

Rob J Hyndman
George Athanasopoulos

FORECASTING

PRINCIPLES AND PRACTICE

A comprehensive introduction to the latest forecasting methods using R. Learn to improve your forecast accuracy using dozens of real data examples.



3RD EDITION

 **OTexts**
Oxford Texts in Finance and Probability

9. ARIMA models

9.3 Autoregressive models

OTexts.org/fpp3/

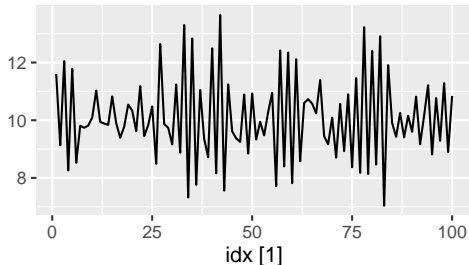
Autoregressive models

Autoregressive model - AR(p):

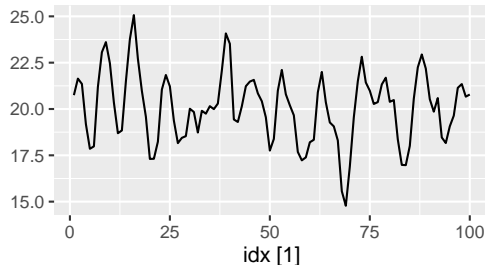
$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t,$$

where ε_t is white noise. This is a multiple regression with **lagged values** of y_t as predictors.

AR(1)



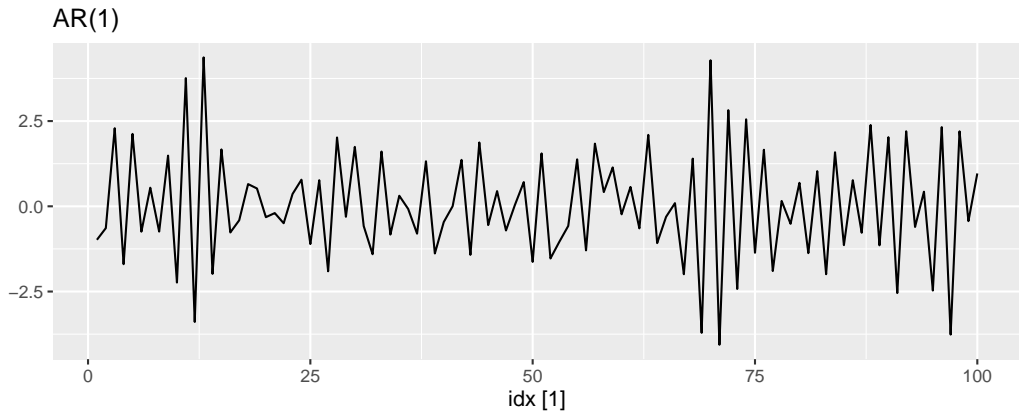
AR(2)



AR(1) model

$$y_t = -0.8y_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$



AR(1) model

$$y_t = \phi_1 y_{t-1} + \varepsilon_t$$

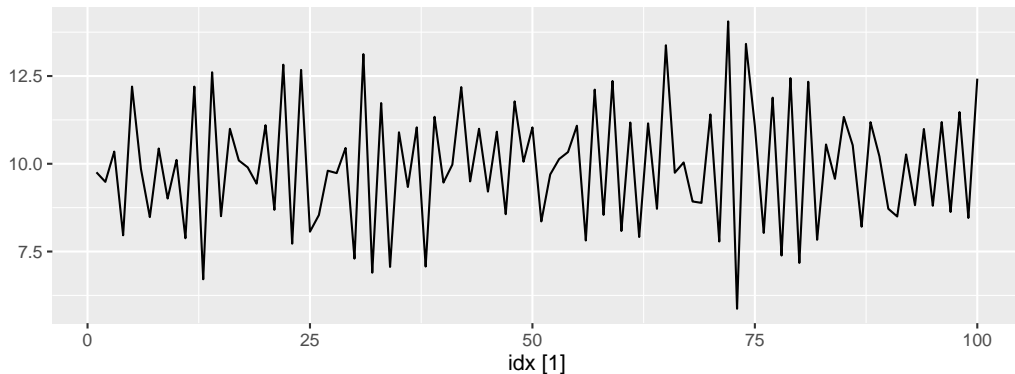
- When $\phi_1 = 0$, y_t is **equivalent to a WN**
- When $\phi_1 = 1$, y_t is **equivalent to a RW**
- We require $|\phi_1| < 1$ for stationarity. The closer ϕ_1 is to the bounds the more the process wanders above or below it's unconditional mean (zero in this case).
- When $\phi_1 < 0$, y_t tends to **oscillate between positive and negative values**.

