



Time Series Analysis and Forecasting



Chapter 3: ARIMA Models for Non-Stationary Data

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Why Non-Stationarity Matters

The Problem

Many economic and financial time series are **non-stationary**:

- GDP, stock prices, exchange rates, inflation indices
- They exhibit trends, changing means, or growing variance

Consequences of Non-Stationarity

- Standard ARMA models assume stationarity
- OLS regression with non-stationary data leads to **spurious regression**
- Sample moments (mean, variance, ACF) are not consistent estimators
- Statistical inference becomes invalid

Types of Non-Stationarity

Deterministic Trend

$$Y_t = \alpha + \beta t + \varepsilon_t$$

- Trend is a deterministic function of time
- Can be removed by **detrending**
- Shocks have temporary effects

Stochastic Trend (Unit Root)

$$Y_t = Y_{t-1} + \varepsilon_t$$

- Random walk process
- Must be removed by **differencing**
- Shocks have permanent effects

Key Distinction

Correct identification is crucial: detrending a unit root process or differencing a trend-stationary process both lead to misspecification!

Definition 1 (Random Walk)

A **random walk** is defined as:

$$Y_t = Y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim WN(0, \sigma^2)$$

With initial condition $Y_0 = 0$, we have:

$$Y_t = \sum_{i=1}^t \varepsilon_i$$

Properties of Random Walk

- $\mathbb{E}[Y_t] = 0$ (constant mean)
- $\text{Var}(Y_t) = t\sigma^2$ (variance grows with time!)
- $\text{Cov}(Y_t, Y_{t-k}) = (t - k)\sigma^2$ for $k \leq t$
- ACF: $\rho_k = \sqrt{\frac{t-k}{t}} \rightarrow 1$ as $t \rightarrow \infty$

Definition 2 (Random Walk with Drift)

A random walk with drift includes a constant term:

$$Y_t = \mu + Y_{t-1} + \varepsilon_t$$

Equivalently:

$$Y_t = Y_0 + \mu t + \sum_{i=1}^t \varepsilon_i$$

Properties

- $\mathbb{E}[Y_t] = Y_0 + \mu t$ (mean grows linearly)
- $\text{Var}(Y_t) = t\sigma^2$ (variance still grows)
- The drift μ creates an upward or downward trend
- Still non-stationary despite having a “trend”

Definition 3 (Integrated Process of Order d)

A time series $\{Y_t\}$ is **integrated of order d** , written $Y_t \sim I(d)$, if:

- Y_t is non-stationary
- $(1 - L)^d Y_t = \Delta^d Y_t$ is stationary
- $(1 - L)^{d-1} Y_t$ is still non-stationary

Common Cases

- $I(0)$: Stationary process (e.g., ARMA)
- $I(1)$: First difference is stationary (most common for economic data)
- $I(2)$: Second difference is stationary (less common)

The Difference Operator

Definition 4 (First Difference)

The **first difference operator** Δ is defined as:

$$\Delta Y_t = Y_t - Y_{t-1} = (1 - L)Y_t$$

where L is the lag operator ($LY_t = Y_{t-1}$).

Higher-Order Differences

- Second difference: $\Delta^2 Y_t = \Delta(\Delta Y_t) = (1 - L)^2 Y_t$
- $\Delta^2 Y_t = Y_t - 2Y_{t-1} + Y_{t-2}$
- d -th difference: $\Delta^d Y_t = (1 - L)^d Y_t$

Key Result

If $Y_t \sim I(d)$, then $\Delta^d Y_t \sim I(0)$ (stationary).

Example: Differencing a Random Walk

Random Walk to White Noise

Let $Y_t = Y_{t-1} + \varepsilon_t$ (random walk).

Taking the first difference:

$$\Delta Y_t = Y_t - Y_{t-1} = \varepsilon_t$$

The first difference is white noise – a stationary process!

Interpretation

- A random walk is $I(1)$
- One difference transforms it to $I(0)$
- The “changes” in a random walk are stationary

Overdifferencing

Warning: Overdifferencing

Differencing more than necessary introduces problems:

- Creates artificial negative autocorrelation
- Inflates variance
- Loses information

Example

If $Y_t \sim I(1)$, then $\Delta Y_t \sim I(0)$.

But if we difference again:

$$\Delta^2 Y_t = \Delta Y_t - \Delta Y_{t-1} = \varepsilon_t - \varepsilon_{t-1}$$

This is an MA(1) with $\theta = 1$ (non-invertible boundary)!

