

DS-GA 3001.001
Probabilistic time series analysis
Lecture 3
AR(I)MA

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Quick recap

stochastic process

$$\{X_1, X_2, \dots, X_t \dots\}$$

$$P(X_1 \leq x_1, \dots, X_t \leq x_t \dots)$$

Examples of stochastic process

$$W_t \sim \mathcal{N}(0, \sigma^2) \quad \text{i.i.d.} \quad \text{white noise}$$

$$v_t = \frac{1}{3} (w_{t-1} + w_t + w_{t+1}) \quad \text{filtered white noise} \quad \textbf{Moving Average}$$

$$x_t = x_{t-1} - 0.9x_{t-2} + w_t \quad \textbf{Auto-Regressive process}$$

**ARIMA models provide a general treatment
for studying such processes and their generalizations**

Quick recap

Basic statistical properties

mean

$$\mu_X(t) = \mathbb{E}(X_t)$$

covariance

$$R_X(t, u) = \text{cov}(X_t, X_u)$$

ACF

$$\rho_X(t, u) = \frac{R_X(t, u)}{\sqrt{R_X(t, t), R_X(u, u)}}$$

Causality, stationarity

$$\{X_t, \dots, X_{t+K}\}$$

Identically distributed subsets

$$\{X_{t+h}, \dots, X_{t+h+K}\}$$

for all t,h,K

jointly gaussian -> strongly stationary, 2 moments, linear prediction

For a gaussian stationary process, the optimal predictor for $X_{t+h}|X_t = x_t$

takes the form:

$$f(x_t) = \mathbf{E}(X_{t+h}|X_t = x_t) = \mu + \rho_X(h)(x_t - \mu) \quad \text{Linear in } x_t$$

With MSE

$$\mathbf{E}(|X_{t+h} - f(x_t)|^2, |X_t = x_t|) = \sigma^2(1 - \rho_X(h)^2)$$

The higher the autocorrelation coefficient,
the better the prediction

For more complicated processes, the best **linear** predictor

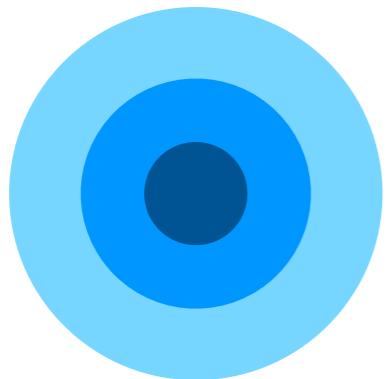
$$\mathbf{E}(|X_{t+h} - \alpha - \beta X_t|^2) = E(\alpha, \beta)$$

$$\alpha = \mu(1 - \rho_X(h)) , \beta = \rho_X(h)$$

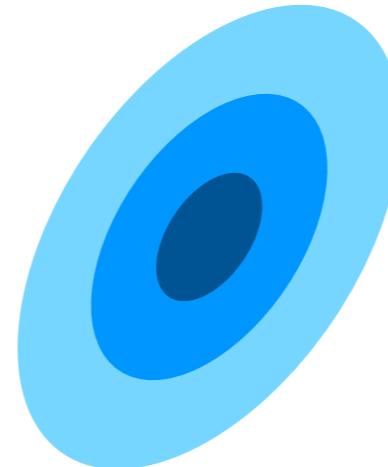
$$MSE = \sigma^2(1 - \rho_X(h)^2)$$

Philosophy or AR(I)MA models

White noise



Linear transform

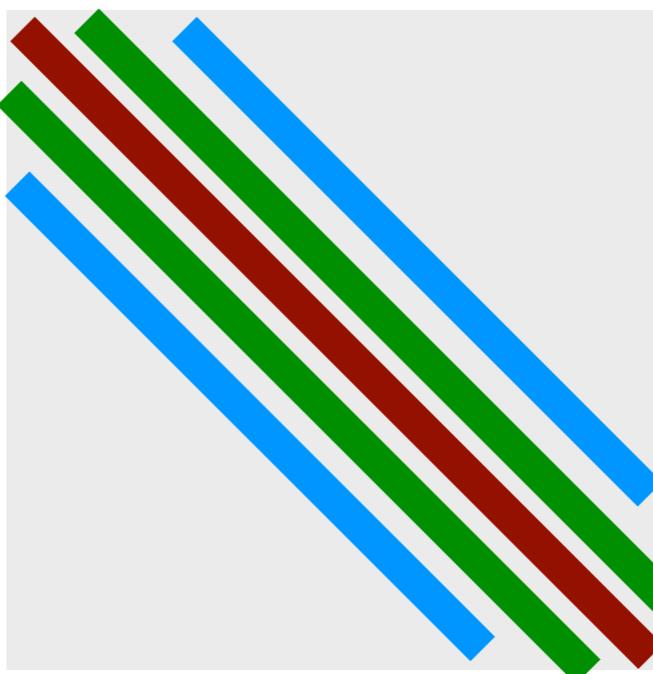


models require a variable
no. of parameters

The goal is to capture the
cov. structure of the data with
as few as possible parameters

$$\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \Rightarrow (\mathbf{Ax} + \mathbf{y}) \sim \mathcal{N}(\mathbf{A}\boldsymbol{\mu} + \mathbf{y}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T)$$

Most generally,
 $T \times T$ covariance
Additional assumptions
on shared parameters



$\text{Cov}(x_t, x_{t+2})$
 $\text{Cov}(x_t, x_{t+1})$
 $\text{Var}(x_t)$

Let's first formally define these models

Moving averages, e.g. MA(1)

