



Chapter 1: Introduction to Time Series

Fundamentals and Concepts



Learning Objectives

By the end of this chapter, you will be able to:

1. **Define** time series and distinguish from cross-sectional and panel data
2. **Decompose** time series into trend, seasonal, and residual components
3. **Apply** exponential smoothing (SES, Holt, Holt-Winters, ETS)
4. **Evaluate** forecasts using MAE, RMSE, MAPE; train/validation/test splits
5. **Model** seasonality using dummy variables or Fourier terms
6. **Handle** trend and seasonality through detrending and adjustment
7. **Understand** stochastic processes and stationarity
8. **Compute** ACF/PACF and conduct stationarity tests (ADF, KPSS)

Chapter Outline

- 1 What is a Time Series?
- 2 Time Series Decomposition
- 3 Exponential Smoothing Methods
- 4 Forecast Evaluation
- 5 Modeling Seasonality
- 6 Handling Trend and Seasonality
- 7 Stochastic Processes
- 8 Stationarity
- 9 White Noise and Random Walk
- 10 Autocorrelation Functions
- 11 Lag Operator and Differencing
- 12 Testing for Stationarity
- 13 Financial Data Application
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Definition 1 (Time Series)

A **time series** is a sequence of observations $\{X_t\}$ indexed by time:

$$\{X_t : t \in \mathcal{T}\}$$

where \mathcal{T} is an index set representing time points.

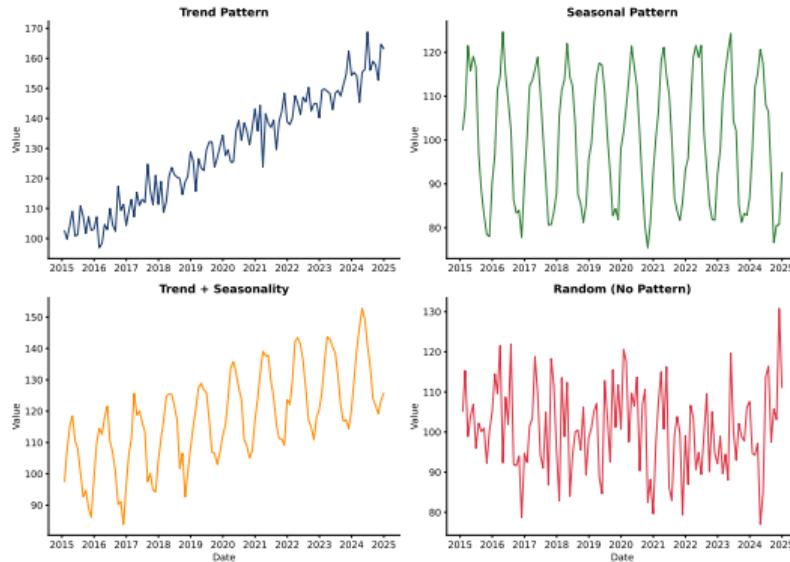
Key characteristics:

- **Ordered:** Observations have a natural temporal ordering
- **Dependent:** Consecutive observations are typically correlated
- **Discrete or Continuous:** Time index can be discrete ($t = 1, 2, 3, \dots$) or continuous

Notation:

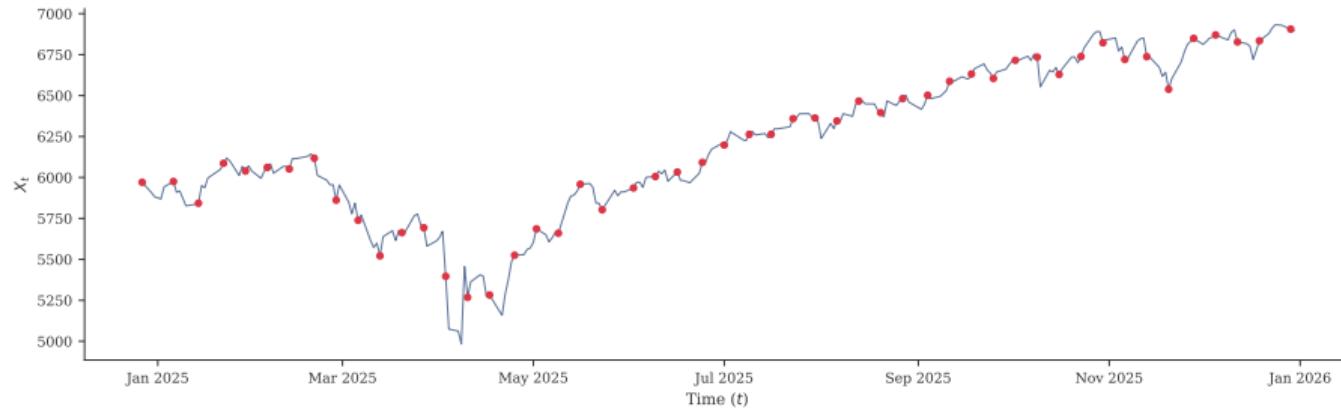
- X_t = observation at time t
- $\{X_t\}_{t=1}^T$ = finite time series with T observations

Common Time Series Patterns



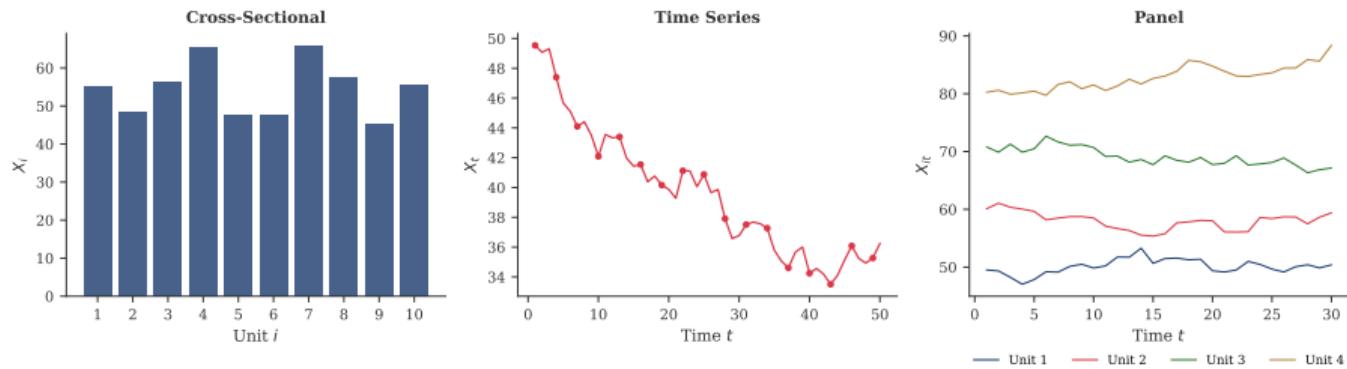
- **Trend:** Long-term increase or decrease in the data
- **Seasonal:** Regular periodic patterns (e.g., monthly, quarterly)
- **Random:** No systematic pattern – unpredictable fluctuations

Time Series: Visual Definition



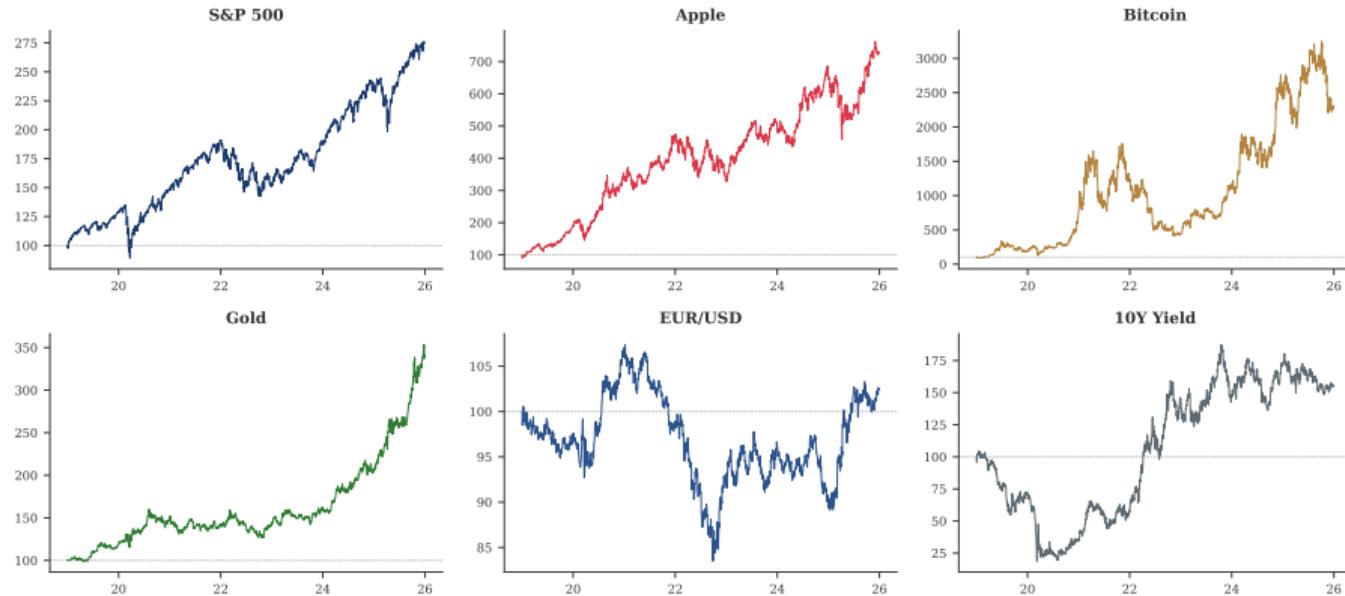
Each point X_t represents a measurement at discrete time t . Data: S&P 500 (2024).

Types of Data: Comparison



Data Type	Units (N)	Time (T)	Example
Cross-sectional	Many	1	Survey of 1000 households
Time series	1	Many	Daily S&P 500 prices
Panel	Many	Many	GDP of 50 countries, 20 years

Examples of Time Series Data



Real financial data from Yahoo Finance (2019–2025). Normalized to base 100.

Why Decompose a Time Series?

Decomposition separates a time series into interpretable components:

Goals:

- Understand underlying patterns
- Remove seasonality for modeling
- Identify trend direction
- Isolate irregular fluctuations
- Improve forecasting accuracy

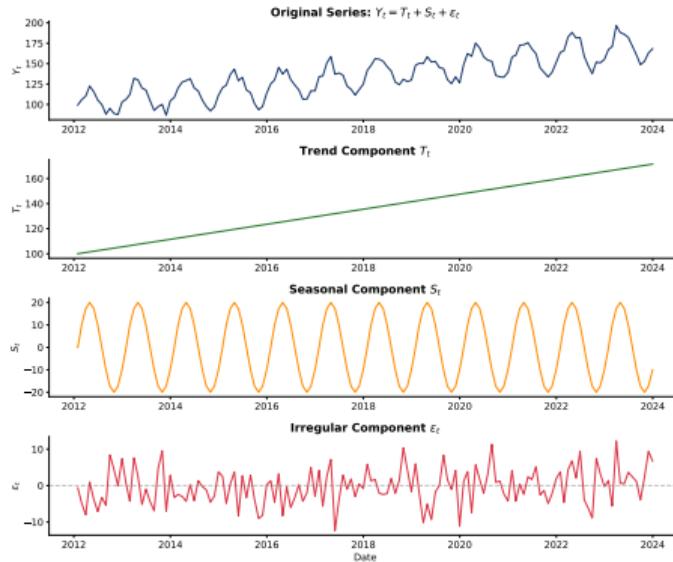
Components:

- T_t = **Trend**: Long-term movement
- S_t = **Seasonal**: Regular periodic pattern
- C_t = **Cyclical**: Business cycle fluctuations
- ε_t = **Residual**: Random noise

Classical Decomposition Models

- **Additive**: $X_t = T_t + S_t + \varepsilon_t$
- **Multiplicative**: $X_t = T_t \times S_t \times \varepsilon_t$

Time Series Decomposition: Visual Example



- **Original:** The observed time series with all components
- **Trend:** Underlying long-term movement extracted via smoothing
- **Seasonal:** Regular periodic pattern that repeats each cycle
- **Residual:** Random noise after removing trend and seasonality

The Cyclical Component

Cyclical component C_t : Medium-term fluctuations (2–10 years)

Characteristics:

- Business cycle fluctuations
- No fixed period (unlike seasonal)
- Duration varies: 2–10 years
- Amplitude varies over time

Examples:

- Economic expansions/recessions
- Credit cycles
- Real estate cycles
- Commodity price cycles

Practical Note

Often combined with trend as **trend-cycle** component because:

- Difficult to separate from trend with short data
- Many decomposition methods estimate $T_t + C_t$ together

Additive Decomposition Model

Formula: $X_t = T_t + S_t + \varepsilon_t$

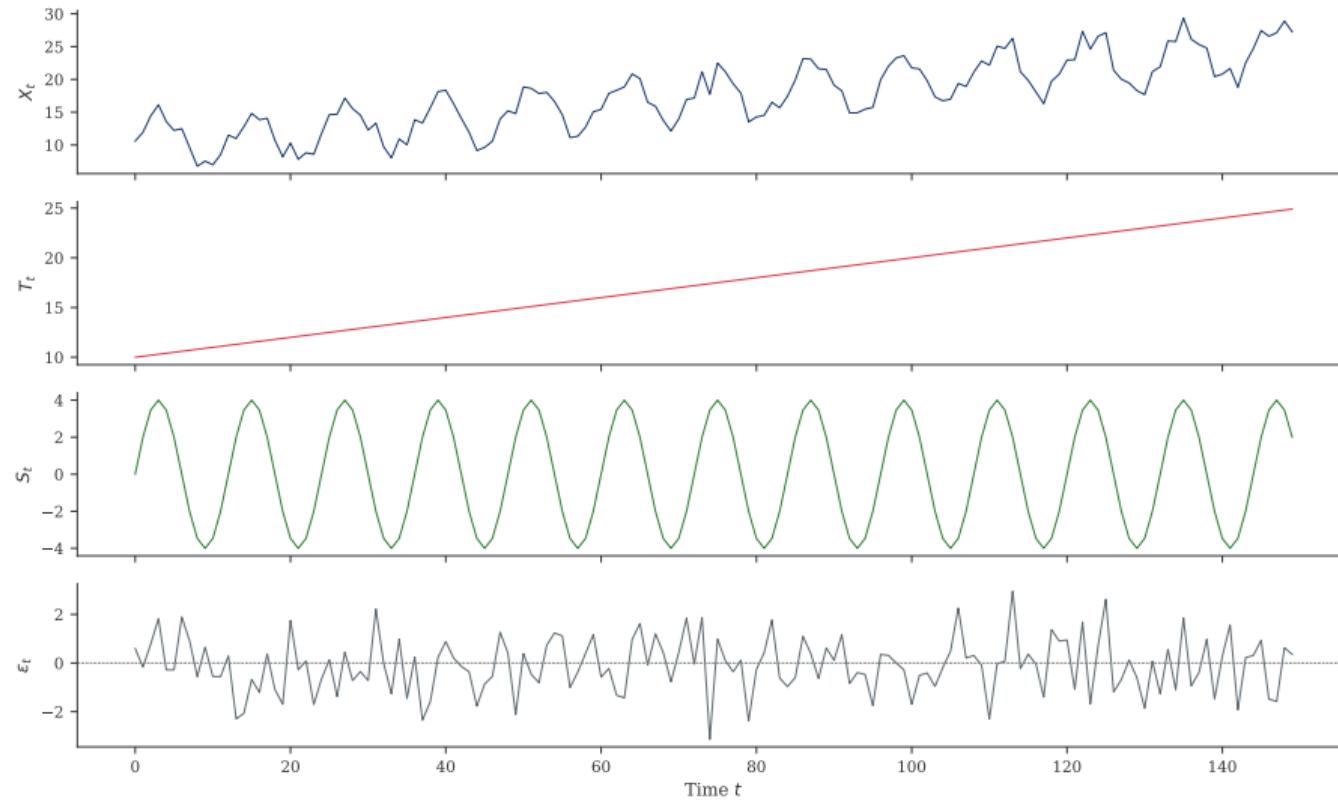
When to use:

- Seasonal fluctuations are **constant** over time
- Variance of the series is **stable**

Properties:

- $\mathbb{E}[\varepsilon_t] = 0$ (zero mean residuals)
- $\sum_{j=1}^s S_j = 0$ (seasonal sums to zero)
- Units of S_t same as X_t

Additive Decomposition: Visualization



Multiplicative Decomposition Model

Formula: $X_t = T_t \times S_t \times \varepsilon_t$

When to use:

