

# Chapter 1: Introduction to Time Series

Fundamentals and Concepts



**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

# Definition of a Time Series

## 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.

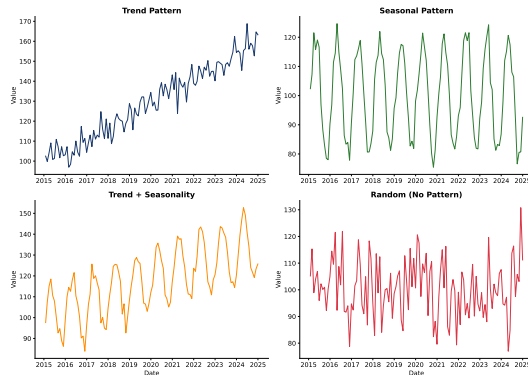
### Key characteristics:

- **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:

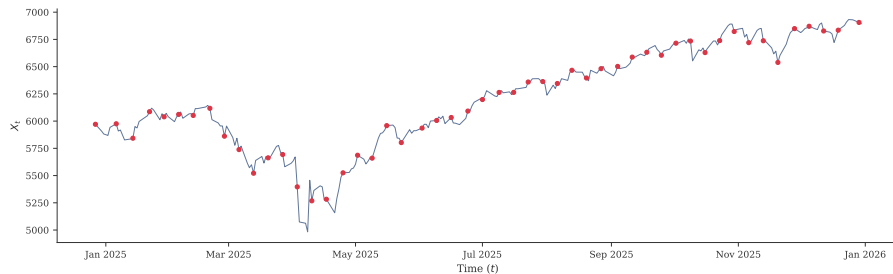
- $X_t$  = observation at time  $t$
- $\{X_t\}_{t=1}^T$  = finite time series with  $T$  observations

# Common Time Series Patterns



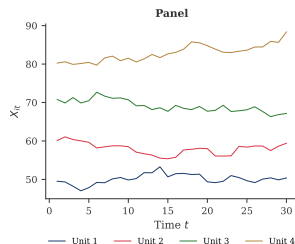
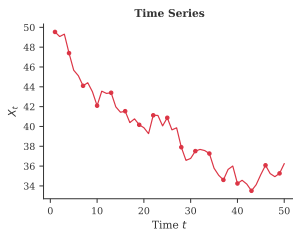
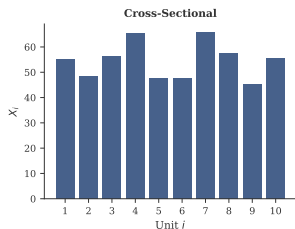
- **Trend:** Long-term increase or decrease in the data
- **Seasonal:** Regular periodic patterns (e.g., monthly, quarterly)
- **Random:** No systematic pattern – unpredictable fluctuations

## Time Series: Visual Definition



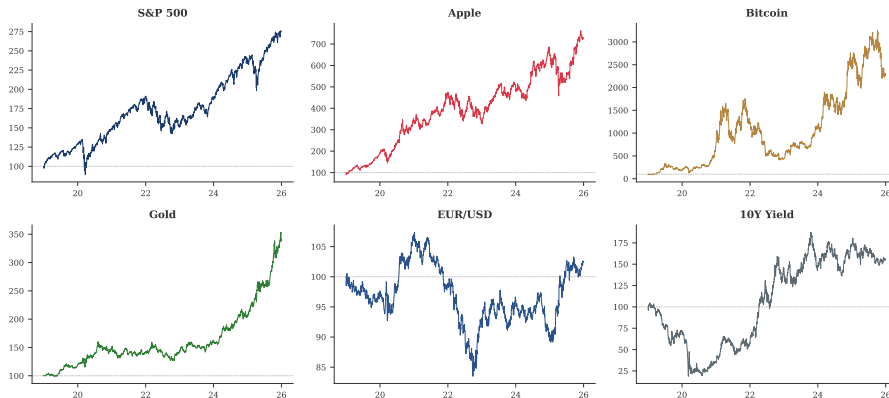
Each point  $X_t$  represents a measurement at discrete time  $t$ . Data: S&P 500 (2024).

# 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

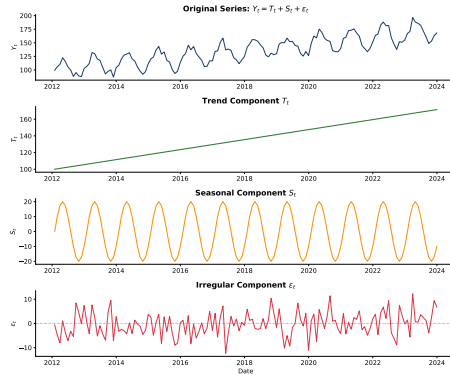
## Components:

- $T_t = \textbf{Trend}$ : Long-term movement
- $S_t = \textbf{Seasonal}$ : Regular periodic pattern
- $C_t = \textbf{Cyclical}$ : Business cycle fluctuations
- $\varepsilon_t = \textbf{Residual}$ : 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:**  $X_t = T_t + S_t + \varepsilon_t$

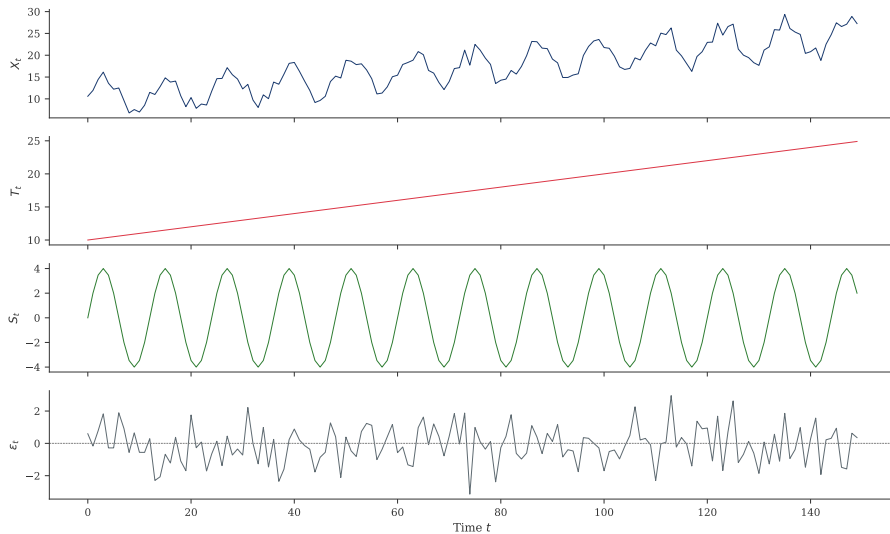
**When to use:**

- 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:**

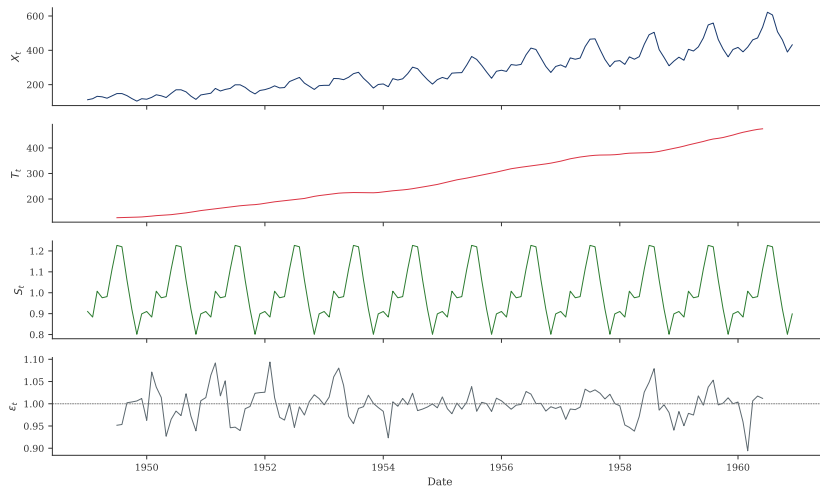
- Seasonal fluctuations **grow** with series level
- Variance **increases** over time

