Time Series Analysis and Forecasting

Chapter 2: ARMA Models
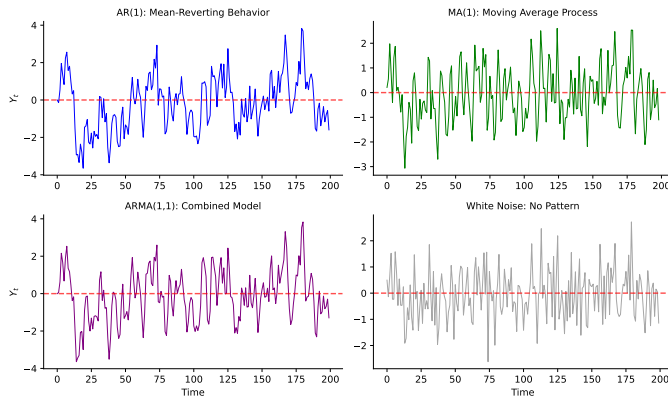
Stationary Time Series

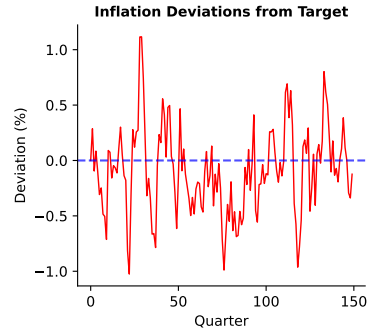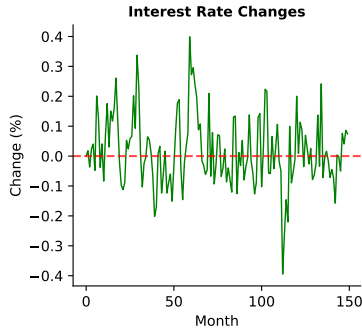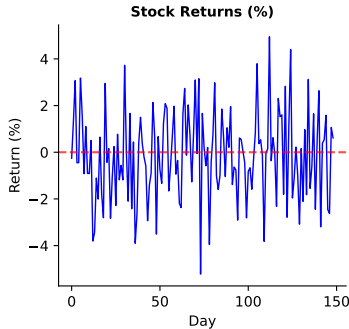# Outline

Motivating Example: Stationary Processes

- **AR processes**: Current value depends on past values — mean-reverting behavior
- **MA processes**: Current value depends on past shocks — short memory
- **ARMA**: Combines both mechanisms for flexible modeling

Real-World Applications of ARMA

Key Insight

Many economic and financial series become stationary after simple transformations (returns, growth rates, deviations from trend) — perfect for ARMA modeling!

Model Identification via ACF Patterns

AR(1) Process — **MA(1) Process** — **ARMA(1,1) Process**

ACF: Exponential Decay — **ACF: Cuts Off at Lag 1** — **ACF: Decay After Lag 1**
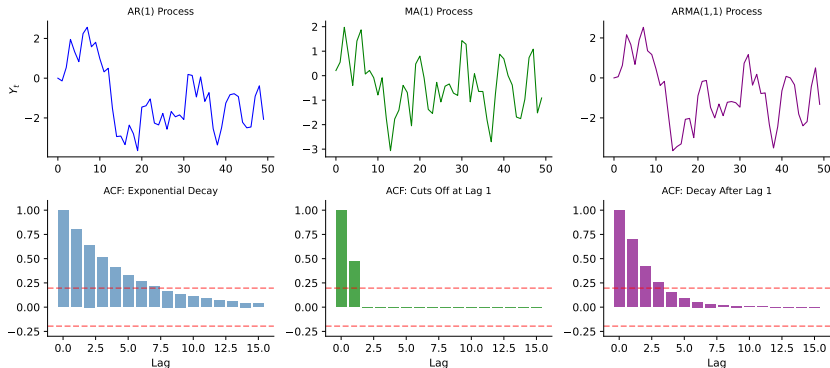
The ACF Reveals Model Structure

Different ARMA models produce distinct ACF patterns — we can identify the model by examining the data!

Recap: Stationarity

From Chapter 1: A process $\{X_t\}$ is **weakly stationary** if:

1. $\mathbb{E}[X_t] = \mu$ (constant mean)
2. $\text{Var}(X_t) = \sigma^2 < \infty$ (constant, finite variance)
3. $\text{Cov}(X_t, X_{t+h}) = \gamma(h)$ (covariance depends only on lag h)

Why stationarity matters for ARMA:

- ARMA models assume the underlying process is stationary
- Non-stationary data must be differenced first (ARIMA)
- Stationarity ensures stable model parameters

Today: We build models for stationary time series using past values and past errors.

The Lag Operator (Backshift Operator)

Definition 1 (Lag Operator)

The **lag operator** L (or backshift operator B) shifts a time series back by one period:
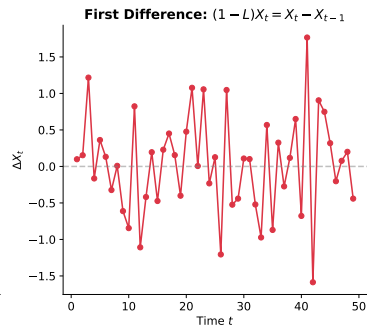
$$LX_t = X_{t-1}$$

Properties:

- $L^k X_t = X_{t-k}$ (shift back k periods)
- $L^0 X_t = X_t$ (identity)
- $(1 - L)X_t = X_t - X_{t-1} = \Delta X_t$ (first difference)
- $(1 - L)^d X_t = \Delta^d X_t$ (d-th difference)

Lag Polynomials:

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$$
$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$$

Lag Operator: Visual Illustration
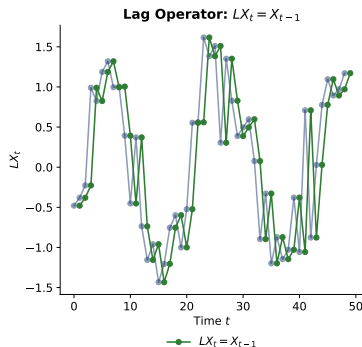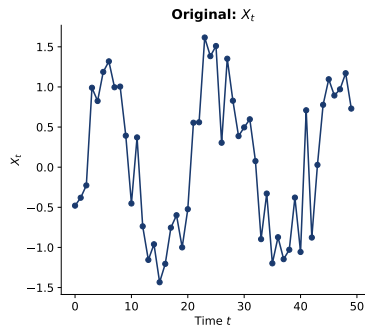
Key insight: The lag operator is the foundation of ARMA model notation

White Noise Process

Definition 2 (White Noise)

A process $\{\varepsilon_t\}$ is **white noise**, denoted $\varepsilon_t \sim WN(0, \sigma^2)$, if:

1. $\mathbb{E}[\varepsilon_t] = 0$ for all t
2. $\mathrm{Var}(\varepsilon_t) = \sigma^2$ for all t
3. $\mathrm{Cov}(\varepsilon_t, \varepsilon_s) = 0$ for all $t \neq s$

Properties:

- White noise is the "building block" of ARMA models
- ACF: $\rho(0) = 1$, $\rho(h) = 0$ for $h \neq 0$
- PACF: same pattern
- **Gaussian white noise:** additionally $\varepsilon_t \sim N(0, \sigma^2)$

Note: White noise is *not* predictable — it's pure randomness.

AR(1) Model: Definition

Definition 3 (AR(1) Process)

An **autoregressive process of order 1** is:

$$X_t = c + \phi X_{t-1} + \varepsilon_t$$

where $\varepsilon_t \sim WN(0, \sigma^2)$ and $|\phi| < 1$ for stationarity.
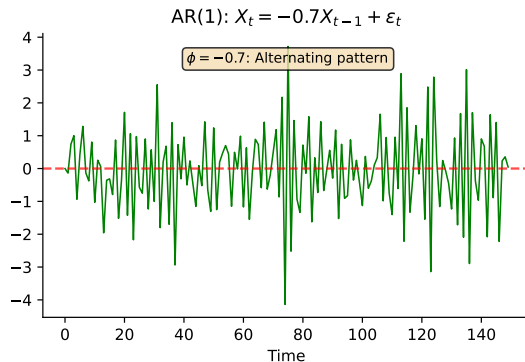
Interpretation:

- c: constant (intercept)
- ϕ: autoregressive coefficient — measures persistence
- ε_t: innovation (unpredictable shock)

Using lag operator:

$$(1 - \phi L)X_t = c + \varepsilon_t$$
$$\phi(L)X_t = c + \varepsilon_t \quad \text{where } \phi(L) = 1 - \phi L$$

AR(1): Visual Illustration

AR(1): $X_t = 0.8 X_{t-1} + \varepsilon_t$

$\phi = 0.8$: Persistent, slow decay

AR(1): $X_t = -0.7 X_{t-1} + \varepsilon_t$

$\phi = -0.7$: Alternating pattern
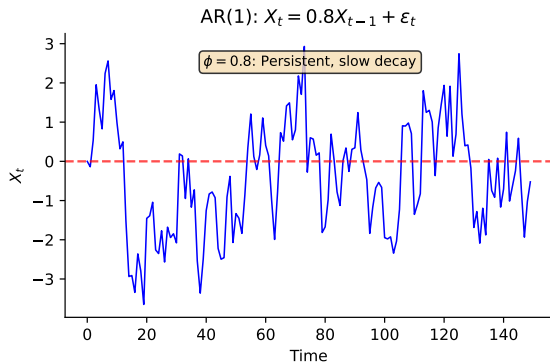
Left: positive ϕ creates persistent, smooth patterns. Right: negative ϕ creates oscillating behavior around the mean.

AR(1) Stationarity Condition

For AR(1) to be stationary: $|\phi| < 1$

Intuition:

- If $|\phi| < 1$: shocks decay over time $\rightarrow$ stationary
- If $|\phi| = 1$: random walk $\rightarrow$ non-stationary (unit root)
- If $|\phi| > 1$: explosive process $\rightarrow$ non-stationary

Characteristic equation:

$$\phi(z) = 1 - \phi z = 0 \implies z = \frac{1}{\phi}$$

Stationarity requires the root $z = 1/\phi$ to lie **outside the unit circle**, i.e., $|z| > 1$, which means $|\phi| < 1$.

