Stationarity

Modeling Intensive Longitudinal Data

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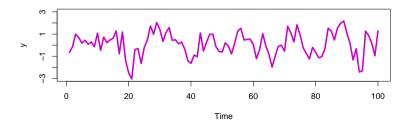


Stationarity

Stationarity implies that all moments (i.e., means, variances, covariances, lagged covariances, etc.) are invariant over time.

A time series is stationary when:

- ▶ the mean is stable over time (i.e, no trend or seasonality)
- ▶ the variances and autocovariances are stable over time
- ► (and all high-order moments are stable over time)





Non-stationarity

Reasons for nonstationarity:

- ► the process has a **unit root** (e.g., a random walk)
- ► there is a **trend over time** (e.g., growth curve, day-of-week effect)
- ► the parameters (e.g., autoregressive parameter) change over time

Different forms of nonstationarity require:

- ▶ different ways to **detect** them (e.g., specific tests, model features)
- ▶ different ways to **handle** them (e.g., detrending versus differencing)

Nonstationarity is discussed as a **property of**:

- ► the **model** (i.e., the data-generating mechanism)
- ► the observed data



Stationarity of an AR(1)

For an AR(1) to be stationary, $|\phi| < 1$.

To see why, we rewrite the AR(1) as an MA(∞):

$$y_{t} = \phi_{1}y_{t-1} + \epsilon_{t}$$

$$= \phi_{1}(\phi_{1}y_{t-2} + \epsilon_{t-1}) + \epsilon_{t}$$

$$= \phi_{1}^{2}y_{t-2} + \phi_{1}\epsilon_{t-1} + \epsilon_{t}$$

$$= \phi_{1}^{2}(\phi_{1}y_{t-3} + \epsilon_{t-2}) + \phi_{1}\epsilon_{t-1} + \epsilon_{t}$$

$$= \phi_{1}^{3}y_{t-3} + \phi_{1}^{2}\epsilon_{t-2} + \phi_{1}\epsilon_{t-1} + \epsilon_{t}$$

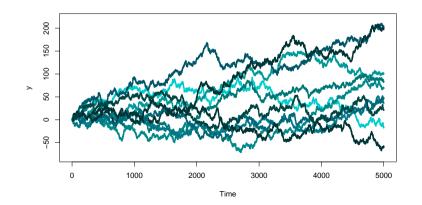
$$= \dots$$

$$= \sum_{k=0}^{\infty} \phi_{1}^{k}\epsilon_{t-k}$$



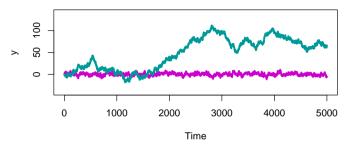
Random walk examples

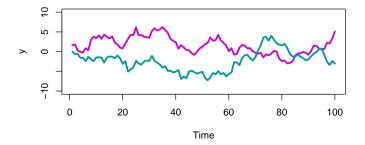
$$y_t = y_{t-1} + \epsilon_t = \sum_{k=0}^{\infty} \epsilon_{t-k}$$





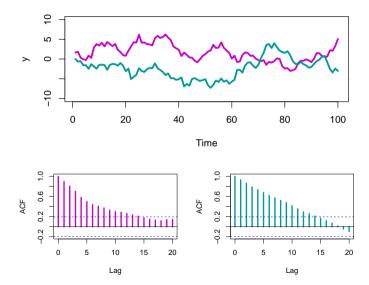
AR(1) versus random walk







AR(1) versus random walk

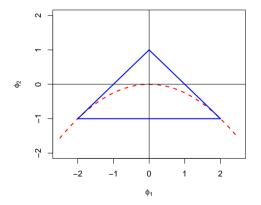




Stationarity of an AR(2)

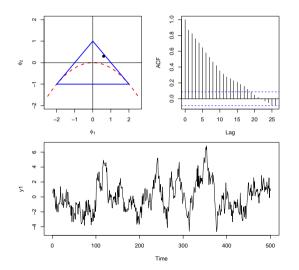
For an AR(2) process to be **stationary** we need:

- ▶ $\phi_2 \phi_1 < 1$
- ▶ $\phi_2 + \phi_1 < 1$
- ▶ $|\phi_2| < 1$



AR(2) example: Slow decay in ACF

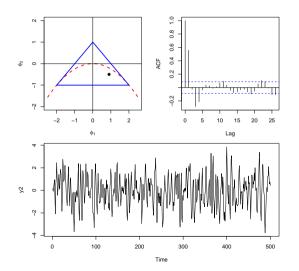
$$y_t = 0.6y_{t-1} + 0.3y_{t-2} + \epsilon_t$$





AR(2) example: Oscillating

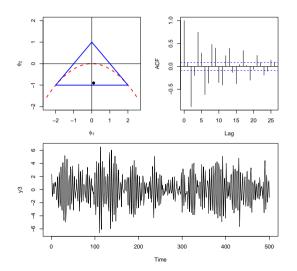
$$y_t = 0.9y_{t-1} - 0.5y_{t-2} + \epsilon_t$$





AR(2) example: Oscillating

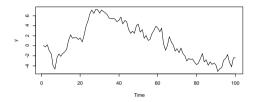
$$y_t = 0.1y_{t-1} - 0.9y_{t-2} + \epsilon_t$$





Random walk as part of the ARIMA model

A random walk: $y_t = y_{t-1} + \epsilon_t$



Taking the difference gives white noise: $\Delta y_t = y_t - y_{t-1} = \epsilon_t$

ARIMA(p,d,q) process: Autoregressive integrated moving average model with:

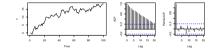
- ▶ p number of AR components
- ▶ d number of times the data need to be differenced to be stationary
- ► q number of MA components



Trends over time

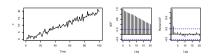
Random walk with drift:

$$y_t = y_{t-1} + \delta + \epsilon_t$$



Deterministic time trend, e.g.:

$$y_t = \alpha + \beta t + \epsilon_t$$





Three useful unit root tests

The (augmented) Dickey-Fuller test for a unit root:

H0: a unit root H1: stationarity

Use adf.test(data) in R

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for level:

H0: mean-stationarity
H1: not mean-stationary

Use kpss.test(data) in R

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for trend:

H0: trend-stationarity (but note: only a linear trend!)

H1: not trend-stationary

Use kpss.test(data, null = "Trend") in R



Accounting for deterministic trends and seasonality

To account for deterministic trends, we can:

- detrend the data and model the residuals
- ► include the trend as part of the model

Seasonality may refer to:

- ► time-of-day effects in ESM
- day-of-week effects in daily diary
- ► monthly and annual patterns

Seasonality may be handled by:

- ▶ including dummies: flexible but "expensive"
- smoother trends (e.g., a sine wave)



Conclusion

- ► Many popular time series models assume stationarity
- ► There are different reasons for nonstationarity
- ► There are tests, but these only test for one particular form of nonstationarity
- ► Depending on the kind of nonstationarity, different remedies can be used