**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)

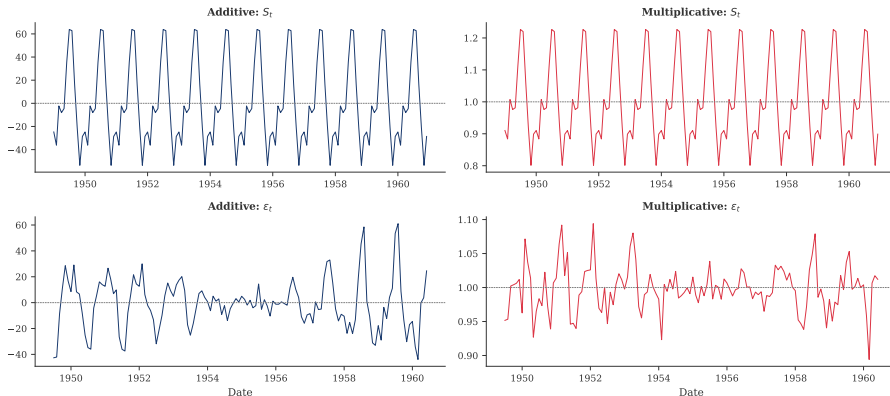
**Tip:** Log transform converts to additive model.

# 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:

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

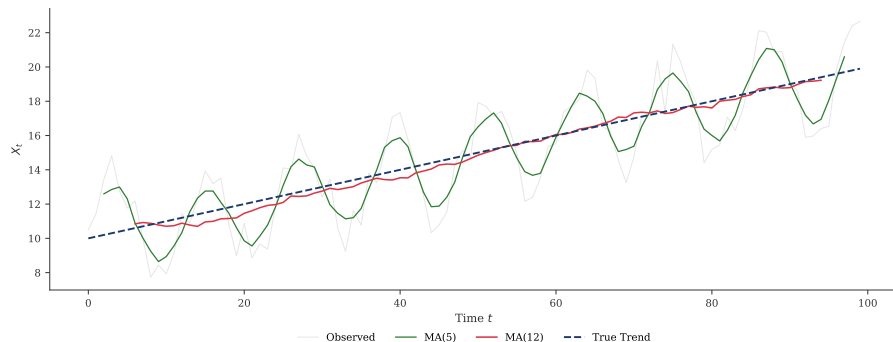
**For seasonal data:**

- 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:**  $D_t = X_t / \hat{T}_t$

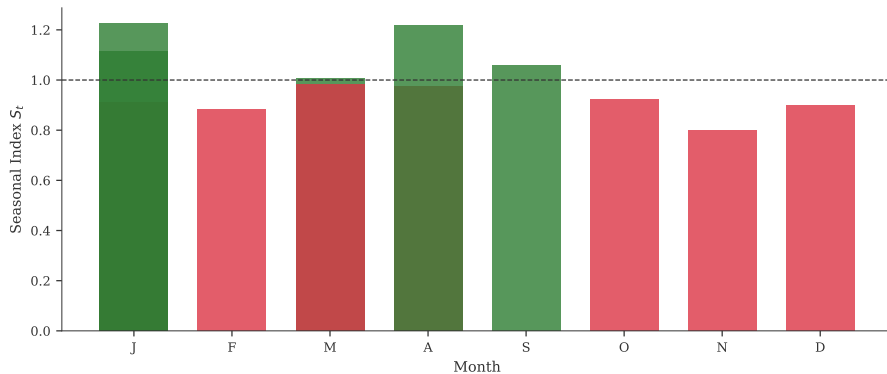
③ **Estimate Seasonal:** Average  $D_t$  for each season  $j$

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

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:

$$X_t = T_t + S_t + R_t$$

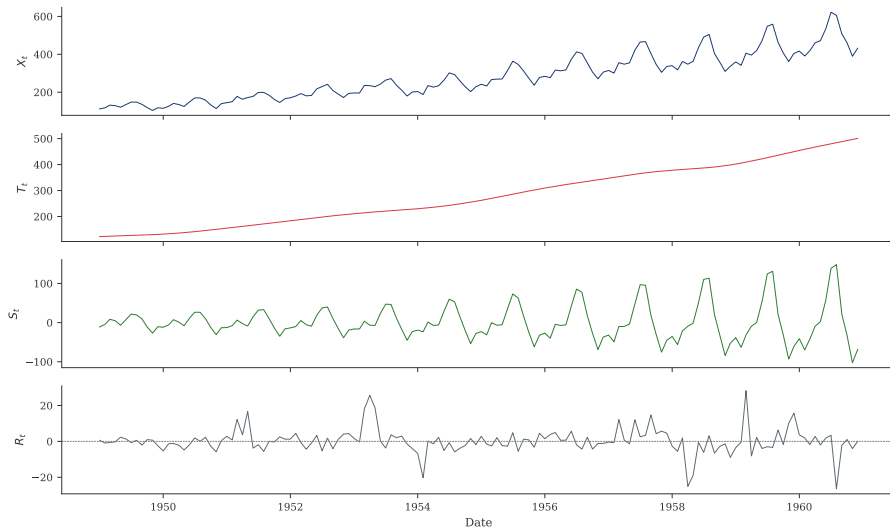
### Advantages over classical decomposition:

- 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.

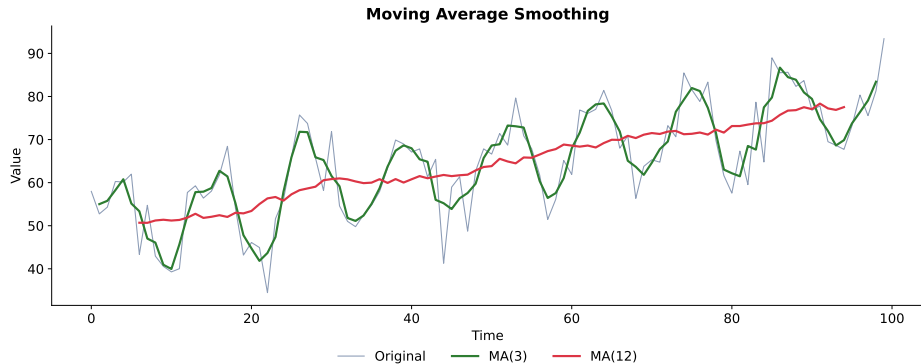
## Why Exponential Smoothing?