Definition 5 (ARIMA(p,d,q))

A time series $\{Y_t\}$ follows an **ARIMA(p,d,q)** process if:

$$\phi(L)(1 - L)^d Y_t = c + \theta(L)\varepsilon_t$$

where:

- $\phi(L) = 1 - \phi_1L - \phi_2L^2 - \dots - \phi_pL^p$ (AR polynomial)
- $\theta(L) = 1 + \theta_1L + \theta_2L^2 + \dots + \theta_qL^q$ (MA polynomial)
- d is the order of integration (number of differences)
- $\varepsilon_t \sim WN(0, \sigma^2)$

ARIMA Components

AR(p)

I(d)

MA(q)

Autoregressive
Memory

Integration
Differencing

Moving Average
Shocks

Special Cases

- ARIMA(p,0,q) = ARMA(p,q) – stationary
- ARIMA(0,1,0) = Random walk
- ARIMA(0,1,1) = IMA(1,1) – exponential smoothing
- ARIMA(1,1,0) = ARI(1,1) – differenced AR(1)

ARI(1,1) Model

$$\Delta Y_t = c + \phi_1 \Delta Y_{t-1} + \varepsilon_t$$

Equivalently:

$$(1 - \phi_1 L)(1 - L)Y_t = c + \varepsilon_t$$

Interpretation

- The **changes** in Y_t follow an AR(1) process
- If $|\phi_1| < 1$, the changes are stationary
- Y_t itself has a stochastic trend
- Common model for many economic time series

IMA(1,1) Model

$$\Delta Y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

Equivalently:

$$(1 - L)Y_t = c + (1 + \theta_1 L)\varepsilon_t$$

Connection to Exponential Smoothing

The IMA(1,1) model is equivalent to **simple exponential smoothing**:

$$\hat{Y}_{t+1} = \alpha Y_t + (1 - \alpha) \hat{Y}_t$$

where $\alpha = 1 + \theta_1$ (for $-1 < \theta_1 < 0$).

Constant Term in ARIMA(p,d,q)

When $d > 0$, the constant c has a different interpretation:

$$\phi(L)(1 - L)^d Y_t = c + \theta(L)\varepsilon_t$$

Important Implications

- For $d = 1$: c represents the **drift** (average change)

$$\mathbb{E}[\Delta Y_t] = \frac{c}{1 - \phi_1 - \dots - \phi_p}$$

- For $d = 2$: c affects the **curvature** of the trend
- Often $c = 0$ is assumed when $d \geq 1$

Why Test?

Before fitting an ARIMA model, we need to determine:

- ① Is the series stationary? (Is $d = 0$?)
- ② If not, how many differences are needed? (What is d ?)

Common Unit Root Tests

- **Dickey-Fuller (DF)** and **Augmented Dickey-Fuller (ADF)**
- **Phillips-Perron (PP)**
- **KPSS** (stationarity test – reversed null hypothesis)

The Dickey-Fuller Test

Setup

Consider the AR(1) model: $Y_t = \phi Y_{t-1} + \varepsilon_t$

Subtract Y_{t-1} from both sides:

$$\Delta Y_t = (\phi - 1) Y_{t-1} + \varepsilon_t = \gamma Y_{t-1} + \varepsilon_t$$

where $\gamma = \phi - 1$.

Hypotheses

- $H_0: \gamma = 0$ (unit root, $\phi = 1$, non-stationary)
- $H_1: \gamma < 0$ (stationary, $|\phi| < 1$)

Key Issue

Under H_0 , the t -statistic does **not** follow a standard t -distribution! Must use Dickey-Fuller critical values.

Three Specifications

- ① No constant, no trend:

$$\Delta Y_t = \gamma Y_{t-1} + \varepsilon_t$$

- ② With constant (drift):

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \varepsilon_t$$

- ③ With constant and trend:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \varepsilon_t$$

Choosing the Right Specification

- Examine the data: does it have a visible trend?
- Including unnecessary terms reduces power
- Excluding necessary terms leads to incorrect inference

Augmented Dickey-Fuller (ADF) Test

The Problem with Simple DF

If the true model has AR dynamics beyond AR(1), the DF test residuals will be autocorrelated, invalidating the test.

Definition 6 (ADF Test)

Add lagged differences to absorb serial correlation:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{j=1}^k \delta_j \Delta Y_{t-j} + \varepsilon_t$$

Test $H_0 : \gamma = 0$ using ADF critical values.

