Univariate Time Series Data and Model Card

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This report provides an automated, comprehensive analysis of univariate time series data. Generated by Cardtale, it explores basic aspects and potential challenges in your data to support informed decision-making and modeling choices.

Generated: 2025-02-04 23:32

Series Name: M12

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Other aspects were explored but omitted from the final report:

Trend

Hypothesis testing (KPSS, Augmented Dickey-Fuller) indicates that the time series does not exhibit a significant trend. Taking first differences or feature extraction for trend inclusion did not improve forecasting accuracy in preliminary tests.

Variance

Hypothesis testing suggests that the time series has constant variance (homoskedasticity). In preliminary tests, common transformations for variance stabilization did not improve forecasting accuracy

Change Detection

No change point was found according to offline change detection methods

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Data Overview

This section examines the core characteristics and statistical properties of the time series. Understanding these attributes is important for assessing data quality and gaining a preliminary context. We explore the temporal structure, summary statistics, and distribution patterns to create a baseline understanding of your data.

Time Series Plot

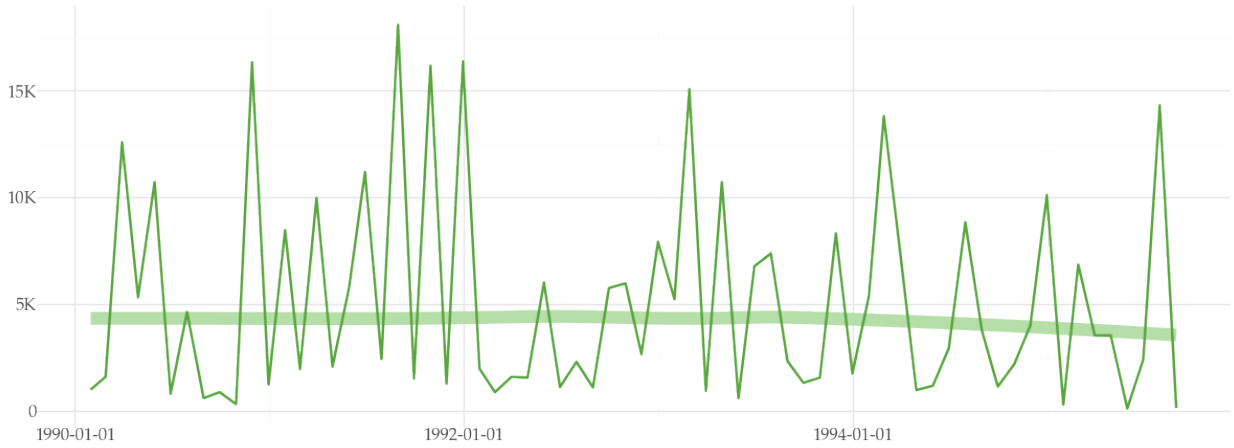

Figure 1: Time series line plot.

- A total of 68 observations spanning from January 1990 to August 1995. These are collected with a monthly sampling frequency.
- The data ranges from a minimum of 120 to a maximum of 18100, starting in 1000 and ending in 140 during the observed period. The average growth percentage per observation is 264.66% (median equal to 18.18%), with an average value of 5077.94. There are no missing values in the time series.