AR(1) Properties

For a stationary AR(1) with $|\phi| < 1$:

Mean:

$$\mu = \mathbb{E}[X_t] = \frac{c}{1 - \phi}$$

Variance:

$$\gamma(0) = \text{Var}(X_t) = \frac{\sigma^2}{1 - \phi^2}$$
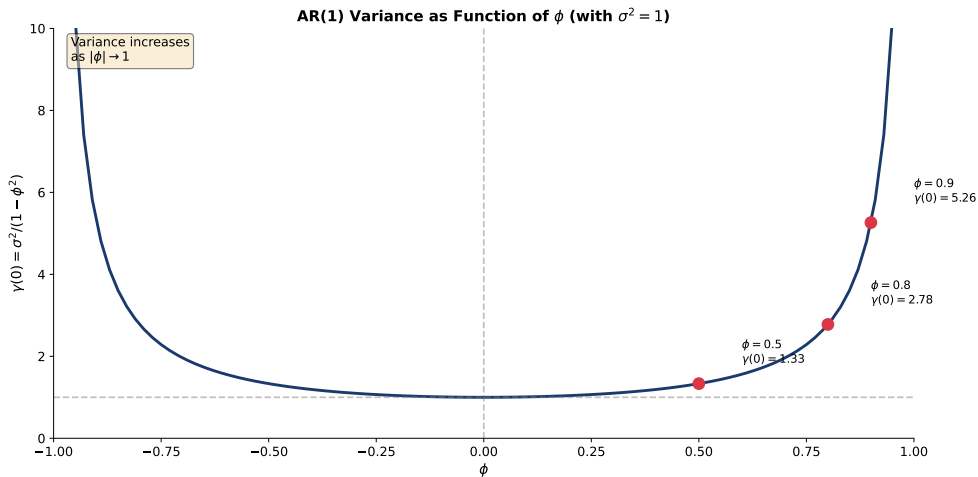
Autocovariance:

$$\gamma(h) = \phi^h \gamma(0) = \frac{\phi^h \sigma^2}{1 - \phi^2}$$

Autocorrelation (ACF):

$$\rho(h) = \phi^h$$
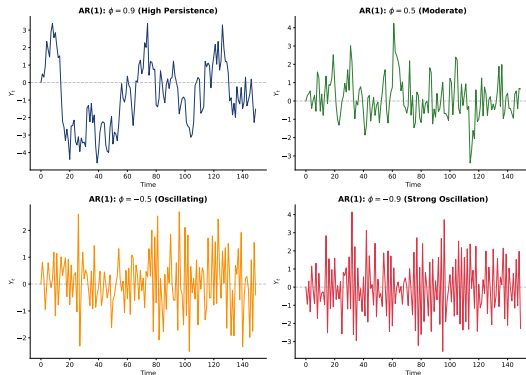
Key insight: ACF decays exponentially at rate ϕ

AR(1) Variance as Function of ϕ

AR(1) Variance as Function of ϕ (with $\sigma^2 = 1$)
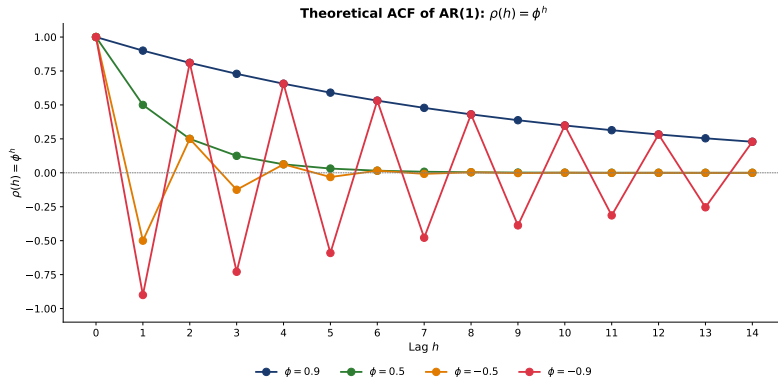
Key insight: As $|\phi| \to 1$, variance explodes $\to$ non-stationarity

AR(1) Simulations: Effect of ϕ

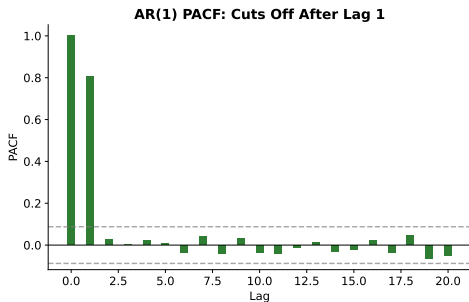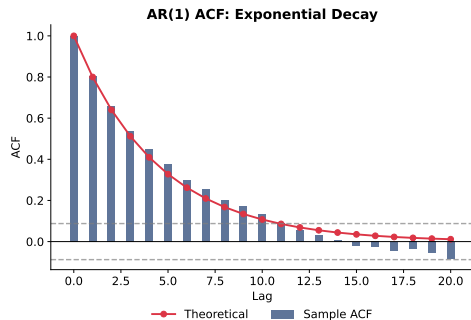- Different ϕ values produce distinct behavior: higher $|\phi|$ means more persistence
- Positive ϕ creates smooth, trending patterns; negative ϕ creates oscillations
- As $|\phi| \to 1$, the process becomes more persistent and approaches non-stationarity

AR(1) Theoretical ACF

Theoretical ACF of AR(1): $\rho(h) = \phi^h$

Pattern: $\rho(h) = \phi^h$ — exponential decay (or alternating for $\phi < 0$)

AR(1) ACF and PACF: Theory vs Sample

- **ACF**: Exponential decay at rate ϕ – theoretical formula: $\rho(h) = \phi^h$
- **PACF**: Single spike at lag 1, then cuts off – this identifies AR(1)
- Sample estimates (bars) fluctuate around theoretical values; use confidence bands

AR(1) ACF and PACF Patterns

ACF of AR(1):
- Decays exponentially: $\rho(h) = \phi^h$
- If $\phi > 0$: all positive, gradual decay
- If $\phi < 0$: alternating signs, decay in magnitude

PACF of AR(1):
- **Cuts off after lag 1**
- $\pi_1 = \phi$, $\pi_k = 0$ for $k > 1$

	ACF	PACF
AR(1)	Exponential decay	Cuts off at lag 1

This is the key identification pattern for AR(1)!

AR(p) Model: General Form

Definition 4 (AR(p) Process)

An **autoregressive process of order p** is:

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t$$

Using lag operator:

$$\phi(L)X_t = c + \varepsilon_t$$

where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$
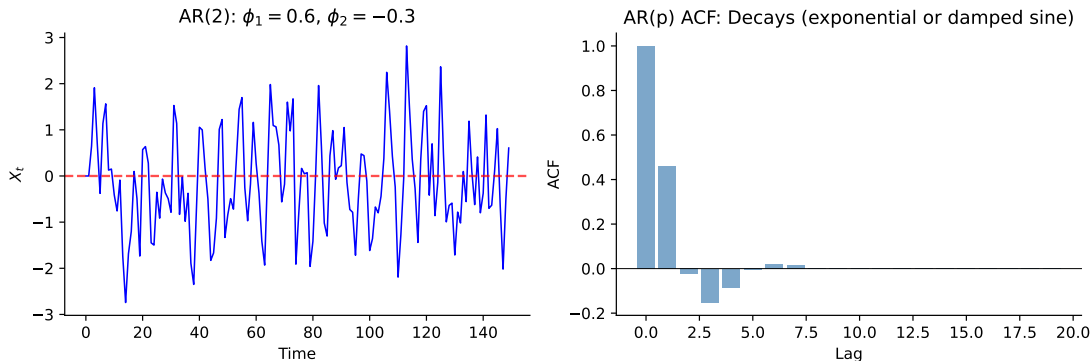
Stationarity condition:

- All roots of $\phi(z) = 0$ must lie **outside** the unit circle
- Equivalently: all roots have modulus > 1

PACF pattern:

- PACF cuts off after lag p
- ACF decays (exponentially or with damped oscillations)

AR(p): Visual Illustration

AR(2) can exhibit cyclic behavior. ACF shows damped decay pattern characteristic of AR processes.

AR(2) Stationarity: Unit Circle Visualization

Stationary AR(2)
$\phi_1 = 0.5$, $\phi_2 = 0.3$

Roots OUTSIDE
unit circle

Non-Stationary AR(2)
$\phi_1 = 1.2$, $\phi_2 = -0.5$

Root INSIDE
unit circle
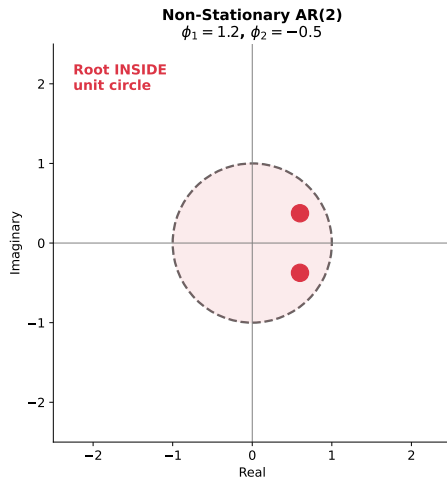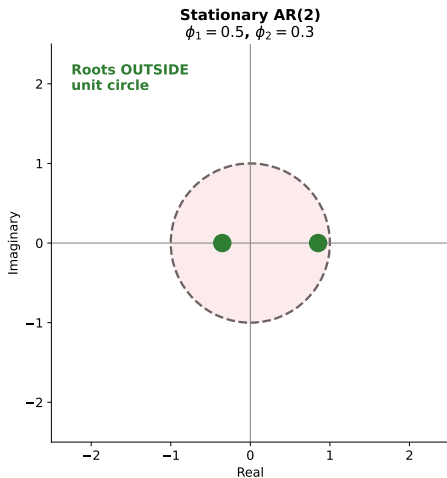
Rule: All roots of $\phi(z) = 0$ must lie **outside** the shaded unit circle

