

WEEK-12 LAQ

Explain in detail Classical Decomposition and its types.

Classical Decomposition: Unveiling the Patterns in Time Series Data

Classical decomposition is a fundamental technique used in time series analysis to break down a time series into its constituent components: trend, seasonality, and noise. This method helps understand the underlying structure of the data, identify key patterns, and ultimately, improve forecasting accuracy.

1. Key Concepts:

- **Trend:** The long-term, overall direction of the time series. It can be linear, exponential, or non-linear.
- **Seasonality:** Recurring patterns in the data that repeat over a specific period (e.g., yearly, monthly, daily).
- **Noise:** Random fluctuations in the data that are not explained by trend or seasonality.

2. Types of Classical Decomposition:

There are two main types of classical decomposition based on how the components are combined:

a) Additive Decomposition:

- **Assumption:** The time series is the sum of its components: $Y(t) = T(t) + S(t) + N(t)$
- **Example:** Consider monthly sales data where the trend is increasing, there's a seasonal peak during the holiday season, and there's random fluctuation throughout the year.

b) Multiplicative Decomposition:

- **Assumption:** The time series is the product of its components: $Y(t) = T(t) * S(t) * N(t)$
- **Example:** Imagine monthly sales data where the trend is increasing, the seasonal peak during the holiday season is proportional to the overall sales, and there's random fluctuation proportional to the overall sales at each point in time.

3. Steps for Classical Decomposition:

Step 1: Identify the Time Series Type: Determine whether the data is additive or multiplicative. This can be done by examining the relationship between the magnitude of the seasonal fluctuations and the level of the data. If the fluctuations are roughly constant, it's likely additive. If the fluctuations grow proportionally with the level, it's likely multiplicative.

Step 2: Calculate the Trend Component: This is usually done using moving averages. A moving average smooths out the data by calculating the average of a fixed number of consecutive data points. The window size for the moving average should be chosen based on the seasonality period.

Step 3: Calculate the Seasonal Component:

- **Additive:** Subtract the trend from the original data and calculate the average of the residuals for each season.
- **Multiplicative:** Divide the original data by the trend and calculate the average of the residuals for each season. This gives you the seasonal index.

Step 4: Calculate the Noise Component:

- **Additive:** Subtract the trend and seasonality components from the original data.
- **Multiplicative:** Divide the original data by the trend and seasonality components.

4. Applications of Classical Decomposition:

- **Understanding Time Series Dynamics:** It helps identify underlying patterns and understand how different factors influence the data.
- **Forecasting:** By removing seasonality and noise, we can isolate the underlying trend, which can then be used to forecast future values.
- **Data Smoothing:** By removing noise, we can obtain a smoother representation of the data, making it easier to analyze trends and patterns.
- **Outlier Detection:** Noise can highlight unusual observations that might indicate outliers or anomalies in the data.

5. Advantages of Classical Decomposition:

- **Simplicity:** The method is relatively straightforward to understand and implement.
- **Visual Understanding:** The decomposed components provide a clear visual representation of the data structure.
- **Flexibility:** It can be applied to different types of time series data.

6. Limitations of Classical Decomposition:

- **Assumption Dependence:** The accuracy of the decomposition depends heavily on the correctness of the assumed additive or multiplicative relationship between the components.
- **Subjectivity:** The selection of moving average window size and other parameters can be subjective and influence the results.

- **Non-Stationarity:** Classical decomposition can be less accurate for non-stationary time series where the trend is not constant over time.

7. Alternative Approaches:

- **Decomposition Methods Based on Filtering:** Using filters to isolate the different frequency components of the time series.
- **Time Series Models:** Using models like ARIMA or SARIMA to directly capture the trend, seasonality, and noise in a single model.

In conclusion, classical decomposition is a valuable tool for analyzing time series data and extracting its underlying components. It provides a simple and intuitive way to understand the patterns within the data and can be used for forecasting, smoothing, and outlier detection. However, it's essential to consider its limitations and explore alternative approaches when necessary.