Choosing Lag Length k

- Use information criteria (AIC, BIC)
- Start with k_{max} and reduce until last lag is significant

ADF Test Critical Values

Model	1%	5%	10%
No constant, no trend	-2.58	-1.95	-1.62
With constant	-3.43	-2.86	-2.57
With constant and trend	-3.96	-3.41	-3.13

Table: Asymptotic critical values for ADF test (approximate)

Decision Rule

- If test statistic $<$ critical value \Rightarrow Reject H_0 (stationary)
- If test statistic \geq critical value \Rightarrow Fail to reject H_0 (unit root)

The KPSS Test

Reversed Hypotheses

Unlike ADF, the KPSS test has:

- H_0 : Series is stationary (possibly around a trend)
- H_1 : Series has a unit root

KPSS Procedure

Decompose: $Y_t = \xi t + r_t + \varepsilon_t$

where $r_t = r_{t-1} + u_t$ is a random walk.

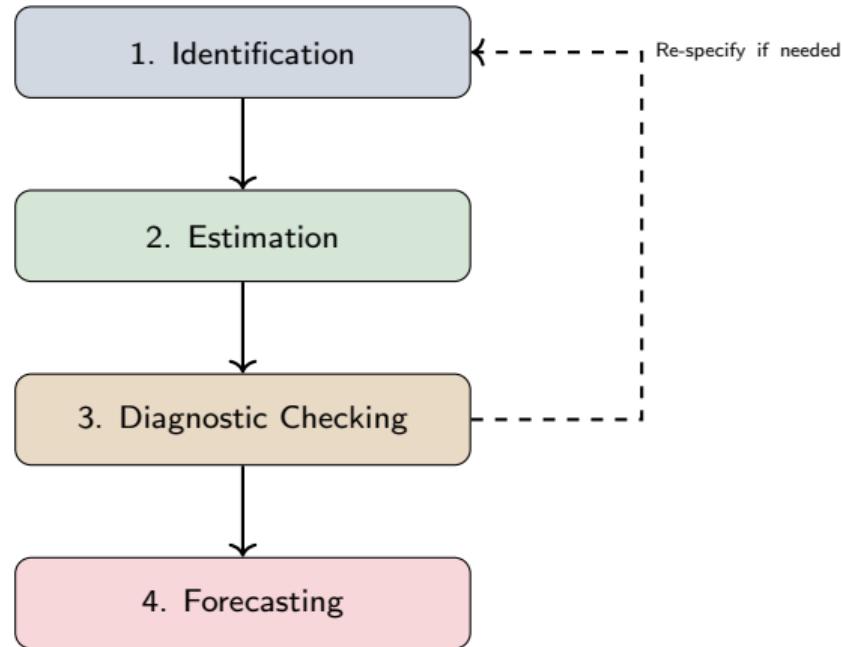
Test whether $\text{Var}(u_t) = 0$ (stationarity).

Complementary Use

Use ADF and KPSS together:

- ADF rejects, KPSS doesn't reject \Rightarrow Stationary
- ADF doesn't reject, KPSS rejects \Rightarrow Unit root
- Both reject or neither \Rightarrow Inconclusive

The Box-Jenkins Methodology



Step 1: Determining d

Procedure

- ① Plot the time series – look for trends, changing variance
- ② Examine ACF – slow decay suggests non-stationarity
- ③ Apply unit root tests (ADF, KPSS)
- ④ If non-stationary, difference and repeat

Practical Guidelines

- Most economic series: $d = 1$ is sufficient
- Rarely need $d > 2$
- If ACF of ΔY_t still decays slowly, try $d = 2$
- Watch for overdifferencing (ACF with $\rho_1 \approx -0.5$)

Step 2: Determining p and q

After Differencing

Once $W_t = \Delta^d Y_t$ is stationary, use ACF/PACF to identify ARMA(p,q):

Model	ACF	PACF
AR(p)	Decays exponentially	Cuts off after lag p
MA(q)	Cuts off after lag q	Decays exponentially
ARMA(p,q)	Decays	Decays

Information Criteria

When patterns are unclear, compare models using:

- AIC = $-2 \ln(L) + 2k$
- BIC = $-2 \ln(L) + k \ln(n)$

Lower is better. BIC penalizes complexity more.

Automated Model Selection

Modern software can automatically select (p, d, q) :

- Python: `pmdarima.auto_arima()`
- R: `forecast::auto.arima()`

How Auto-ARIMA Works

- ① Use unit root tests to determine d
- ② Fit models for various (p, q) combinations
- ③ Select model with lowest AIC/BIC
- ④ Optionally use stepwise search for efficiency

Caution

Automated selection is helpful but not infallible. Always check diagnostics!