$$X_t = W_t + \lambda W_{t-1}$$

Where $\{W_t\}$ is white noise
causal

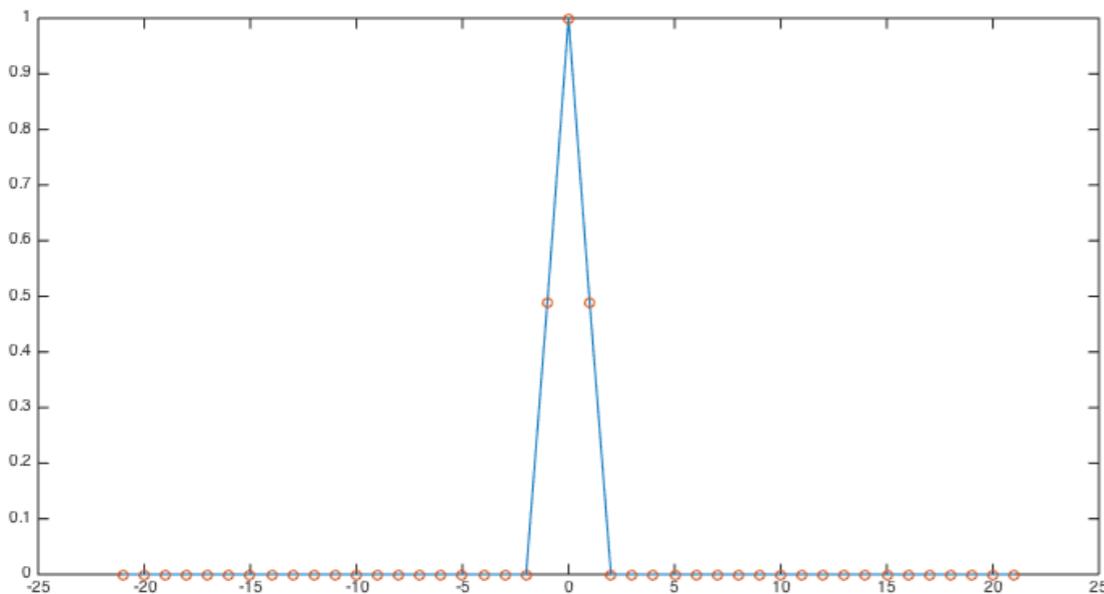
Moments:

$$\mu_X = 0$$

$$R_X(t, t+h) = \begin{cases} \sigma^2 (1 + \lambda^2), & h = 0 \\ \sigma^2 \lambda, & |h| = 1 \\ 0, & \text{otherwise} \end{cases}$$

stationary

MA(1) ACF



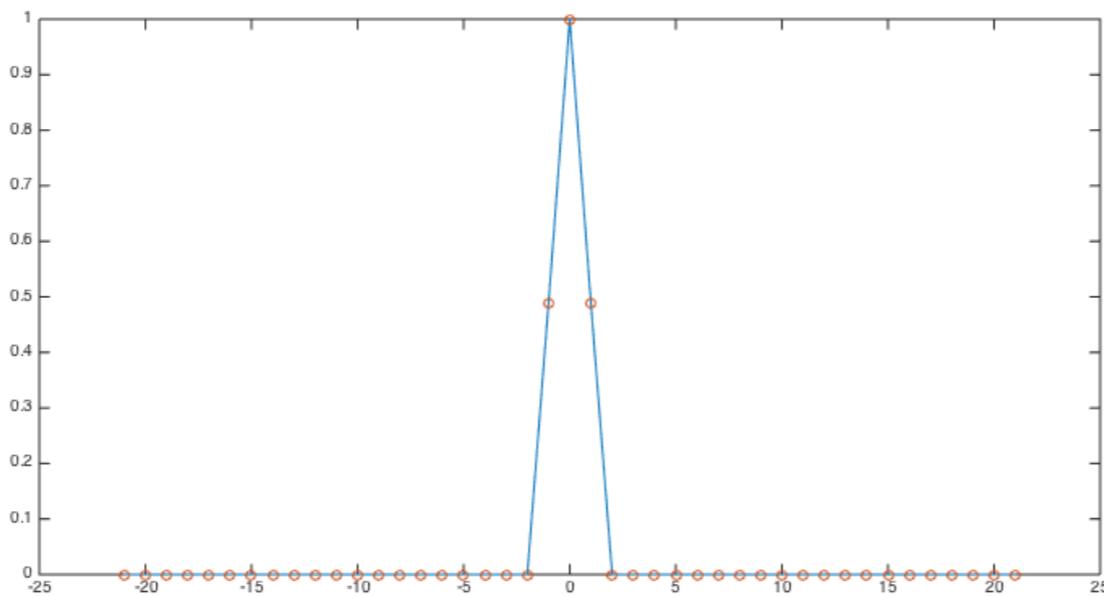
Increasing complexity: MA(q)

Definition *The moving average model of order q , or $\text{MA}(q)$ model, is defined to be*

$$x_t = w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots + \theta_q w_{t-q},$$

where $w_t \sim \text{wn}(0, \sigma_w^2)$, and $\theta_1, \theta_2, \dots, \theta_q$ ($\theta_q \neq 0$) are parameters.

MA(1) ACF



Autoregressive process AR(1)

$$X_t = \lambda X_{t-1} + W_t$$

Where $\{W_t\}$ is white noise and $|\lambda| < 1$

By expanding the recursion we get: $X_t = W_t + \lambda W_{t-1} + \lambda^2 W_{t-2} + \dots$

$$\mu_X = \mathbb{E} \left[\sum_{h=0}^{\infty} \lambda^h W_{t-h} \right] = 0$$

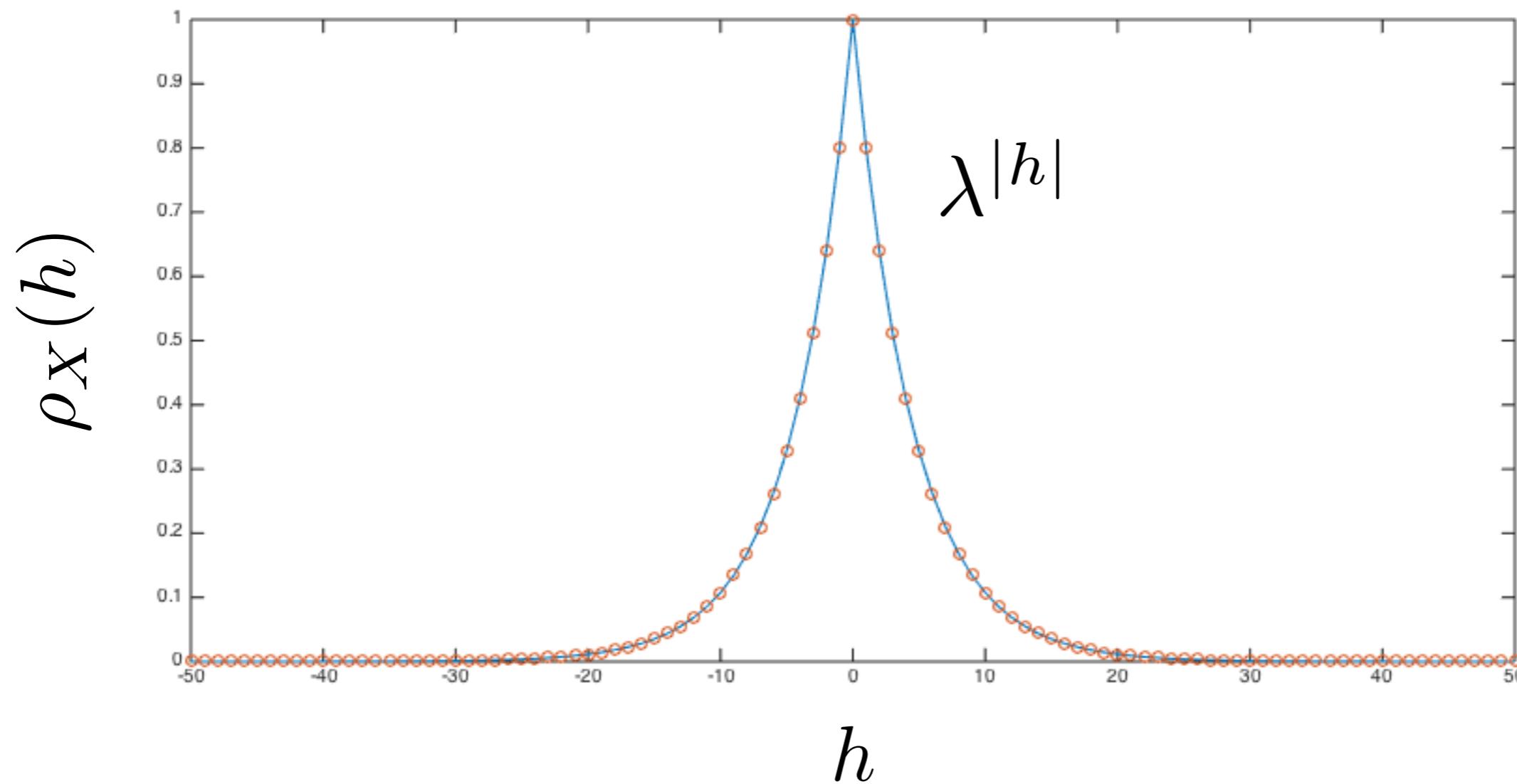
$$\mathbb{E} [X_t^2] = \mathbb{E} \left[\sum_h \lambda^{2h} W_{t-h}^2 \right] = \sigma^2 \sum \lambda^{2h} = \frac{\sigma^2}{1-\lambda^2}$$