AR(2) Stationarity Triangle
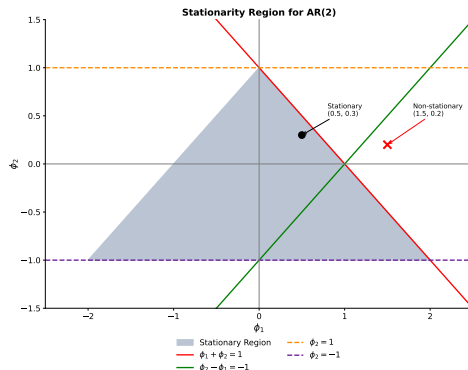
- The triangular region defines all stationary AR(2) parameter combinations
- Boundaries: $\phi_1 + \phi_2 < 1$, $\phi_2 - \phi_1 < 1$, and $|\phi_2| < 1$
- Points outside this region lead to non-stationary or explosive processes

Characteristic Polynomial Roots

AR(2) Model
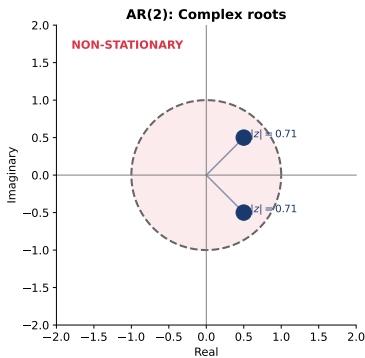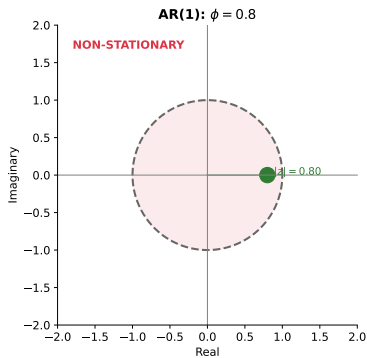
Definition 5 (AR(2) Process)

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \varepsilon_t$$

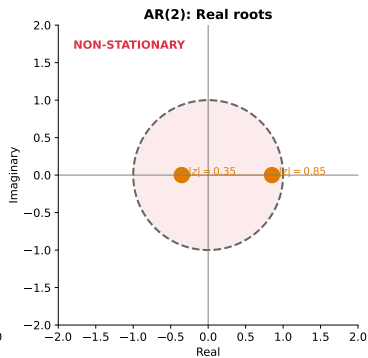**Stationarity conditions for AR(2):**

1. $\phi_1 + \phi_2 < 1$
2. $\phi_2 - \phi_1 < 1$
3. $|\phi_2| < 1$

ACF behavior depends on roots:

- **Real roots:** mixture of two exponential decays
- **Complex roots:** damped sinusoidal pattern (pseudo-cycles)

PACF: Cuts off after lag 2 ($\pi_k = 0$ for $k > 2$)

Quiz: AR Stationarity

Question

For which value of ϕ is the AR(1) process $X_t = c + \phi X_{t-1} + \varepsilon_t$ stationary?

- **A** $\phi = 1.2$
- **B** $\phi = 1.0$
- **C** $\phi = -0.8$
- **D** $\phi = -1.5$

Quiz: AR Stationarity – Answer

Correct Answer: (C) $\phi = -0.8$

AR(1) is stationary if and only if $|\phi| < 1$. Only $|-0.8| = 0.8 < 1$.

MA(1) Model: Definition
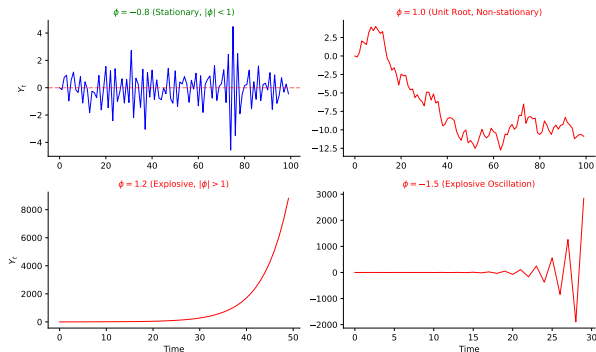
Definition 6 (MA(1) Process)

A **moving average process of order 1** is:

$$X_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}$$

where $\varepsilon_t \sim WN(0, \sigma^2)$.

Interpretation:

- μ: mean of the process
- θ: MA coefficient — measures impact of past shock
- Current value depends on current and one past shock

Using lag operator:

$$X_t = \mu + \theta(L)\varepsilon_t$$

where $\theta(L) = 1 + \theta L$

Key property: MA processes are **always stationary** for any finite θ

MA(1): Visual Illustration

MA(1): $X_t = \varepsilon_t + 0.7\varepsilon_{t-1}$

MA(1) ACF: Cuts off after lag 1
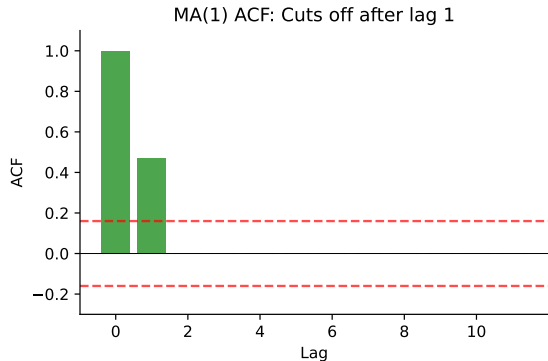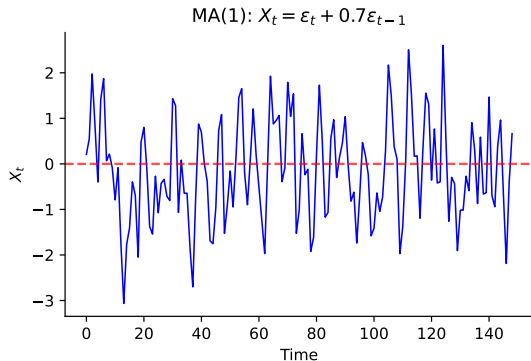
MA(1) process on the left. ACF on the right shows characteristic cutoff after lag 1.

MA(1) Properties

For MA(1): $X_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}$

Mean:

$$\mathbb{E}[X_t] = \mu$$

Variance:

$$\gamma(0) = \text{Var}(X_t) = \sigma^2(1 + \theta^2)$$

Autocovariance:

$$\gamma(1) = \theta\sigma^2, \quad \gamma(h) = 0 \text{ for } h > 1$$

Autocorrelation (ACF):

$$\rho(1) = \frac{\theta}{1 + \theta^2}, \quad \rho(h) = 0 \text{ for } h > 1$$

Key insight: ACF **cuts off** after lag 1

MA(1) Simulations: Effect of θ
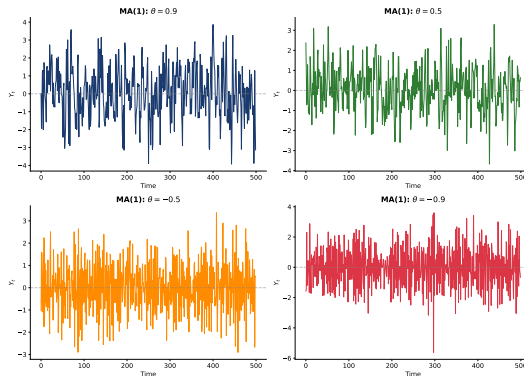
- MA(1) is always stationary regardless of θ – finite memory of only one lag
- Positive θ smooths the series; negative θ creates more rapid fluctuations
- Unlike AR(1), MA(1) shocks only affect the process for one period

MA(1) ACF and PACF Patterns

ACF of MA(1):

- **Cuts off after lag 1**
- $\rho(1) = \frac{\theta}{1+\theta^2}$, $\rho(h) = 0$ for $h > 1$
- Note: $|\rho(1)| \leq 0.5$ always (maximum at $\theta = \pm 1$)

PACF of MA(1):

- Decays exponentially (or with alternating signs)
- Does *not* cut off

	ACF	PACF
MA(1)	Cuts off at lag 1	Exponential decay

This is the opposite pattern from AR(1)!

MA(1) ACF and PACF: Visual Comparison
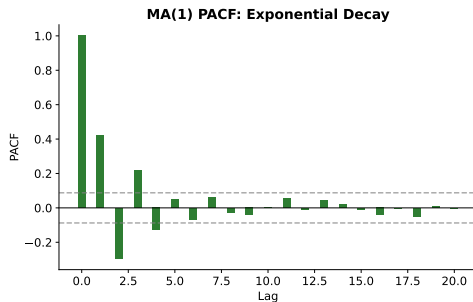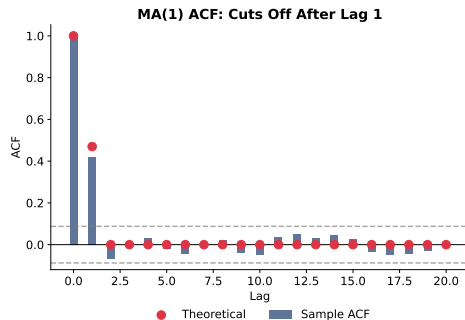
- **ACF**: Single spike at lag 1, then cuts off immediately – key MA(1) signature
- **PACF**: Exponential decay – opposite pattern from AR(1)
- This reversal of ACF/PACF patterns distinguishes MA from AR processes

Invertibility of MA Models

Definition 7 (Invertibility)

An MA process is **invertible** if it can be written as an infinite AR process:

$$X_t = \mu + \sum_{j=1}^{\infty} \pi_j(X_{t-j} - \mu) + \varepsilon_t$$

For MA(1): Invertible if $|\theta| < 1$

For MA(q): All roots of $\theta(z) = 0$ must lie outside the unit circle

Why invertibility matters:

- Ensures unique representation
- Required for forecasting and estimation
- Creates correspondence: $AR(\infty) \leftrightarrow MA(q)$

Note: Stationarity is for AR, Invertibility is for MA

Invertibility: Visual Illustration

Invertibility: Root outside unit circle

- ● Invertible: $|\theta| < 1$
- ✕ Non-invertible: $|\theta| > 1$

AR(∞) weights: $X_t = \sum \pi_j X_{t-j} + \varepsilon_t$

- ● $\theta = 0.6$: Decaying
- ■ $\theta = 1.2$: Exploding
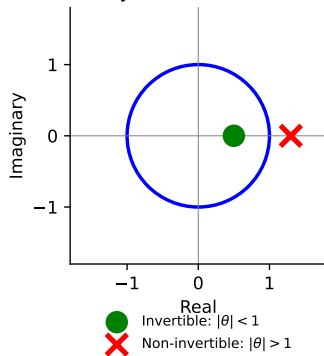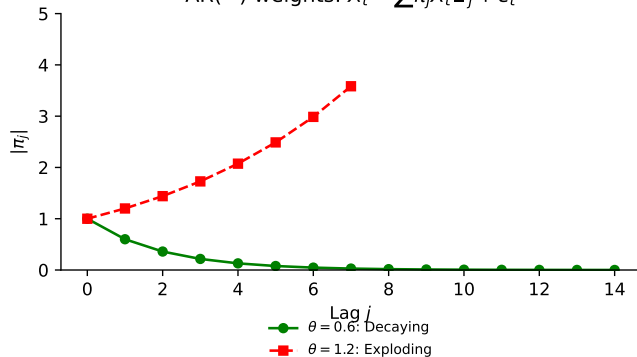
Left: invertibility requires roots outside unit circle. Right: AR(∞) weights decay only when $|\theta| < 1$.

