

3. Examples of stationary time series

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6:27 AM

Classic Examples §1.4 Brockwell & Davis

Ex iid Noise

independent, identically distributed

$\{X_t\}$ iid noise, written $\{X_t\} \sim \text{iid}(0, \sigma^2)$

means ① All X_t have the same distribution
(and this distribution has 0 mean and variance σ^2)

② All X_t, X_s are independent ($t \neq s$)

If our residual is iid Noise, it means we've successfully extracted out all useful information/structure.
(that would be great, though usually we'll be less ambitious)

Is this stationary? ① Is mean constant (independent of t)? Yes.

$$\textcircled{2} \gamma_X(t+h, t) := \text{Cov}(X_{t+h}, X_t) = \begin{cases} \sigma^2 & h=0 \\ 0 & h \neq 0 \end{cases}$$

doesn't depend on t ,
so this is stationary

Ex White noise $\{X_t\} \sim \text{WN}(0, \sigma^2)$

means each X_t can have a different distribution, as long as that distribution has ① 0 mean, ② σ^2 variance
and

③ X_t, X_s ($t \neq s$) are uncorrelated

So this is less strict than iid noise ($\text{iid}(0, \sigma^2)$ is also $\text{WN}(0, \sigma^2)$ but not vice-versa)

Just like $\text{iid}(0, \sigma^2)$, this is also stationary.

This is what we'll settle for making our residuals look like
(if residual is $\text{WN}(0, \sigma^2)$ it means we've extracted most of the signal, "as best we can tell")
i.e., it's not easy to distinguish observations of $\text{iid}(0, \sigma^2)$ from $\text{WN}(0, \sigma^2)$

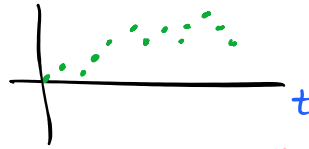
Note: as a preview (or for anyone whose had an EE linear

Systems course) the spectrum of WN is flat

Ex Random Walk

Let $\{X_t\} \sim \text{iID}(0, \sigma^2)$, define $S_t = \sum_{i=1}^t X_i$
"random walk"

Classic ex:
 $X_t \sim \text{Bernoulli}(1/2)$
 $\in \{\pm 1\}$



Is S_t stationary? ① Check if mean is constant. $E(X_t) = 0$
 $E(S_t) = E(\sum_{i=1}^t X_i) \stackrel{E \text{ is linear}}{=} \sum_{i=1}^t E(X_i) = 0$ independent of t ✓

② Check covariance.

If it is stationary, then $\text{Var}(S_t) = \text{Var}(S_1) \forall t$

$$\begin{aligned} \text{Var}(S_1) &= \text{Var}(X_1) = \sigma^2 \\ \text{Var}(S_t) &= \text{Var}(X_1 + X_2 + \dots + X_t) \quad \left\{ \begin{array}{l} \text{not equal for all } t \\ \text{since } X_1, X_2 \text{ are uncorrelated} \end{array} \right. \\ &= \text{Var}(X_1) + \dots + \text{Var}(X_t) \\ &= t \cdot \sigma^2 \quad \text{So not stationary} \end{aligned}$$

Ex MA(1) i.e. First-Order Moving Average

Let $\{Z_t\} \sim \text{WN}(0, \sigma^2)$. Not very interesting, and Z_t gives (almost no) help to predict Z_{t+1}

The MA(1) process is $\{X_t\}$
defined by

$$X_t = Z_t + \theta Z_{t-1} \quad \forall t \in \mathbb{Z}$$

Ex: $\theta = 1$
then this is averaging pairs

Is $\{X_t\}$ stationary? Fixed constant

① check for constant mean

$$\begin{aligned} E(X_t) &= E(Z_t + \theta Z_{t-1}) \\ &= E(Z_t) + \theta E(Z_{t-1}) \\ &= 0 + \theta \cdot 0 = 0. \quad \text{Independent of } t \quad \checkmark \end{aligned}$$

