
📊 Forecasting Intermittent Demand Using Croston's Method

1. Understanding Croston's Method

Croston's method is tailored for forecasting intermittent demand—characterized by sporadic non-zero values interspersed with zeros. It decomposes the demand series into two components:

- **Demand Size**: The magnitude of non-zero demands.
- **Inter-Demand Interval**: The time between successive non-zero demands.

Each component is smoothed using exponential smoothing, and the forecast is computed as the ratio of the smoothed demand size to the smoothed interval.

2. Rolling Forecast Implementation

To evaluate the model's performance over time, a rolling forecast approach was employed:

- **Procedure**: At each time point t, the model is trained on data up to $t-1$ and forecasts the demand for time t.
- **Outcome**: This yields a sequence of one-step-ahead forecasts that can be compared directly with actual observed values.

3. Performance Metrics Analysis

The model's accuracy was assessed using the following metrics:

- **Mean Absolute Error (MAE)**: 10.02
  - Indicates the average absolute difference between forecasts and actual values.
- **Root Mean Squared Error (RMSE)**: 24.28
  - Provides a measure sensitive to large errors, penalizing them more than MAE.
- **Symmetric Mean Absolute Percentage Error (sMAPE)**: 178.33%
  - Reflects the average percentage error between forecasts and actuals, adjusted for symmetry.
- **Mean Absolute Scaled Error (MASE)**: 0.398
  - Compares the model's MAE to that of a naive forecast; values less than 1 suggest better performance than the naive model.

Interpretation:

- The relatively low MAE and MASE values indicate that the model performs better than a naive forecast.
- However, the high sMAPE suggests significant relative errors, possibly due to the intermittent nature of the data.

4. Visualization Insights

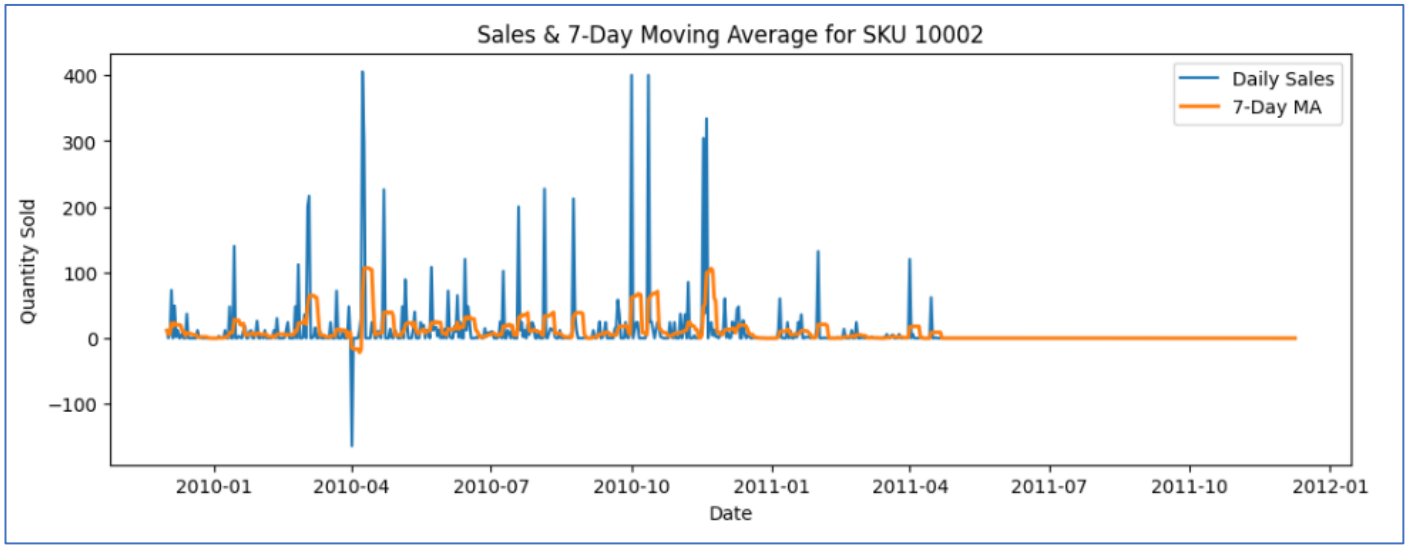
Plots comparing actual and forecasted values reveal:

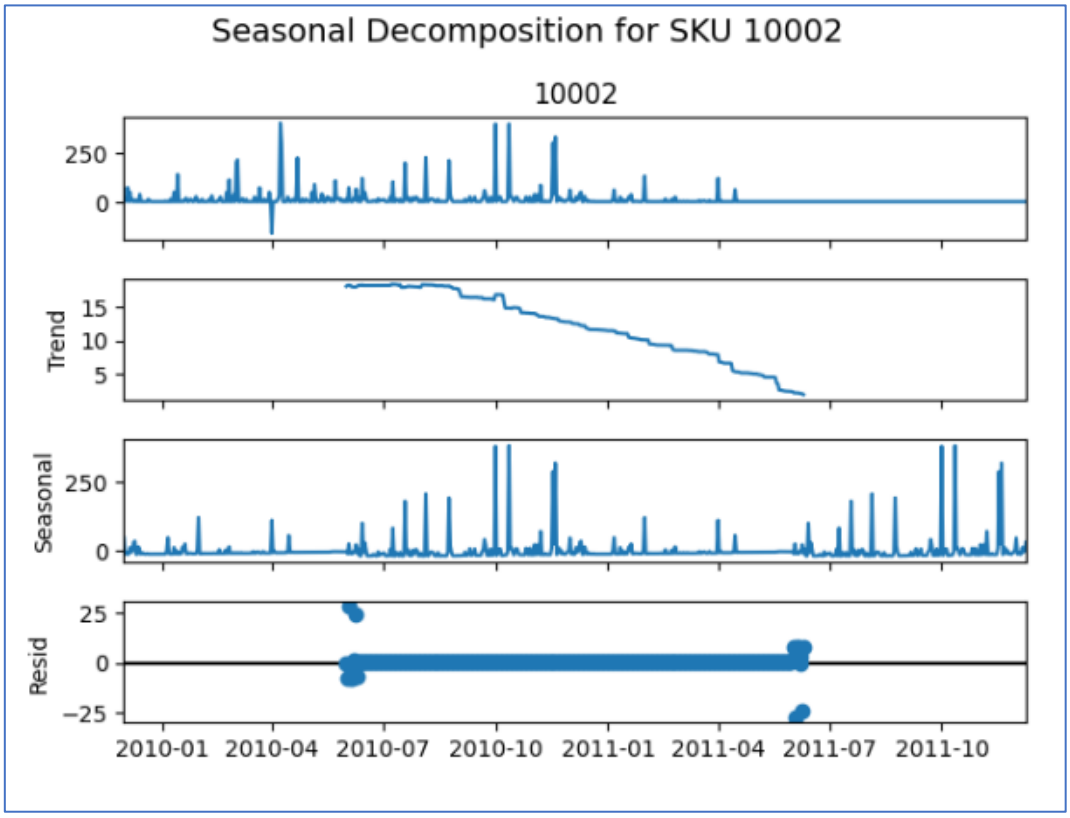
- The forecast remains constant between non-zero demands, aligning with the nature of Croston's method.
- Discrepancies between forecasts and actuals occur when demand patterns change abruptly, highlighting the model's limitations in capturing sudden shifts.

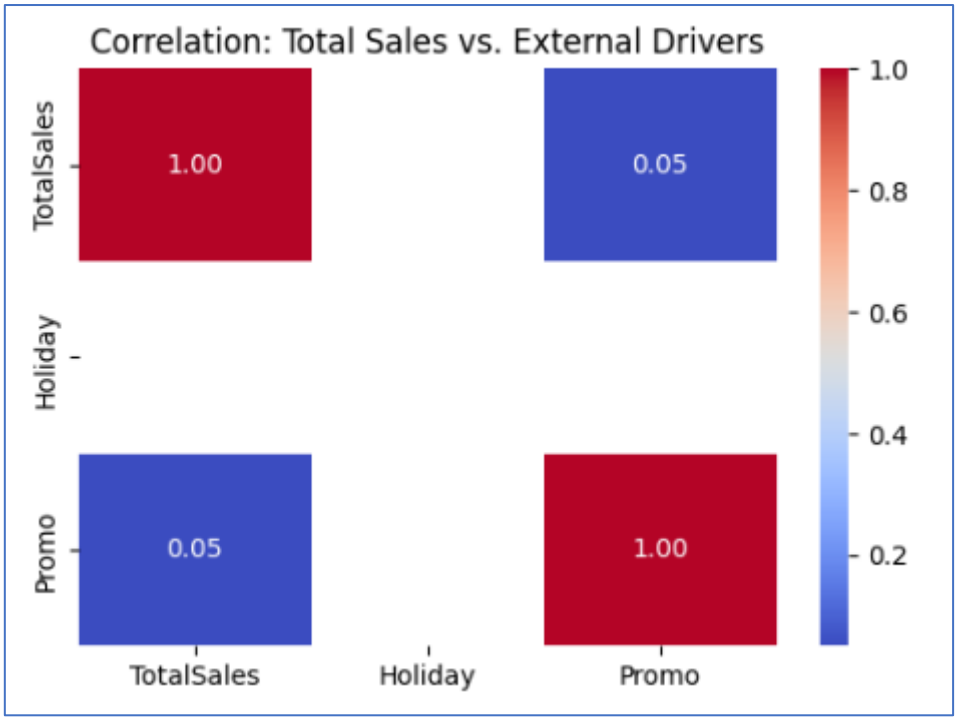
5. Recommendations for Improvement

To enhance forecasting accuracy:

- **Alternative Models**:
    - **Syntetos–Boylan Approximation (SBA)**: Introduces a bias correction to Croston's method, potentially improving accuracy.
    - **Teunter–Syntetos–Babai (TSB) Model**: Incorporates demand probability, offering a more nuanced approach.
- **Machine Learning Approaches**:
    - Utilize models capable of capturing complex patterns, such as Gradient Boosting Machines or Recurrent Neural Networks, especially if the data exhibits trends or seasonality.
- **Dashboard & Reporting**:
    - Develop interactive dashboards using tools like Plotly and ipywidgets in Jupyter Notebook to visualize forecasts and actuals dynamically.
    - Export key views and compile concise PDF reports summarizing data insights for stakeholders.







Forecasts vs Actual values