MA(q) Model: General Form

Definition 8 (MA(q) Process)

A **moving average process of order q** is:

$$X_t = \mu + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q}$$

Using lag operator:

$$X_t = \mu + \theta(L)\varepsilon_t$$

where $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$

Properties:

- Always stationary (finite variance)
- ACF cuts off after lag q: $\rho(h) = 0$ for $h > q$
- PACF decays gradually
- Invertible if all roots of $\theta(z) = 0$ lie outside unit circle

MA(q): Visual Illustration

MA(3): $X_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_3\varepsilon_{t-3}$

MA(q) ACF: Cuts off after lag q
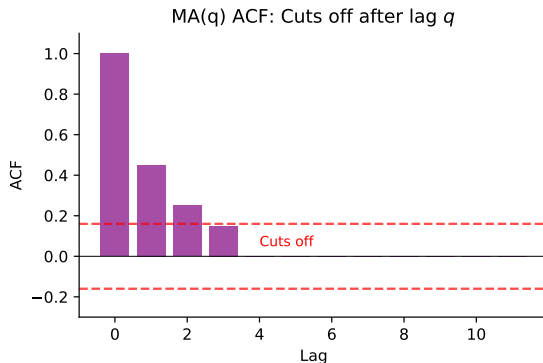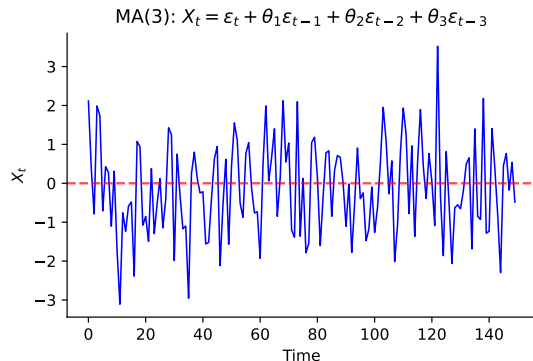
MA(3) process. Key signature: ACF cuts off after lag q (here, lag 3).

Quiz: ACF/PACF Pattern Recognition

Question

You observe: ACF has spike at lag 1, then cuts off. PACF decays gradually. What model?

- Ⓐ AR(1)
- Ⓑ MA(1)
- Ⓒ ARMA(1,1)
- Ⓓ White noise

Correct Answer: (B) MA(1)

ACF cuts off → MA process; PACF decays → confirms MA(1)
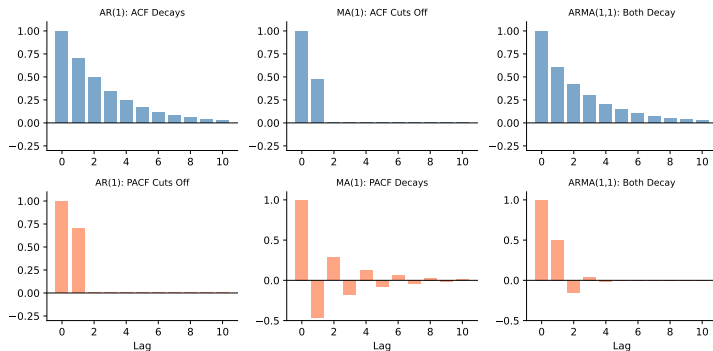
Quiz: MA Invertibility

Question

Is MA(1) $X_t = \varepsilon_t + 1.5\varepsilon_{t-1}$ invertible?

- **A** Yes, MA processes are always invertible
- **B** Yes, because $1.5 > 0$
- **C** No, because $|\theta| = 1.5 > 1$
- **D** No, MA processes are never invertible

Quiz: MA Invertibility

Question

Is MA(1) $X_t = \varepsilon_t + 1.5\varepsilon_{t-1}$ invertible?

- Ⓐ Yes, MA processes are always invertible
- Ⓑ Yes, because $1.5 > 0$
- Ⓒ No, because $|\theta| = 1.5 > 1$
- Ⓓ No, MA processes are never invertible

Answer: (C)

Invertibility requires $|\theta| < 1$. Here $|\theta| = 1.5 > 1$, so not invertible.

ARMA(p,q) Model: Definition

Definition 9 (ARMA(p,q) Process)

An **autoregressive moving average process** of order (p,q) is:

$$X_t = c + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

Compact form using lag operators:

$$\phi(L)(X_t - \mu) = \theta(L)\varepsilon_t$$

or equivalently:

$$\phi(L)X_t = c + \theta(L)\varepsilon_t$$

where $\mu = \frac{c}{1 - \phi_1 - \cdots - \phi_p}$

Key idea: Combines AR and MA components for more flexible modeling

ARMA: Visual Illustration

ARMA(1,1): $X_t = 0.6X_{t-1} + \varepsilon_t + 0.4\varepsilon_{t-1}$

ARMA ACF: Decay after lag q
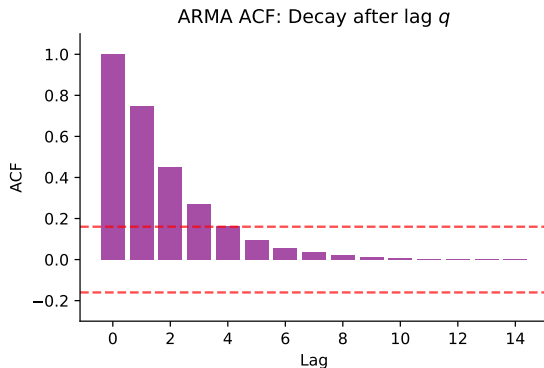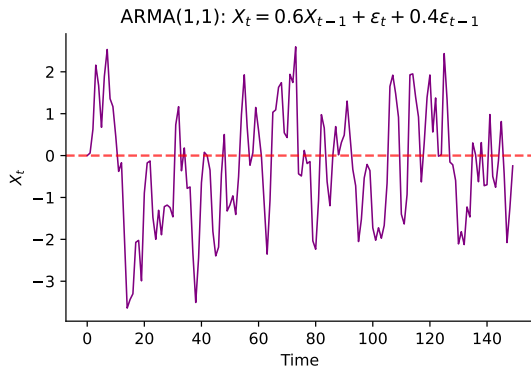
ARMA(1,1) process. ACF shows decay after initial lag, combining AR and MA characteristics.

ARMA Model Structure

ARMA(p,q) Model Structure

$$X_t = \phi_1 X_{t-1} + \ldots + \phi_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$$
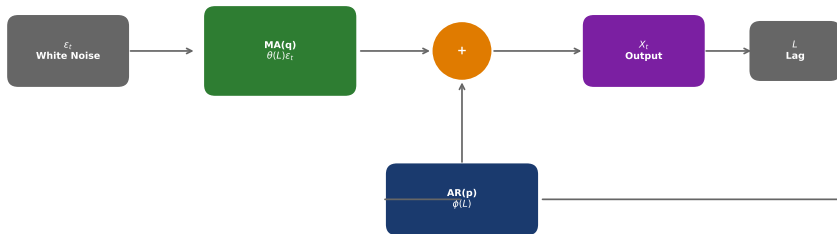
How ARMA Simulation Works

ARMA Examples

ARMA(1,1): $\phi = 0.7$, $\theta = 0.4$

ARMA(2,1): $\phi_1 = 0.5$, $\phi_2 = 0.3$, $\theta = 0.4$
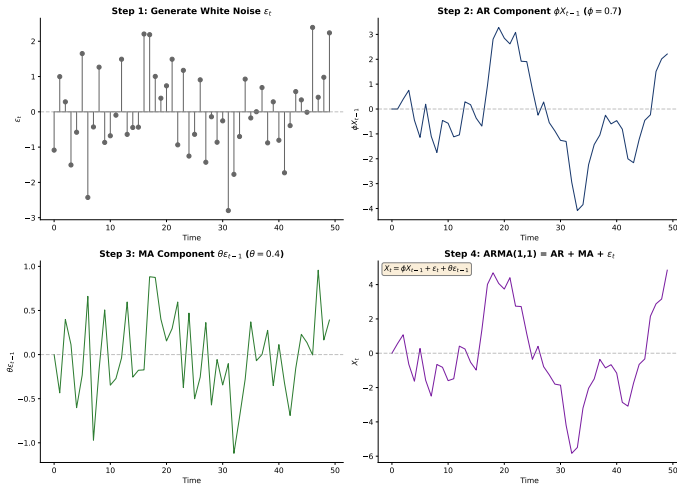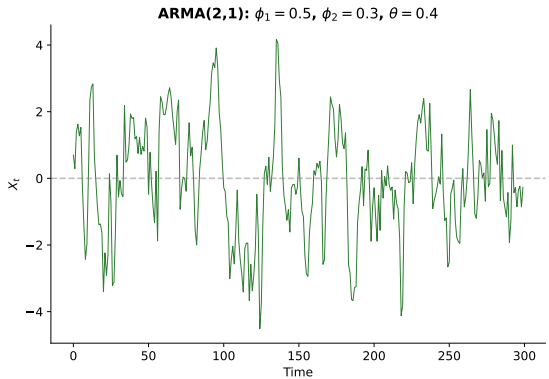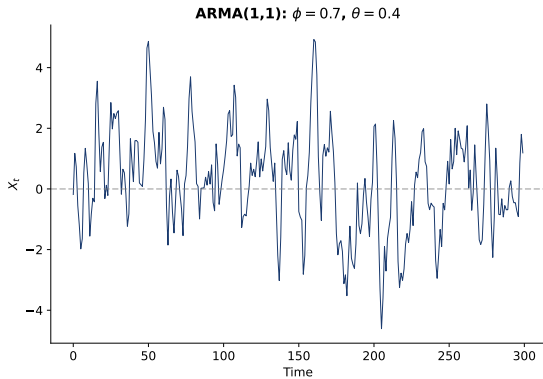
ARMA(1,1) Model