AR(1) model including a constant

$$y_t = 18 - 0.8y_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$

AR(1)



AR(1) model including a constant

$$y_t = c + \phi_1 y_{t-1} + \varepsilon_t$$

- When $\phi_1 = 0$ and $c = 0$, y_t is equivalent to WN;
- When $\phi_1 = 1$ and $c = 0$, y_t is equivalent to a RW;
- When $\phi_1 = 1$ and $c \neq 0$, y_t is equivalent to a RW with drift;

AR(1) model including a constant

$$y_t = c + \phi_1 y_{t-1} + \varepsilon_t$$

- c is related to the mean of y_t .
- Let $E(y_t) = \mu$

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AR(1) model including a constant

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- c is related to the mean of y_t .
- Let $E(y_t) = \mu$
- $\mu = c + \phi_1 \mu$
- $\mu = \frac{c}{1-\phi_1}$
- `ARIMA()` takes care of whether you need a constant or not, or you can override it.

AR(1) model including a constant

- If included estimated model returns w/ mean

Series: sim

Model: ARIMA(1,0,0) w/ mean

Coefficients:

	ar1	constant
	-0.8381	18.3527
s.e.	0.0540	0.1048

sigma² estimated as 1.11: log likelihood=-146.7

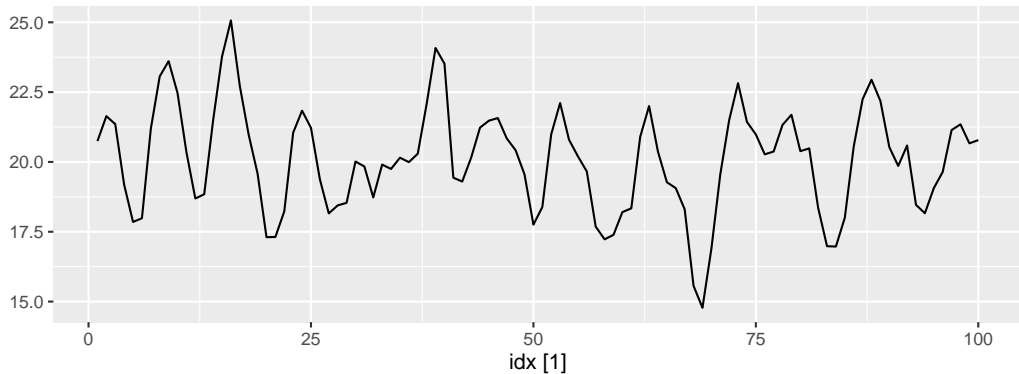
AIC=299.4 AICc=299.7 BIC=307.2

AR(2) model

$$y_t = 8 + 1.3y_{t-1} - 0.7y_{t-2} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, 1), \quad T = 100.$$

AR(2)



Stationarity conditions

We normally restrict autoregressive models to stationary data, and then some constraints on the values of the parameters are required.

General condition for stationarity

Complex roots of $1 - \phi_1 z - \phi_2 z^2 - \dots - \phi_p z^p$ lie outside the unit circle on the complex plane.

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We normally restrict autoregressive models to stationary data, and then some constraints on the values of the parameters are required.

General condition for stationarity

Complex roots of $1 - \phi_1 z - \phi_2 z^2 - \dots - \phi_p z^p$ lie outside the unit circle on the complex plane.

- For $p = 1$: $-1 < \phi_1 < 1$.
- For $p = 2$:
 $-1 < \phi_2 < 1 \quad \phi_2 + \phi_1 < 1 \quad \phi_2 - \phi_1 < 1$.
- More complicated conditions hold for $p \geq 3$.
- Estimation software takes care of this.