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

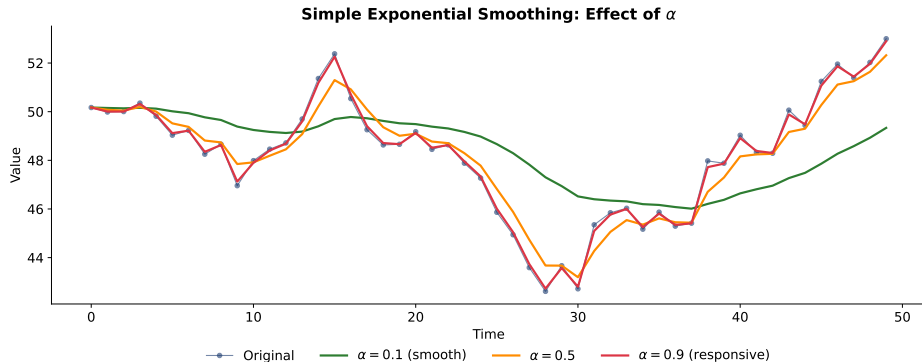
where  $\alpha \in (0, 1)$  is the **smoothing parameter**.

**How it works:**

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

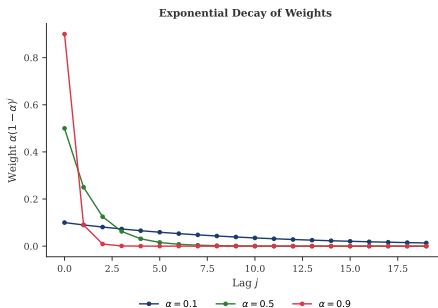
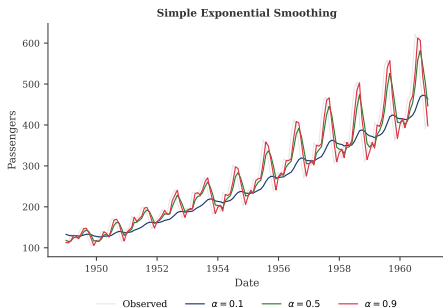
**Level form:**  $\ell_t = \alpha X_t + (1 - \alpha)\ell_{t-1}$

# Exponential Smoothing: Effect of Alpha



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

# Simple Exponential Smoothing: Effect of $\alpha$



Smaller  $\alpha$  produces smoother forecasts; larger  $\alpha$  follows data more closely.

# Holt's Linear Trend Method

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

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

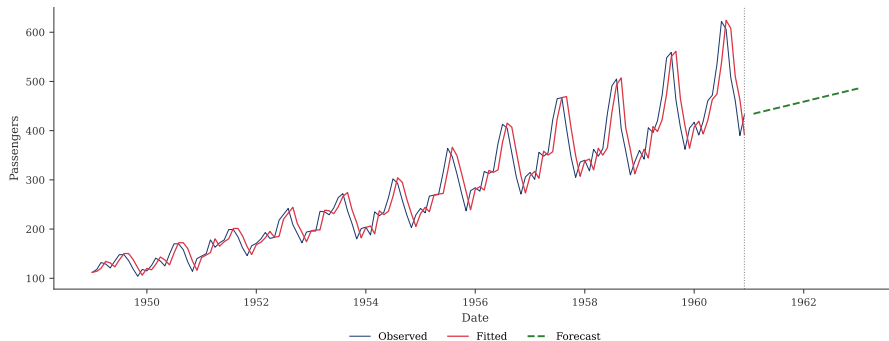
**Trend:**  $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$

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

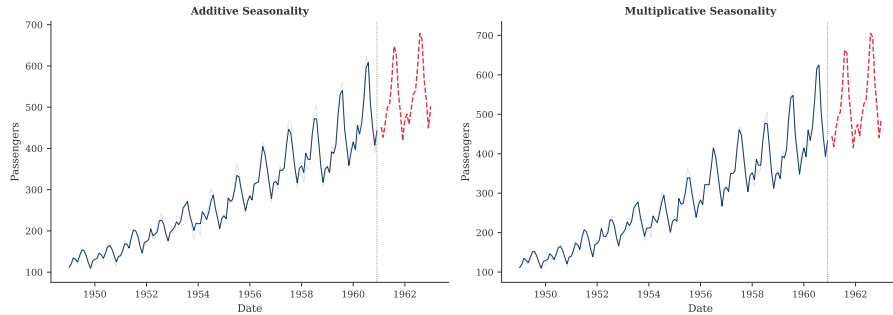
**Seasonal:**  $S_t = \gamma(X_t - \ell_t) + (1 - \gamma)S_{t-s}$

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

**Parameters:**

- $\alpha$ : Level smoothing
- $\beta^*$ : Trend smoothing
- $\gamma$ : 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:

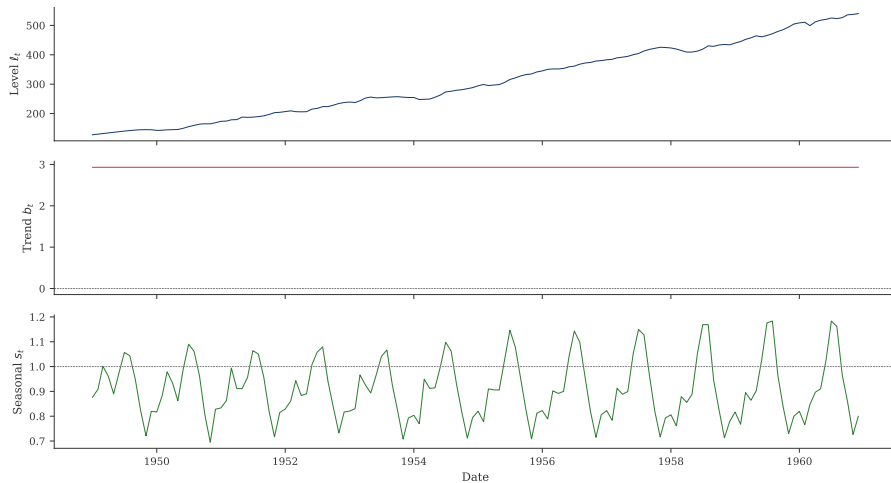
Component	N	A	M
Error (E)	–	Additive	Multiplicative
Trend (T)	None	Additive	Multiplicative
Seasonal (S)	None	Additive	Multiplicative

### Examples:

- $\text{ETS}(A, N, N)$  = Simple Exponential Smoothing
- $\text{ETS}(A, A, N)$  = Holt's Linear Method
- $\text{ETS}(A, A, A)$  = Holt-Winters Additive
- $\text{ETS}(M, A, M)$  = 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:

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

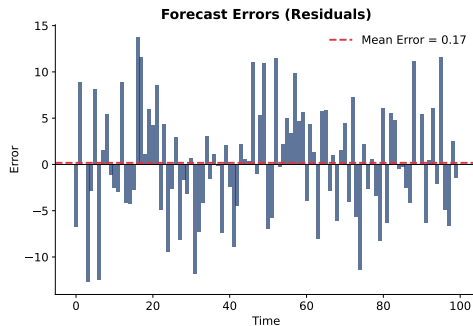
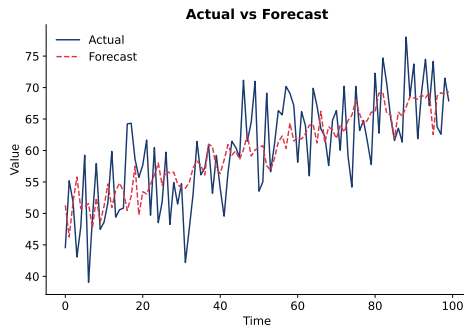
## Scale-Independent:

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

## Which to use?

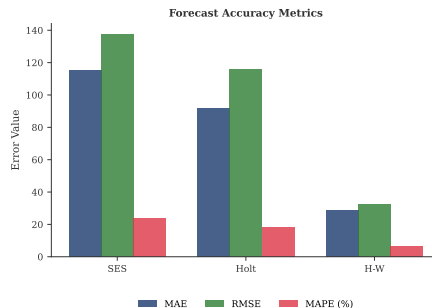
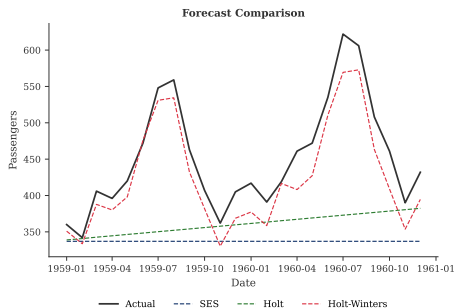
- Same series: RMSE, MAE
- Compare across series: MAPE, sMAPE

# 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)

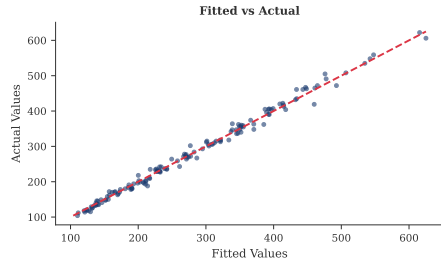
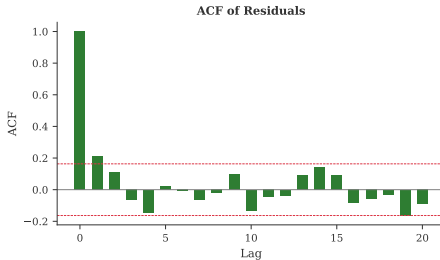
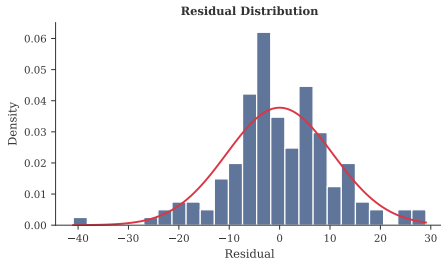
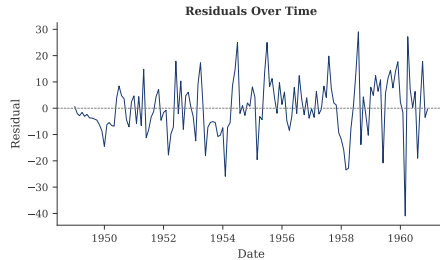
**Diagnostic tests:**

- **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

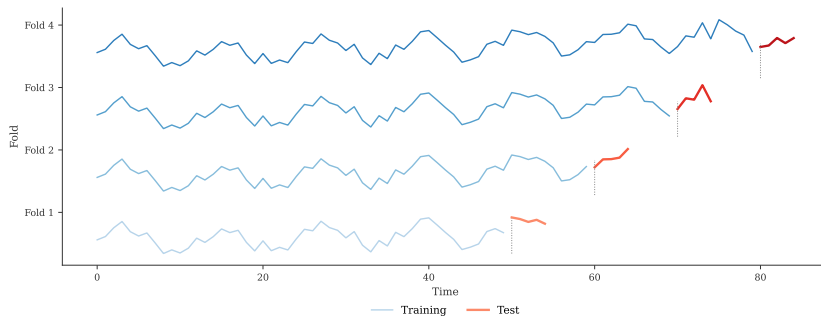


# Time Series Cross-Validation

**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

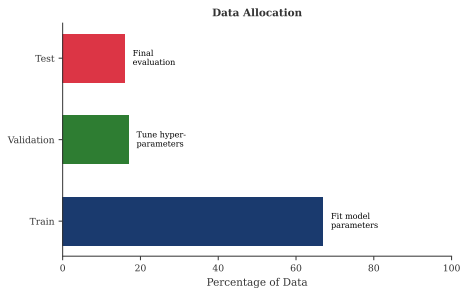
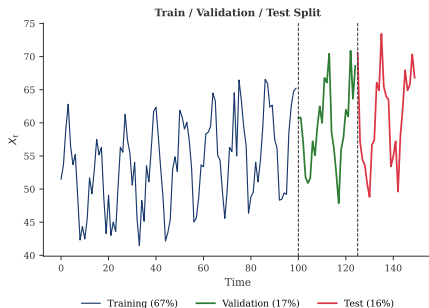
- Fit model parameters
- Largest portion (60–80%)
- Used for estimation

## Validation Set

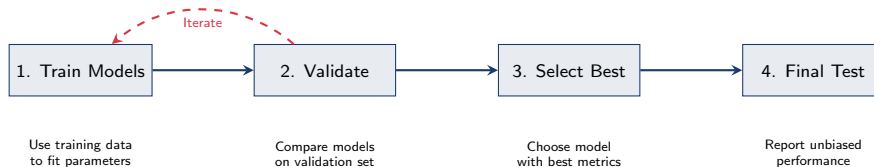
- Tune hyperparameters
- Compare models
- Select best approach