Definition 10 (ARMA(1,1) Process)

$$X_t = c + \phi X_{t-1} + \varepsilon_t + \theta \varepsilon_{t-1}$$

Properties (assuming stationarity and invertibility):

- Mean: $\mu = \frac{c}{1-\phi}$
- Variance: $\gamma(0) = \frac{(1+2\phi\theta+\theta^2)\sigma^2}{1-\phi^2}$

ACF:

$$\rho(1) = \frac{(1+\phi\theta)(\phi+\theta)}{1+2\phi\theta+\theta^2}$$

$$\rho(h) = \phi \cdot \rho(h-1) \quad \text{for } h \geq 2$$

Pattern: ACF decays exponentially after lag 1 (like AR), but starting point depends on both ϕ and θ

ACF/PACF Patterns: AR vs MA vs ARMA
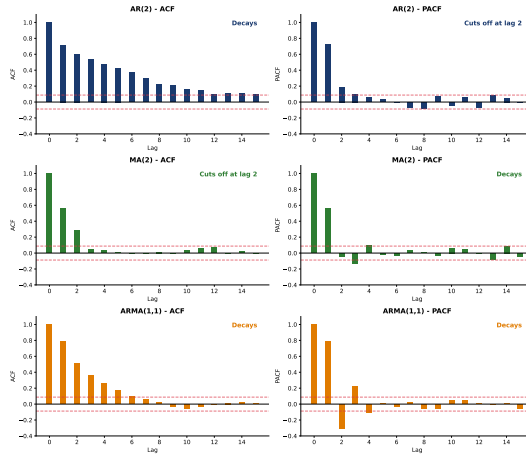
ARMA ACF and PACF Patterns

Model	ACF	PACF
AR(p)	Decays (exp./damped)	Cuts off at lag p
MA(q)	Cuts off at lag q	Decays (exp./damped)
ARMA(p,q)	Decays after lag $q - p$	Decays after lag $p - q$

Key identification rule:

- **PACF cuts off** $\rightarrow$ AR process (order = cutoff lag)
- **ACF cuts off** $\rightarrow$ MA process (order = cutoff lag)
- **Both decay** $\rightarrow$ ARMA process

Caution: In practice, sample ACF/PACF are noisy; use confidence bands

Impulse Response Functions
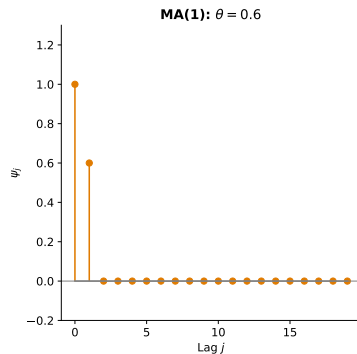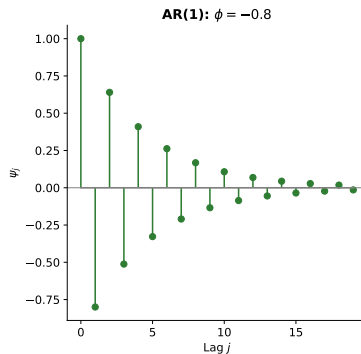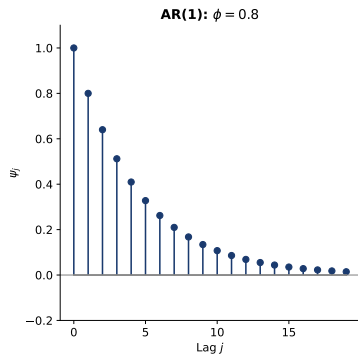
Interpretation: Shows how a unit shock propagates through the system over time

Stationarity and Invertibility Summary

For ARMA(p,q) to be well-behaved:

Condition	Requirement
Stationarity	Roots of $\phi(z) = 0$ outside unit circle
Invertibility	Roots of $\theta(z) = 0$ outside unit circle

Implications:

- **Stationarity:** Can write as MA(∞): $X_t = \mu + \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$
- **Invertibility:** Can write as AR(∞): $X_t = \mu + \sum_{j=1}^{\infty} \pi_j (X_{t-j} - \mu) + \varepsilon_t$

Causal representation: X_t depends only on *past* shocks (not future)

Wold's Decomposition Theorem

AR(1) Process: $X_t = 0.8 X_{t-1} + \varepsilon_t$

ψ-weights: $\psi_j = \phi^j$

$X_t = \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$

Cumulative Impulse Response

Long-run: $1/(1-\phi) = 5.0$
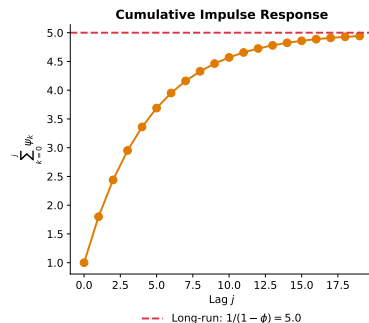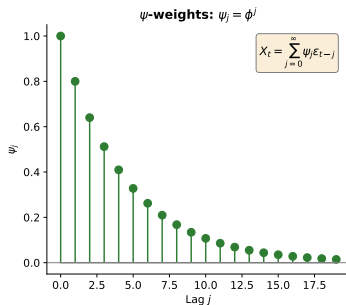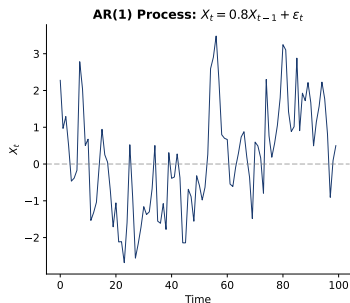
Any stationary process can be written as MA(∞): $X_t = \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$

Quiz: ARMA Representation

The compact form $\phi(L)X_t = \theta(L)\varepsilon_t$ represents which model?

- Ⓐ Pure AR model
- Ⓑ Pure MA model
- Ⓒ ARMA model
- Ⓓ None of the above

Quiz: ARMA Representation

Question

The compact form $\phi(L)X_t = \theta(L)\varepsilon_t$ represents which model?

- **A** Pure AR model
- **B** Pure MA model
- **C** ARMA model
- **D** None of the above

Answer: (C) ARMA model

$\phi(L)$ is the AR polynomial, $\theta(L)$ is the MA polynomial $\rightarrow$ ARMA(p,q)

Quiz: Lag Operator

Question

What is $(1 - L)^2 X_t$?

- Ⓐ $X_t - X_{t-1}$
- Ⓑ $X_t - 2X_{t-1} + X_{t-2}$
- Ⓒ $X_t + X_{t-1} + X_{t-2}$
- Ⓓ $X_t - X_{t-2}$

Quiz: Lag Operator

- Ⓐ $X_t - X_{t-1}$
- Ⓑ $X_t - 2X_{t-1} + X_{t-2}$
- Ⓒ $X_t + X_{t-1} + X_{t-2}$
- Ⓓ $X_t - X_{t-2}$

Answer: (B)

$(1 - L)^2 = 1 - 2L + L^2$, so $(1 - L)^2 X_t = X_t - 2X_{t-1} + X_{t-2}$

The Box-Jenkins Methodology

Box-Jenkins Methodology
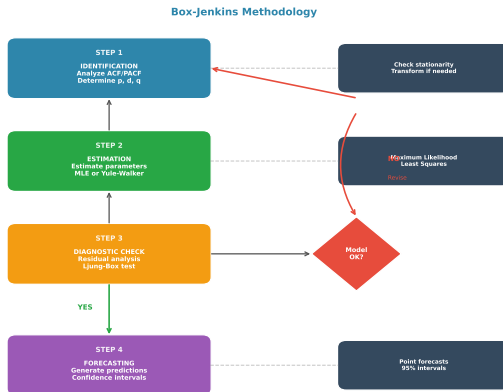
Model Identification Summary Table

Model Identification: ACF/PACF Patterns

Model	ACF Pattern	PACF Pattern
AR(p)	Exponential decay or damped oscillation	Cuts off after lag p
MA(q)	Cuts off after lag q	Exponential decay or damped oscillation
ARMA(p,q)	Exponential decay after lag q-p	Exponential decay after lag p-q

Practical tip: Start simple (low p, q), increase if diagnostics fail

ACF/PACF Identification Rules

Theoretical patterns for stationary processes:

Model	ACF Pattern	PACF Pattern
AR(1)	Exponential decay	Spike at lag 1, then 0
AR(2)	Damped exponential/sine	Spikes at lags 1-2, then 0
AR(p)	Decays gradually	Cuts off after lag p
MA(1)	Spike at lag 1, then 0	Exponential decay
MA(2)	Spikes at lags 1-2, then 0	Damped exponential/sine
MA(q)	Cuts off after lag q	Decays gradually
ARMA(p,q)	Decays	Decays

ACF/PACF Patterns: Visual Guide
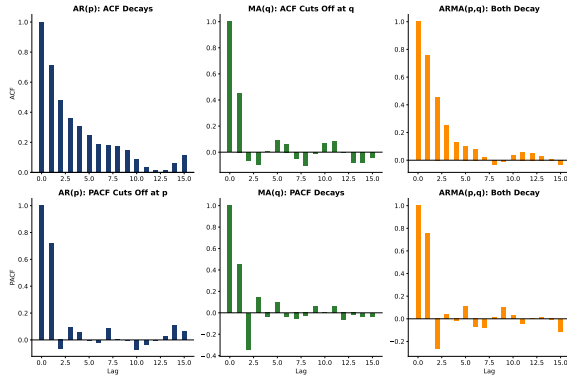
- **AR**: ACF decays, PACF cuts off — use PACF to identify order *p*
- **MA**: ACF cuts off, PACF decays — use ACF to identify order *q*
- **ARMA**: Both decay — requires information criteria for model selection