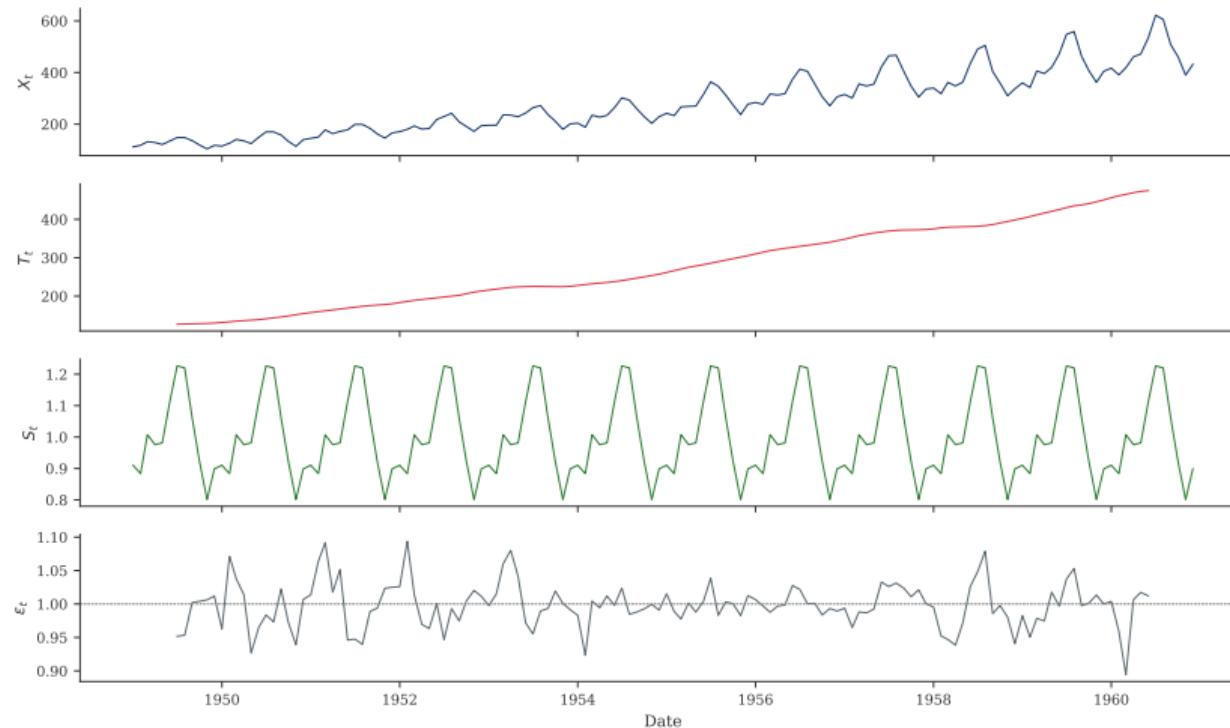
- Seasonal fluctuations **grow** with series level
- Variance **increases** over time

Properties:

- $\mathbb{E}[\varepsilon_t] = 1$ (residuals centered at 1)
- $\frac{1}{s} \sum S_j = 1$ (seasonal averages to 1)
- S_t is a ratio (dimensionless)

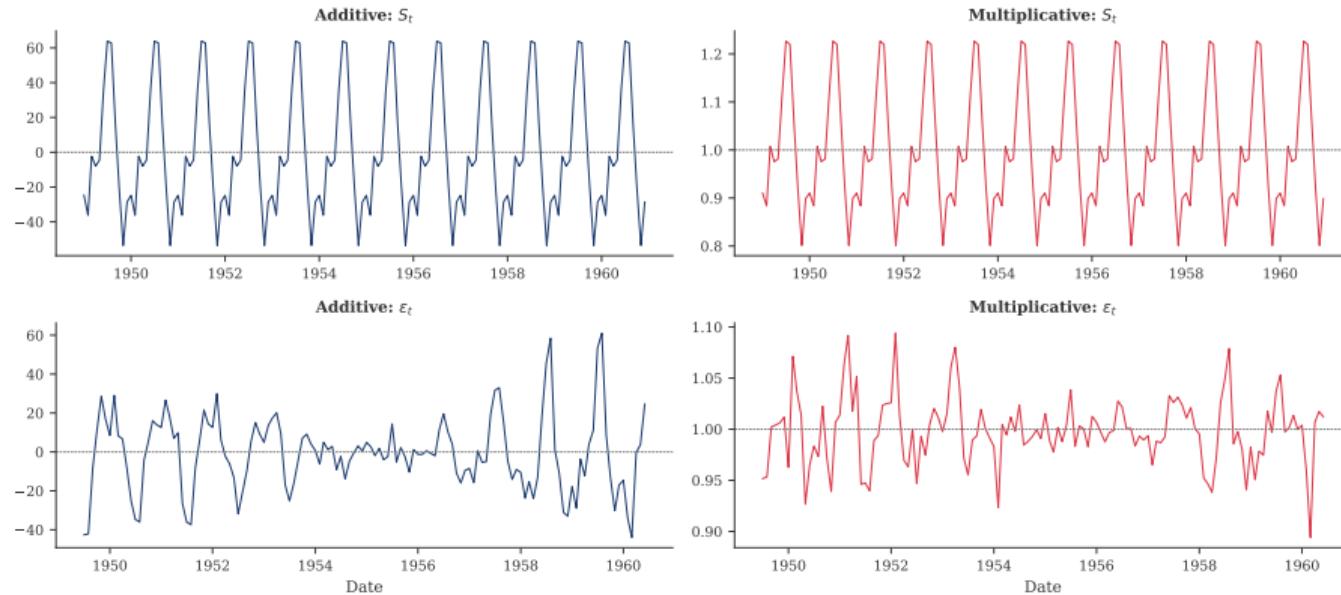
Tip: Log transform converts to additive model.

Multiplicative Decomposition: Real Data



Classic Box-Jenkins airline passengers dataset (1949–1960).

Additive vs Multiplicative: Comparison



Key difference: In multiplicative model, seasonal component is a *ratio* (centered at 1), while in additive model it's in *absolute units* (centered at 0).

Definition 2 (Centered Moving Average)

The **centered moving average** of order $2q + 1$ is:

$$\hat{T}_t = \frac{1}{2q+1} \sum_{j=-q}^q X_{t+j}$$

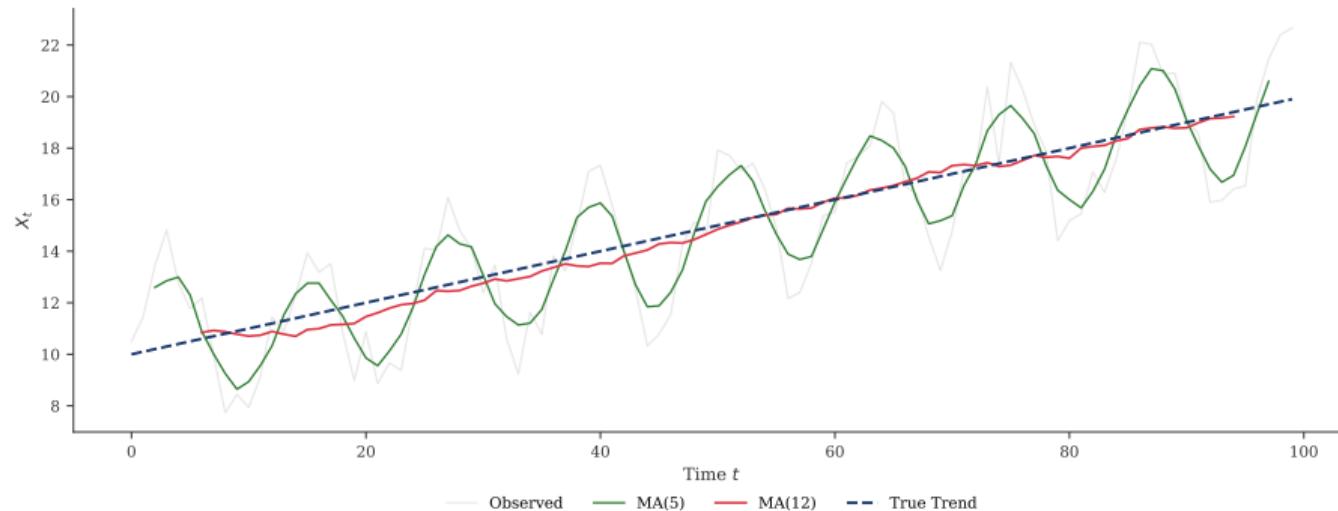
For seasonal data:

- If period s is **odd**: simple average over s observations
- If period s is **even** (e.g., 12): use $2 \times s$ MA with half-weights at ends

Properties:

- Smooths out seasonal and random fluctuations
- Larger window \Rightarrow smoother trend
- Trade-off: lose data at endpoints

Moving Average: Effect of Window Size



Larger window sizes produce smoother trends but lose more data at boundaries.

Classical Decomposition Algorithm

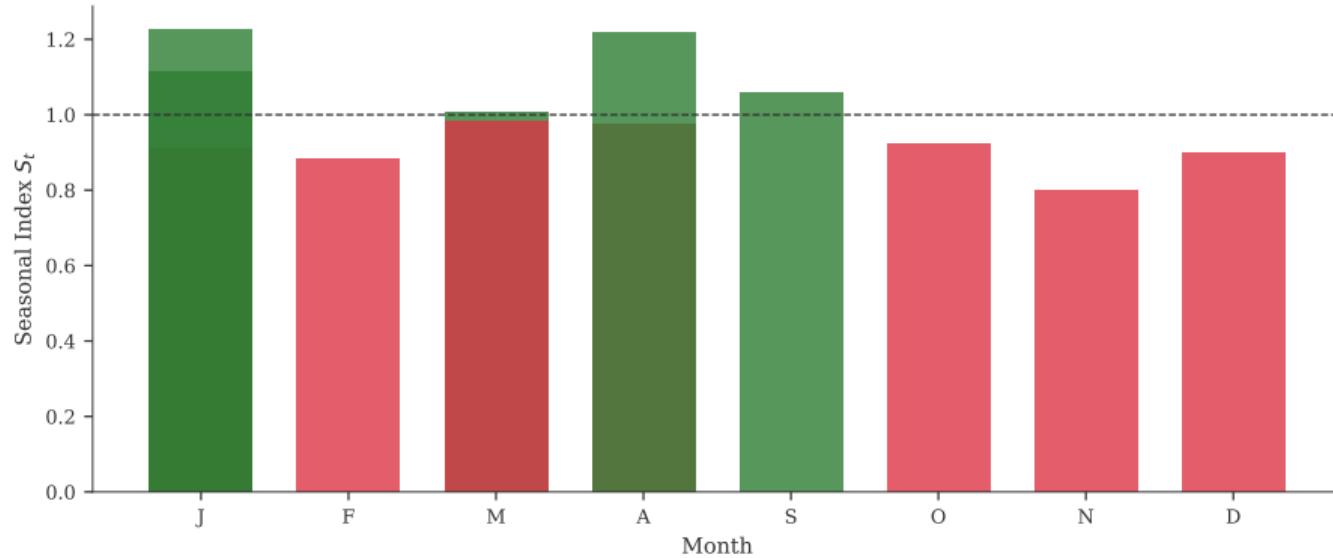
Steps for Multiplicative Decomposition:

- ① **Estimate Trend:** $\hat{T}_t = MA_s(X_t)$
- ② **Detrend:** $D_t = X_t / \hat{T}_t$
- ③ **Estimate Seasonal:** Average D_t for each season j

$$\hat{S}_j = \text{mean}(D_t \text{ for all } t \text{ in season } j)$$

- ④ **Normalize:** Scale so $\frac{1}{s} \sum_{j=1}^s \hat{S}_j = 1$
- ⑤ **Compute Residuals:** $\hat{\varepsilon}_t = X_t / (\hat{T}_t \times \hat{S}_t)$

Seasonal Indices: Interpretation



Interpretation: $S_t > 1$ means above-average activity; $S_t < 1$ means below-average. Airline data shows peak travel in July–August.

Definition 3 (STL - Seasonal-Trend decomposition using LOESS)

STL uses locally weighted regression (LOESS) to estimate components:

$$X_t = T_t + S_t + R_t$$

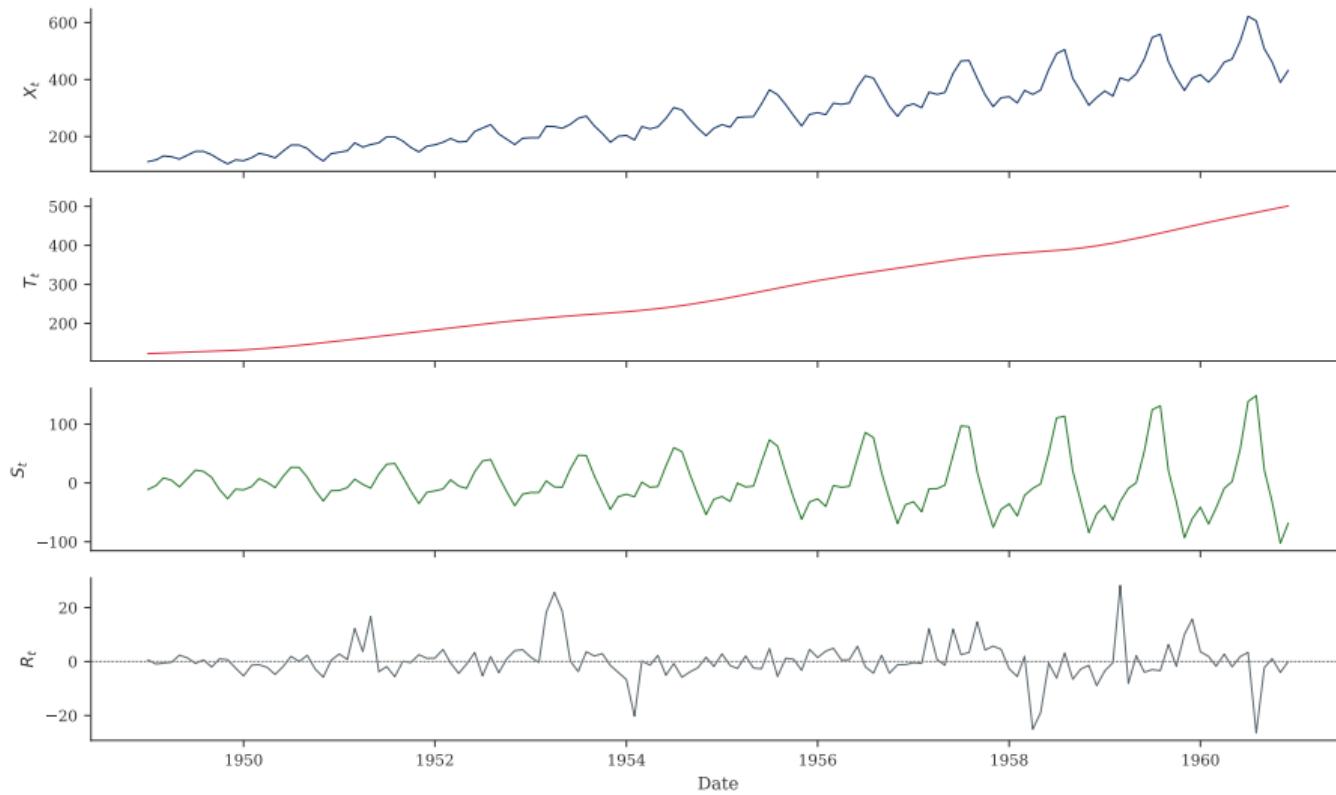
Advantages over classical decomposition:

- Handles **any seasonal period** (not just 4 or 12)
- Seasonal component can **change over time**
- **Robust** to outliers (with robust=True option)
- Provides **smooth** trend estimates

Key parameters:

- **period**: Seasonal period (e.g., 12 for monthly)
- **seasonal**: Window for seasonal smoothing (odd integer)
- **robust**: Use robust fitting to downweight outliers

STL Decomposition: Example



Exponential Smoothing: Overview

Exponential smoothing methods produce forecasts based on weighted averages of past observations, with weights decaying exponentially.

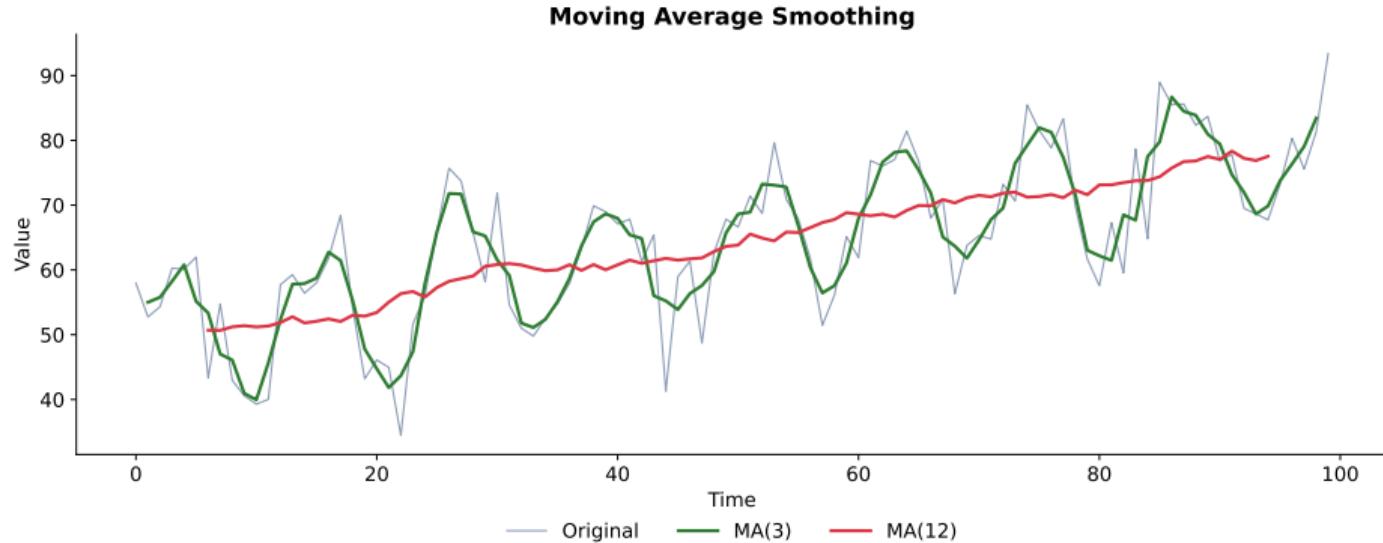
Why Exponential Smoothing?