Trend, Seasonality, and Residuals

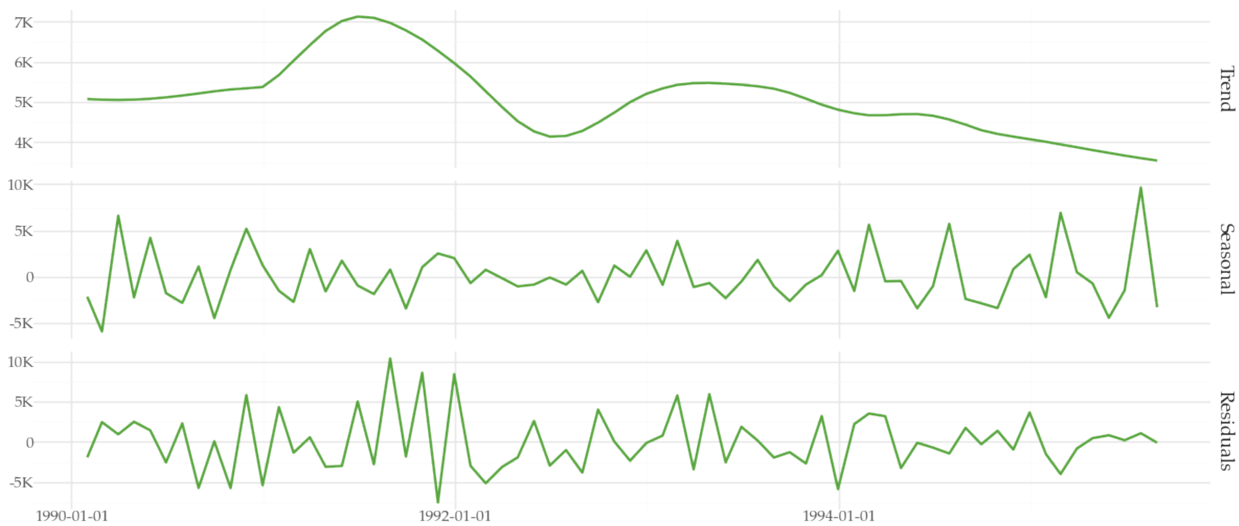

Figure 2: Seasonal, Trend, and Residuals components after decomposition on a monthly frequency using the STL (Season-Trend decomposition using LOESS) method.

- The trend strength is 0.1 (ranges from 0 to 1). All hypothesis tests carried out (KPSS, Augmented Dickey-Fuller, and Philips-Perron) indicate that the time series is stationary in trend or level.
- The seasonal strength is 0.41 (ranges from 0 to 1). Tests for yearly seasonal stationarity show mixed results: the OCSB test indicates presence of a seasonal unit root, while the Wang-Smith-Hyndman test suggests stationarity.
- The STL decomposition residuals show balanced behavior: 47.06% of residuals are positive and 52.94% negative. The average magnitude of positive residuals is 2983.699 compared to -2642.836 for negative residuals. In terms of auto-correlation structure, the residuals show significant temporal dependency in some of the first 12 lags according to the Ljung-Box test. This suggests that the decomposition method is missing some systematic patterns.

Auto-Correlation

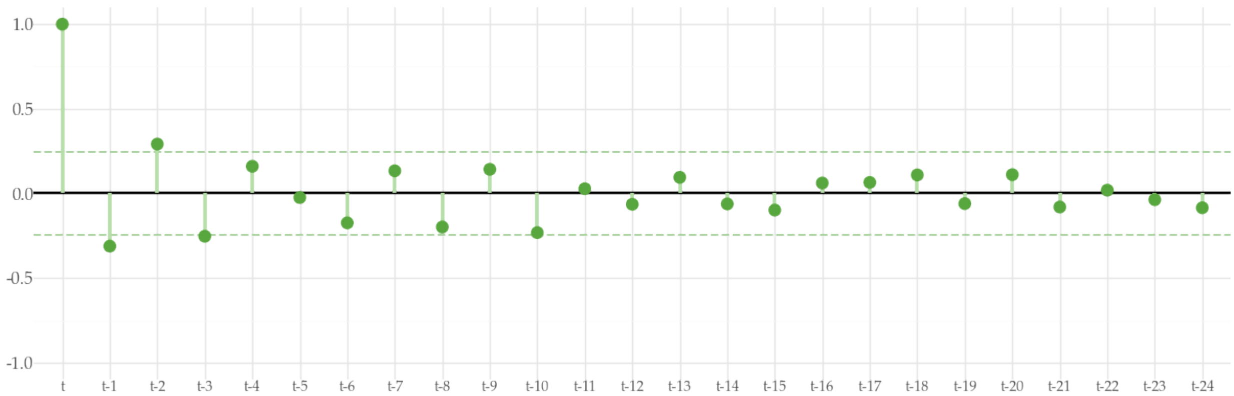

Figure 3: Auto-correlation plot up to 24 lags.

