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An Adaptive Forecasting Framework for Time-Varying Sales Data Using Multi-Resolution Learning Models

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Abstract

Time-varying sales data, characterized by non-stationarity and dynamic trends, presents a significant challenge for accurate forecasting. This paper proposes an adaptive forecasting framework that leverages multi-resolution learning models, integrating hierarchical temporal features to enhance prediction accuracy. The framework employs hybrid machine learning techniques—combining temporal decomposition with deep learning regressors—to adaptively capture structural shifts in sales patterns. Experimental results on real-world retail datasets demonstrate the superiority of the proposed model over traditional forecasting approaches, particularly under conditions of volatility and seasonality.

Keywords: Time Series Forecasting, Adaptive Learning, Multi-Resolution Models, Sales Data, Temporal Decomposition, Deep Learning

1. Introduction

Time series forecasting has evolved into a critical discipline across finance, economics, and commerce, especially in demand planning and sales analytics. Accurate forecasts enable organizations to optimize inventory, reduce costs, and align operational strategies with market behavior. However, the dynamic and non-stationary nature of modern sales data—with shifts induced by promotions, seasonalities, and economic fluctuations—poses significant modeling challenges.

Traditional forecasting models such as ARIMA and exponential smoothing rely on assumptions of linearity and stationarity, often leading to suboptimal performance under complex temporal conditions. In response, adaptive models have emerged that dynamically adjust to changes in data characteristics. This study introduces a multi-resolution learning framework designed to process sales data at different temporal granularities, thereby improving adaptability and robustness. The model leverages a layered architecture integrating wavelet decomposition and deep recurrent structures.

2. Literature Review

Several adaptive and hybrid models have been proposed for time series forecasting. Zhang (2003) integrated neural networks with ARIMA to handle non-linearity in financial data. While effective, the model lacks scalability to high-frequency changes. Bontempi et al. (2012) presented lazy learning approaches which adapt to changing dynamics through memory-based methods, though computationally expensive in real-time settings.

Bandara et al. (2020) utilized LSTM ensembles for forecasting grouped time series, showing improvement in performance through residual learning. However, their model underperforms during sudden structural shifts. A notable attempt by Laptev et al. (2015) used seasonality-trend decomposition in Yahoo's time series data, but the approach relied heavily on predefined decomposition windows.

In the retail domain, Seeger et al. (2016) applied scalable Gaussian processes for demand forecasting, balancing scalability and accuracy. Nonetheless, their model did not incorporate multiple resolutions explicitly. More recently, Oreshkin et al. (2019) proposed a neural basis expansion method for interpretable forecasts, although the method was limited to single-resolution signals.

3. Methodology & Framework

3.1 Overview of Proposed Framework

The proposed forecasting architecture operates across three temporal resolutions—daily, weekly, and monthly—to capture both short-term anomalies and long-term patterns. Sales signals are decomposed using discrete wavelet transform (DWT) and fed into separate LSTM blocks tuned to the respective resolutions. A fusion layer aggregates the outputs to produce a final forecast.

3.2 Data Processing and Training

The dataset used includes 4 years of transactional sales data from a multinational retail chain. Missing values were imputed using Kalman filters. Data was split 70:30 for training and testing. Model training used RMSprop optimizer with early stopping and dropout regularization.