## Test Set

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



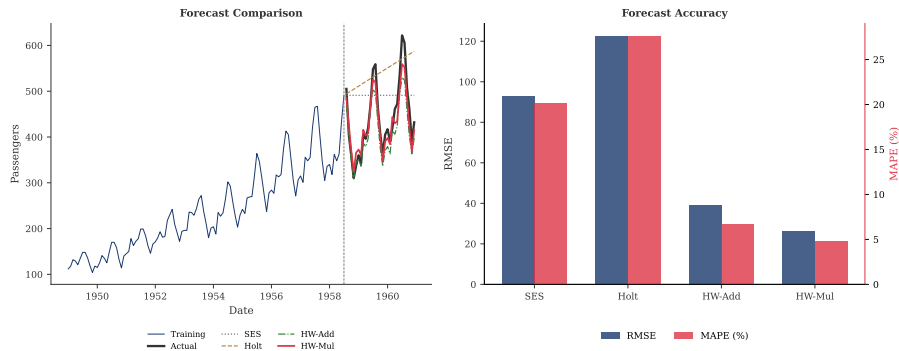
# Model Development Workflow



## Critical Rule

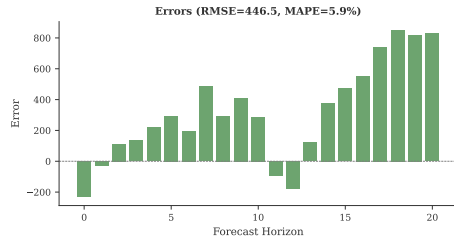
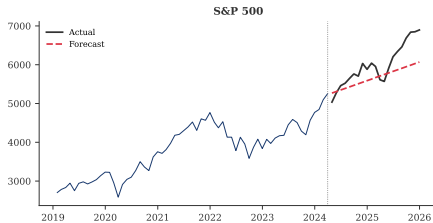
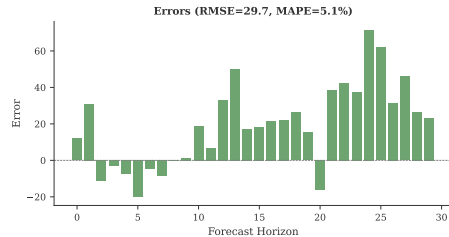
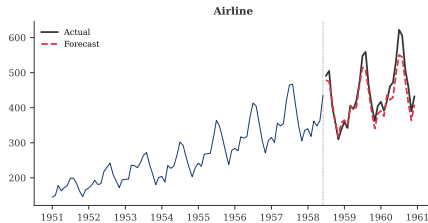
**Never** use test set for model selection! This causes *data leakage* and overly optimistic performance estimates.

# 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:

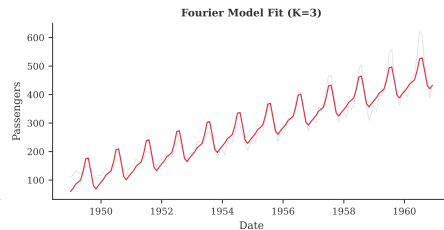
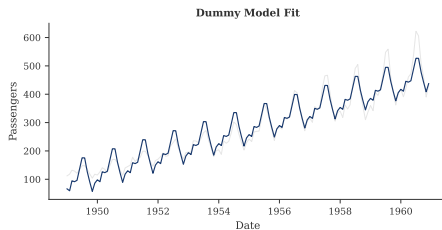
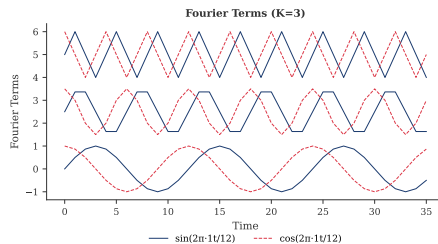
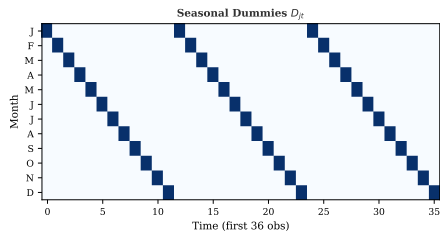
$$X_t = \mu + \sum_{k=1}^K [\alpha_k \sin(\cdot) + \beta_k \cos(\cdot)]$$

- 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

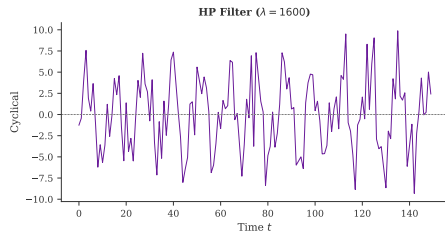
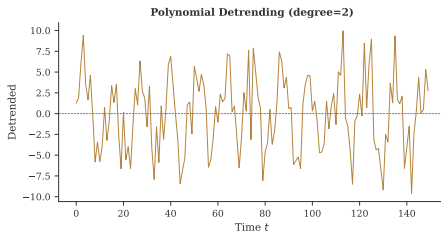
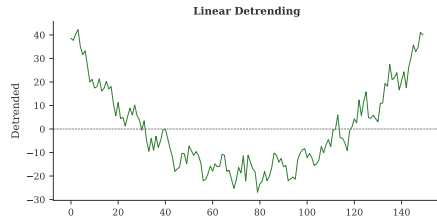
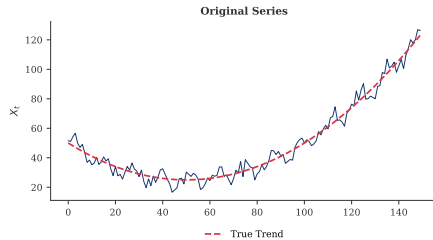
## Six common detrending approaches:

- 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

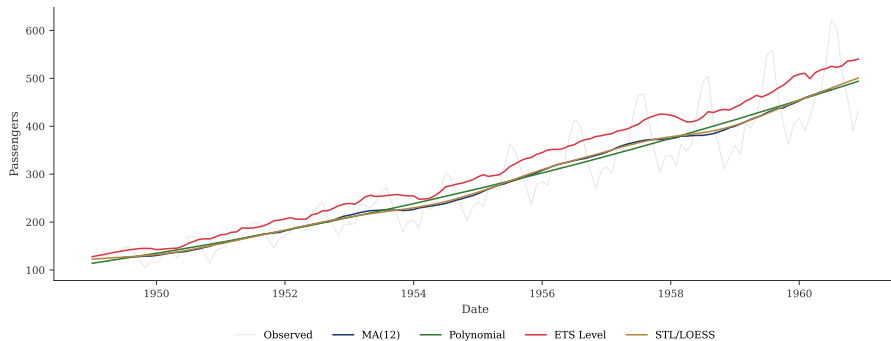
## Choice depends on:

- 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.

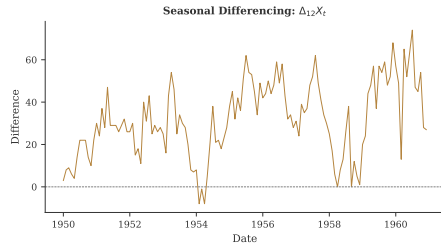
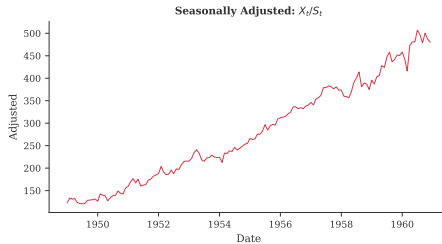
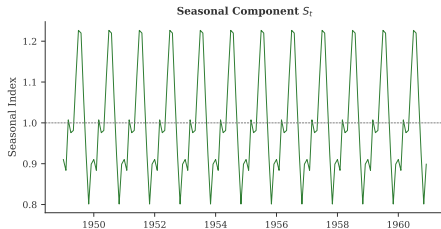
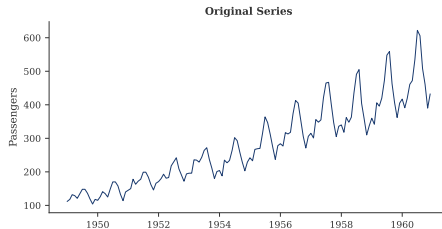
# Seasonality Removal Methods