For now, assume $h > 0$

$$\begin{aligned} R_x(h) &= \text{cov}(X_t, X_{t+h}) = \text{cov}(X_t, \lambda X_{t+h-1} + W_{t+h}) \\ &= \lambda \text{cov}(X_t, X_{t+h-1}) \\ &= \lambda^h \text{cov}(X_t, X_t) \\ &= \sigma^2 \frac{\lambda^{|h|}}{1-\lambda^2} \end{aligned}$$

stationary

AR(1) ACF



$$X_t = \lambda X_{t-1} + W_t$$

What happens when $|\lambda| > 1$?

$$Q(B)W_t = \sum_{k \geq 0} \lambda^k B^k W_t \quad \text{does not converge}$$

But we can rewrite everything
(essentially flipping time axis)

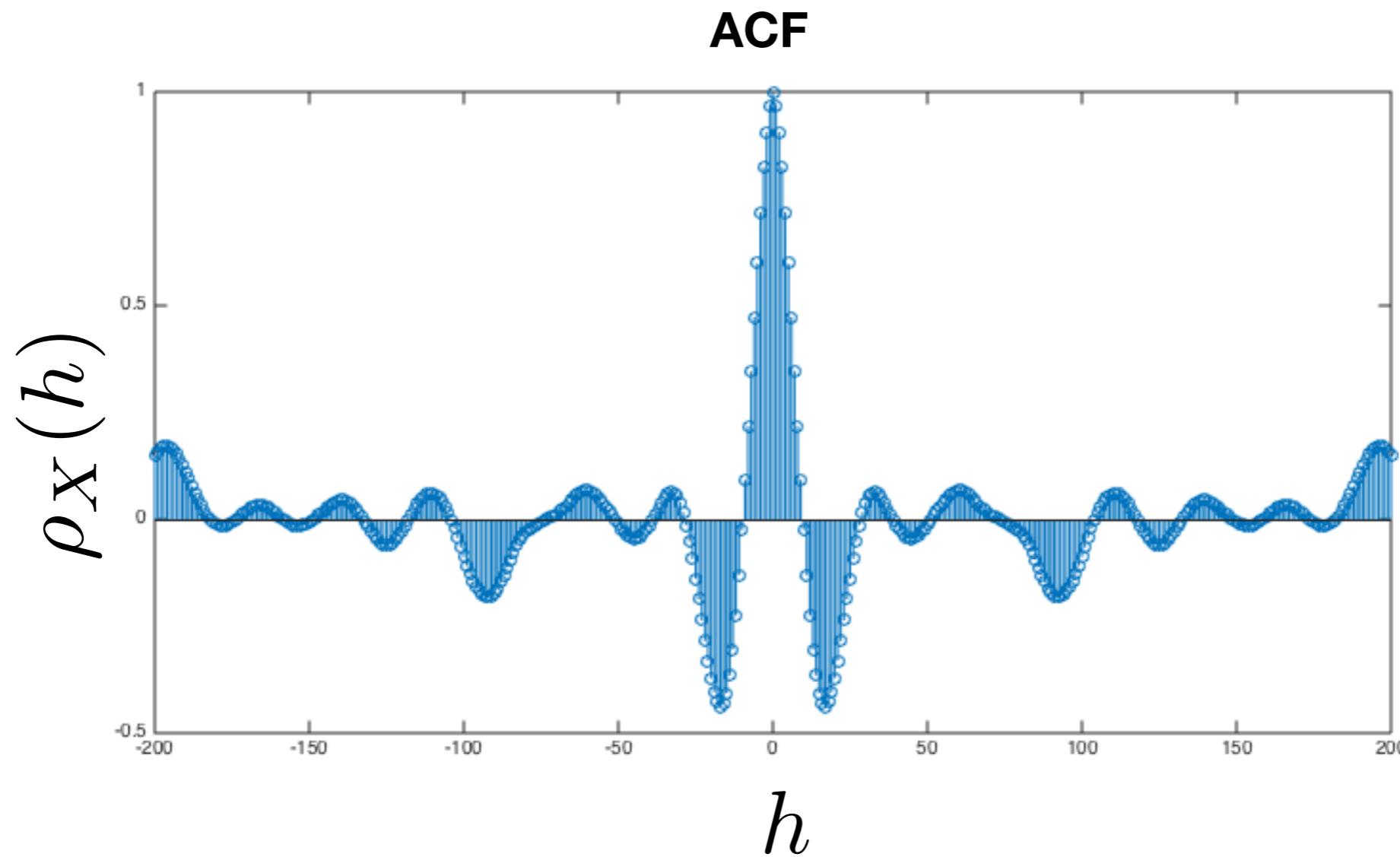
$$\frac{1}{\lambda} X_t = \frac{\lambda}{\lambda} X_{t-1} + \frac{1}{\lambda} W_t$$

$$X_{t-1} = \lambda^{-1} X_t - \lambda^{-1} W_t$$

Anti-causal: future determines the past

$$X_t = - \sum_{k=1}^{\infty} \lambda^{-k} W_{t+k}$$

How do we use this to model real data?