Information Criteria

Purpose: Balance goodness-of-fit against model complexity

Akaike Information Criterion (AIC):

$$\text{AIC} = -2\ln(\hat{L}) + 2k$$

Bayesian Information Criterion (BIC/SBC):

$$\text{BIC} = -2\ln(\hat{L}) + k\ln(n)$$

where $\hat{L}$ = maximized likelihood, k = number of parameters, n = sample size

Usage:

- Lower values are better
- BIC penalizes complexity more strongly than AIC
- AIC tends to choose larger models; BIC more parsimonious
- Compare models fit to the *same data*

AIC vs BIC: Model Selection
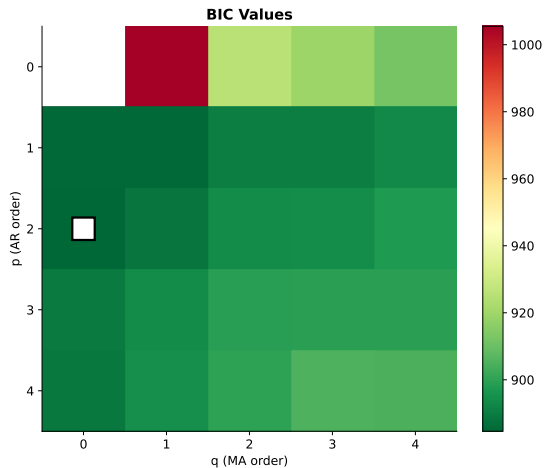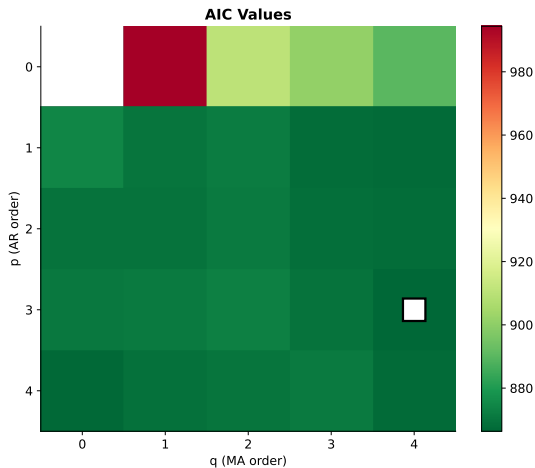
Note: White square marks the best model; lower values (green) are better

Parsimony Principle: Bias-Variance Trade-off
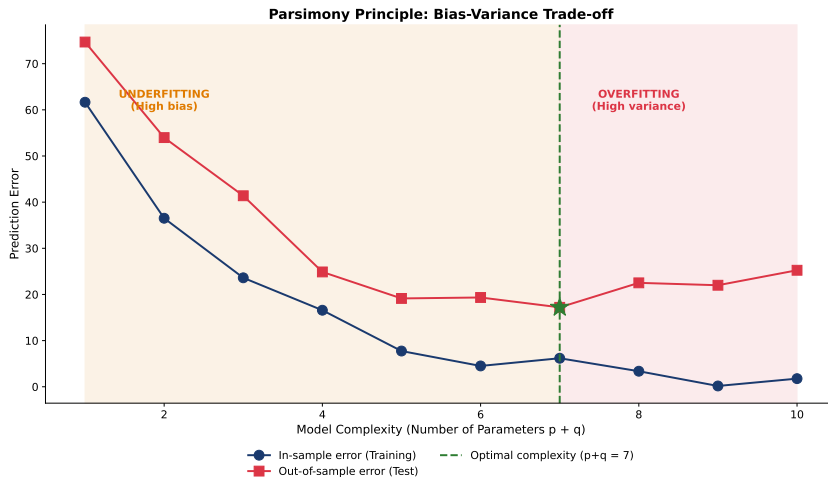
Automatic Model Selection

Grid search approach:

1. Fit ARMA(p,q) for $p = 0, 1, \ldots, p_{max}$ and $q = 0, 1, \ldots, q_{max}$
2. Select model with lowest AIC or BIC
3. Verify with diagnostic checks

In Python (statsmodels):

- `pm.auto_arima()` from pmdarima package
- Automatically tests stationarity, searches over orders
- Returns best model by AIC/BIC

Caution:

- Automatic selection is a starting point, not final answer
- Always check diagnostics
- Consider domain knowledge

Quiz: Information Criteria

Question

Comparing ARMA(1,1) vs ARMA(2,1) using BIC, which is correct?

- **A** Lower BIC always means better forecasts
- **B** BIC penalizes complexity less than AIC
- **C** The model with lower BIC is preferred
- **D** BIC can only compare models with same # of parameters

Correct Answer: (C) The model with lower BIC is preferred

Lower BIC indicates better fit-complexity trade-off. BIC penalizes complexity *more* than AIC.

AIC vs BIC: Lower is Better

Estimation Methods Overview
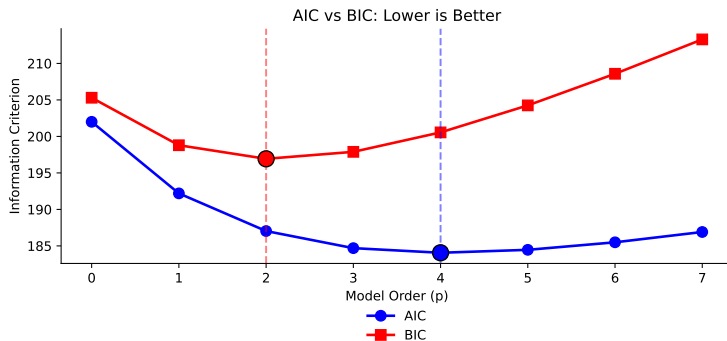
Three main approaches:

1. Method of Moments / Yule-Walker (AR only)

- Match sample autocorrelations to theoretical values
- Simple, closed-form for AR models
- Not efficient for MA components

2. Maximum Likelihood Estimation (MLE)

- Most common approach
- Requires distributional assumption (usually Gaussian)
- Efficient and consistent

3. Conditional Least Squares

- Minimize sum of squared residuals
- Conditioning on initial observations
- Computationally simpler than exact MLE

Estimation Methods Comparison

ARMA Parameter Estimation Methods

Yule-Walker	Maximum Likelihood	Conditional LS
Pros:	**Pros:**	**Pros:**
+ Simple computation	+ Most efficient	+ Simple to implement
+ Closed-form solution	+ Works for ARMA	+ Fast computation
Cons:	**Cons:**	**Cons:**
- AR only	- Iterative	- Biased for small n
- Less efficient	- Local optima risk	- Ignores initial values

**Recommendation: Use MLE for final estimation,
Yule-Walker for initial values**

Yule-Walker Equations for AR(p)

Theoretical ACF for AR(2)
$\phi_1 = 0.6$, $\phi_2 = 0.2$
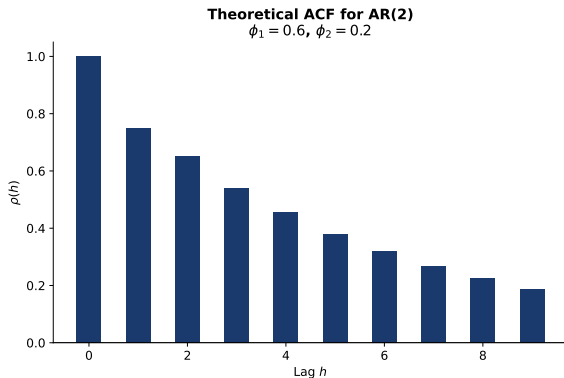
Yule-Walker Equations

$$\rho(1) = \phi_1 + \phi_2 \rho(1)$$

$$\rho(2) = \phi_1 \rho(1) + \phi_2$$

Matrix form: $R \cdot \phi = \rho$

R = autocorrelation matrix

Solution: $\hat{\phi} = R^{-1} \rho$

Yule-Walker Equations: Matrix Form

For AR(p): $X_t = \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \varepsilon_t$

Yule-Walker equations:

$$\rho(k) = \phi_1 \rho(k-1) + \phi_2 \rho(k-2) + \cdots + \phi_p \rho(k-p)$$

for $k = 1, 2, \ldots, p$

Matrix form:

$$\begin{pmatrix} \rho(0) & \rho(1) & \cdots & \rho(p-1) \\ \rho(1) & \rho(0) & \cdots & \rho(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ \rho(p-1) & \rho(p-2) & \cdots & \rho(0) \end{pmatrix} \begin{pmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_p \end{pmatrix} = \begin{pmatrix} \rho(1) \\ \rho(2) \\ \vdots \\ \rho(p) \end{pmatrix}$$

Estimation: Replace $\rho(k)$ with sample autocorrelations $\hat{\rho}(k)$

Maximum Likelihood Estimation

Assuming Gaussian errors: $\varepsilon_t \sim N(0, \sigma^2)$

Log-likelihood for ARMA(p,q):

$$\ell(\boldsymbol{\phi}, \boldsymbol{\theta}, \sigma^2) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{n}\varepsilon_t^2$$

where ε_t are the innovations computed recursively.

Estimation procedure:

1. Initialize: use method of moments or OLS for starting values
2. Optimize: numerical methods (e.g., BFGS, Newton-Raphson)
3. Iterate until convergence

In practice: Use `statsmodels.tsa.arima.model.ARIMA`

Standard Errors and Inference

Asymptotic distribution of MLE:

$$\hat{\theta} \xrightarrow{d} N\left(\theta_0, \frac{1}{n}I(\theta_0)^{-1}\right)$$

where $I(\theta)$ is the Fisher information matrix.