## Four approaches to remove seasonality:

- ❶ **Seasonal differencing:**  $\Delta_s X_t = X_t - X_{t-s}$
- ❷ **Division** (multiplicative):  $X_t^{adj} = X_t / \hat{S}_t$
- ❸ **Subtraction** (additive):  $X_t^{adj} = X_t - \hat{S}_t$
- ❹ **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
- $\varepsilon_t$  is stationary

## Stochastic Trend:

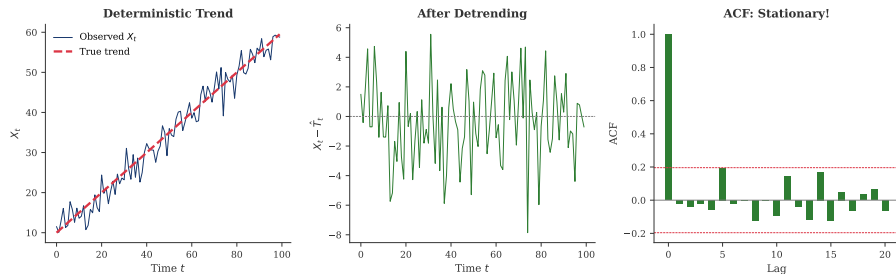
$$X_t = X_{t-1} + \varepsilon_t$$

- Random walk component
- Detrend by differencing
- $\Delta X_t$  is stationary

## Wrong Method = Problems

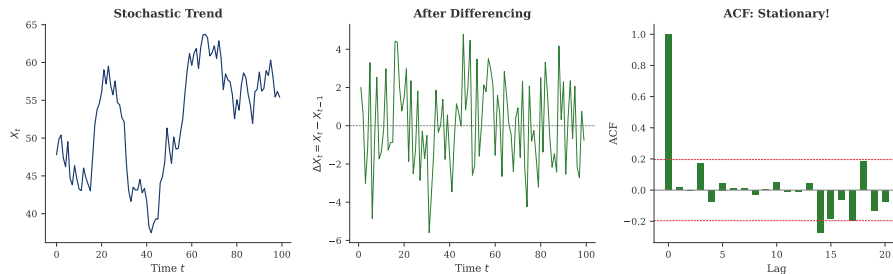
- Differencing deterministic trend  $\Rightarrow$  over-differencing
- Regression on stochastic trend  $\Rightarrow$  spurious regression

## Example: Deterministic Trend



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

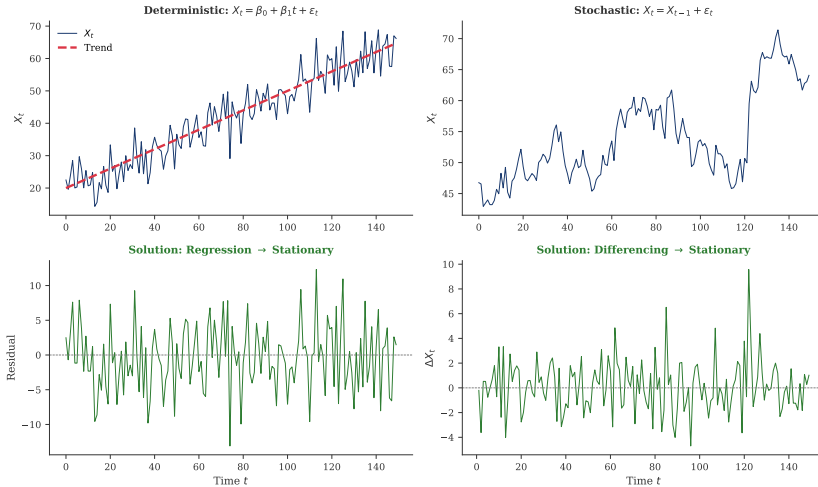
## Example: Stochastic Trend (Random Walk)



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



# Side-by-Side Comparison



**Remember:** Deterministic → regression. Stochastic → differencing.

### Definition 5 (Stochastic Process)

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

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

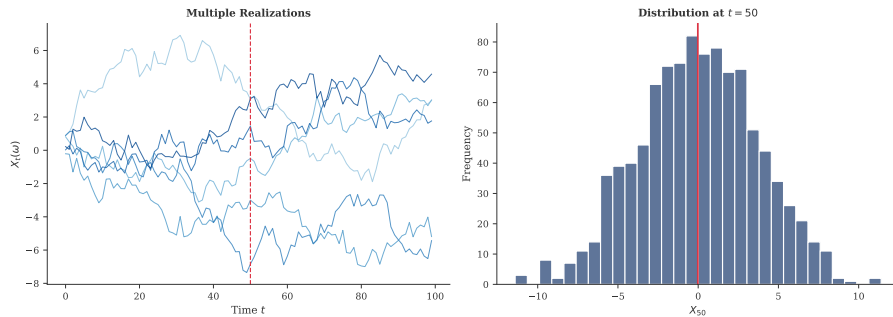
where  $\Omega$  is the sample space of possible outcomes.

#### Two perspectives:

- **Fixed**  $\omega$ : 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

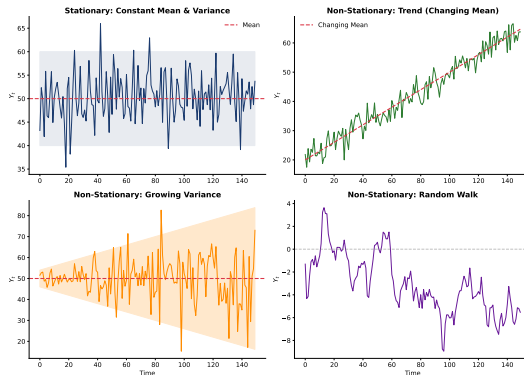
## With Stationarity:

- 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:

- ❶  $\mathbb{E}[\varepsilon_t] = 0$  for all  $t$
- ❷  $\text{Var}(\varepsilon_t) = \sigma^2$  for all  $t$
- ❸  $\text{Cov}(\varepsilon_t, \varepsilon_s) = 0$  for  $t \neq s$