Real life looks a bit more complicated than a simple AR(1)

Can we combine the basic idea of simple linear processes to get more **expressive** power, while keeping math nice and simple?

Increasing complexity: AR(p)

Definition An autoregressive model of order p , abbreviated **AR(p)**, is of the form

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + w_t,$$

where x_t is stationary, $w_t \sim \text{wn}(0, \sigma_w^2)$, and $\phi_1, \phi_2, \dots, \phi_p$ are constants ($\phi_p \neq 0$). The mean of x_t in (3.1) is zero. If the mean, μ , of x_t is not zero, replace x_t by $x_t - \mu$ in (3.1),

$$x_t - \mu = \phi_1(x_{t-1} - \mu) + \phi_2(x_{t-2} - \mu) + \cdots + \phi_p(x_{t-p} - \mu) + w_t,$$

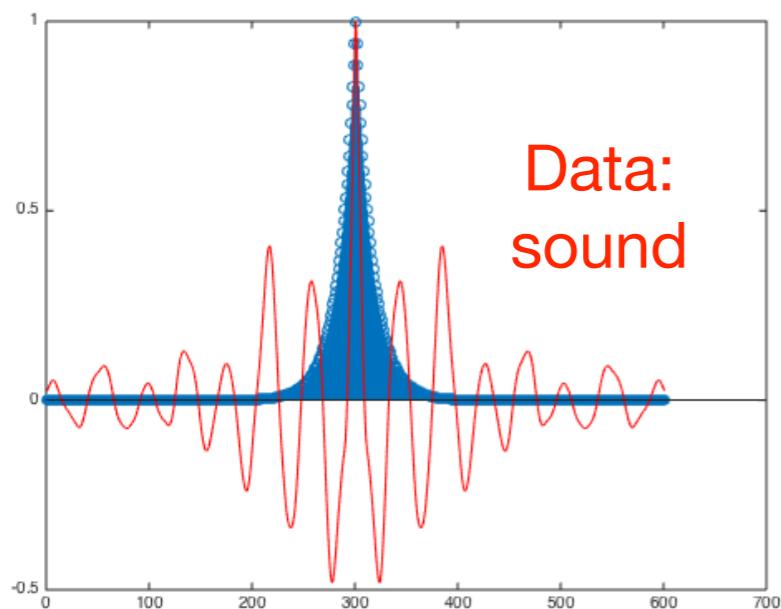
or write

$$x_t = \alpha + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + w_t,$$

where $\alpha = \mu(1 - \phi_1 - \cdots - \phi_p)$.

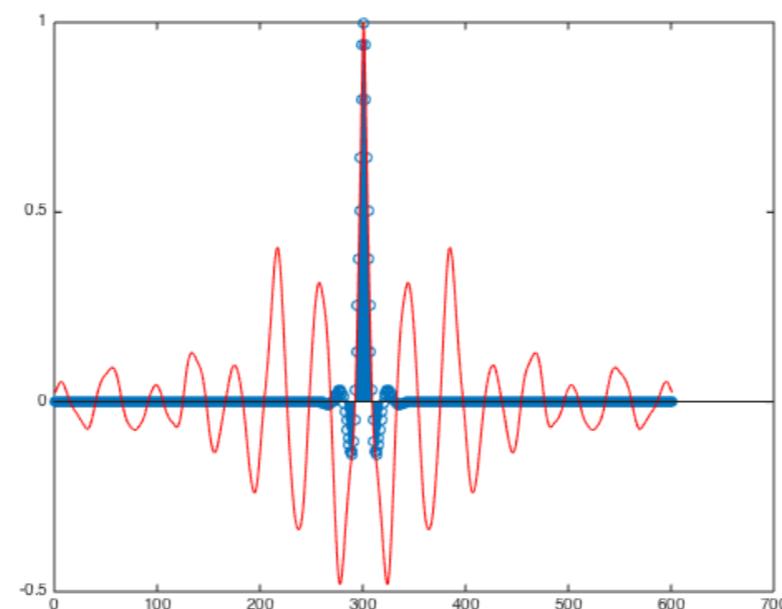
Increasing complexity: AR(p)

AR(1)

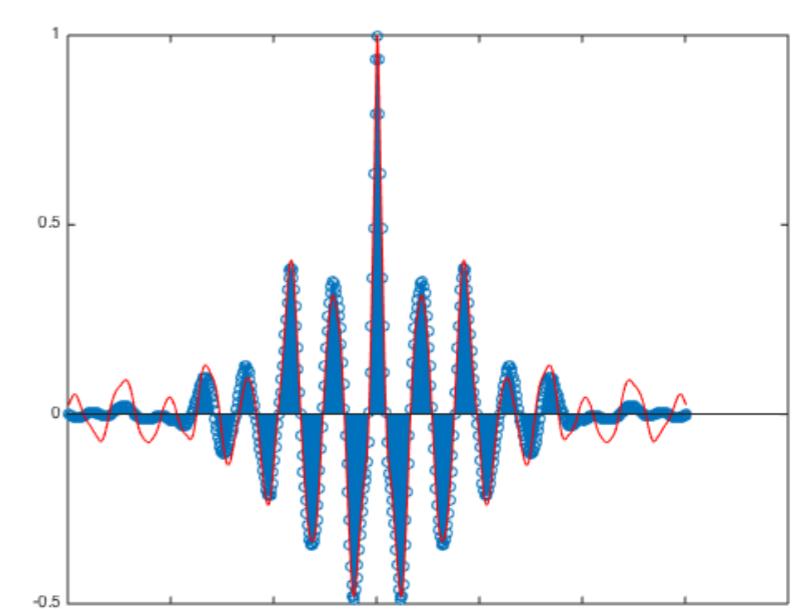


Data:
sound

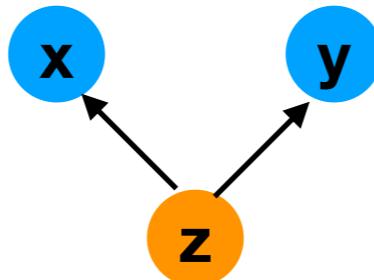
AR(4)



AR(16)



Partial correlations



$$\rho_{XY|Z} = \text{corr}\{X - \hat{X}, Y - \hat{Y}\}.$$

Definition 3.9 *The partial autocorrelation function (PACF) of a stationary process, x_t , denoted ϕ_{hh} , for $h = 1, 2, \dots$, is*

$$\phi_{11} = \text{corr}(x_{t+1}, x_t) = \rho(1) \quad (3.55)$$

and

$$\phi_{hh} = \text{corr}(x_{t+h} - \hat{x}_{t+h}, x_t - \hat{x}_t), \quad h \geq 2. \quad (3.56)$$

The reason for using a double subscript will become evident in the next section. The PACF, ϕ_{hh} , is the correlation between x_{t+h} and x_t with the linear dependence of $\{x_{t+1}, \dots, x_{t+h-1}\}$ on each, removed. If the process x_t is Gaussian, then $\phi_{hh} = \text{corr}(x_{t+h}, x_t | x_{t+1}, \dots, x_{t+h-1})$; that is, ϕ_{hh} is the correlation coefficient between x_{t+h} and x_t in the bivariate distribution of (x_{t+h}, x_t) conditional on $\{x_{t+1}, \dots, x_{t+h-1}\}$.