② check covariance

$$\gamma(t, t+h) = \text{Cov}(X_t, X_{t+h})$$

$$= \text{Cov}(Z_t + \theta Z_{t-1}, Z_{t+h} + \theta Z_{t+h-1})$$

$$= \text{Cov}(Z_t, Z_{t+h} + \theta Z_{t+h-1})$$

$$= \underbrace{\text{Cov}(Z_t, Z_{t+h})}_{=0} + \theta \underbrace{\text{Cov}(Z_t, Z_{t+h-1})}_{=0}$$

$$+ \theta \cdot \text{Cov}(Z_{t-1}, Z_{t+h} + \theta Z_{t+h-1})$$

$$= \theta \cdot \text{Cov}(Z_{t-1}, Z_{t+h}) + \theta^2 \cdot \text{Cov}(Z_{t-1}, Z_{t+h-1})$$

Use: $Z_t \sim \text{WN}(0, \sigma^2)$

$$\text{so } \text{Cov}(Z_t, Z_s) = \begin{cases} \sigma^2 & t=s \\ 0 & t \neq s \end{cases}$$

$$ACVF \rightarrow \begin{cases} \sigma^2 + \theta^2 \sigma^2 & h=0 \\ \theta \cdot \sigma^2 & h=+1 \text{ or } -1 \\ 0 & \text{else} \end{cases} \quad \text{independent of } t \text{ so it is stationary}$$

To summarize (we'll use this later),

the **ACF** for $MA(1)$ is $\rho(h) = \begin{cases} 1 & h=0 \\ \frac{\theta}{1+\theta^2} & h=\pm 1 \\ 0 & |h|>1 \end{cases} \quad \rho(0)=1 \text{ always!}$

Ex AR(1) aka 1st order Auto Regressive process

$MA(1)$ is straightforward since it's explicit

$AR(1)$ is weirder at first since it's self-referential

... think of it as a **difference equation**, which is analogous to an **ODE** for continuous time.

Again, let $\{Z_t\} \sim WN(0, \sigma^2)$

but now assume $\{X_t\}$ is a $\textcircled{2}$ stationary series that satisfies

$$\textcircled{3} \quad X_t = \phi X_{t-1} + Z_t$$

} existence, uniqueness of a solution?
Be patient

and $\textcircled{4} \quad Z_t$ is uncorrelated w/ X_s for $s < t$

$$\textcircled{5} \quad |\phi| < 1 \quad (\text{like a noisy contraction})$$

We've assumed it's stationary, so $E[X_t] = E[X_{t-1}] = \mu$

What is μ ?

By $E[\textcircled{3}]$ (using linearity) we have

$$\mu = \phi \mu + 0, \quad \text{i.e. } (1-\phi)\mu = 0$$

So since $\phi \neq 1$, $\mu = 0$.

What is **ACVF** γ or the **ACF** ρ ?

Apply $\text{Cov}(X_{t-h}, \cdot)$ to $\textcircled{3}$ so

$$\text{Cov}(X_{t-h}, X_t) \stackrel{\textcircled{3}}{=} \phi \text{Cov}(X_{t-h}, X_{t-1}) + \text{Cov}(X_{t-h}, Z_t)$$

via linearity

$$\begin{aligned} \underbrace{\gamma(-h)}_{\gamma(h)} &= \phi \gamma(h-1) + 0 \\ &= \phi^2 \gamma(h-2) \\ &= \phi^h \gamma(0) \end{aligned}$$

Since $\rho(h) = \frac{\gamma(h)}{\gamma(0)}$ this means we know ρ :

$$\rho(h) = \phi^{|h|} \quad \forall h \in \mathbb{Z}$$

(see book: easy to work out $\gamma(0) = \text{Var}(X_t) = \frac{\sigma^2}{1 - \phi^2}$)

i.e., if $\sigma^2 = 0$ so no noise, then $\{X_t\}$ is deterministic