

Gefördert durch:

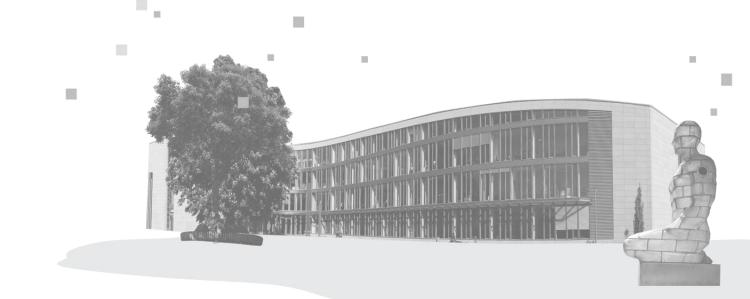


Time Series Forecasting

2.2 Preparing the Target

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Design IT. Create Knowledge.



What we'll cover in this video

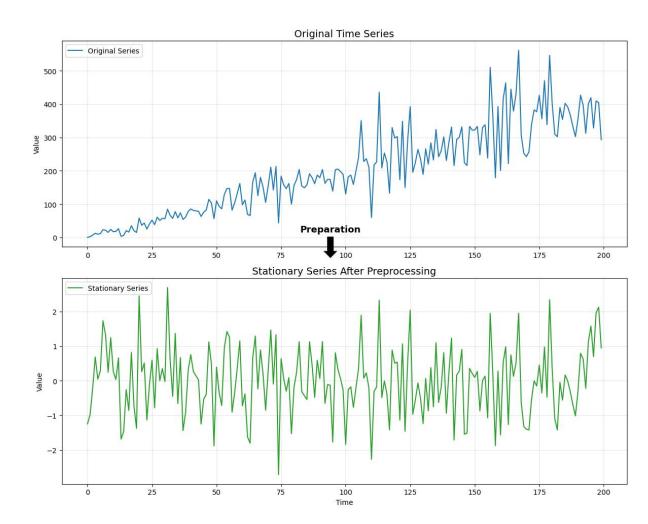


- Why preparing the target is crucial for forecasting accuracy
- Checking and fixing non-stationarity
 - ADF test
 - Differencing transforms
 - Variance stabilization (log, Box-Cox)
- Detecting and handling trends
 - Deterministic vs stochastic
 - Mann-Kendall trend test
 - Detrending methods
- Detecting and handling seasonality
 - STL decomposition

Why prepare the target?



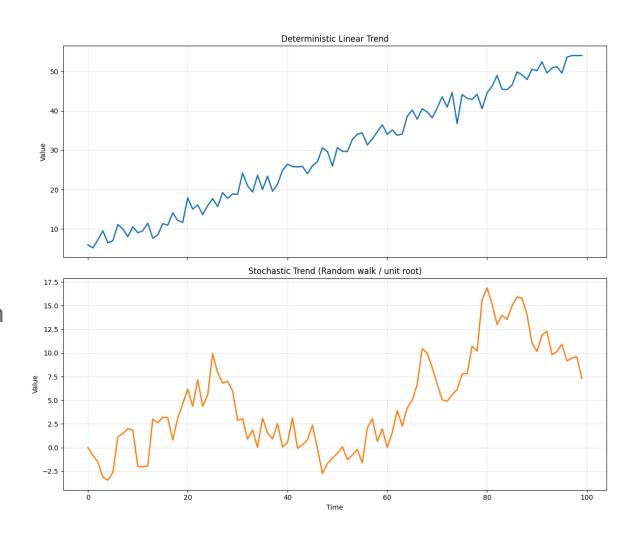
- Raw time series often break model assumptions
- Common issues:
 - Non-stationarity (changing mean over time)
 - Trends and seasonality
 - Heteroscedasticity (changing variance)
- Poor preparation → biased forecasts, lower accuracy
- Goal: Make the target variable stable, clean, and predictable