- Simple yet effective forecasting methods
- More recent observations get higher weights
- Handles trend and seasonality
- Foundation for ETS models

Three main methods:

- ① **Simple Exponential Smoothing (SES)**: Level only
- ② **Holt's Method**: Level + Trend
- ③ **Holt-Winters**: Level + Trend + Seasonality

Moving Average Smoothing



- **Small window** (e.g., 5): Responsive to changes but noisy
- **Large window** (e.g., 30): Smoother but slower to react
- Trade-off between noise reduction and lag in detecting changes

Simple Exponential Smoothing (SES)

Forecast: $\hat{X}_{t+1|t} = \alpha X_t + (1 - \alpha) \hat{X}_{t|t-1}$

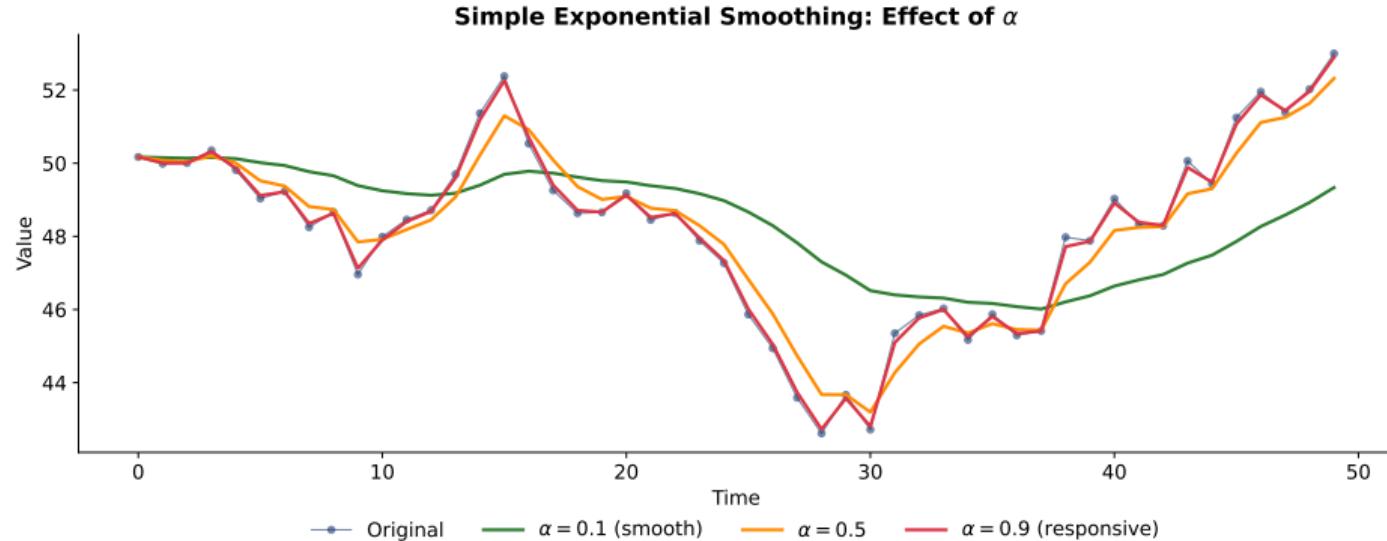
where $\alpha \in (0, 1)$ is the **smoothing parameter**.

How it works:

- Weights decay exponentially into the past
- Large α : responsive to recent changes
- Small α : smoother, more stable forecasts

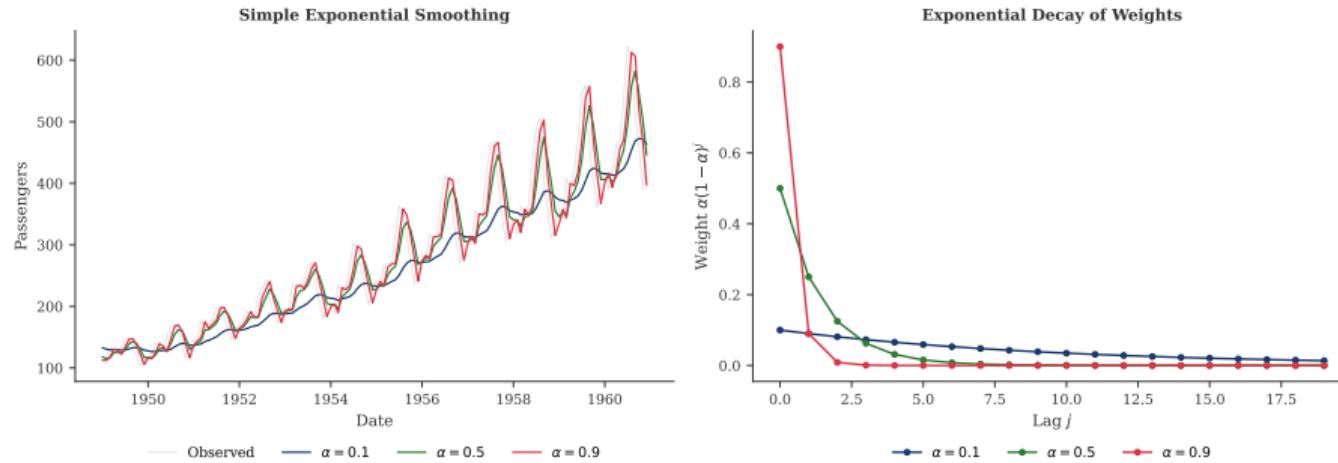
Level form: $\ell_t = \alpha X_t + (1 - \alpha) \ell_{t-1}$

Exponential Smoothing: Effect of Alpha



- **Low α** (e.g., 0.1): More weight on past – smoother, slower adaptation
- **High α** (e.g., 0.9): More weight on recent – responsive, more volatile
- Choose α based on how quickly the underlying process changes

Simple Exponential Smoothing: Effect of α



Smaller α produces smoother forecasts; larger α follows data more closely.

Holt's Linear Trend Method

Extends SES to capture **linear trend** using two equations:

Level: $\ell_t = \alpha X_t + (1 - \alpha)(\ell_{t-1} + b_{t-1})$

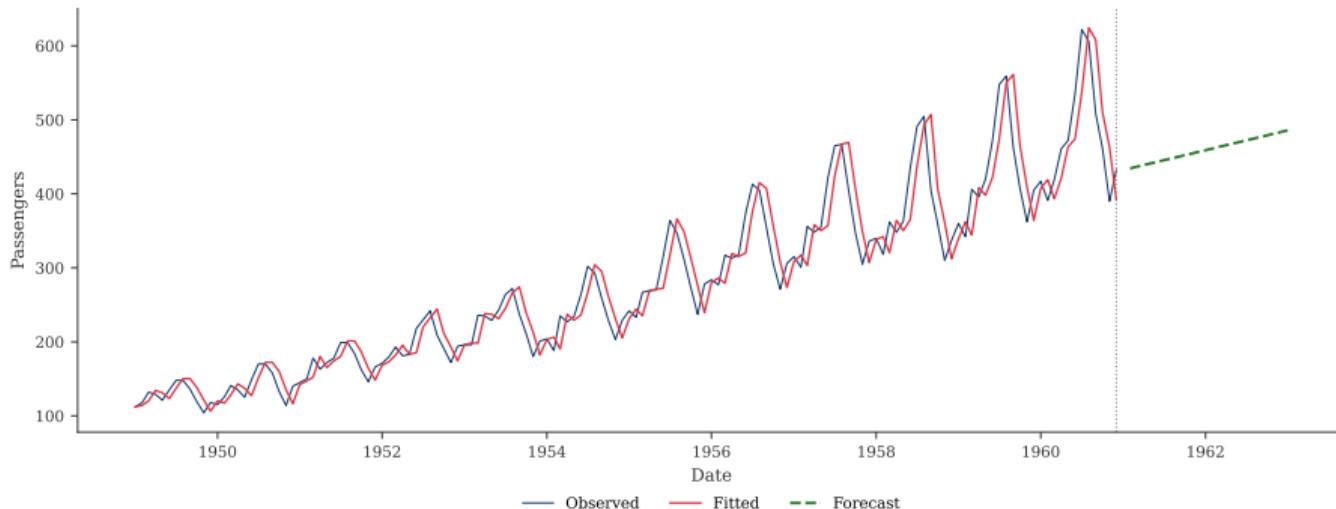
Trend: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$

Forecast: $\hat{X}_{t+h|t} = \ell_t + h \cdot b_t$

Parameters:

- $\alpha \in (0, 1)$: Level smoothing parameter
- $\beta^* \in (0, 1)$: Trend smoothing parameter
- ℓ_t : Estimated level at time t
- b_t : Estimated trend (slope) at time t

Holt's Method: Visualization



Holt's method captures both level and trend, projecting them into the forecast horizon.

Holt-Winters Seasonal Method

Extends Holt's method to include **seasonality** with three equations:

Level: $\ell_t = \alpha(X_t - S_{t-s}) + (1 - \alpha)(\ell_{t-1} + b_{t-1})$

Trend: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$

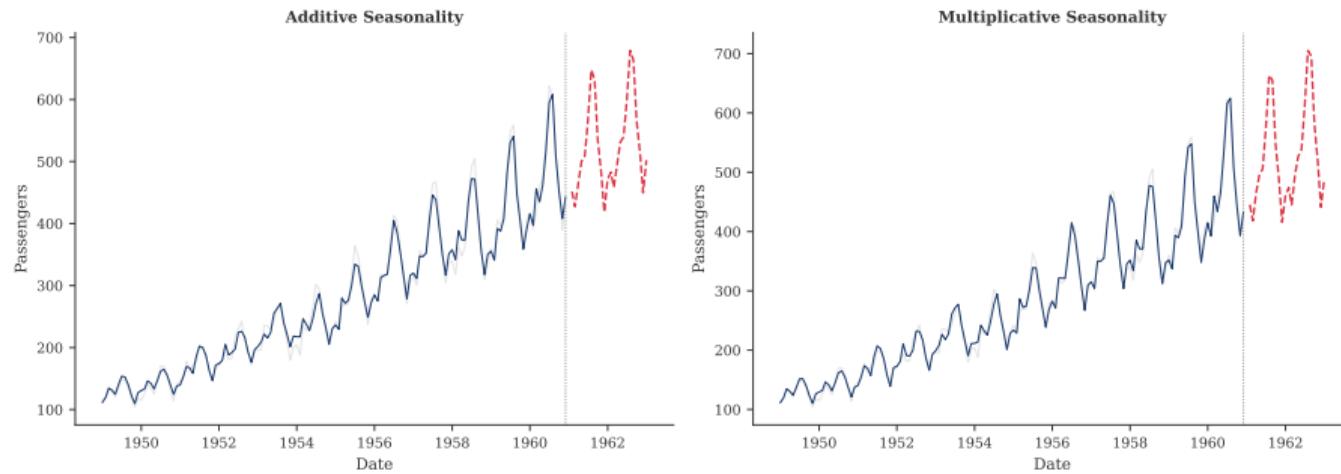
Seasonal: $S_t = \gamma(X_t - \ell_t) + (1 - \gamma)S_{t-s}$

Forecast: $\hat{X}_{t+h|t} = \ell_t + h \cdot b_t + S_{t+h-s(k+1)}$

Parameters:

- α : Level smoothing
- β^* : Trend smoothing
- γ : Seasonal smoothing
- s : Seasonal period (e.g., 12 for monthly)

Holt-Winters: Capturing Seasonality



Holt-Winters decomposes the series and produces seasonal forecasts.

Definition 4 (ETS Models)

The **ETS framework** generalizes exponential smoothing with explicit error structure:

$$\text{ETS}(E, T, S)$$

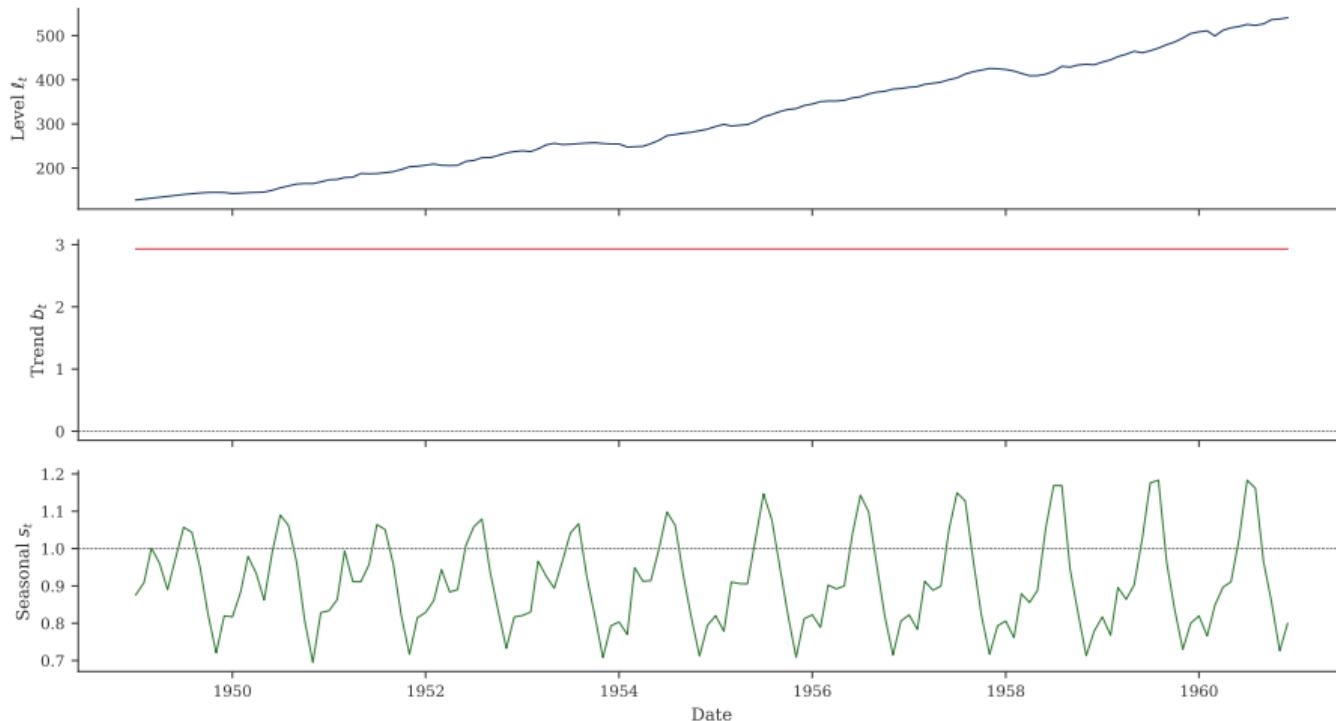
where each component can be:

Component	N	A	M
Error (E)	—	Additive	Multiplicative
Trend (T)	None	Additive	Multiplicative
Seasonal (S)	None	Additive	Multiplicative

Examples:

- $\text{ETS}(A,N,N) = \text{Simple Exponential Smoothing}$
- $\text{ETS}(A,A,N) = \text{Holt's Linear Method}$
- $\text{ETS}(A,A,A) = \text{Holt-Winters Additive}$
- $\text{ETS}(M,A,M) = \text{Multiplicative errors, additive trend, multiplicative seasonal}$

ETS Model Selection



The ETS framework provides a systematic way to choose the best model using AIC/BIC.