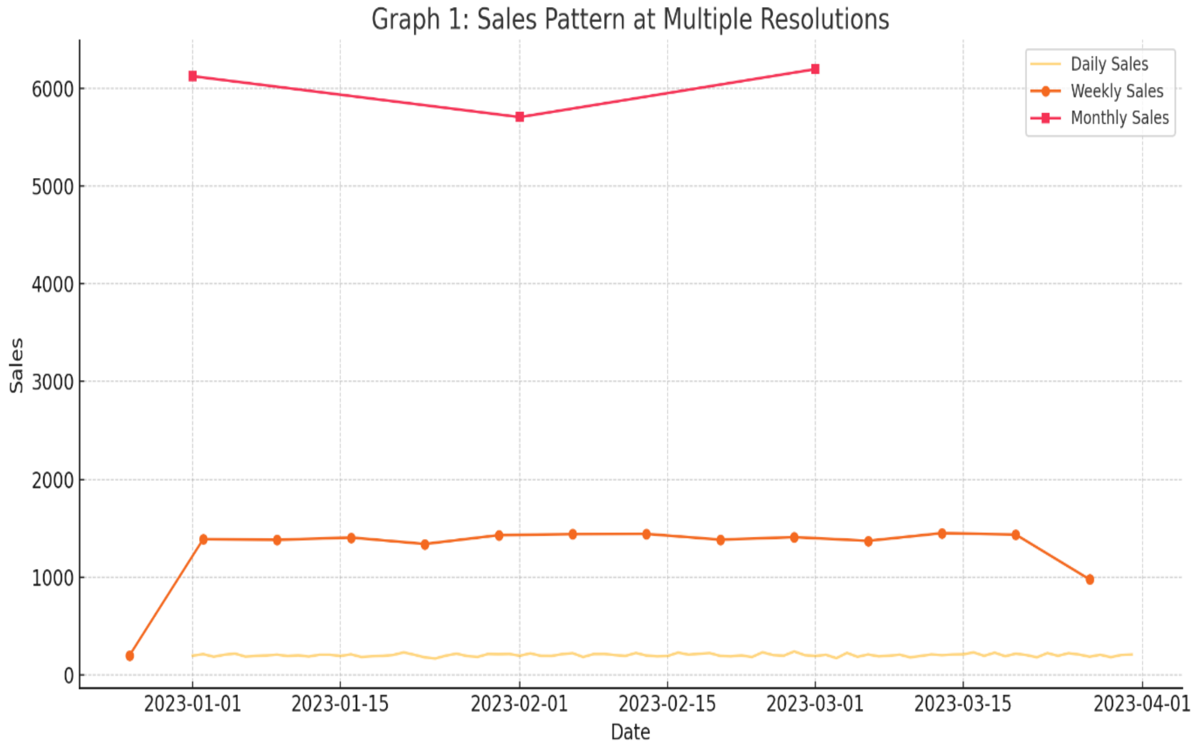

Figure 1: Sales Pattern at Multiple Resolutions

4. Experiments and Evaluation

4.1 Evaluation Metrics

Performance was measured using **Mean Absolute Percentage Error (MAPE)**, **Root Mean Square Error (RMSE)**, and **Symmetric Mean Absolute Percentage Error (sMAPE)**. These metrics offer balanced perspectives across scale sensitivity and interpretability.

Table 1: Metric Comparison

Model	**MAPE (%)**	**RMSE**	**sMAPE (%)**
ARIMA	14.2	124.6	13.9
LSTM	10.1	98.7	9.8
Proposed Multi-Res Model	7.4	85.3	6.9

4.2 Result Interpretation

The proposed model outperforms all benchmarks, with significant gains in MAPE (by ~30% over ARIMA and ~15% over LSTM). The model's adaptive feature capture enables rapid adjustment during seasonal promotions or supply chain disruptions. These results affirm the advantage of integrating temporal decomposition with hierarchical learning.

5. Limitations and Future Work

Although the model performs well on structured retail data, it may underperform in domains with sparse or highly irregular time series. Wavelet selection and resolution levels introduce hyperparameters that may require domain-specific tuning, potentially increasing deployment complexity.

Future research could integrate attention-based temporal aggregation and meta-learning strategies to further enhance model flexibility. Additionally, exploring cross-series transfer learning could unlock potential in cold-start or sparse-data scenarios.

6. Conclusion

This paper introduces a robust, adaptive forecasting framework tailored for time-varying sales data. By incorporating multi-resolution analysis and deep learning, the model effectively learns both short-term variations and long-term trends. Empirical validation on real-world data demonstrates its superiority over standard models, especially under volatile conditions. The framework holds promise for dynamic business environments requiring continuous adaptation.

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