- The following lags show significant autocorrelation: t-1, t-2, and t-3. Some lags show a significant negative autocorrelation (t-1 and t-3), while others have a positive autocorrelation (t-2)
- The following seasonal lags show a significant autocorrelation: t-24

Partial Auto-Correlation

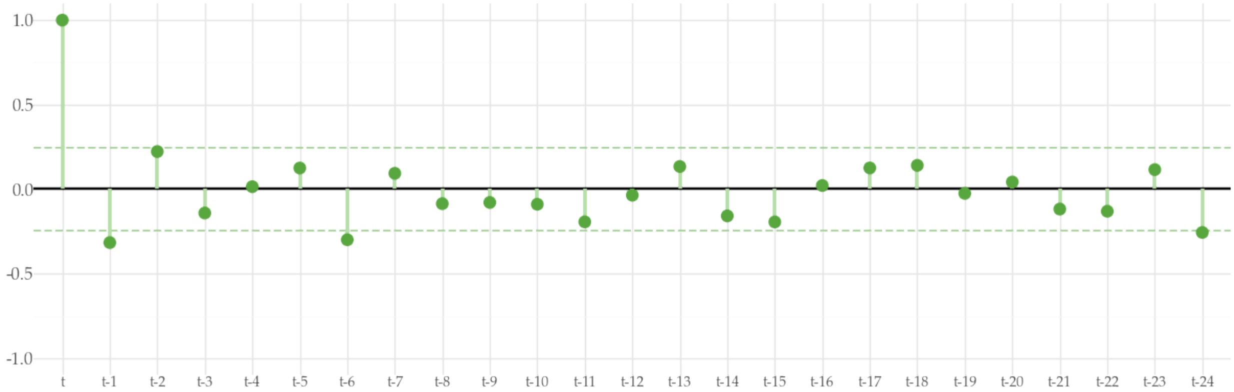

Figure 4: Partial Auto-correlation plot up to 24 lags. At each lag, the partial auto-correlation takes into account the previous correlations.

- The following lags show significant partial autocorrelation: t-1, t-6, and t-24.
- The following seasonal lags show a significant partial autocorrelation: t-24

Seasonality

Seasonality represents recurring patterns or cycles that appear at regular intervals in time series data. These are predictable fluctuations that reflect periodic influences such as monthly, quarterly, or yearly cycles. Understanding seasonal patterns is crucial for forecasting, trend analysis, and identifying anomalies. This section examines the presence, strength, and characteristics of seasonal components in the input time series.

Seasonal Line Plot (Monthly)

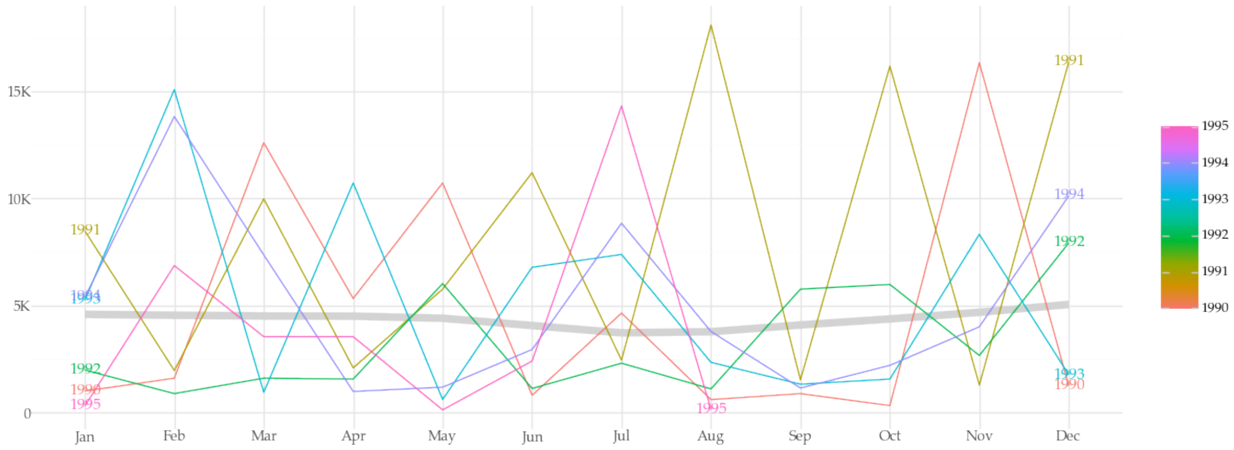

Figure 5: Seasonal plot of monthly values grouped by year.