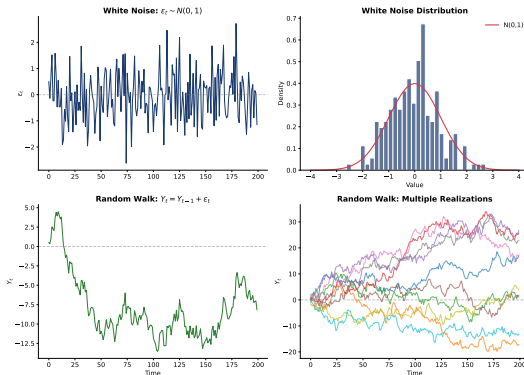
**ACF of White Noise:**

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

**Types:**

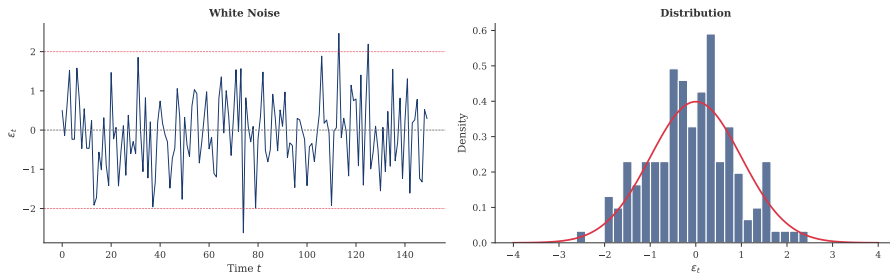
- **Weak white noise:** Uncorrelated (conditions above)
- **Strong white noise:** Independent and identically distributed (i.i.d.)
- **Gaussian white noise:**  $\varepsilon_t \stackrel{iid}{\sim} N(0, \sigma^2)$

# 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:**  $X_t = \sum_{i=1}^t \varepsilon_i$

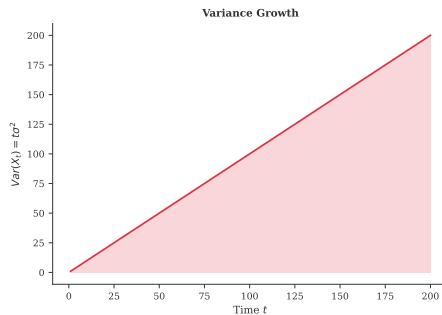
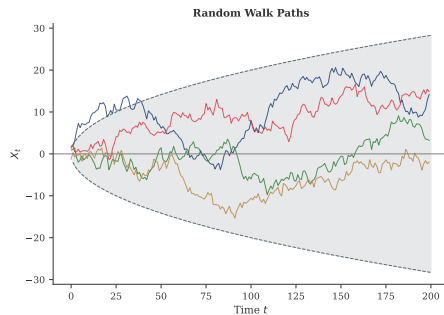
**Properties:**

- $\mathbb{E}[X_t] = 0$  (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!**

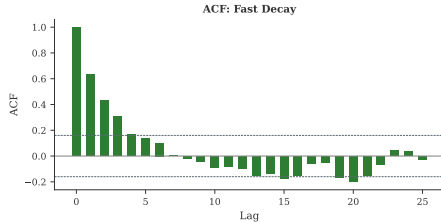
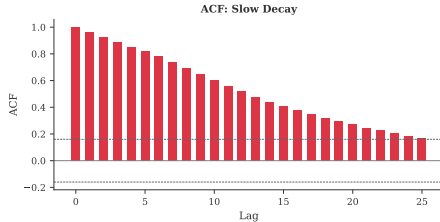
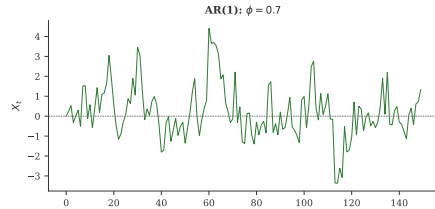
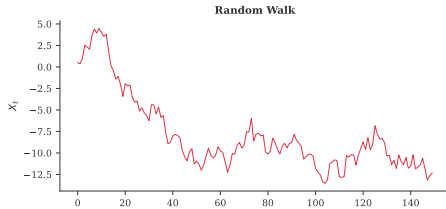
Random walk is **not stationary** because variance depends on  $t$ .

# 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:**

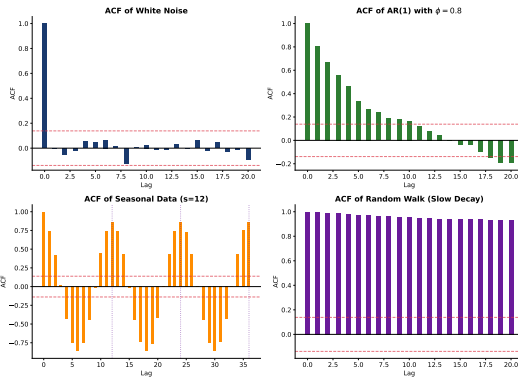
- $\hat{\rho}(0) = 1$  always
- $|\hat{\rho}(h)| \leq 1$

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

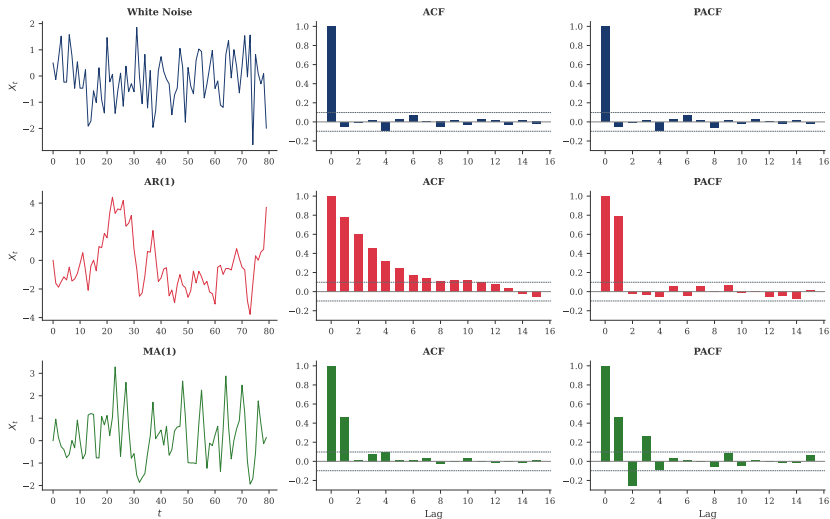
### Interpretation:

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

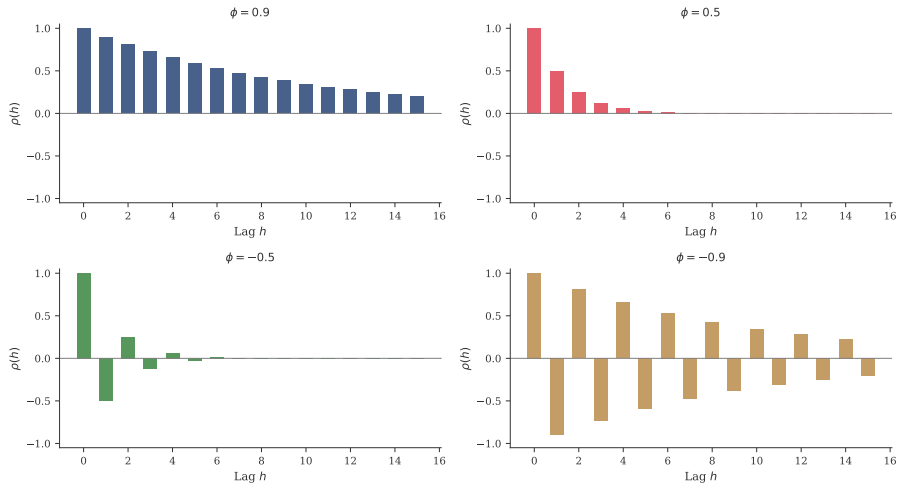
**Key application:** Identify AR order

- 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( $p$ ):  $(1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p)X_t = \varepsilon_t$