Damped Trend Methods

Introduces **damping parameter** $\phi \in (0, 1)$ to prevent over-projection:

Level: $\ell_t = \alpha X_t + (1 - \alpha)(\ell_{t-1} + \phi b_{t-1})$

Trend: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)\phi b_{t-1}$

Forecast: $\hat{X}_{t+h|t} = \ell_t + \phi \frac{1-\phi^h}{1-\phi} b_t$

Key insight:

- As $h \rightarrow \infty$: forecast $\rightarrow \ell_t + \frac{\phi}{1-\phi} b_t$ (constant)
- Prevents unrealistic long-term extrapolation
- Often best for longer forecast horizons

Forecast Accuracy Metrics

Forecast Error: $e_t = X_t - \hat{X}_t$ (actual minus predicted)

Scale-Dependent:

- MAE = $\frac{1}{n} \sum |e_t|$
- MSE = $\frac{1}{n} \sum e_t^2$
- RMSE = $\sqrt{\text{MSE}}$

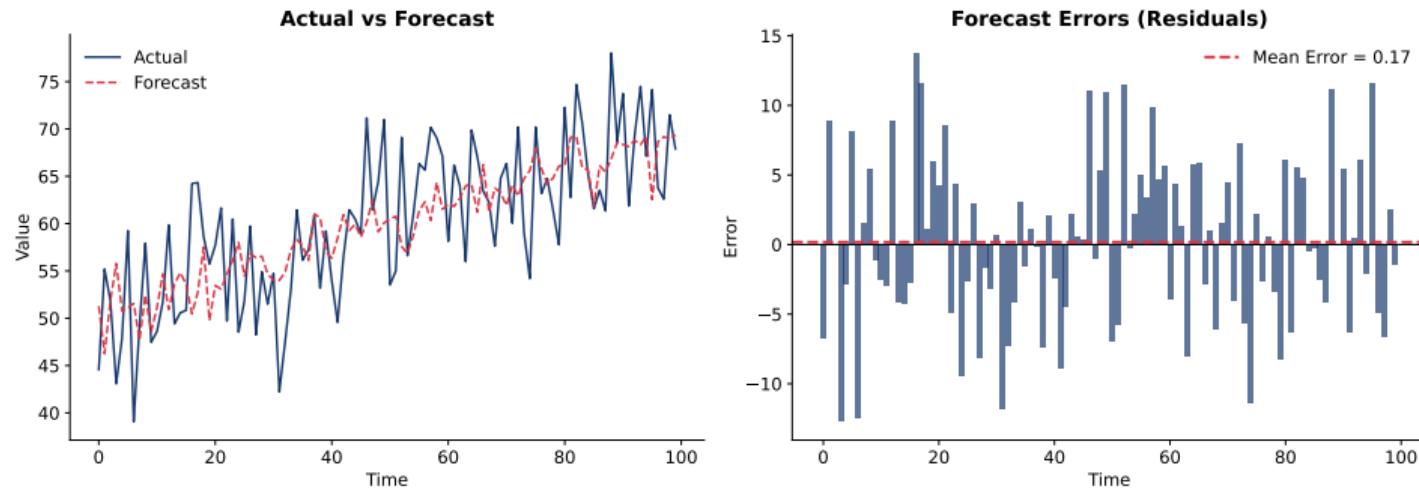
Scale-Independent:

- MAPE = $\frac{100}{n} \sum \left| \frac{e_t}{X_t} \right|$
- sMAPE (symmetric)

Which to use?

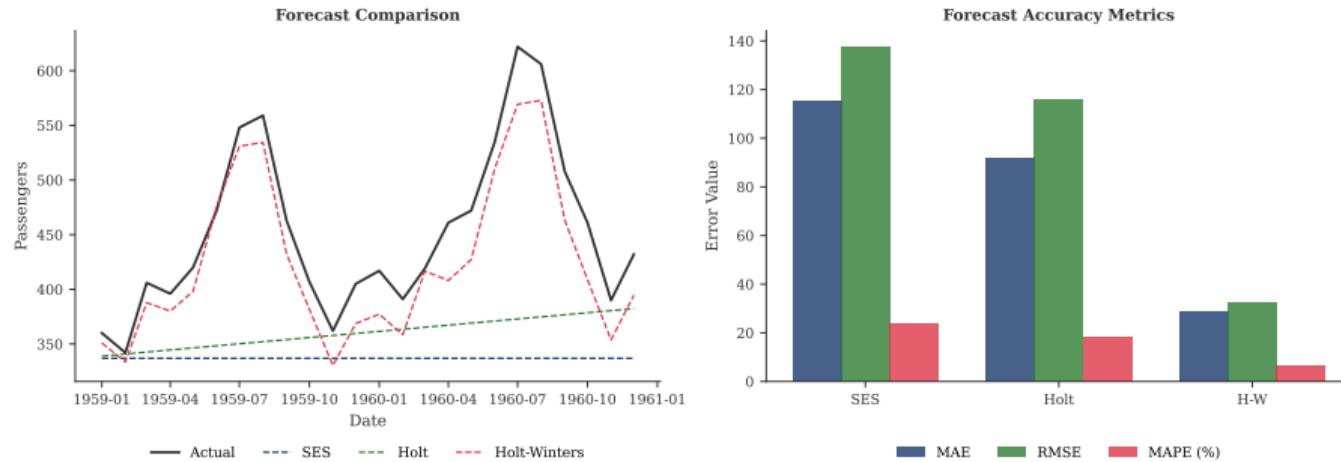
- Same series: RMSE, MAE
- Compare across series: MAPE, sMAPE

Forecast Evaluation: Visual Example



- **Top:** Actual values vs. forecasted values – visual assessment of fit
- **Bottom:** Residuals should be centered around zero with no pattern
- Good forecasts have small, random residuals with constant variance

Comparing Forecast Methods



Left: Comparing SES, Holt, and Holt-Winters forecasts. **Right:** Error metrics for each method.

Residual Diagnostics

Good forecasts should have residuals that are:

- ① **Zero mean:** $\mathbb{E}[e_t] = 0$ (unbiased)
- ② **Uncorrelated:** $\text{Cov}(e_t, e_{t-k}) = 0$ for $k \neq 0$
- ③ **Constant variance:** $\text{Var}(e_t) = \sigma^2$ (homoscedastic)
- ④ **Normally distributed:** $e_t \sim N(0, \sigma^2)$ (for prediction intervals)

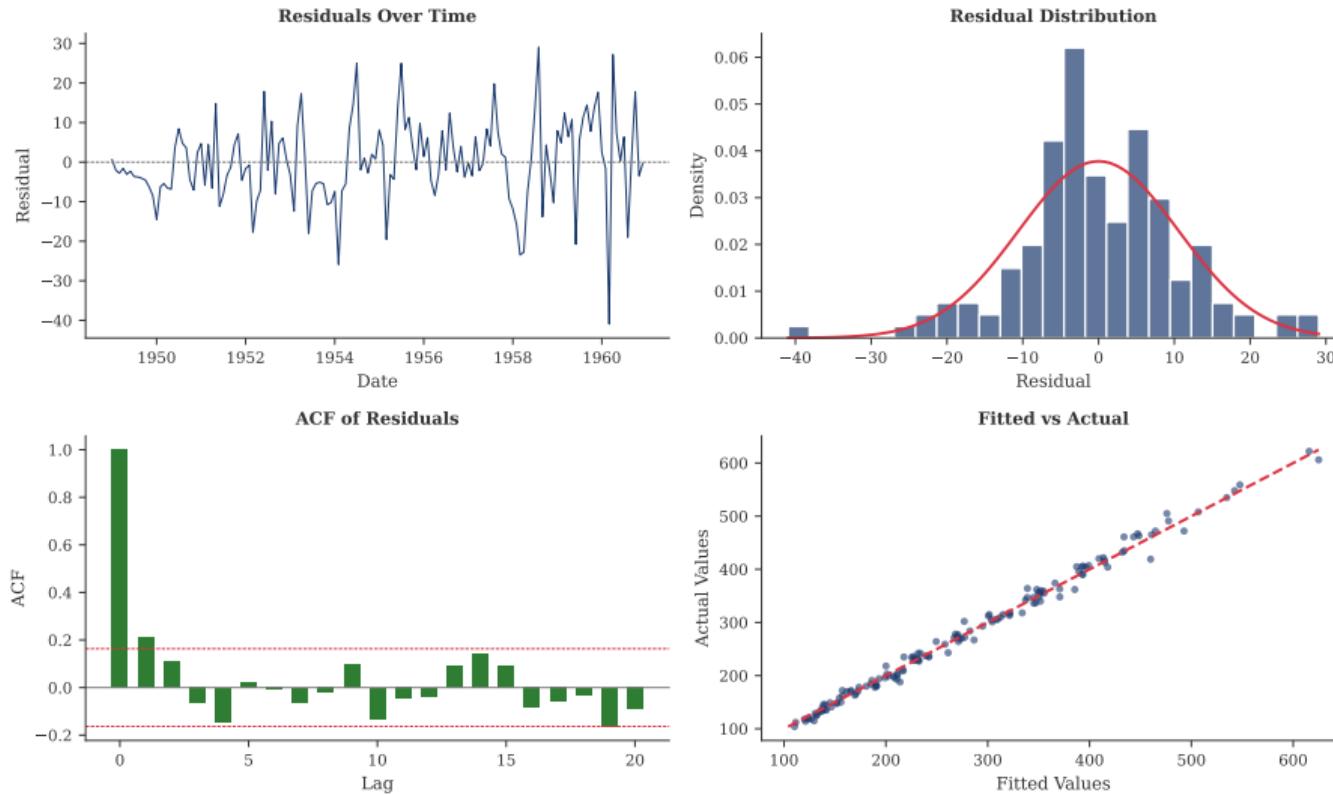
Diagnostic tests:

- **Ljung-Box test:** Tests for autocorrelation in residuals

$$Q = T(T+2) \sum_{k=1}^h \frac{\hat{\rho}_k^2}{T-k} \sim \chi_h^2$$

- **Jarque-Bera test:** Tests for normality

Residual Diagnostics: Visualization

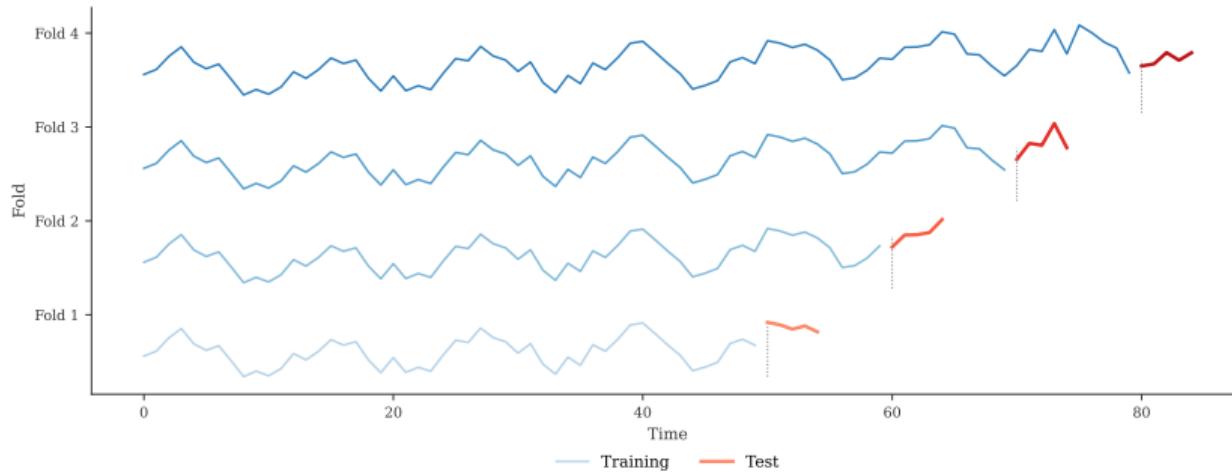


Time Series Cross-Validation

Standard CV doesn't work for time series (temporal dependence).

Rolling Origin CV: Expanding windows

- ① Train on $\{X_1, \dots, X_t\}$, forecast \hat{X}_{t+h}
- ② Increment t , repeat



Train / Validation / Test Split

Three-way split for model development:

Training Set

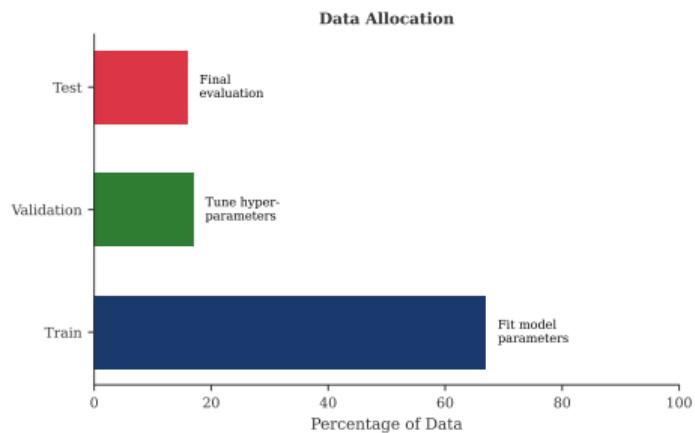
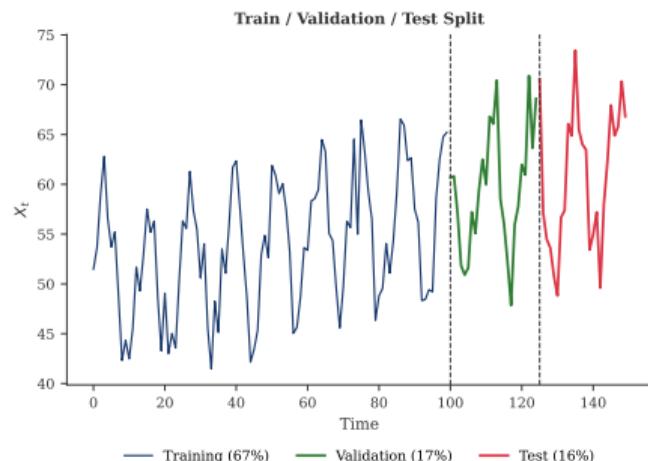
- Fit model parameters
- Largest portion (60–80%)
- Used for estimation

Validation Set

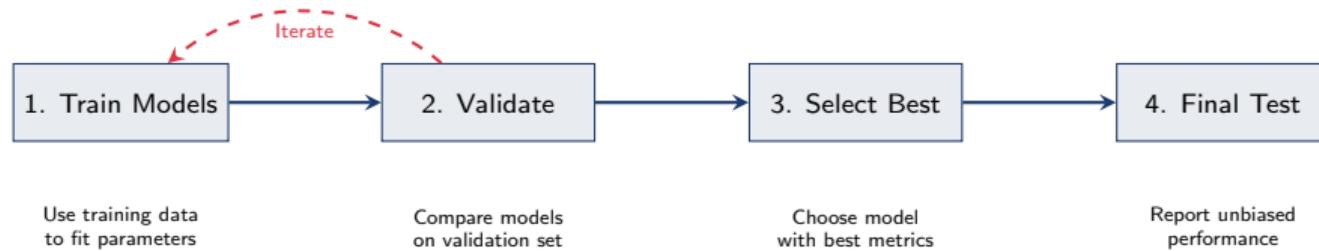
- Tune hyperparameters
- Compare models
- Select best approach

Test Set

- Final evaluation only
- Never used for tuning
- Unbiased performance



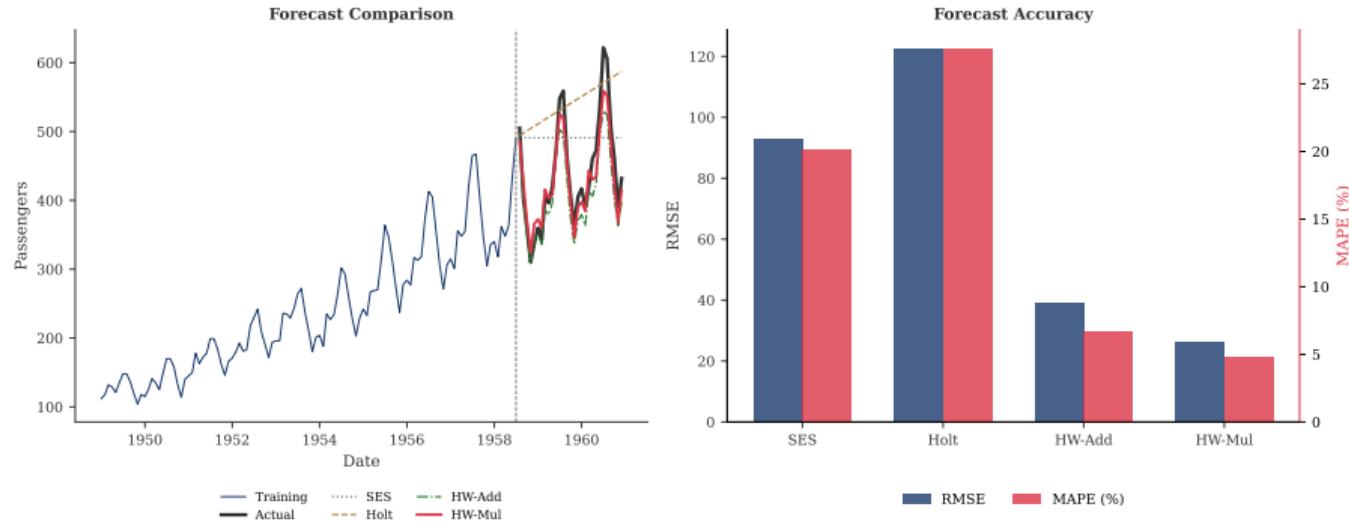
Model Development Workflow



Critical Rule

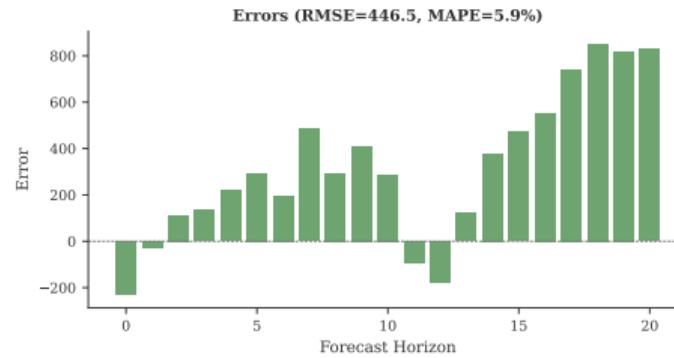
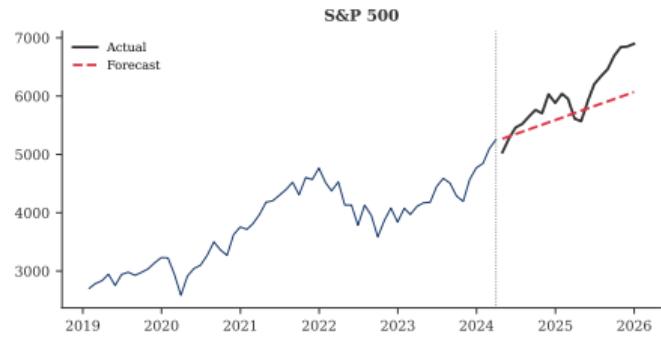
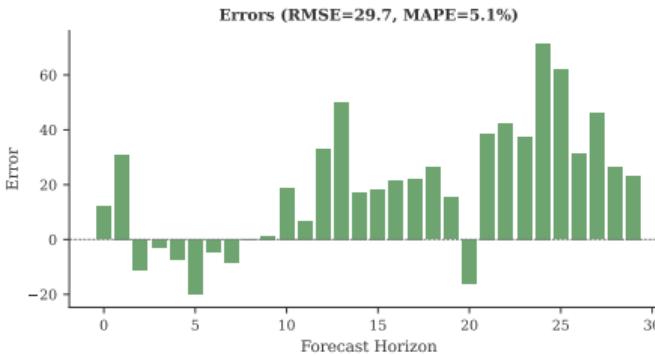
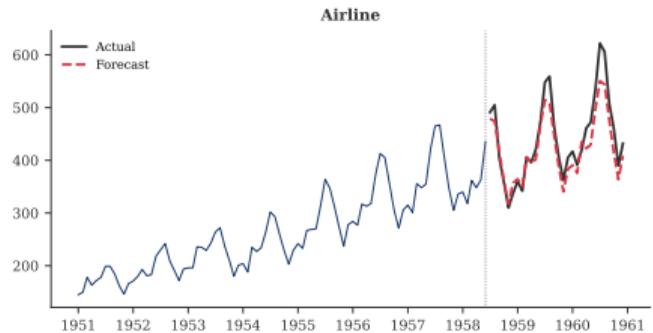
Never use test set for model selection! This causes *data leakage* and overly optimistic performance estimates.