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Types of trends

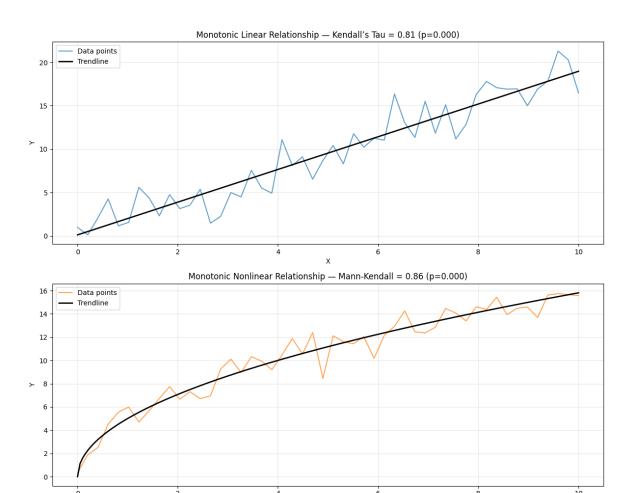
- Trends are long-term movements in the series
- Two main types:
 - Deterministic trend: predictable over time (e.g., straight line or known curve)
 - Stochastic trend: evolves randomly, often following a random walk
- Different trends require different treatments (detrending methods)



HPI

Trend detection tests

- Kendall's Tau: Measures strength of monotonic relationship between time and the variable
 - Value close to +1 → strong upward trend
 - Value close to $-1 \rightarrow$ strong downward trend
- Mann-Kendall (MK) Test: Statistical test for trend detection
 - **Ho**: No trend present
 - H1: Trend exists (upward or downward)
 - Works well for non-linear trends and missing values

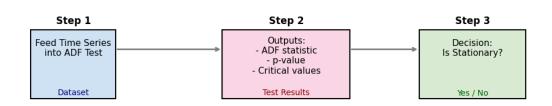


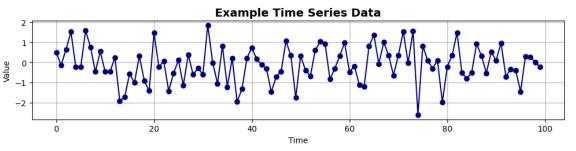
Checking for Unit Roots - ADF Test

- Purpose: Detect non-stationarity in a time series
- Augmented Dickey-Fuller (ADF) Test:
 - Ho: Unit root exists → series is nonstationary
 - **H**₁: No unit root → series is stationary
- Interpretation:
 - p-value < 0.05 → reject H₀ → stationary
 - p-value $\geq 0.05 \rightarrow$ fail to reject $H_0 \rightarrow$ nonstationary
- Often followed by differencing or transformations if needed