# Differencing

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

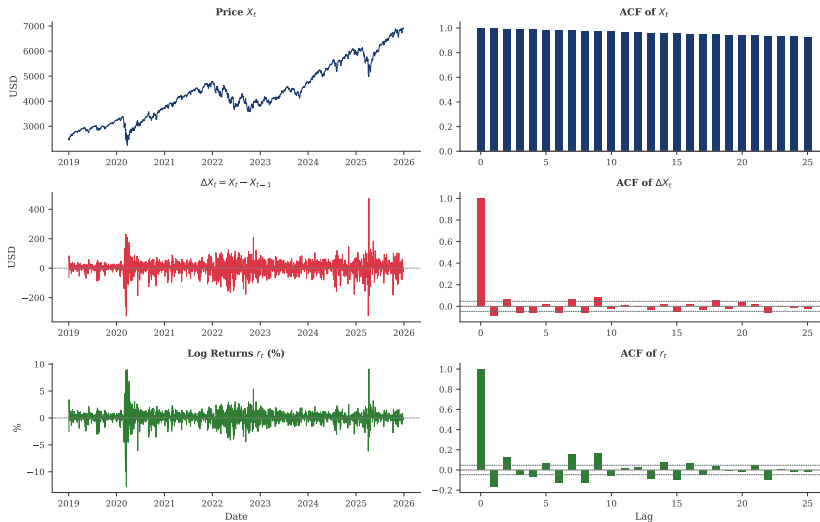
**Why difference?**

- 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:

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



**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  $S_t = \sum_{i=1}^t \hat{\varepsilon}_i$

**Decision:**

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

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

## Using ADF and KPSS Together

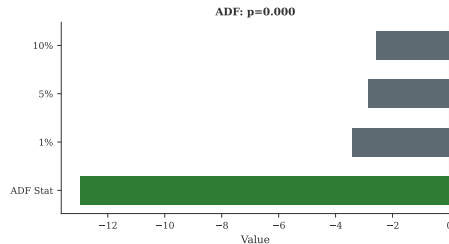
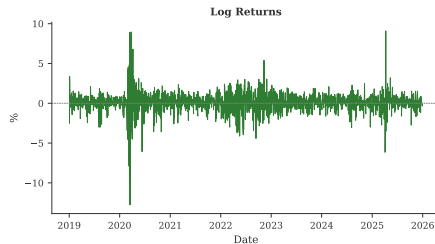
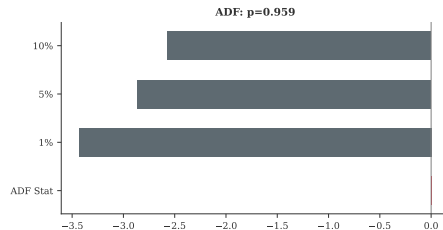
**Confirmatory testing** for robust conclusions:

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

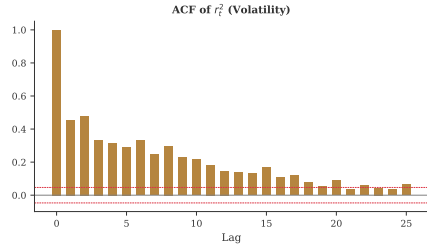
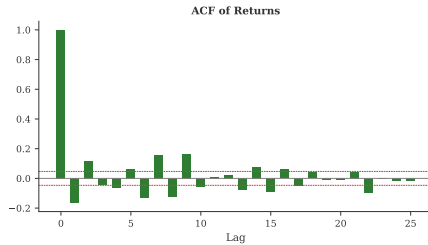
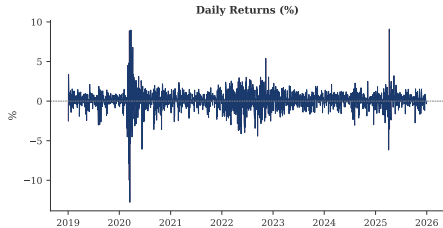
**Recommended workflow:**

- 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)

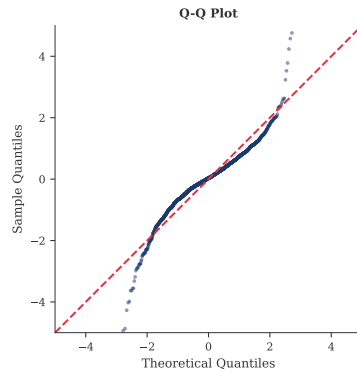
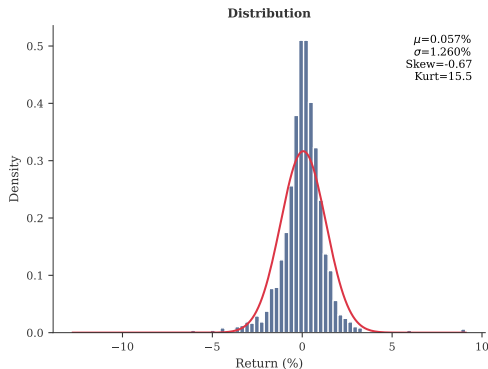
# ADF Test: Visualization with S&P 500



# S&P 500 Analysis: Overview



# Stylized Facts of Financial Returns



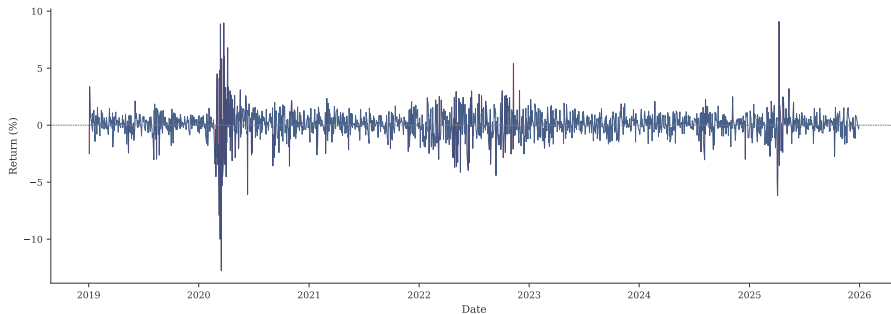
## Observed properties:

- 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

- ➊ **Time series** = observations indexed by time with temporal dependence
- ➋ **Decomposition**: Additive  $X_t = T_t + S_t + \varepsilon_t$  or Multiplicative
- ➌ **Exponential Smoothing**: SES (level), Holt (trend), Holt-Winters (seasonal)
- ➍ **Forecast Evaluation**: MAE, RMSE, MAPE; use train/validation/test splits
- ➎ **Seasonality Modeling**: Dummy variables (any pattern) or Fourier terms (smooth)
- ➏ **Trend Handling**: Differencing (stochastic) or regression (deterministic)
- ➐ **Stationarity**: Mean, variance, autocovariance constant over time
- ➑ **ACF/PACF**: Essential for identifying dependence structure
- ➒ **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)