Standard errors: Square root of diagonal of $\frac{1}{n}\hat{I}^{-1}$

Hypothesis testing:

- $H_0 : \phi_j = 0$ (or $\theta_j = 0$)
- Test statistic: $z = \frac{\hat{\phi}_j}{SE(\hat{\phi}_j)} \sim N(0,1)$ asymptotically
- Reject if $|z| > 1.96$ at 5% level

Confidence interval: $\hat{\phi}_j \pm 1.96 \cdot SE(\hat{\phi}_j)$

Residual Analysis

If model is correctly specified, residuals should be white noise:

1. Plot residuals over time
- Should fluctuate around zero
- No obvious patterns or trends
- Constant variance (no heteroskedasticity)

2. Check ACF of residuals
- All correlations should be within confidence bands
- No significant spikes $\rightarrow$ white noise

3. Check histogram / Q-Q plot
- Should be approximately normal (if assuming Gaussian)
- Heavy tails suggest non-normal errors

Residual Diagnostics: Example
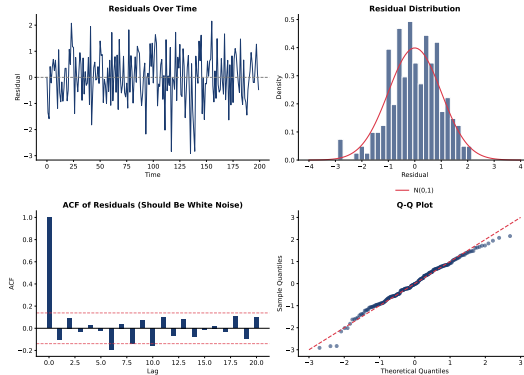
- **Residual plot**: Should show random scatter around zero with constant variance
- **ACF of residuals**: No significant spikes indicates white noise (good fit)
- **Q-Q plot**: Points on diagonal line indicate normally distributed residuals

Ljung-Box Test

Definition 11 (Ljung-Box Test)

Tests whether residuals are independently distributed (no autocorrelation).

Test statistic:

$$Q(m) = n(n+2) \sum_{k=1}^{m} \frac{\hat{\rho}_k^2}{n-k}$$

Hypotheses:

- H_0: Residuals are white noise (no autocorrelation up to lag m)
- H_1: Residuals are autocorrelated

Distribution: Under H_0, $Q(m) \sim \chi^2(m - p - q)$ approximately

Decision:

- p-value $> 0.05 \rightarrow$ fail to reject $H_0 \rightarrow$ residuals look like white noise (good!)
- p-value $< 0.05 \rightarrow$ significant autocorrelation remains $\rightarrow$ model inadequate

Ljung-Box Test: Visual Illustration
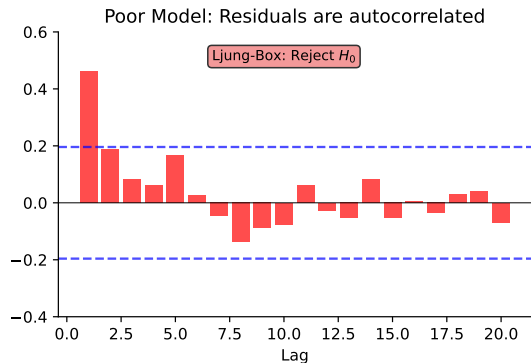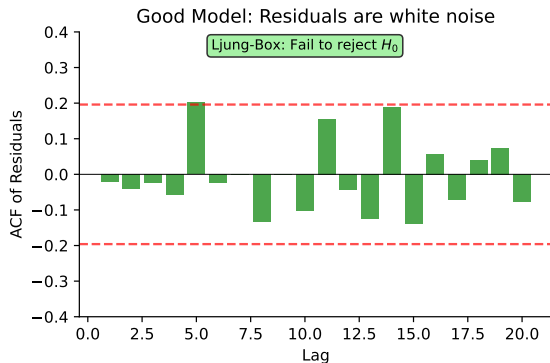
Left: Good model – residuals are white noise (no significant ACF). Right: Poor model – residuals show autocorrelation.

Diagnostic Checklist

A good ARMA model should satisfy:

1. **Stationarity:** AR roots outside unit circle
   ✓ Check with `arroots`
2. **Invertibility:** MA roots outside unit circle
   ✓ Check with `maroots`
3. **White noise residuals:** No significant ACF
   ✓ ACF plot, Ljung-Box test
4. **Normal residuals:** (if assumed)
   ✓ Q-Q plot, Jarque-Bera test
5. **No heteroskedasticity:** Constant variance
   ✓ Plot residuals, ARCH test
6. **Parsimonious:** Lowest AIC/BIC among adequate models

If diagnostics fail: Return to identification, try different orders

Quiz: Ljung-Box Test

Question

After fitting an ARMA model, you run the Ljung-Box test on residuals and get p-value = 0.03. What does this mean?

- A Model is adequate, residuals are white noise
- B Model is inadequate, residuals have autocorrelation
- C Need to increase sample size
- D Test is inconclusive

Correct Answer: (B) Model is inadequate

p-value < 0.05 rejects H_0 (white noise), indicating remaining autocorrelation.

Point Forecasts
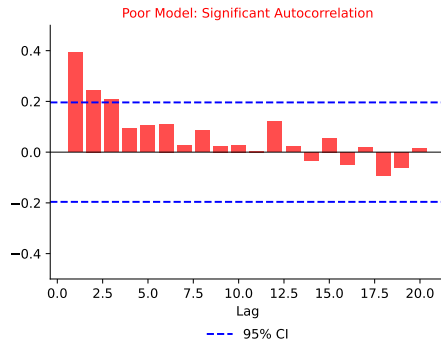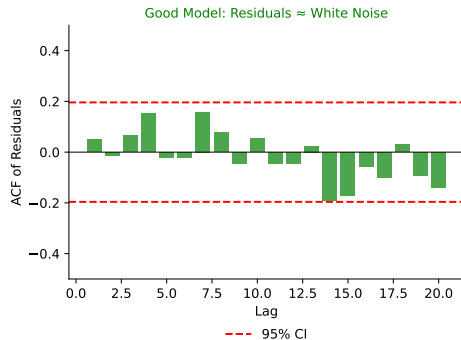
Optimal forecast: Conditional expectation minimizes MSE

$$\hat{X}_{n+h|n} = \mathbb{E}[X_{n+h}|X_n, X_{n-1}, \ldots]$$

For AR(1): $X_t = c + \phi X_{t-1} + \varepsilon_t$

$$\hat{X}_{n+1|n} = c + \phi X_n$$
$$\hat{X}_{n+2|n} = c + \phi \hat{X}_{n+1|n} = c(1 + \phi) + \phi^2 X_n$$
$$\hat{X}_{n+h|n} = \mu + \phi^h(X_n - \mu)$$

Key property: Forecasts converge to mean μ as $h \to \infty$

For MA(1): $X_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}$

$$\hat{X}_{n+1|n} = \mu + \theta\varepsilon_n$$
$$\hat{X}_{n+h|n} = \mu \quad \text{for } h > 1$$

Forecast Uncertainty

Forecast error:

$$e_{n+h|n} = X_{n+h} - \hat{X}_{n+h|n}$$

Mean squared forecast error (MSFE):

$$\text{MSFE}(h) = \mathbb{E}[e_{n+h|n}^2] = \sigma^2 \sum_{j=0}^{h-1} \psi_j^2$$

where ψ_j are the MA(∞) coefficients.

For AR(1): $\psi_j = \phi^j$

$$\text{MSFE}(h) = \sigma^2 \frac{1 - \phi^{2h}}{1 - \phi^2} \to \frac{\sigma^2}{1 - \phi^2} = \text{Var}(X_t)$$

Key insight: Forecast uncertainty increases with horizon, eventually reaching unconditional variance

ARMA Forecasting with Confidence Intervals

ARMA(1,1) Forecast with 95% Confidence Interval

Forecasts revert to mean

— Observed — Forecast ▮ 95% CI ⋯⋯ Mean = -0.34

AR(1) Forecasting: Mean Reversion
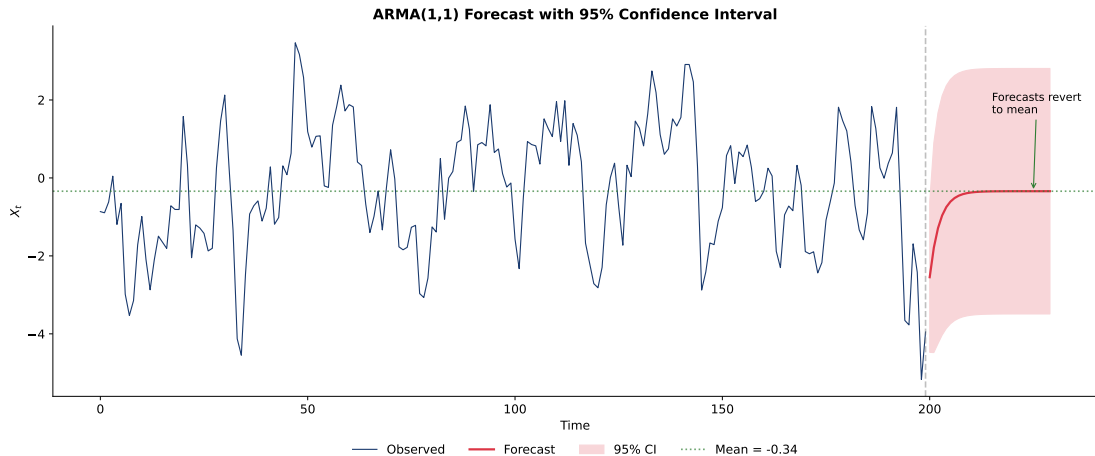
AR(1) Forecasting: Mean Reversion
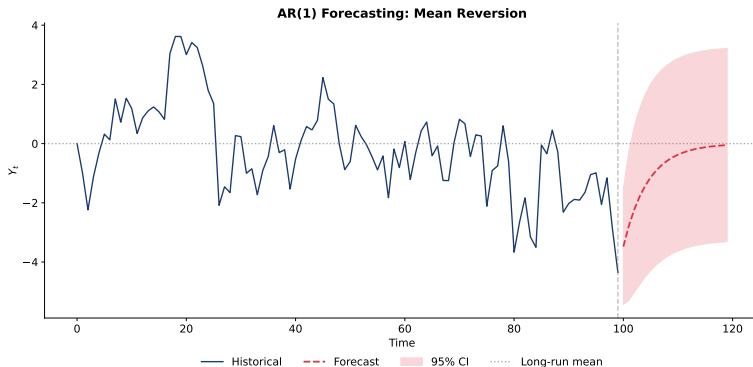
- Forecasts converge to the unconditional mean μ as horizon increases
- Rate of convergence depends on $|\phi|$: higher values mean slower reversion
- Confidence intervals widen with horizon, eventually reaching unconditional variance