Matrix inversion is costly: use **Durbin-Levinson** instead

$$\phi_{nn} = \frac{\rho(n) - \sum_{k=1}^{n-1} \phi_{n-1,k} \rho(n-k)}{1 - \sum_{k=1}^{n-1} \phi_{n-1,k} \rho(k)}, \quad P_{n+1}^n = P_n^{n-1}(1 - \phi_{nn}^2),$$

where, for $n \geq 2$,

$$\phi_{nk} = \phi_{n-1,k} - \phi_{nn} \phi_{n-1,n-k}, \quad k = 1, 2, \dots, n-1.$$

$$\phi_{00} = 0, \quad P_1^0 = \gamma(0).$$

Replacing the ACF/CCF with **empirical estimates**

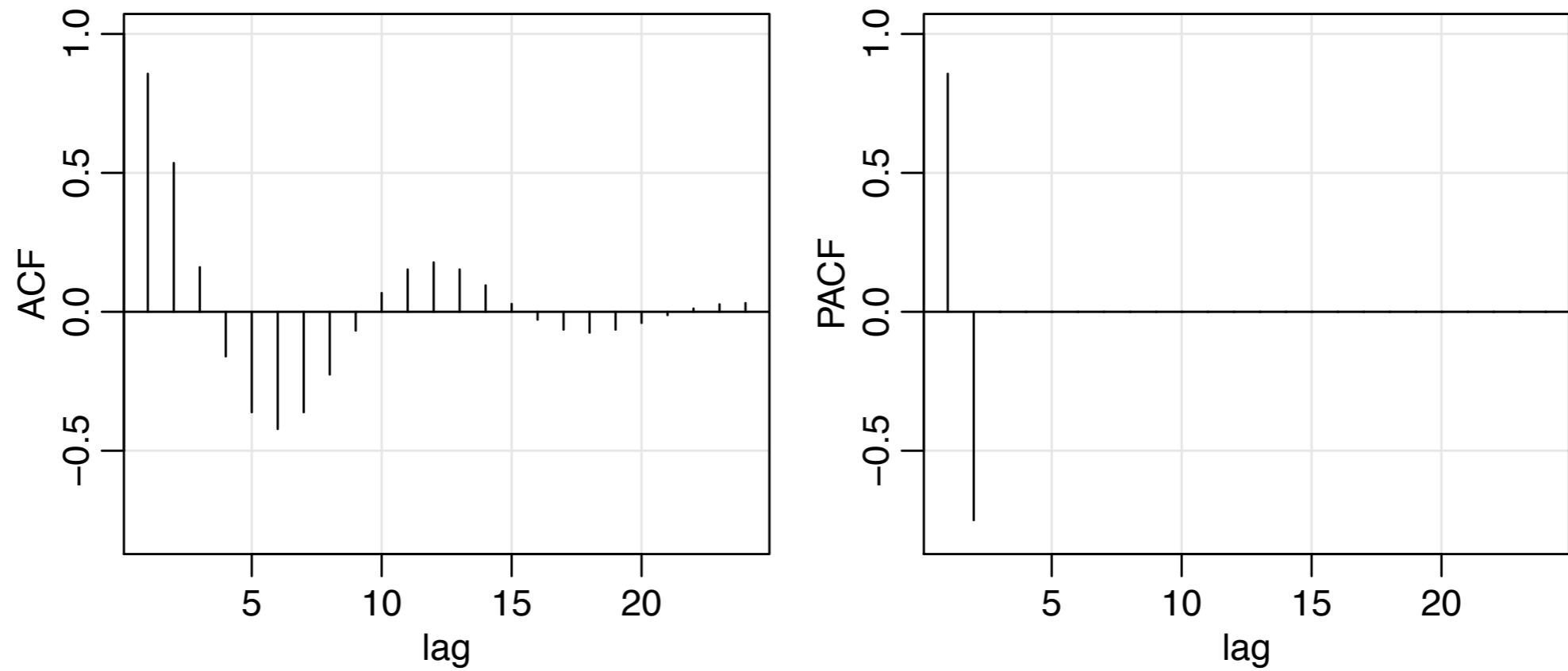


Fig. 3.5. The ACF and PACF of an AR(2) model with $\phi_1 = 1.5$ and $\phi_2 = -.75$.

AR and **MA** are special instances of **linear processes**

$$x_t = \mu + \sum_{j=-\infty}^{\infty} \psi_j w_{t-j}, \quad \sum_{j=-\infty}^{\infty} |\psi_j| < \infty.$$

$$\mu_X = \mu$$

$$R_X(h) = \sigma^2 \sum_k \psi_k \psi_{k+h}$$

Special cases:

$$\mu = 0$$

MA(1)

$$\psi_k = \begin{cases} 1 & \text{if } k = 0 , \\ \lambda & \text{if } k = 1 , \\ 0 & \text{otherwise.} \end{cases}$$

AR(1)

$$\psi_k = \begin{cases} \lambda^k & \text{if } k \geq 0 , \\ 0 & \text{otherwise.} \end{cases}$$

White noise

$$\psi_k = \begin{cases} 1 & \text{if } k = 0 , \\ 0 & \text{otherwise.} \end{cases}$$

How about the random walk?

$$X_t = \sum_{0 \leq k \leq t} W_{t-k}$$

$$\neq \sum_k \psi_k W_{t-k}$$

Putting it all together: ARMA

An ARMA(p,q) process $\{X_t\}$ is a stationary process that satisfies

$$X_t - \lambda_1 X_{t-1} - \dots - \lambda_p X_{t-p} = W_t + \theta_1 W_{t-1} + \dots + \theta_q W_{t-q},$$

