Brockwell & Davis | Section 1.3.3 | General approach to time series modelling

 $X_t = |m_t| + |s_t| + |Y_t|$ **(*)** Modeling Xt is like replacing ink in a pen.

Remove the **body** which gives it its **shape**

Polynomial regression $X_t - |\hat{m}_t| = |s_t| + |Y_t|$ MA smoothing **Exponential** smoothing

Harmonic regression Take off the **spring** pushing it **back & forth** $X_t = |\hat{m}_t| = |\hat{s}_t| = |Y_t|$ Season (S1) method

Look at the **residual** ink. $X_t - \hat{m}_t - \hat{s}_t = \hat{Y}_t$ Various methods you'll soon learn ♥

Get ink tube that **fits our model of pen**

 $X_t - |\hat{m}_t| = |\hat{s}_t| + |\hat{Y}_t|$ = unknown

Put the **spring** on the new tube $X_t = |\hat{m}_t| + |\hat{s}_t| +$ Put the **body** of the pen back on

= estimated

Stationarity

Time Series in the style of M.C. Escher

STAT 464 / 864 | Fall 2024
Discrete Time Series Analysis
Skyepaphora Griffith, Queen's University

We learned something just now, in Time Series 🕛





Correlation coefficient:

$$\rho(X,Y) = \frac{\operatorname{Cov}(X,Y)}{\sqrt{\operatorname{Var}(X)\operatorname{Var}(Y)}}$$

Correlation = Covariance, standardized to scale of [-1, 1]

What do we tell quin?

Random Vector: $\vec{X}_N = (X_1, X_2, \dots, X_N)$ such as the time series \mathbf{X}_t

Covariance matrix describes pairwise covariances: $\Gamma_N[i,j] = \operatorname{Cov}(X_i,X_j)$

$$\begin{bmatrix} \operatorname{Cov}(X_1, X_1) & \operatorname{Cov}(X_1, X_2) \\ \operatorname{Cov}(X_2, X_1) & \operatorname{Cov}(X_2, X_2) \end{bmatrix}$$

Correlation Matrix ${\cal R}_N$

Same idea as Γ_N , except entries are

Also symmetric

All diagonal entries = 1

 $R_N[i,j] = \rho(X_i, X_j)$







Properties of Γ_N | Proof if time permits

- 1) Symmetric (Recall: covariance is symmetric)
- **2)** Non-negative Definite: $a^T \Gamma_N a \geq 0$ $a \in \mathbb{R}^N$

Proof:
$$0 \le \operatorname{Var}(a^T \vec{X}) = \operatorname{Cov}(a^T \vec{X}, a^T \vec{X})$$
$$= \operatorname{Cov}\left(\sum_{i=1}^N a_i \vec{X}_i, \sum_{i=1}^N a_i \vec{X}_i\right)$$
$$= \sum_{\substack{i=1\\j=1}}^N a_i a_j \operatorname{Cov}(X_i, X_j) = a^T \Gamma_N a$$







Stationarity | Motivation

- $oldsymbol{\mathbb{P}}$ Γ_N is a basic quantity we want to estimate from our $\{\mathbf{X}_{\mathbf{t}}\}$
- Virtually impossible to do this without further assumptions

Example: how do we estimate $Cov(X_i, X_j)$?

We only have one observation (x_i, x_j)

from the joint distribution of (X_i, X_j)

Strong Stationarity

Definition: A time series {Xt} is strongly stationary if

 $orall k \geq 1$ and $h \in \mathbb{Z}$, the joint distribution of $(X_{i_1}, \dots, X_{i_k})$

is the same as the joint distribution of $(X_{i_{1+h}},\ldots,X_{i_{k+h}})$

- $oldsymbol{\Psi}$ When k=1: strongly stationary = identically distributed
- Strong stationarity is rarely verifiable in practice
- Not necessary for estimating second order stats (Var, Cov)







Weak Stationarity

Definition: A time series X is weakly stationary if

1)
$$E[X_t] = \mu$$

$$\forall t \in \mathbb{Z}$$

2)
$$\operatorname{Var}(X_i) = \sigma^2 < \infty$$

3)
$$Cov(X_i, X_j) = Cov(X_{i+h}, X_{j+h}) \quad \forall i, j, h \in \mathbb{Z}$$

Weak Stationarity | Notes $X_t = m_t + s_t + Y_t$ (*)

Assume all models for Y_t are weakly stationary (unless I say otherwise)

"Stationary" will be shorthand for "weakly stationary"

For stationary time series, Γ_N can be expressed as function of 1 variable: lag

$$\gamma_X(h) = \operatorname{Cov}(X_t, X_{t+h}) \quad \forall \ t \in T_N$$







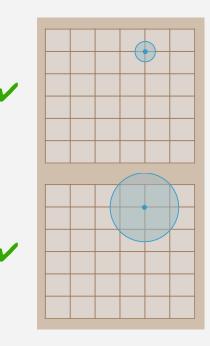
Stationarity | A cute visualization

For your assignment 🕑

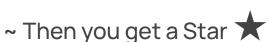
you will determine whether a given $\{X_t\}$ is stationary

Use **covariance formulas & properties** from lecture to derive a closed form expression for **Cov(Xt, Xt+h)** as a **function** of **t** and/or **h** (not **Xt**)

Can you write this function in terms of h only? (Not t!) If so, you've shown $\{X_t\}$ is **stationary**. If not, explain why, and conclude $\{X_t\}$ is **nonstationary**

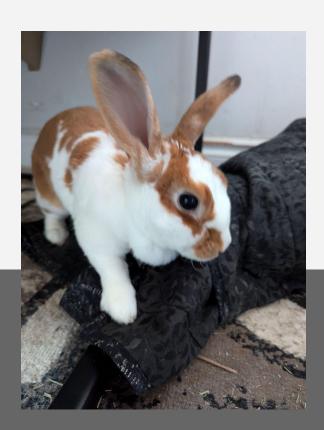






We learned something today, in Time Series 🕛





Observations or RVs within the **same** time series can be correlated with each other.

We can describe the whole situation using a matrix

If the correlations depend on the distance between time points, but not time itself, then the series is called stationary.

Stationarity kinda feels like an M.C. Escher tesselation

What do we tell quin?