Real Data: Forecast Comparison



Airline passengers data: Holt-Winters Multiplicative performs best for seasonal data.

Forecast Performance Across Datasets



Different series require different models. Seasonal data needs seasonal methods.

Modeling Seasonality: Two Approaches

1. Dummy Variables:

$$X_t = \mu + \sum_{j=1}^{s-1} \gamma_j D_{jt} + \varepsilon_t$$

- $D_{jt} = 1$ if t in season j
- $s - 1$ parameters
- Any seasonal pattern

2. Fourier Terms:

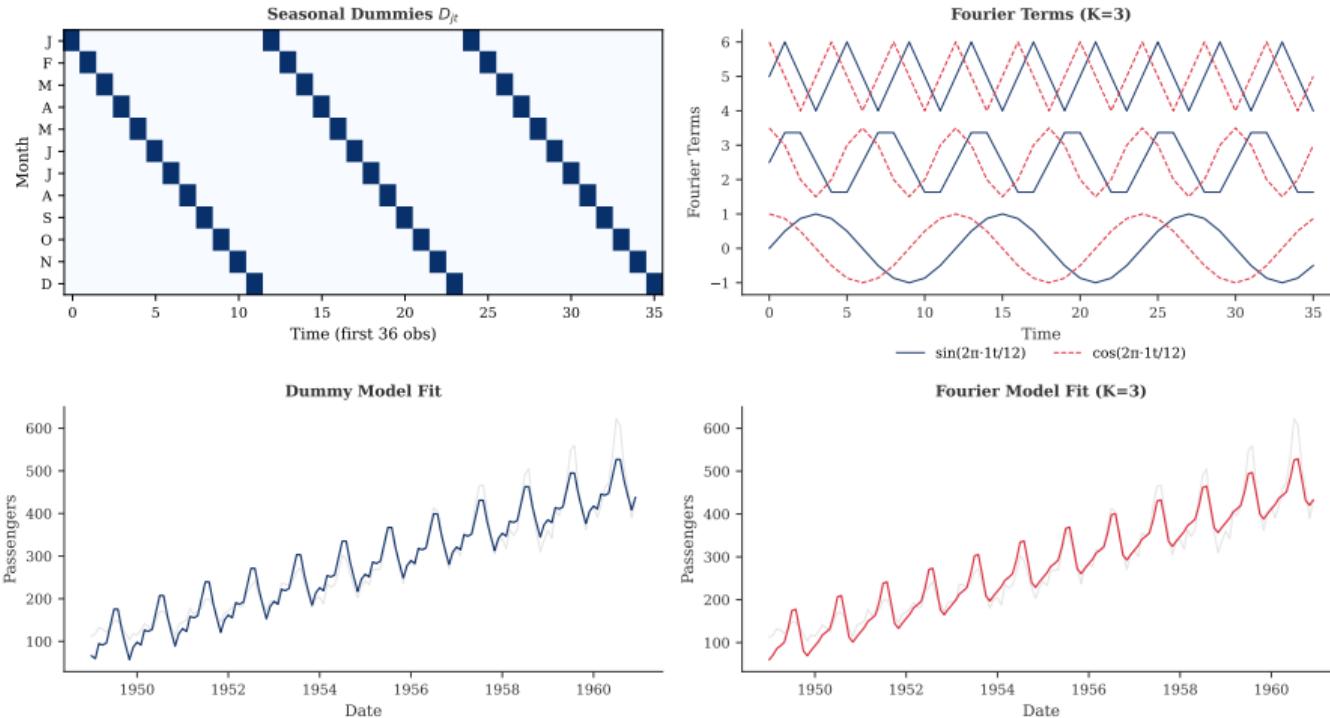
$$X_t = \mu + \sum_{k=1}^K [\alpha_k \sin(\cdot) + \beta_k \cos(\cdot)]$$

- Sinusoidal functions
- $2K$ parameters
- Smooth patterns

Trade-off

Dummies: any pattern, more parameters. Fourier: smooth, fewer parameters.

Dummy Variables vs Fourier Terms



Choosing Between Dummies and Fourier

Criterion	Dummies	Fourier
Parameters (monthly)	11	$2K$ (often 4–6)
Seasonal pattern	Any shape	Smooth/sinusoidal
Interpretation	Direct (month effects)	Frequency components
High-frequency seasons	Many parameters	Efficient
Multiple seasonality	Complex	Easy (add terms)

Guidelines:

- Use **dummies** when seasonal pattern is irregular or you need interpretable coefficients
- Use **Fourier** for smooth patterns, high-frequency seasonality (daily, hourly), or multiple seasonal periods
- **Fourier terms** are used in TBATS models and Facebook Prophet

Why Remove Trend and Seasonality?

Before modeling, we often need to make series stationary:

Reasons to detrend:

- Stationarity requirement
- Focus on fluctuations
- Avoid spurious regression
- Enable valid inference

Reasons to deseasonalize:

- Reveal underlying trend
- Compare across seasons
- Simplify modeling
- Focus on irregular component

Important

After modeling the detrended/deseasonalized series, we must **reverse the transformation** for forecasting.

Trend Removal Methods

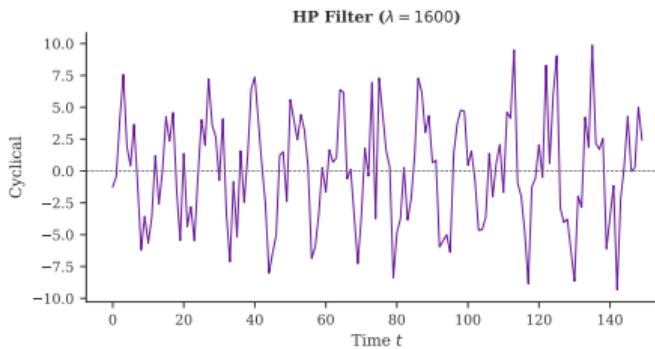
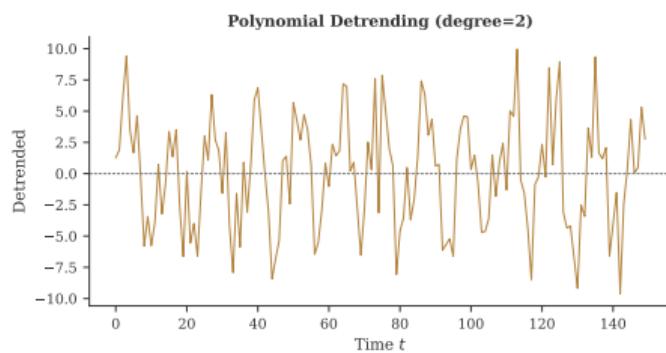
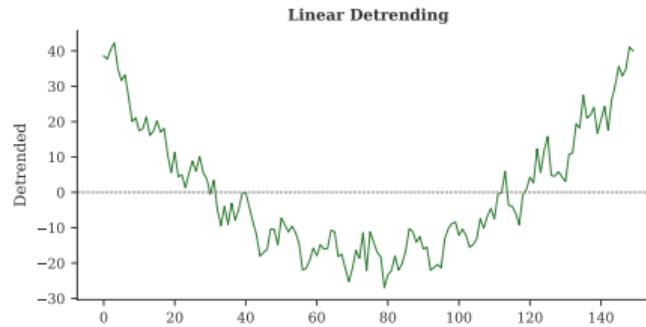
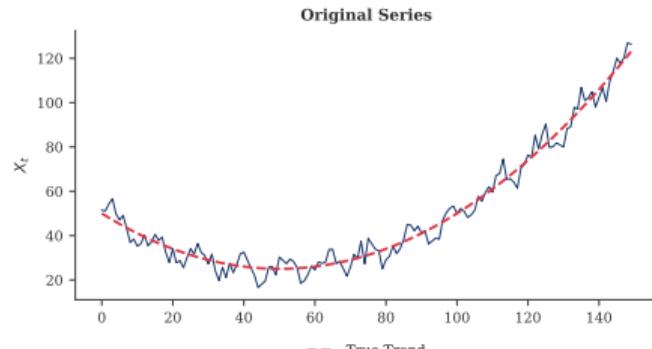
Six common detrending approaches:

- ① **Differencing:** $\Delta X_t = X_t - X_{t-1}$
- ② **Linear regression:** Fit $\hat{T}_t = \hat{\beta}_0 + \hat{\beta}_1 t$
- ③ **Polynomial:** Fit higher-order polynomial
- ④ **HP Filter:** Balance fit vs smoothness
- ⑤ **Moving average:** $\hat{T}_t = MA_q(X_t)$
- ⑥ **LOESS:** Local polynomial regression

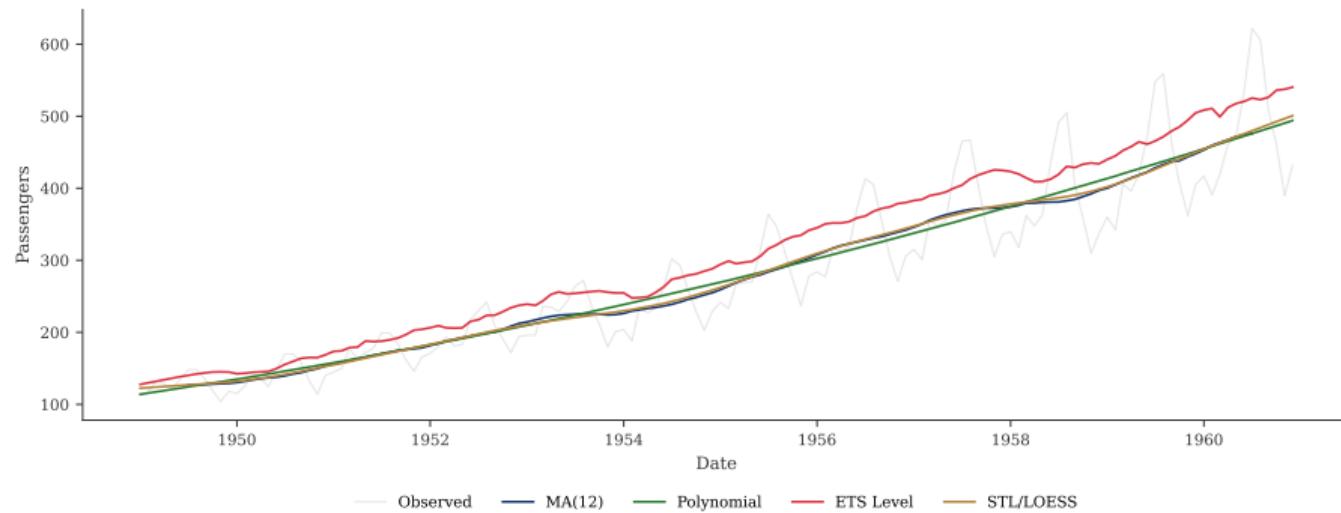
Choice depends on:

- Nature of trend (deterministic vs stochastic)
- Purpose (forecasting vs analysis)

Detrending Methods: Comparison



Trend Estimation: Multiple Approaches



Different methods capture trend at varying levels of smoothness.

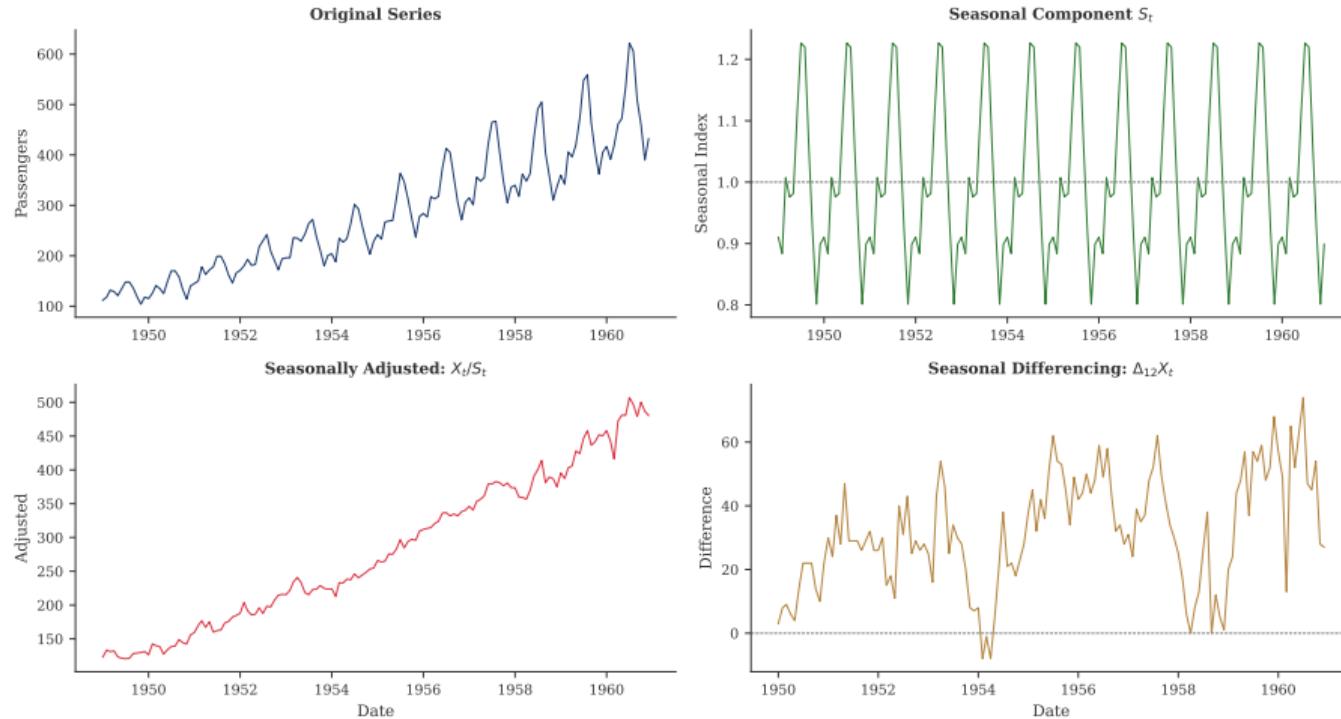
Seasonality Removal Methods

Four approaches to remove seasonality:

- ① **Seasonal differencing**: $\Delta_s X_t = X_t - X_{t-s}$
- ② **Division** (multiplicative): $X_t^{adj} = X_t / \hat{S}_t$
- ③ **Subtraction** (additive): $X_t^{adj} = X_t - \hat{S}_t$
- ④ **X-13ARIMA-SEATS**: Government statistical method

Seasonal period s : Monthly $\Rightarrow s = 12$; Quarterly $\Rightarrow s = 4$

Seasonal Adjustment: Visualization



Deterministic vs Stochastic Trend

Deterministic Trend:

$$X_t = \beta_0 + \beta_1 t + \varepsilon_t$$

- Trend is a function of time
- Detrend by regression
- ε_t is stationary

Stochastic Trend:

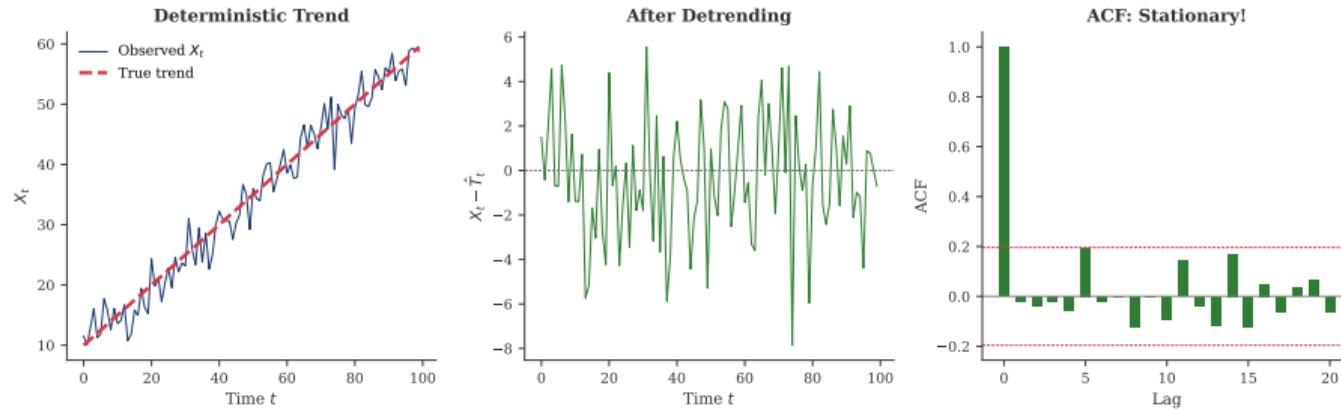
$$X_t = X_{t-1} + \varepsilon_t$$

- Random walk component
- Detrend by differencing
- ΔX_t is stationary

Wrong Method = Problems

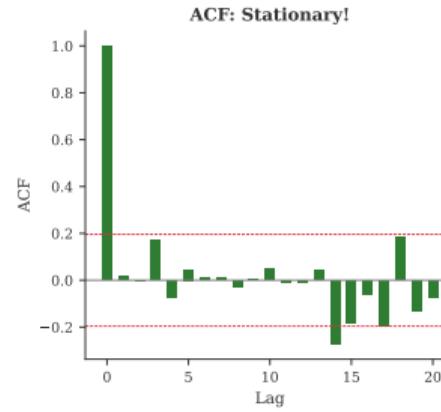
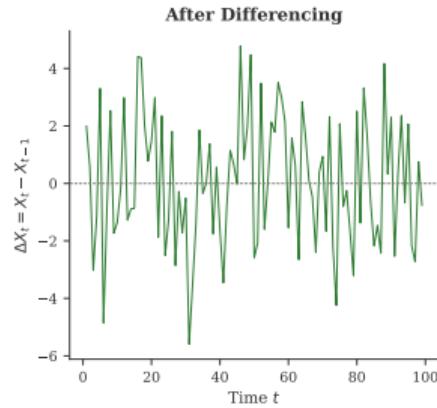
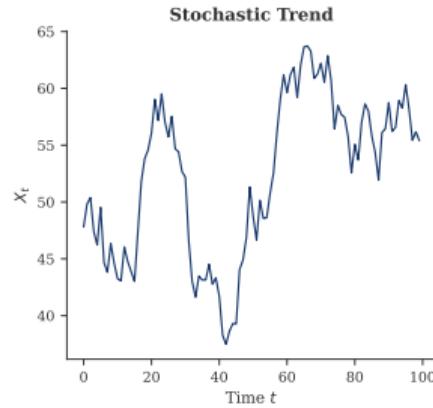
- Differencing deterministic trend \Rightarrow over-differencing
- Regression on stochastic trend \Rightarrow spurious regression

Example: Deterministic Trend



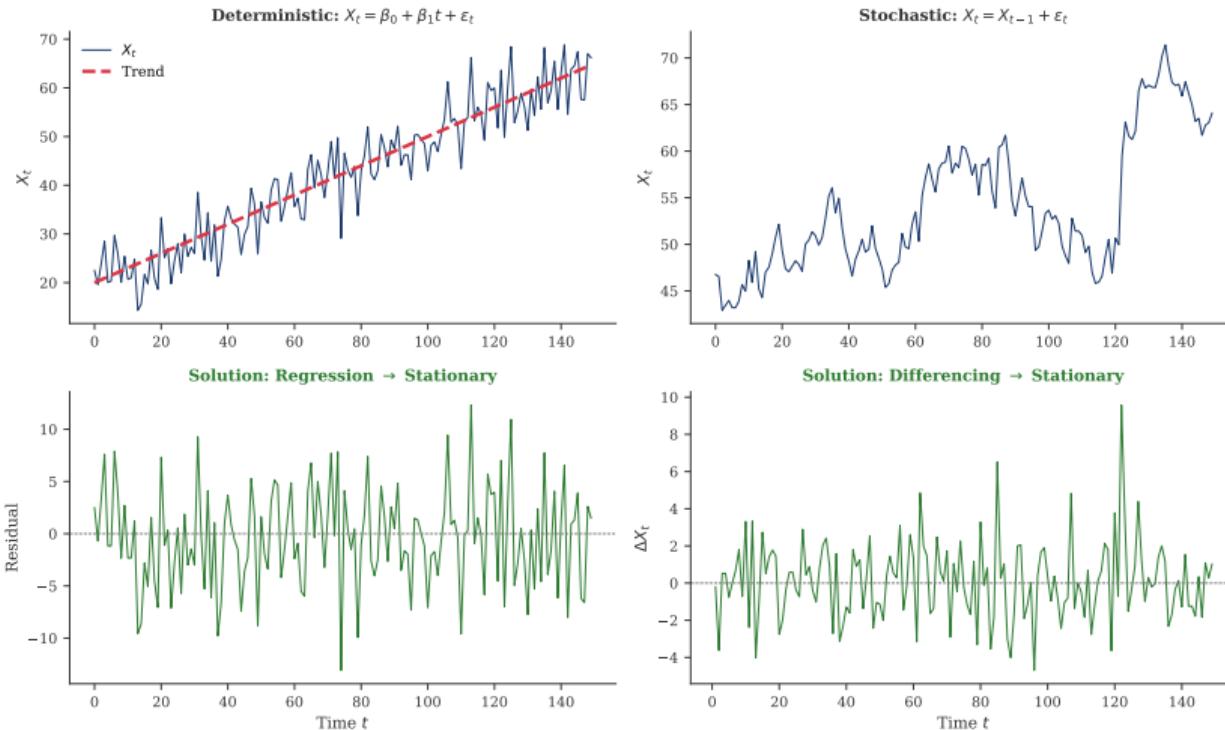
Key: Use **regression** to remove trend \rightarrow residuals are stationary (ACF decays quickly).

Example: Stochastic Trend (Random Walk)



Key: Use **differencing** to remove trend \rightarrow differences are stationary (white noise).

Side-by-Side Comparison



Remember: Deterministic \rightarrow regression. Stochastic \rightarrow differencing.

Definition 5 (Stochastic Process)

A **stochastic process** is a collection of random variables indexed by time:

$$\{X_t(\omega) : t \in \mathcal{T}, \omega \in \Omega\}$$

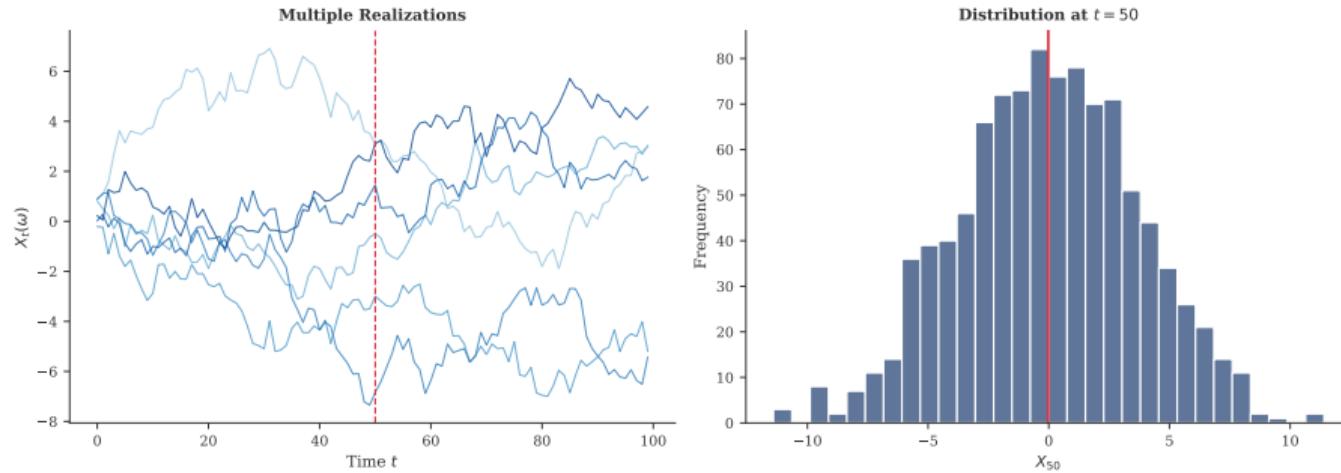
where Ω is the sample space of possible outcomes.

Two perspectives:

- **Fixed ω :** A *realization* or *sample path* $\{X_t(\omega)\}_{t \in \mathcal{T}}$
- **Fixed t :** A *random variable* X_t with distribution $F_t(x)$

Key insight: A time series we observe is **one realization** of the underlying stochastic process. We use this single realization to infer properties of the process.

Realizations vs Ensemble



Left: Multiple realizations from the same process. **Right:** Distribution at fixed time $t = 50$ (ensemble average).

Moments of a Stochastic Process

First two moments characterize weak properties:

Mean Function: $\mu_t = \mathbb{E}[X_t]$

Autocovariance Function (ACVF):

$$\gamma(t, s) = \text{Cov}(X_t, X_s) = \mathbb{E}[(X_t - \mu_t)(X_s - \mu_s)]$$

Autocorrelation Function (ACF):

$$\rho(t, s) = \frac{\gamma(t, s)}{\sqrt{\text{Var}(X_t) \cdot \text{Var}(X_s)}}$$

Properties: $\rho(t, s) \in [-1, 1]$ and $\rho(t, t) = 1$

Why Stationarity Matters

Stationarity is a fundamental assumption for time series analysis:

Without Stationarity:

- Mean, variance change over time
- Past may not predict future
- Standard methods fail
- Spurious correlations

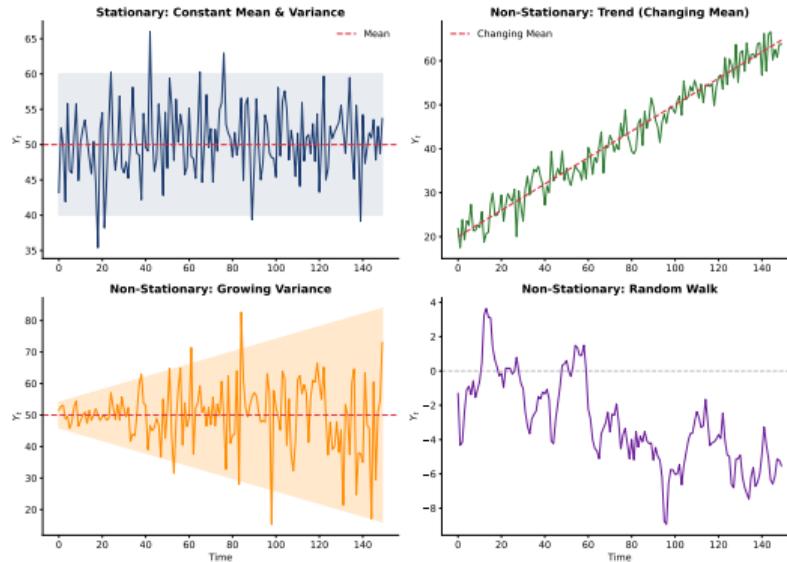
With Stationarity:

- Statistical properties constant
- Can estimate from one realization
- Valid inference possible
- Models are meaningful

Key Principle

Most time series models (ARMA, ARIMA, etc.) require stationarity. Non-stationary series must be transformed (e.g., differencing) before modeling.

Stationary vs Non-Stationary: Visual Comparison



- **Stationary:** Constant mean and variance – fluctuates around a fixed level
- **Non-stationary:** Mean and/or variance change over time
- Visual inspection is the first step; formal tests (ADF, KPSS) confirm

Definition 6 (Strict (Strong) Stationarity)

A process $\{X_t\}$ is **strictly stationary** if for all k , all t_1, \dots, t_k , and all h :

$$(X_{t_1}, X_{t_2}, \dots, X_{t_k}) \stackrel{d}{=} (X_{t_1+h}, X_{t_2+h}, \dots, X_{t_k+h})$$

Interpretation: The joint distribution of any collection of observations is **invariant to time shifts**.

Implications:

- All marginal distributions $F_{X_t}(x)$ are identical
- $\mathbb{E}[X_t] = \mu$ (constant mean)
- $\text{Var}(X_t) = \sigma^2$ (constant variance)
- Joint distributions depend only on time *differences*

Note: Strict stationarity is a strong condition, often impractical to verify.

Weak (Covariance) Stationarity

Definition 7 (Weak Stationarity)

A process $\{X_t\}$ is **weakly stationary** (or covariance 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)

Key property: Autocovariance is a function of lag only:

$$\gamma(h) = \text{Cov}(X_t, X_{t+h}) = \mathbb{E}[(X_t - \mu)(X_{t+h} - \mu)]$$

Autocorrelation function:

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)} = \frac{\text{Cov}(X_t, X_{t+h})}{\text{Var}(X_t)}$$

Note: $\rho(0) = 1$ and $\rho(h) = \rho(-h)$ (symmetry)

Properties of the Autocovariance Function

For a weakly stationary process, the ACVF $\gamma(h)$ satisfies:

- ① **Symmetry:** $\gamma(h) = \gamma(-h)$
- ② **Maximum at zero:** $|\gamma(h)| \leq \gamma(0)$
- ③ **Non-negative definiteness**

Implication: Not every function can be an autocovariance function.

Definition 8 (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 $\text{Var}(\varepsilon_t) = \sigma^2$ for all t
- ③ $\text{Cov}(\varepsilon_t, \varepsilon_s) = 0$ for $t \neq s$

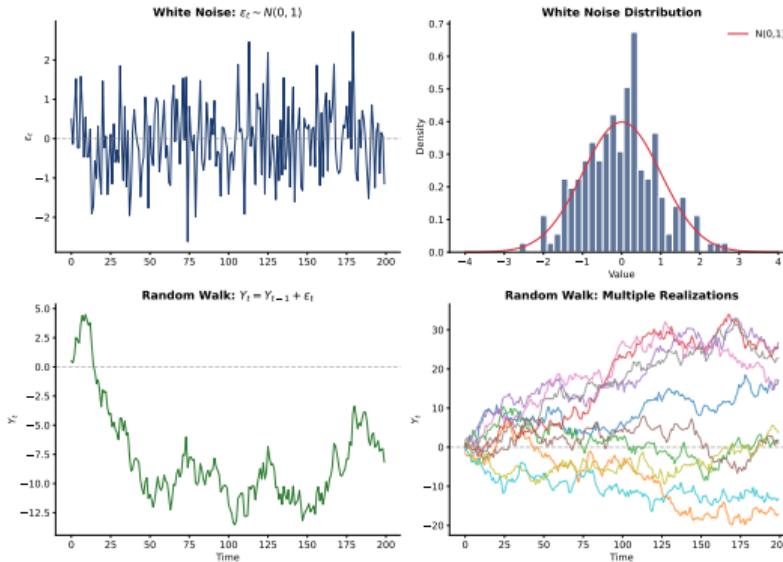
ACF of White Noise:

$$\rho(h) = \begin{cases} 1 & \text{if } h = 0 \\ 0 & \text{if } h \neq 0 \end{cases}$$

Types:

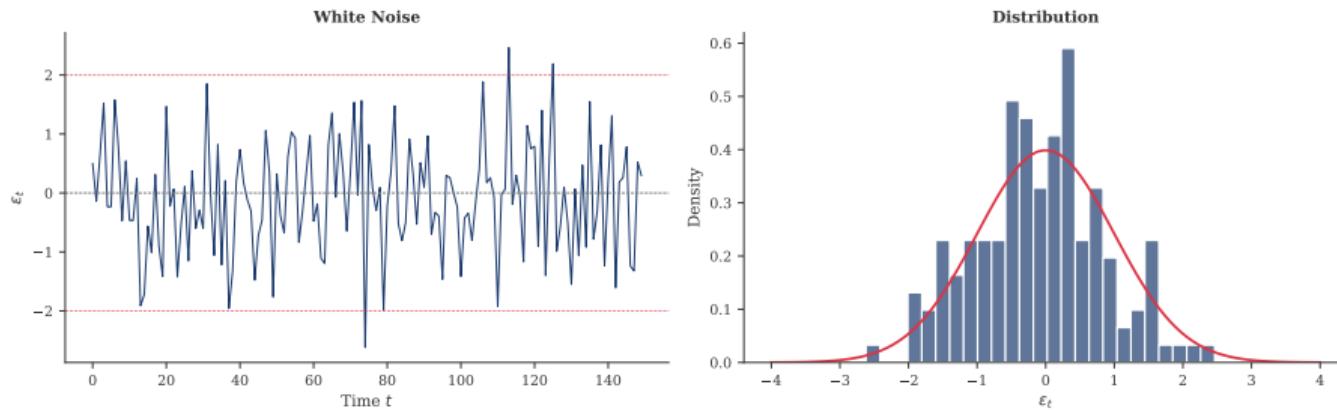
- **Weak white noise:** Uncorrelated (conditions above)
- **Strong white noise:** Independent and identically distributed (i.i.d.)
- **Gaussian white noise:** $\varepsilon_t \stackrel{iid}{\sim} N(0, \sigma^2)$

White Noise vs Random Walk: Comparison



- **White noise:** Fluctuates around zero – stationary, constant variance
- **Random walk:** Cumulative sum of white noise – wanders away, non-stationary
- Random walk is the simplest non-stationary process (unit root)

White Noise: Visualization



White noise is the building block of time series models. It represents unpredictable random shocks.