Where $\{W_t\}$ is white noise

$$\lambda_p \neq 0$$

$$\lambda_q \neq 0$$

What do we do about the mean? ARIMA Integrated models for non-stationary data

Trend stationary processes: varying mean + stationary process

$$x_t = \mu_t + y_t,$$

If **linear** time dependence of the mean

$$\mu_t = \beta_0 + \beta_1 t$$

$$\nabla x_t = x_t - x_{t-1} = \beta_1 + y_t - y_{t-1} = \beta_1 + \nabla y_t.$$

In general, it may take several differentiations to get there
(d-th order polynomial dependence on time)

**We need to compute ACFs for prediction
How do we do that in general?**

The backshift operator

Definition *We define the backshift operator by*

$$Bx_t = x_{t-1}$$

and extend it to powers $B^2x_t = B(Bx_t) = Bx_{t-1} = x_{t-2}$, and so on. Thus,

$$B^k x_t = x_{t-k}. \quad (2.20)$$

Inverse (forward-shift operator)

$$x_t = B^{-1}Bx_t = B^{-1}x_{t-1}$$

Finite differences: $\nabla x_t = (1 - B)x_t$

$$\nabla^d = (1 - B)^d$$

Go back to AR(1), rewrite using backshift operator

Rewrite equation

$$X_t - \lambda X_{t-1} = W_t$$

$$(1 - \lambda B)X_t = W_t$$

$$P(B)X_t = W_t$$

Using B powers:

$$B^2 X_t = BBX_t = BX_{t-1} = X_{t-2},$$

$$B^k X_t = X_{t-k}.$$

$$X_t = \sum_{k=0}^{\infty} \lambda^k W_{t-k} = \boxed{\sum_{k=0}^{\infty} \lambda^k B^k W_t}$$

$$Q(B)$$

$P(B) = 1 - \lambda B$ and $Q(B) = \sum_{k \geq 0} \lambda^k B^k$ are related by

$$P(B)Q(B) = 1 , \quad \text{or } Q(B) = P(B)^{-1} .$$

Since $P(B)X_t = W_t$

we have
$$\begin{aligned} X_t &= P(B)^{-1}W_t \\ &= Q(B)W_t \end{aligned}$$

Operators **P** and **Q** behave like regular polynomials

$$\frac{1}{1 - \lambda z} = \sum_{k \geq 0} \lambda^k z^k , \quad |\lambda| < 1, |z| \leq 1$$

Revisiting MA(1)

$$X_t = W_t + \theta W_{t-1} = (1 + \theta B)W_t = P(B)W_t$$

$$|\theta| < 1.$$

$$\begin{aligned} P(B)^{-1}X_t &= W_t \\ \frac{1}{1 + \theta B}X_t &= W_t \\ (1 - \theta B + \theta^2 B^2 - \theta^3 B^3 + \dots) X_t &= W_t \\ \sum_{k \geq 0} (-\theta)^k X_{t-k} &= W_t , \end{aligned}$$

essentially, we have inverted the roles of X and W

Stationarity and causality

Theorem

- ① *The equation $P(B)X_t = W_t$ has a unique stationary solution if and only if*

$$P(z) = 0 \Rightarrow |z| \neq 1 .$$

We call this unique solution an $AR(p)$ process.

- ② *Moreover, this process is causal if and only if*

$$P(z) = 0 \Rightarrow |z| > 1 .$$

Roots of polynomial determine properties of the stochastic process

DEF: Invertible Process

A linear process $\{X_t\}$ is **invertible** if there exist
 $\psi(B) = \psi_0 + \psi_1 B + \psi_2 B^2 + \dots$ with $\sum_k |\psi_k| < \infty$ and
$$\psi(B)X_t = W_t .$$

AR(1)

$$X_t - \lambda X_{t-1} = (1 - \lambda B)X_t = W_t$$

*Causal (wrt $\{W_t\}$) iff $|\lambda| < 1$.
Always invertible (wrt $\{W_t\}$).*

MA(1)

$$X_t = W_t + \theta W_{t-1} = (1 + \theta B)W_t$$

*Always causal (wrt $\{W_t\}$).
Invertible (wrt $\{W_t\}$) iff $|\theta| < 1$.*

Increasing complexity: AR(p)

An AR(p) process $\{X_t\}$ is a stationary process satisfying

$$X_t - \lambda_1 X_{t-1} - \dots - \lambda_p X_{t-p} = W_t ,$$

Where $\{W_t\}$ is white noise
 $\lambda_p \neq 0$

$$P(B) = 1 - \lambda_1 B - \lambda_2 B^2 - \dots - \lambda_p B^p$$

Constraints on polynomial P(B)

$|z_k^*| \neq 1$ for all (complex) roots of P(B)

Polynomials refresher

A polynomial of order n has n complex roots

If coeff. are real valued-
pairs of conjugate roots

Increasing complexity: MA(q)

The moving average model of order q , or MA(q), is defined as

$$X_t = W_t + \theta_1 W_{t-1} + \theta_2 W_{t-2} + \dots + \theta_q W_{t-q},$$

Where $\{W_t\}$ is white noise
 $\theta_q \neq 0$

$$X_t = \theta(B)W_t$$

$$\theta(B) = 1 + \theta_1 B + \dots + \theta_q B^q$$

Putting it all together: ARMA

An ARMA(p,q) process $\{X_t\}$ is a stationary process that satisfies

$$X_t - \lambda_1 X_{t-1} - \dots - \lambda_p X_{t-p} = W_t + \theta_1 W_{t-1} + \dots + \theta_q W_{t-q},$$

Where $\{W_t\}$ is white noise

$$\lambda_p \neq 0 \quad \theta_q \neq 0$$

The autoregressive operator is defined to be

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p.$$

The moving average operator is

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q.$$

$$\phi(B)x_t = \theta(B)w_t.$$

*NO COMMON ROOTS

Example: minimal models

$$x_t = .4x_{t-1} + .45x_{t-2} + w_t + w_{t-1} + .25w_{t-2},$$

$$(1 - .4B - .45B^2)x_t = (1 + B + .25B^2)w_t$$

$$\theta(B) = (1 + B + .25B^2) = (1 + .5B)^2$$

$$\phi(B) = 1 - .4B - .45B^2 = (1 + .5B)(1 - .9B)$$

Simplified, this is actually ARMA(1,1)

$$x_t = .9x_{t-1} + .5w_{t-1} + w_t$$

Putting it all together: ARMA

An ARMA(p,q) process $\{X_t\}$ is a stationary process that satisfies

$$\phi(B)x_t = \theta(B)w_t.$$

Where $\{W_t\}$ is white noise
*no **common** roots

Special cases

AR(p) = ARMA(p, 0), ie $\theta(B) = 1$.

MA(q) = ARMA(0,q), ie $P(B) = 1$.