Maximum Likelihood Estimation (MLE)

The standard approach for ARIMA:

- Assumes $\varepsilon_t \sim N(0, \sigma^2)$
- Maximizes the likelihood function
- Provides consistent, efficient estimators
- Yields standard errors for inference

Conditional vs Exact MLE

- **Conditional MLE:** Conditions on initial values
- **Exact MLE:** Treats initial values as unknown
- Difference diminishes as sample size grows

Stationarity and Invertibility

The estimated ARIMA model should satisfy:

- **AR stationarity:** Roots of $\phi(z) = 0$ outside unit circle
- **MA invertibility:** Roots of $\theta(z) = 0$ outside unit circle

Checking in Practice

Most software reports:

- Estimated coefficients with standard errors
- Roots of AR and MA polynomials
- Warning if near-unit-root detected

What to Check

If the model is correct, residuals $\hat{\varepsilon}_t$ should be white noise:

- ① Zero mean
- ② Constant variance
- ③ No autocorrelation
- ④ (Optional) Normality

Diagnostic Tools

- **Residual ACF/PACF:** Should show no significant spikes
- **Ljung-Box test:** Tests for autocorrelation at multiple lags
- **Q-Q plot:** Checks normality assumption
- **Residual vs fitted:** Checks for heteroskedasticity

The Ljung-Box Test

Definition 7 (Ljung-Box Q Statistic)

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

Under H_0 (no autocorrelation): $Q(m) \sim \chi^2(m - p - q)$

Usage

- Choose $m \approx \ln(n)$ or $m = 10$ for quarterly, $m = 20$ for monthly
- Degrees of freedom adjusted for estimated parameters
- Reject if $Q(m)$ exceeds critical value

If Test Fails

Consider adding AR or MA terms, or check for structural breaks.

Minimum MSE Forecast

The optimal h -step ahead forecast is the conditional expectation:

$$\hat{Y}_{T+h|T} = \mathbb{E}[Y_{T+h} | Y_T, Y_{T-1}, \dots]$$

ARIMA(1,1,1) Forecasting

Model: $(1 - \phi_1 L)(1 - L)Y_t = c + (1 + \theta_1 L)\varepsilon_t$

One-step forecast:

$$\hat{Y}_{T+1|T} = c + Y_T + \phi_1(Y_T - Y_{T-1}) + \theta_1 \hat{\varepsilon}_T$$

For $h > 1$: replace unknown ε_{T+j} with 0, unknown Y_{T+j} with $\hat{Y}_{T+j|T}$

Forecast Intervals

Forecast Uncertainty

The h -step forecast error variance:

$$\text{Var}(e_{T+h}) = \sigma^2 \sum_{j=0}^{h-1} \psi_j^2$$

where ψ_j are MA(∞) coefficients.

Confidence Intervals

Under normality, $(1 - \alpha)\%$ interval:

$$\hat{Y}_{T+h|T} \pm z_{\alpha/2} \sqrt{\text{Var}(e_{T+h})}$$

Key Property for I(1) Series

For integrated processes, forecast variance grows without bound as $h \rightarrow \infty$. Intervals widen over time!

Behavior as $h \rightarrow \infty$

For ARIMA(p,1,q) with drift c :

- Point forecasts: Linear trend with slope = drift
- Forecast intervals: Width grows with \sqrt{h}

For ARIMA(p,1,q) without drift:

- Point forecasts: Converge to last level
- Forecast intervals: Still grow unboundedly

Practical Implication

ARIMA forecasts are most reliable for short horizons. Long-term forecasts have very wide uncertainty bands.

Example: Modeling GDP Growth

Typical Workflow

- ① **Plot:** Observe trend in $\log(\text{GDP})$
- ② **Test:** ADF suggests $I(1)$
- ③ **Difference:** Work with GDP growth rate
- ④ **Identify:** ACF/PACF suggest ARIMA(1,1,0) or ARIMA(0,1,1)
- ⑤ **Estimate:** Fit both, compare AIC
- ⑥ **Diagnose:** Check residuals
- ⑦ **Forecast:** Generate predictions with intervals

Python Implementation

Key Libraries

```
import pandas as pd
import numpy as np
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import adfuller, kpss
import pmdarima as pm
```

Auto-ARIMA Example

```
# Automatic model selection
model = pm.auto_arima(y, start_p=0, start_q=0,
                      max_p=3, max_q=3, d=None,
                      seasonal=False, trace=True,
                      error_action='ignore')
print(model.summary())
```

Key Takeaways

Main Points

- ① **Non-stationarity** is common in economic data – must be addressed
- ② **Differencing** transforms $I(d)$ to $I(0)$
- ③ **ARIMA(p,d,q)** combines differencing with ARMA modeling
- ④ **Unit root tests** (ADF, KPSS) help determine d
- ⑤ **Box-Jenkins methodology:** Identify → Estimate → Diagnose
- ⑥ **Forecasts** for $I(1)$ series have growing uncertainty

Next Steps

Chapter 4 will extend ARIMA to handle seasonality: SARIMA models.

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