ADF Test Workflow





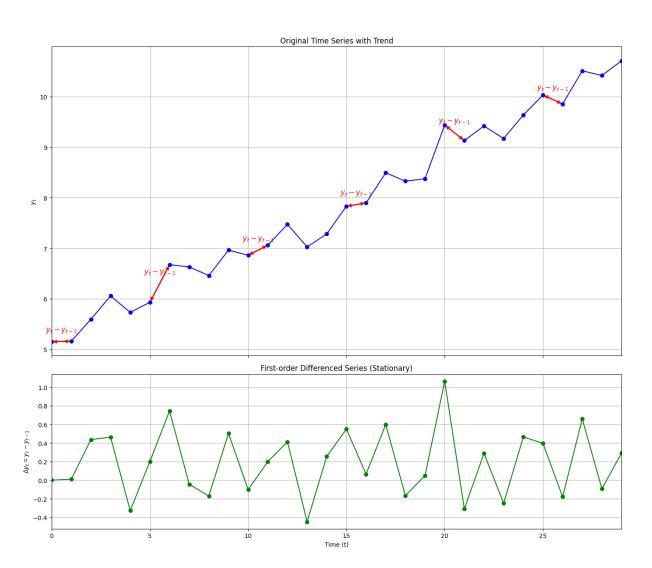
ADF Test Result

ADF Statistic	p-value	Critical Value (5%)	Decision
-3.25	0.015	-2.90	Stationary

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Differencing Transform

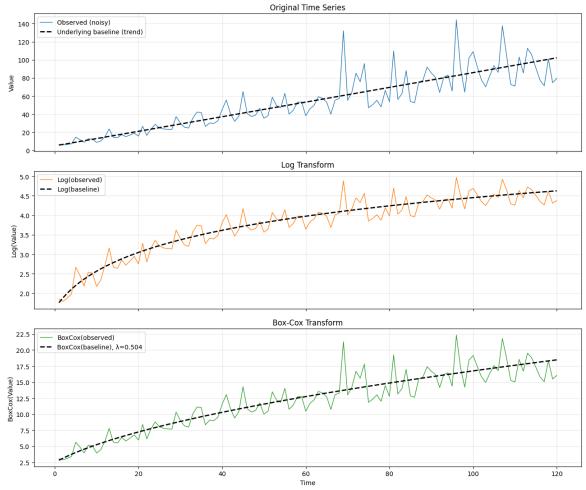
- Purpose: Remove trends and stabilize the mean
- Additive differencing: $y'_t = y_t y_{t-1}$
- Multiplicative differencing: $y'_t = \frac{y_t}{y_{t-1}} 1$
- Apply differencing once or multiple times until stationarity is reached
- Often the first step after ADF test signals non-stationarity



Stabilizing the Variance

- Heteroscedasticity → changing variance over time
- Common test: White Test to detect heteroscedasticity
- Variance stabilizing transforms:
 - Log transform (for positive values)
 - Box-Cox transformation (flexible power transform)
- Goal: Make variance more constant for better forecasting



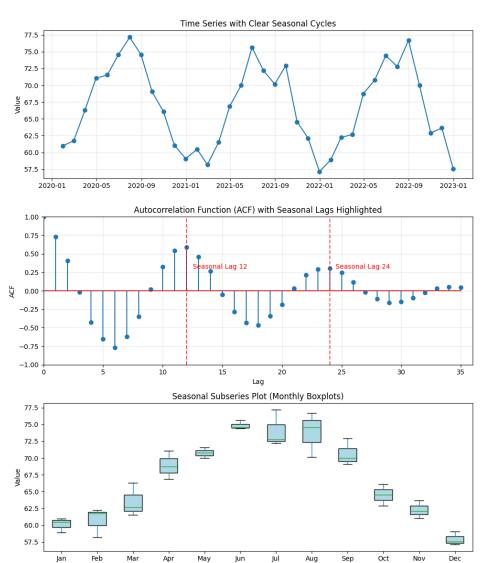


Seasonality

Detecting seasonality

- Common detection methods:
 - Visual inspection of plots
 - Autocorrelation Function (ACF) to spot repeating patterns
 - Seasonal subseries plots
- Statistical tests to detect seasonality:
 - Kruskal-Wallis test: checks for differences between seasonal groups
 - Friedman test: for related samples across seasons
 - Edwards' test: detects cyclical patterns, especially in event data



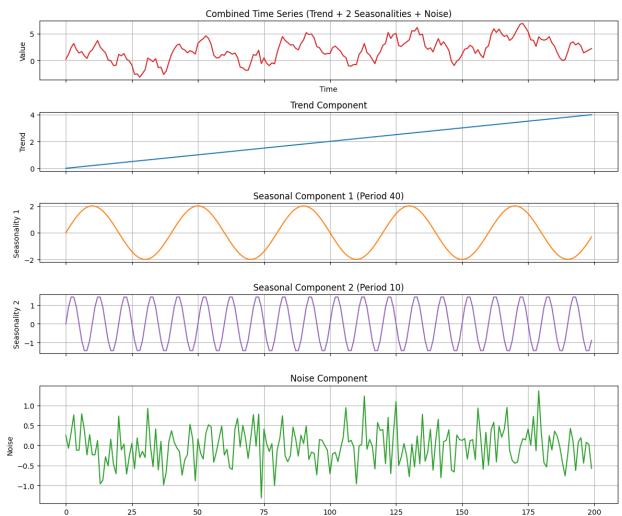


STL Decomposition

Breaking Down the Series

- STL decomposes a time series into three components:
 - Trend
 - Seasonal
 - Residual (noise)
- Uses Loess smoothing, making it very flexible and robust
- Works well with complex seasonal patterns and missing data
- Allows combining with forecasting methods like Naive or ARIMA on components





What we've learnt



- Stationarity matters trends and seasonality can mislead models if not addressed
- Differencing helps remove trends (additive or multiplicative)
- Log and Box-Cox transforms help stabilize variance (hello again, TBATS & BATS!)
- Trends can be detected with statistical tests like Kendall's Tau & M-K test
- Seasonality can be spotted visually, with ACF, subseries plots, and tests like Kruskal-Wallis,
 Friedman, and Edwards'
- STL decomposition is a powerful tool to break down, clean, and prepare series for modeling