Has p+q parameters

For any stationary process with autocovariance R and any k > 0, there is an ARMA process $\{X_t\}$ such that

$$R_X(h) = R(h) , h \leq k .$$

The wonderful world of ARMA polynomials

$$P(B)X_t = \theta(B)W_t$$

Where $P(B)$ has degree p and
 $Q(B)$ has degree q

We can think an ARMA model as concatenating two models:

$$Y_t = \theta(B)W_t , \text{ and } P(B)X_t = Y_t .$$

Theorem

- If P and θ have no common factors, a stationary solution to $P(B)X_t = \theta(B)W_t$ exists iff the roots of $P(z)$ avoid the unit circle: $P(z) = 0 \Rightarrow |z| \neq 1$. This is called an ARMA(p,q) process.
- This process is **causal** iff the roots of $P(z)$ are **outside** the unit circle: $P(z) = 0 \Rightarrow |z| > 1$.
- This process is **invertible** iff the roots of $\theta(B)$ are **outside** the unit circle: $\theta(z) = 0 \Rightarrow |z| > 1$.

How does the polynomial form help with computing the ACF?

The ACF of an AR(2) Process

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + w_t$$

$$\text{E}(x_t x_{t-h}) = \phi_1 \text{E}(x_{t-1} x_{t-h}) + \phi_2 \text{E}(x_{t-2} x_{t-h}) + \text{E}(w_t x_{t-h}).$$

$$\gamma(h) = \phi_1 \gamma(h-1) + \phi_2 \gamma(h-2), \quad h = 1, 2, \dots.$$

Where we used $\text{E}(w_t x_{t-h}) = \text{E}\left(w_t \sum_{j=0}^{\infty} \psi_j w_{t-h-j}\right) = 0$.

This reduces to solving a difference eq

$$\rho(h) - \phi_1 \rho(h-1) - \phi_2 \rho(h-2) = 0, \quad h = 1, 2, \dots.$$

A short intermezzo: difference equations

$$u_1 = \alpha u_0$$

$$u_n - \alpha_1 u_{n-1} - \alpha_2 u_{n-2} = 0,$$

$$u_2 = \alpha u_1 = \alpha^2 u_0$$

$$\alpha(z) = 1 - \alpha_1 z - \alpha_2 z^2,$$

⋮

$$u_n = \alpha u_{n-1} = \alpha^n u_0.$$

2 distinct roots

$$u_n = c_1 z_1^{-n} + c_2 z_2^{-n}$$

$$u_n = \alpha^n c = \left(z_0^{-1}\right)^n c.$$

Same root

$$u_n = z_0^{-n}(c_1 + c_2 n).$$

$$(1 - \alpha B)u_n = 0.$$

In general:

$$u_n - \alpha_1 u_{n-1} - \cdots - \alpha_p u_{n-p} = 0, \quad \alpha_p \neq 0,$$

$$u_n = z_1^{-n} P_1(n) + z_2^{-n} P_2(n) + \cdots + z_r^{-n} P_r(n),$$

where $P_j(n)$, for $j = 1, 2, \dots, r$, is a polynomial in n , of degree $m_j - 1$. Given p initial conditions u_0, \dots, u_{p-1} , we can solve for the $P_j(n)$ explicitly.

The ACF of an AR(2) Process

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + w_t$$

$$\text{E}(x_t x_{t-h}) = \phi_1 \text{E}(x_{t-1} x_{t-h}) + \phi_2 \text{E}(x_{t-2} x_{t-h}) + \text{E}(w_t x_{t-h}).$$

$$\gamma(h) = \phi_1 \gamma(h-1) + \phi_2 \gamma(h-2), \quad h = 1, 2, \dots.$$

This reduces to solving a difference eq

$$\rho(h) - \phi_1 \rho(h-1) - \phi_2 \rho(h-2) = 0, \quad h = 1, 2, \dots.$$

2 roots $\rho(h) = c_1 z_1^{-h} + c_2 z_2^{-h},$ **If complex conjugates**

$$\rho(h) = a|z_1|^{-h} \cos(h\theta + b),$$

Double root $\rho(h) = z_0^{-h} (c_1 + c_2 h),$

Autocovariance of ARMA processes

$$X_t - \lambda_1 X_{t-1} - \dots - \lambda_p X_{t-p} = \theta_0 W_t + \dots + \theta_q W_{t-q}$$

Left side: $\text{cov}(X_t - \lambda_1 X_{t-1} - \dots - \lambda_p X_{t-p}, X_{t-h}) =$
 $\text{cov}(X_t, X_{t-h}) - \lambda_1 \text{cov}(X_{t-1}, X_{t-h}) - \dots - \lambda_p \text{cov}(X_{t-p}, X_{t-h})$

Right side: $\theta_0 \text{cov}(W_t, X_{t-h}) + \dots + \theta_q \text{cov}(W_{t-q}, X_{t-h})$

The auto-covariance satisfies a homogeneous recurrence

$$R_X(h) - \lambda_1 R_X(h-1) - \dots - \lambda_p R_X(h-p) = \sigma^2 \sum_{k=0}^{q-h} \theta_{k+h} \psi_k .$$

Polynomial form defines the ACF of the process!

So the autocorrelation $R_X(h)$ also satisfies an homogeneous recurrence:

$$R_X(h) - \lambda_1 R_X(h-1) - \cdots - \lambda_p R_X(h-p) = 0 , \text{ for } h > q ,$$

with initial conditions given by

$$R_X(h) - \lambda_1 R_X(h-1) - \cdots - \lambda_p R_X(h-p) = \sigma^2 \sum_{k=0}^{q-h} \theta_{k+h} \psi_k , \quad (h = 0, \dots, q-1)$$

What do we do with this?

Linear homogeneous eq of order p

$$a_0 X_t + a_1 X_{t-1} + \cdots + a_p X_{t-p} = 0 .$$

$$(a_0 + a_1 B + \cdots + a_p B^p) X_t = 0 .$$

$$a(B) X_t = 0 , \text{ with } a(z) = a_0 + a_1 z + \cdots + a_p z^p$$

with characteristic polynomial $a(z) = a_p(z - z_1)(z - z_2) \dots (z - z_p)$

Big picture

Goal: solve

$$a_0 X_t + \cdots + a_p X_{t-p} = 0$$

With initial conditions X_1, \dots, X_p .

