2"

....attr(*, "tsp")= num [1:3] 1928 2006 12

....attr(*, "class")= chr [1:2] "mts" "ts"

$ trendcomp : Time-Series [1:936] from 1928 to 2006: NA NA ...
```











Chesapeake bay







o para a Ciência e a Tecnoloria

Chesapeake bay: annual components



para a Ciência e a Tecnologia

Chesapeake bay: trend components



Package ArDec

- implements autoregressive-based time series decomposition
- model-based, additive decomposition
- yields periods of physically-relevant (non-damped) components
- extracts flexible, time-varying estimates of such components
- option of Bayesian framework for autoregressive estimation





Thanks!