Random Walk Process

Definition: $X_t = X_{t-1} + \varepsilon_t$ where $\varepsilon_t \sim WN(0, \sigma^2)$, $X_0 = 0$

Explicit form: $X_t = \sum_{i=1}^t \varepsilon_i$

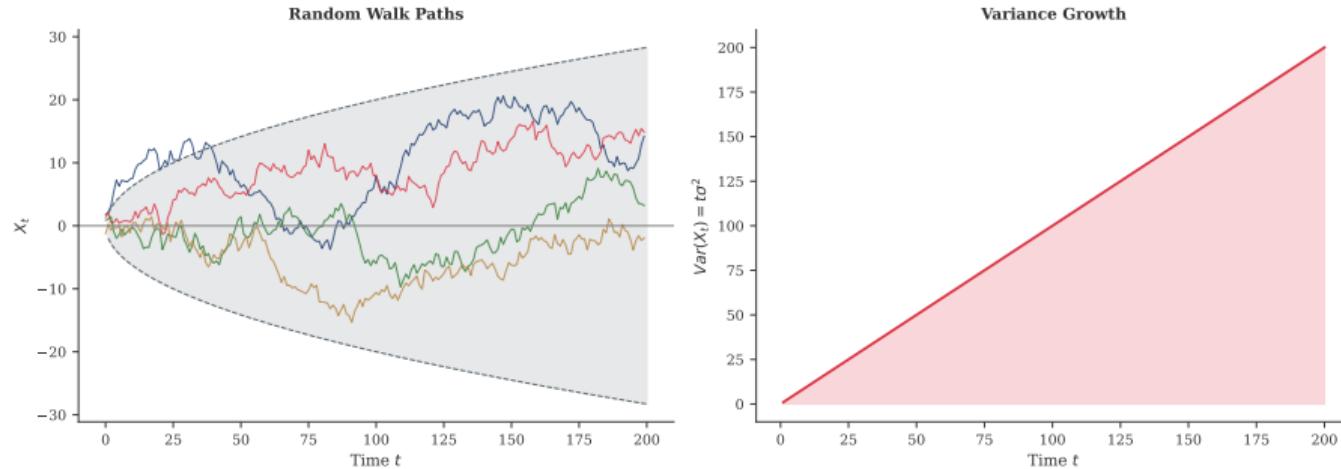
Properties:

- $\mathbb{E}[X_t] = 0$ (constant mean)
- $\text{Var}(X_t) = t\sigma^2$ (variance grows with time!)
- $\text{Cov}(X_t, X_s) = \min(t, s) \cdot \sigma^2$

Non-Stationary!

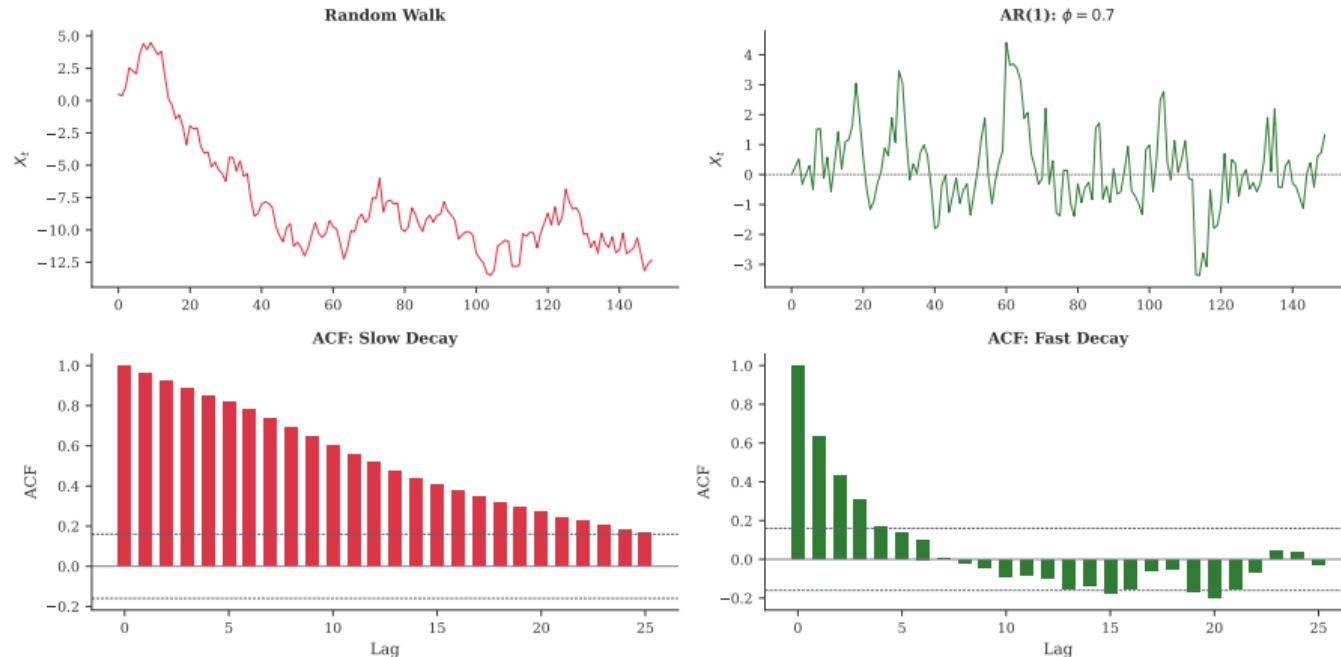
Random walk is **not stationary** because variance depends on t .

Random Walk: Visualization



Left: Multiple paths diverge over time. **Right:** Variance grows linearly: $\text{Var}(X_t) = t\sigma^2$.

Stationary vs Non-Stationary: Comparison



Key diagnostic: ACF of stationary process decays quickly; ACF of random walk decays very slowly.

Sample Autocorrelation Function

Sample ACF at lag h :

$$\hat{\rho}(h) = \frac{\sum_{t=1}^{T-h} (x_t - \bar{x})(x_{t+h} - \bar{x})}{\sum_{t=1}^T (x_t - \bar{x})^2}$$

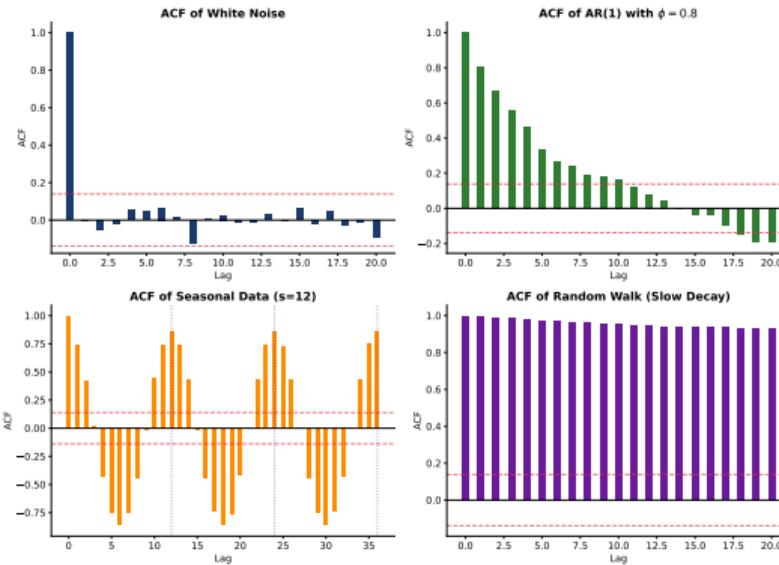
Properties:

- $\hat{\rho}(0) = 1$ always
- $|\hat{\rho}(h)| \leq 1$

Significance test: Under white noise, $\hat{\rho}(h) \approx N(0, 1/T)$

95% bounds: $\pm 1.96/\sqrt{T}$

ACF Patterns for Different Processes



- **White noise:** ACF drops to zero immediately (no dependence)
- **AR(1):** ACF decays exponentially – indicates autoregressive structure
- **Seasonal:** ACF shows spikes at seasonal lags (e.g., 12, 24 for monthly)
- **Random walk:** ACF decays very slowly – sign of non-stationarity

Partial Autocorrelation Function (PACF)

PACF ϕ_{hh} : Correlation between X_t and X_{t+h} after removing the linear effect of $X_{t+1}, \dots, X_{t+h-1}$.

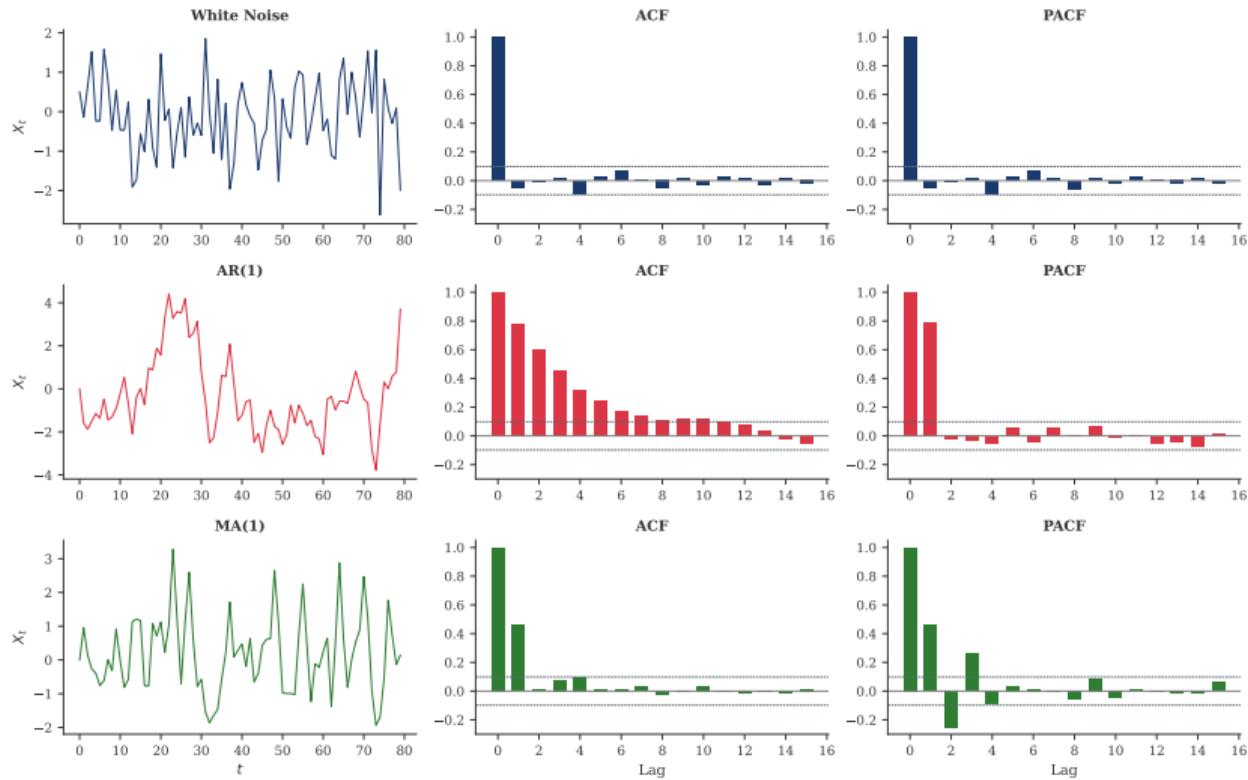
Interpretation:

- $\phi_{11} = \rho(1)$ (same as ACF at lag 1)
- $\phi_{22} = \text{correlation of } X_t, X_{t+2} \text{ controlling for } X_{t+1}$
- Measures *direct* dependence at lag h

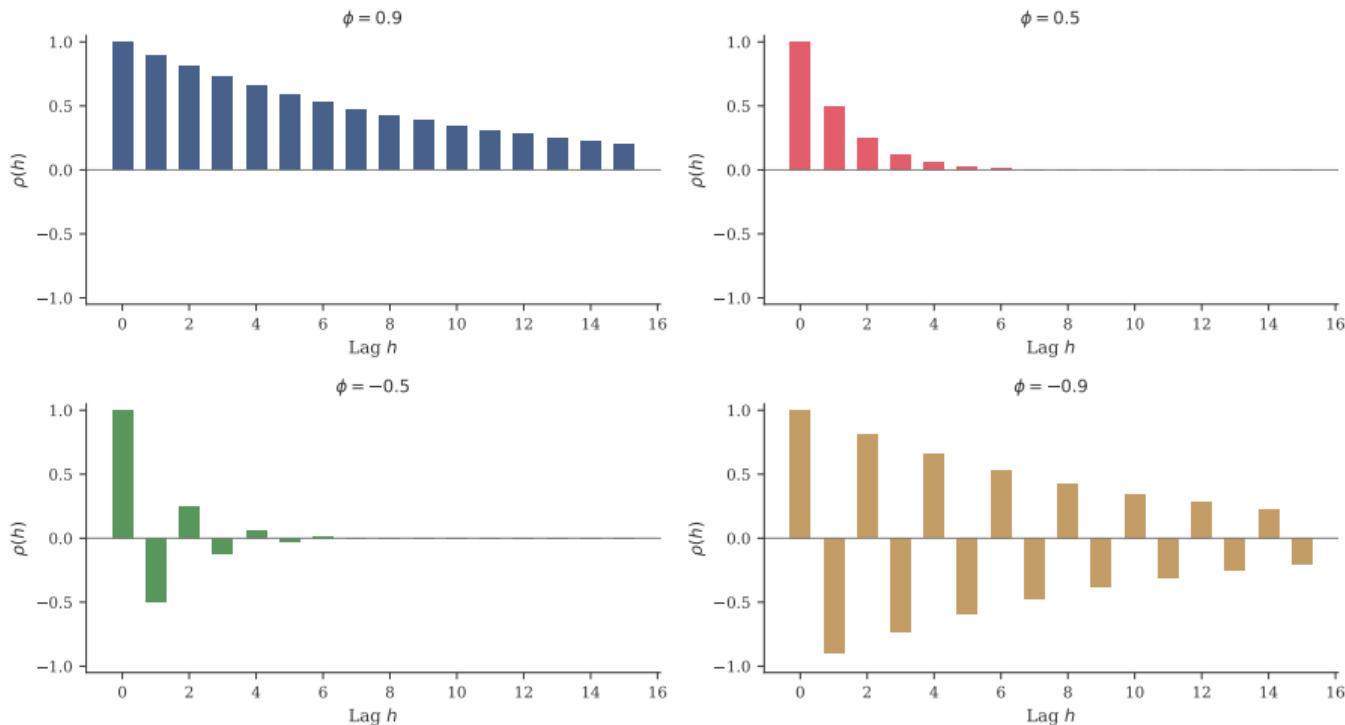
Key application: Identify AR order

- For AR(p): PACF **cuts off** after lag p
- For MA(q): ACF **cuts off** after lag q

ACF and PACF Patterns



Theoretical ACF for AR(1)



For AR(1): $X_t = \phi X_{t-1} + \varepsilon_t$, the theoretical ACF is $\rho(h) = \phi^h$.

The Lag Operator

Definition 9 (Lag Operator)

The **lag operator** (or backshift operator) L is defined by:

$$LX_t = X_{t-1}$$

Properties:

- $L^k X_t = X_{t-k}$ (lag by k periods)
- $L^0 = I$ (identity)
- $(1 - \phi L)X_t = X_t - \phi X_{t-1}$

Examples:

- AR(1): $(1 - \phi L)X_t = \varepsilon_t$
- MA(1): $X_t = (1 + \theta L)\varepsilon_t$
- AR(p): $(1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p)X_t = \varepsilon_t$

Differencing

First difference: $\Delta X_t = X_t - X_{t-1} = (1 - L)X_t$

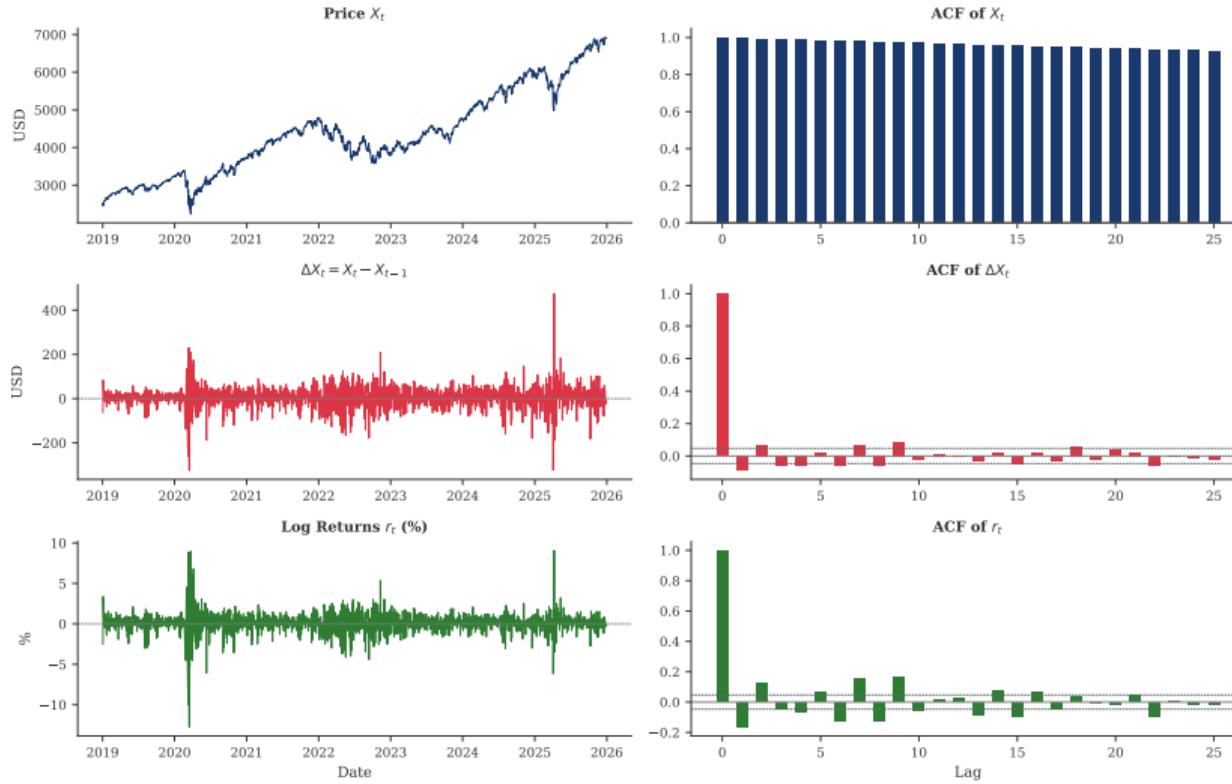
Why difference?