Equivalent to finding the roots of polynomial

$$(z - z_1)^{m_1} \cdots (z - z_k)^{m_k} = 0$$

General solution
of the form*

$$X_t = c_1(t)z_1^{-t} + \cdots + c_k(t)z_k^{-t}$$

Where $c_i(t)$ polynomials of order $m_i - 1$

Coefficients adjusted from initial conditions

*Note: proof tsa4.pdf, page 91

ARIMA inference

parameters-> covariance-> optimal linear predictor

B operator, polynomial form-> roots -> covariance

Mathematical justification: homogeneous difference equations

What do we do about the mean? ARIMA Integrated models for non stationary data

Trend stationary processes: varying mean + stationary process

$$x_t = \mu_t + y_t,$$

If linear time dependence $\mu_t = \beta_0 + \beta_1 t$

$$\nabla x_t = x_t - x_{t-1} = \beta_1 + y_t - y_{t-1} = \beta_1 + \nabla y_t.$$

In general, it may take several differentiations to get there
(d-th order polynomial dependence on time)

A process is ARIMA (p,d,q) if d-th difference

$$\nabla^d x_t = (1 - B)^d x_t \quad \text{is ARMA (p,q)}$$

$$\phi(B)(1 - B)^d x_t = \theta(B)w_t$$

These are tricky to use,
motivate state space models

How do we estimate the model parameters?

Estimating ARMA parameters from data

2 methods: **Maximum likelihood**
Method of moments

Assume: model known, and zero mean (preprocessing)

Gaussian stats

$$P(B)X_t = \theta(B)W_t$$

Where $\{W_t\}$ is iid gaussian noise
0 mean, σ^2 variance

Find parameters λ_i , Θ_j σ^2
that maximize likelihood

$$\mathcal{L}(\lambda, \theta, \sigma^2) = f_{\lambda, \theta, \sigma^2}(x_1, \dots, x_n)$$

Jointly gaussian

$$\mathcal{L}(\lambda, \theta, \sigma^2) = (2\pi)^{-n/2} |\Gamma_n|^{-1/2} \exp\left(-\frac{1}{2} \mathbf{x}^T \Gamma_n^{-1} \mathbf{x}\right)$$

Where we've collated the data in vector $\mathbf{x} = (x_1, \dots, x_n)$

Maximum likelihood

Pros: efficient, works well even if model assumptions not 100% right

Cons: unpleasant optimization, need good initialization

We need to find a cheap initial guess **Yule Walker equations**

$$x_t = \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + w_t,$$

$$\gamma(h) = \phi_1 \gamma(h-1) + \cdots + \phi_p \gamma(h-p), \quad h = 1, 2, \dots, p,$$

$$\sigma_w^2 = \gamma(0) - \phi_1 \gamma(1) - \cdots - \phi_p \gamma(p).$$

Solve for parameters:

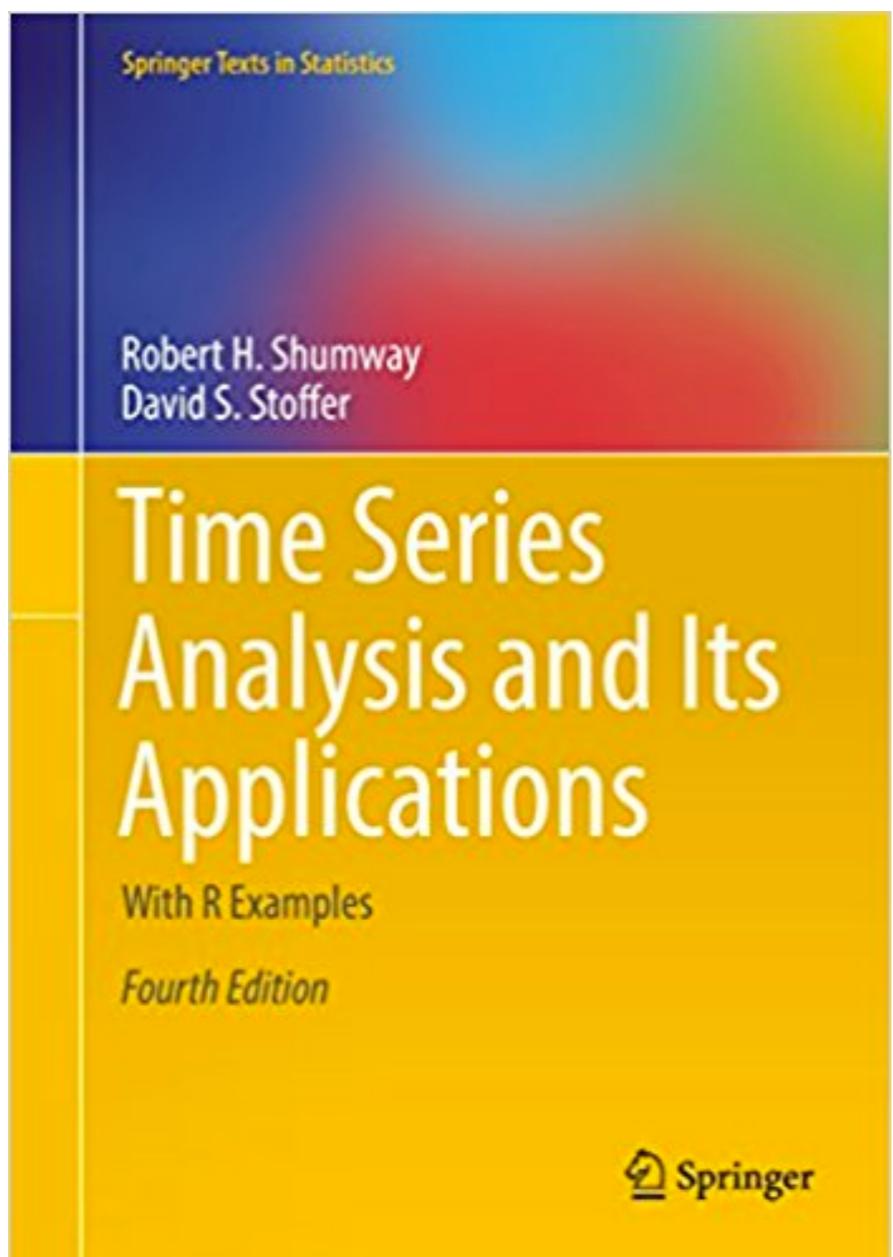
$$\Gamma_p \phi = \gamma_p, \quad \sigma_w^2 = \gamma(0) - \phi' \gamma_p,$$

Replace with empirical estimates

$$\hat{\phi} = \hat{\Gamma}_p^{-1} \hat{\gamma}_p, \quad \hat{\sigma}_w^2 = \hat{\gamma}(0) - \hat{\gamma}'_p \hat{\Gamma}_p^{-1} \hat{\gamma}_p.$$

Nice asymptotic convergence properties, see book for details

Chapter 1 & 3



**Homework 1:
posted tonight,
due in 2 weeks,
just before class**