- The seasonal strength is 0.41. This score ranges from 0 to 1 and values above 0.64 are considered significant. The following tests indicate that the time series is non-stationary in seasonality for a yearly period: OCSB. On the other hand, other tests (Wang-Smith-Hyndman) fail to reject the stationary null hypothesis.

- **Preliminary experiments:** Modeling yearly patterns can improve forecast accuracy. Different approaches were tested relative to a base model using only lag-based features (96.31% SMAPE):
    - Fourier terms: 86.47% SMAPE
    - Seasonal differencing: 101.81% SMAPE
    - Monthly time features: 93.08% SMAPE

Seasonal Sub-series Plot (Quarterly)

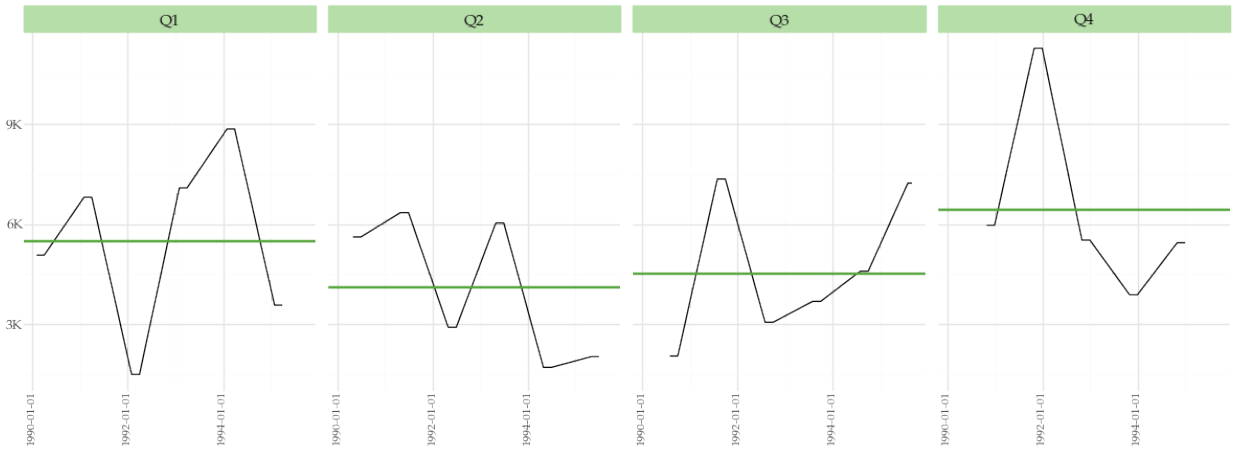

Figure 6: Quarterly seasonal sub-series. This plot helps to understand how the data varies within and across quarterly groups.

- Statistical analysis of quarterly data shows no evidence of systematic differences across quarters, with both means (Kruskal-Wallis test) and variances (Levene's test) being statistically similar.

- Tests for quarterly seasonal stationarity show mixed results: the OCSB test indicates presence of a seasonal unit root, while the Wang-Smith-Hyndman test suggests stationarity.

- **Preliminary experiments:** There is evidence for a quarterly seasonal pattern based on statistical tests. Besides, modeling quarterly patterns can improve forecast accuracy. Different approaches were tested relative to a base model using only lag-based features (96.31% SMAPE):
    - Fourier terms: 102.31% SMAPE
    - Quarterly seasonal differencing: 71.93% SMAPE
    - Quarterly time features: 98.82% SMAPE