- Removes trend and unit root
- Random walk: $\Delta X_t = \varepsilon_t$ (white noise)

Integrated process: $X_t \sim I(d)$ if $\Delta^d X_t$ is stationary

- $I(0)$: Stationary (no differencing needed)
- $I(1)$: One difference needed
- $I(2)$: Two differences needed

Effect of Differencing: S&P 500



Augmented Dickey-Fuller (ADF) Test

Model: $\Delta X_t = \alpha + \gamma X_{t-1} + \sum_{i=1}^p \delta_i \Delta X_{t-i} + \varepsilon_t$

Hypotheses:

- $H_0: \gamma = 0$ (unit root)
- $H_1: \gamma < 0$ (stationary)

Decision:

- $\tau < \text{critical value} \Rightarrow \text{Reject } H_0 \Rightarrow \text{Stationary}$
- $\tau \geq \text{critical value} \Rightarrow \text{Non-stationary}$

Critical values: Dickey-Fuller distribution (not normal)

Test statistic:

$$\tau = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$$

KPSS Test

Model: $X_t = \xi t + r_t + \varepsilon_t$ where $r_t = r_{t-1} + u_t$

Hypotheses (opposite of ADF):

- $H_0: \sigma_u^2 = 0$ (stationary)
- $H_1: \sigma_u^2 > 0$ (unit root)

Test statistic:

$$LM = \frac{\sum_{t=1}^T S_t^2}{T^2 \hat{\sigma}^2}$$

where $S_t = \sum_{i=1}^t \hat{e}_i$

Decision:

- $LM >$ critical value \Rightarrow Reject $H_0 \Rightarrow$ Non-stationary
- $LM \leq$ critical value \Rightarrow Stationary

Note: KPSS complements ADF—use both for robust conclusions.

Using ADF and KPSS Together

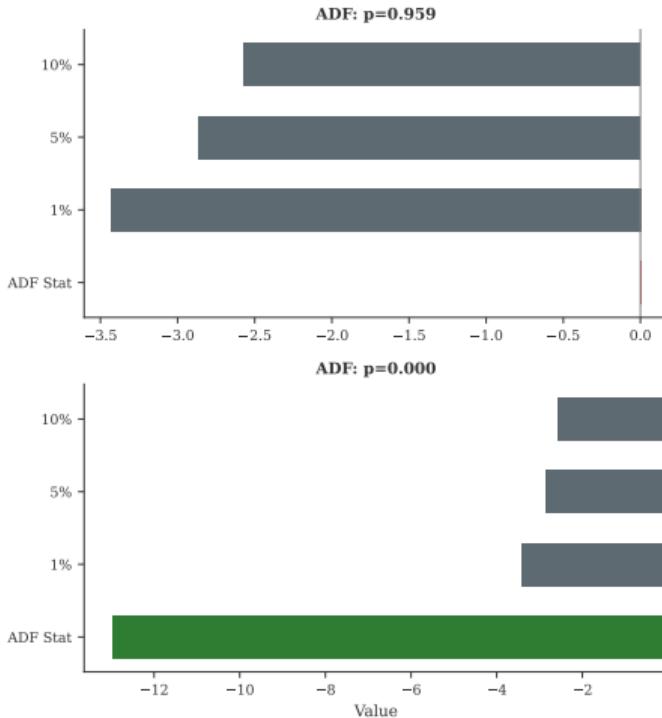
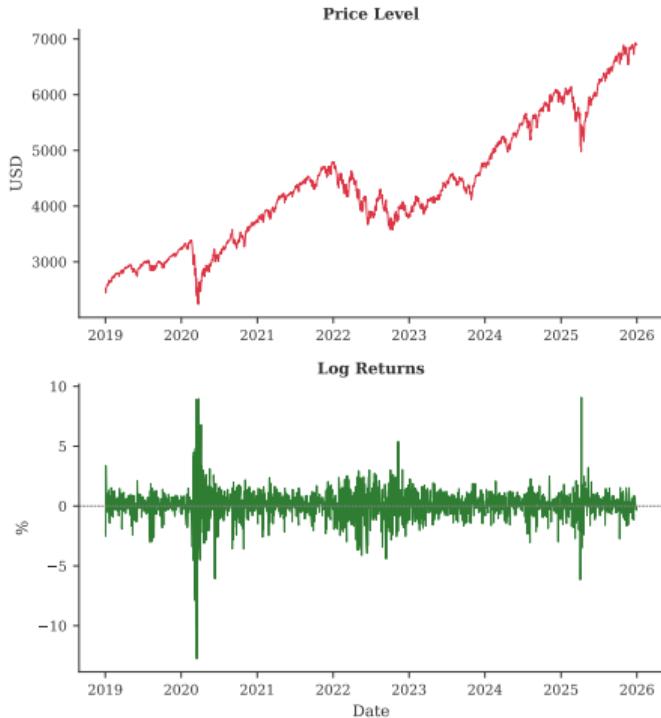
Confirmatory testing for robust conclusions:

ADF	KPSS	Conclusion
Reject H_0	Fail to reject H_0	Stationary
Fail to reject H_0	Reject H_0	Unit Root
Reject H_0	Reject H_0	Inconclusive
Fail to reject H_0	Fail to reject H_0	Inconclusive

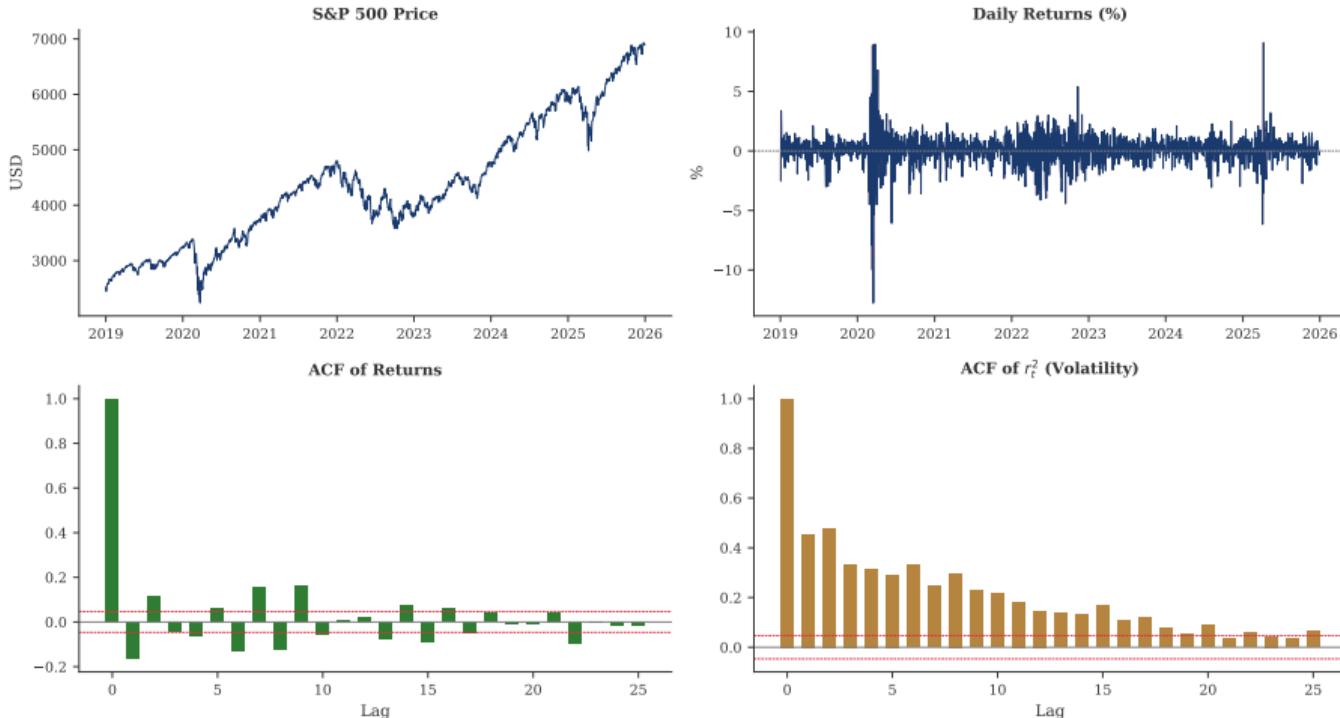
Recommended workflow:

- ① Run ADF test (null = unit root)
- ② Run KPSS test (null = stationary)
- ③ If results agree, proceed with confidence
- ④ If inconclusive, consider alternative tests (PP, DF-GLS)

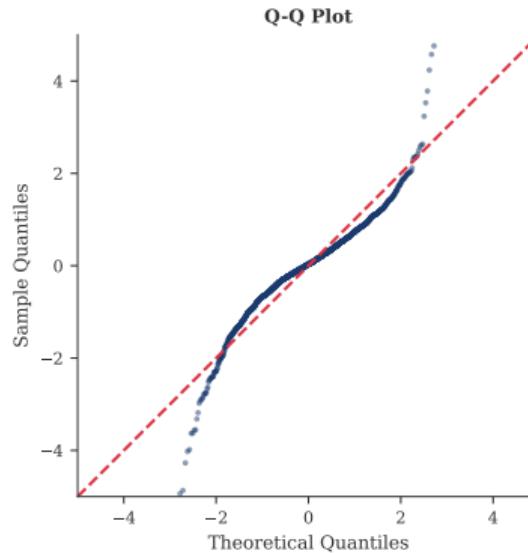
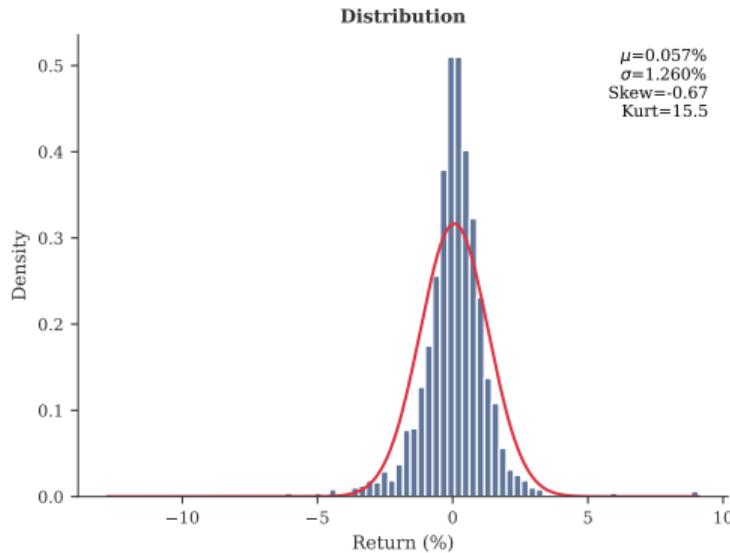
ADF Test: Visualization with S&P 500



S&P 500 Analysis: Overview



Stylized Facts of Financial Returns



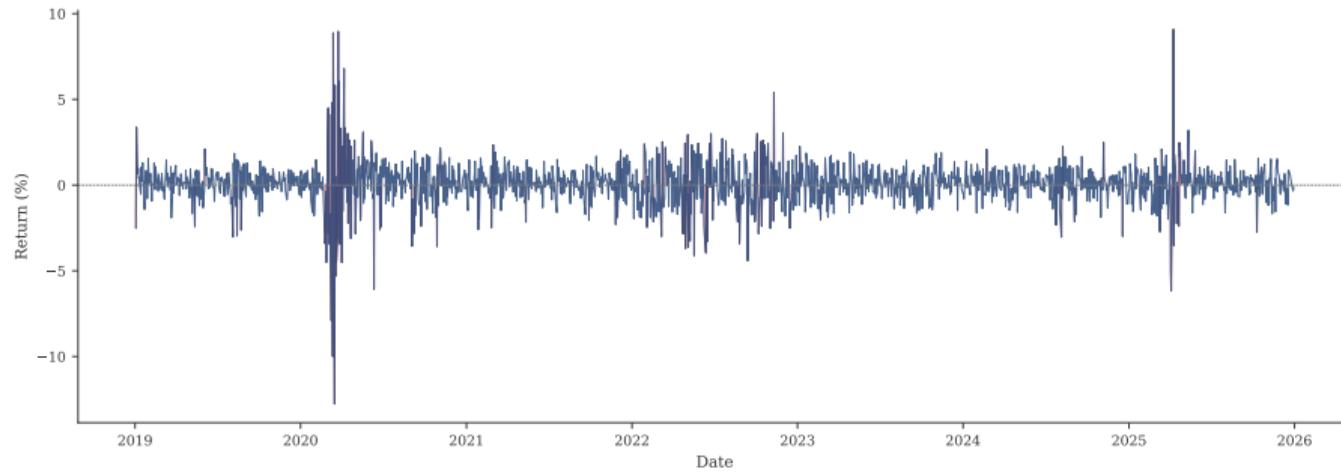
Observed properties:

- Negative skewness (left tail)
- Excess kurtosis ($\gg 3$)
- Heavy tails (fat tails)

Implications:

- Normal distribution inadequate
- Extreme events more likely
- Need Student-t or similar

Volatility Clustering



Stylized Fact

Large returns (positive or negative) tend to be followed by large returns. This **volatility clustering** motivates ARCH/GARCH models (future chapters).

Key Takeaways

- ① **Time series** = observations indexed by time with temporal dependence
- ② **Decomposition**: Additive $X_t = T_t + S_t + \varepsilon_t$ or Multiplicative
- ③ **Exponential Smoothing**: SES (level), Holt (trend), Holt-Winters (seasonal)
- ④ **Forecast Evaluation**: MAE, RMSE, MAPE; use train/validation/test splits
- ⑤ **Seasonality Modeling**: Dummy variables (any pattern) or Fourier terms (smooth)
- ⑥ **Trend Handling**: Differencing (stochastic) or regression (deterministic)
- ⑦ **Stationarity**: Mean, variance, autocovariance constant over time
- ⑧ **ACF/PACF**: Essential for identifying dependence structure
- ⑨ **Unit root tests**: ADF (H_0 : unit root) vs KPSS (H_0 : stationary)

Important Formulas I

Decomposition

Additive: $X_t = T_t + S_t + \varepsilon_t$ Multiplicative: $X_t = T_t \times S_t \times \varepsilon_t$

Simple Exponential Smoothing (SES)

$$\hat{X}_{t+1|t} = \alpha X_t + (1 - \alpha) \hat{X}_{t|t-1} \quad \text{where } \alpha \in (0, 1)$$

Holt's Linear Trend

$$\ell_t = \alpha X_t + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \quad b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$$

Holt-Winters Additive

$$\ell_t = \alpha(X_t - S_{t-s}) + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \quad S_t = \gamma(X_t - \ell_t) + (1 - \gamma)S_{t-s}$$

Important Formulas II

Moving Average (Trend Estimation)

$$\hat{T}_t = \frac{1}{2q+1} \sum_{j=-q}^q X_{t+j}$$

Autocovariance and Autocorrelation

$$\gamma(h) = \text{Cov}(X_t, X_{t+h}) \quad \rho(h) = \frac{\gamma(h)}{\gamma(0)}$$

Random Walk

$$X_t = X_{t-1} + \varepsilon_t \quad \Rightarrow \quad \text{Var}(X_t) = t\sigma^2 \text{ (non-stationary)}$$

Differencing

$$\Delta X_t = (1 - L)X_t = X_t - X_{t-1}$$

Chapter 2: ARMA Models

- Autoregressive (AR) models
- Moving Average (MA) models
- Combined ARMA models
- Model identification using ACF/PACF
- Parameter estimation
- Model diagnostics
- Forecasting

Thank You!

Questions?

All charts generated using Python (yfinance, statsmodels, matplotlib)

Data source: Yahoo Finance (2019–2025)