Forecast Error Variance Over Horizon

Forecast Error Variance: AR(1) with $\phi = 0.8$

- - - Unconditional variance = 2.78

Forecast Uncertainty Grows with Horizon

Uncertainty increases
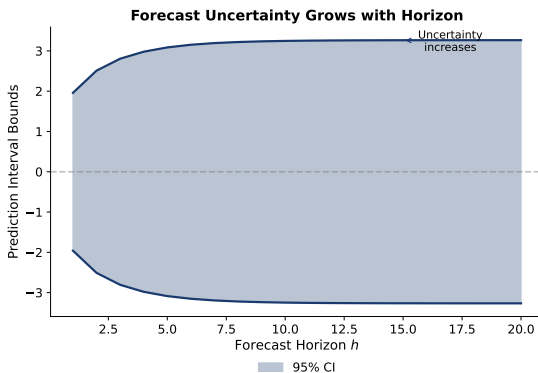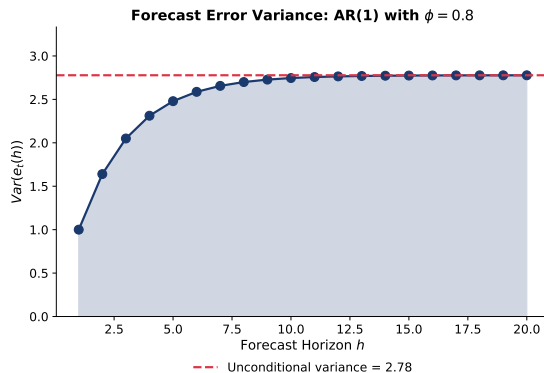
95% CI

Confidence Intervals for Forecasts

Assuming Gaussian errors:

$$X_{n+h}|X_n, \ldots \sim N\left(\hat{X}_{n+h|n}, \mathsf{MSFE}(h)\right)$$

$(1 - \alpha)$ **confidence interval:**

$$\hat{X}_{n+h|n} \pm z_{\alpha/2} \cdot \sqrt{\mathsf{MSFE}(h)}$$

where $z_{\alpha/2} = 1.96$ for 95% CI.

Properties:

- Intervals widen as horizon increases
- Eventually converge to unconditional interval: $\mu \pm z_{\alpha/2}\sigma_X$
- Width depends on model parameters (AR coefficients, etc.)

In Python: `model.get_forecast(h).conf_int()`

Forecast Evaluation

Out-of-sample testing:

1. Split data: training set (fit model) and test set (evaluate)
2. Generate forecasts for test period
3. Compare forecasts to actual values

Metrics (from Chapter 1):

- MAE $= \frac{1}{n} \sum |e_t|$
- RMSE $= \sqrt{\frac{1}{n} \sum e_t^2}$
- MAPE $= \frac{100}{n} \sum \left| \frac{e_t}{X_t} \right|$

Rolling/expanding window:

- Re-estimate model as new data arrives
- More realistic assessment of forecast performance

ARMA Forecasting: Train/Validation/Test Split with 95% Confidence Intervals
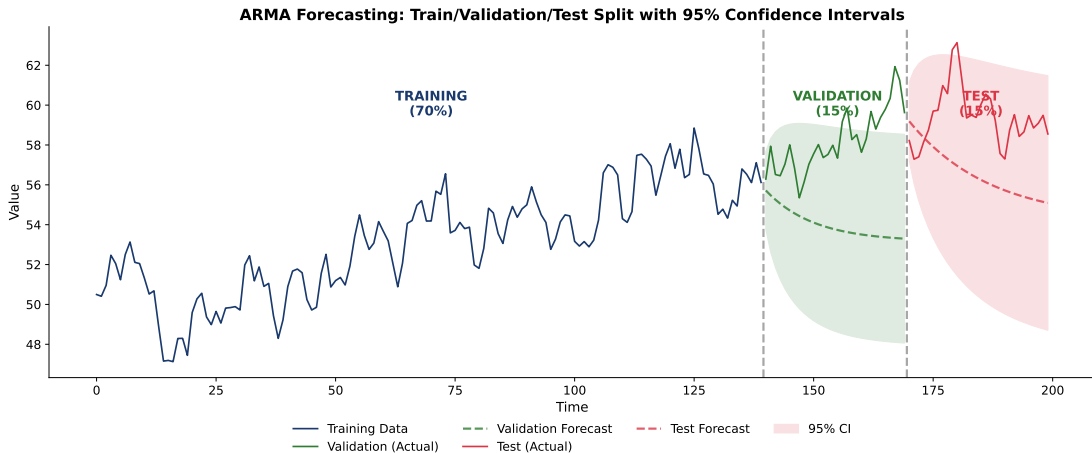
Quiz: Forecast Properties

Question

For a stationary AR(1) model, what happens to forecasts as horizon $h \to \infty$?

- **A** Forecasts grow without bound
- **B** Forecasts oscillate forever
- **C** Forecasts converge to the unconditional mean μ
- **D** Forecasts become more accurate

Quiz: Forecast Properties – Answer

Correct Answer: (C) Forecasts converge to μ

$\hat{X}_{n+h|n} = \mu + \phi^h(X_n - \mu) \to \mu$ as $h \to \infty$ (since $|\phi| < 1$)

AR(1) Forecasts Converge to Unconditional Mean
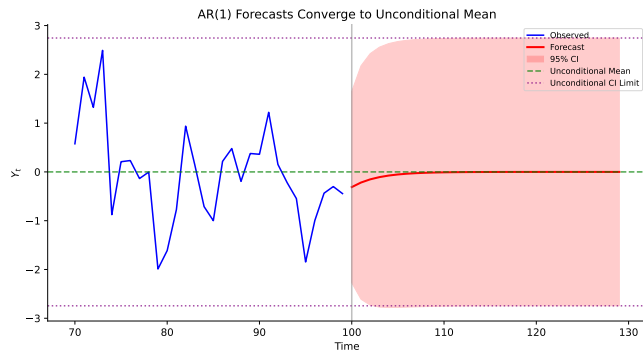
Python Implementation: Fitting ARMA

Using statsmodels:

```python
from statsmodels.tsa.arima.model import ARIMA

# Fit ARMA(2,1) -- note:  ARIMA(p,d,q) with d=0
model = ARIMA(data, order=(2, 0, 1))
results = model.fit()

# Summary
print(results.summary())

# Forecasting
forecast = results.get_forecast(steps=10)
print(forecast.predicted_mean)
print(forecast.conf_int())
```

Note: ARIMA with $d = 0$ is equivalent to ARMA

Python: Model Selection with pmdarima

Automatic ARIMA selection:

```python
import pmdarima as pm

# Auto ARIMA with AIC criterion
model = pm.auto_arima(data,
            start_p=0, max_p=5,
            start_q=0, max_q=5,
            d=0, # No differencing for stationary data
            seasonal=False,
            information_criterion='aic',
            trace=True)

print(model.summary())
```

Output: Best model order and fitted parameters

Workflow Summary

1. Data preparation
- Check for missing values, outliers
- Transform if necessary (log, differencing)

2. Stationarity check
- Visual inspection: time plot, ACF
- Formal tests: ADF, KPSS
- Difference if non-stationary

3. Model identification
- ACF/PACF patterns
- Information criteria grid search

4. Estimation and diagnostics
- Fit model, check significance
- Residual analysis, Ljung-Box test

5. Forecasting
- Point forecasts with confidence intervals
- Out-of-sample validation

Key Takeaways

1. **AR(p) models:** Current value depends on p past values
   - Stationarity: roots of $\phi(z)$ outside unit circle
   - PACF cuts off at lag p
2. **MA(q) models:** Current value depends on q past shocks
   - Always stationary; invertibility: roots of $\theta(z)$ outside unit circle
   - ACF cuts off at lag q
3. **ARMA(p,q):** Combines AR and MA for flexible modeling
   - Both ACF and PACF decay
4. **Box-Jenkins:** Identify $\rightarrow$ Estimate $\rightarrow$ Diagnose $\rightarrow$ Forecast
5. **Diagnostics:** Residuals must be white noise
6. **Forecasts:** Converge to mean; uncertainty increases with horizon

Next Chapter Preview

Chapter 3: ARIMA and Seasonal Models

- ARIMA(p,d,q): Integrated models for non-stationary data
- Seasonal ARIMA: SARIMA(p,d,q)(P,D,Q)$_s$
- Seasonal differencing
- Real-world applications with seasonal patterns

Reading:

- Hyndman & Athanasopoulos, *Forecasting: Principles and Practice*, Ch. 9
- Box, Jenkins, Reinsel & Ljung, *Time Series Analysis*, Ch. 3-4

References

📄 Box, G.E.P., Jenkins, G.M., Reinsel, G.C., & Ljung, G.M. (2015). *Time Series Analysis: Forecasting and Control*. 5th ed., Wiley.

📄 Hamilton, J.D. (1994). *Time Series Analysis*. Princeton University Press.

📄 Hyndman, R.J., & Athanasopoulos, G. (2021). *Forecasting: Principles and Practice*. 3rd ed., OTexts.

📄 Brockwell, P.J., & Davis, R.A. (2016). *Introduction to Time Series and Forecasting*. 3rd ed., Springer.

📄 Shumway, R.H., & Stoffer, D.S. (2017). *Time Series Analysis and Its Applications*. 4th ed., Springer.

Data Sources

Simulated Data Used in This Chapter

- **AR(1), AR(2) processes**: Simulated with various ϕ parameters
- **MA(1), MA(q) processes**: Simulated with various θ parameters
- **ARMA(p,q) processes**: Combined AR and MA simulations

Software & Tools

- **Python**: statsmodels (ARIMA), numpy, matplotlib
- **R**: forecast, tseries packages
- **Key functions**: ARIMA(), auto.arima(), acf(), pacf()

Thank You!

Questions?