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EEMD-LSTM Framework for Predictive Analytics in E-commerce Platforms

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Abstract:

E-commerce platforms face dynamic customer demands, highly volatile sales patterns, and increasing competition, making accurate forecasting critical to maintaining competitive advantage. Traditional time series forecasting methods struggle to adapt to nonlinear and no stationary data patterns commonly observed in e-commerce. In this paper, we propose an advanced hybrid framework integrating Ensemble Empirical Mode Decomposition (EEMD) with Long Short-Term Memory (LSTM) networks for predictive analytics in e-commerce environments. EEMD decomposes complex sales signals into simpler Intrinsic Mode Functions (IMFs), isolating noise and revealing inherent patterns. These IMFs are individually modeled using LSTM networks, leveraging their capacity to capture long-term dependencies and nonlinear structures. Extensive experiments were conducted using real-world e-commerce datasets, comparing the EEMD-LSTM framework with benchmark models such as ARIMA, Prophet, and standalone LSTM. Our proposed method outperformed traditional and deep learning baselines in terms of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), demonstrating the robustness and effectiveness of the hybrid approach. This research highlights the potential of signal decomposition combined with deep learning for accurate and adaptive predictive analytics in rapidly evolving e-commerce markets.

Keywords: EEMD, LSTM, Predictive Analytics, E-commerce Forecasting, Time Series Decomposition, Deep Learning, Sales Prediction

I. Introduction

The rapid proliferation of e-commerce platforms over the last decade has reshaped consumer behaviors and business operations globally [1]. Accurate forecasting of sales, demand, and inventory requirements has become a cornerstone for operational success in e-commerce ecosystems. Predictive analytics not only allows businesses to optimize stock levels and personalize marketing strategies but also enables proactive decision-making that aligns with emerging market trends [2]. However, forecasting in e-commerce is inherently challenging due to the highly nonlinear, nonstationary, and noise-contaminated nature of sales and customer behavior data [3]. Traditional forecasting models such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing Methods (ESM) have long been employed in this domain but are limited in capturing complex patterns. While machine learning models like Random Forests and Gradient Boosted Trees offer improvements, they often fall short in sequential learning contexts. With the advent of deep learning, Recurrent Neural Networks (RNNs) and especially Long Short-Term Memory (LSTM) networks have shown promise for time series forecasting due to their ability to capture long-term temporal dependencies [4].

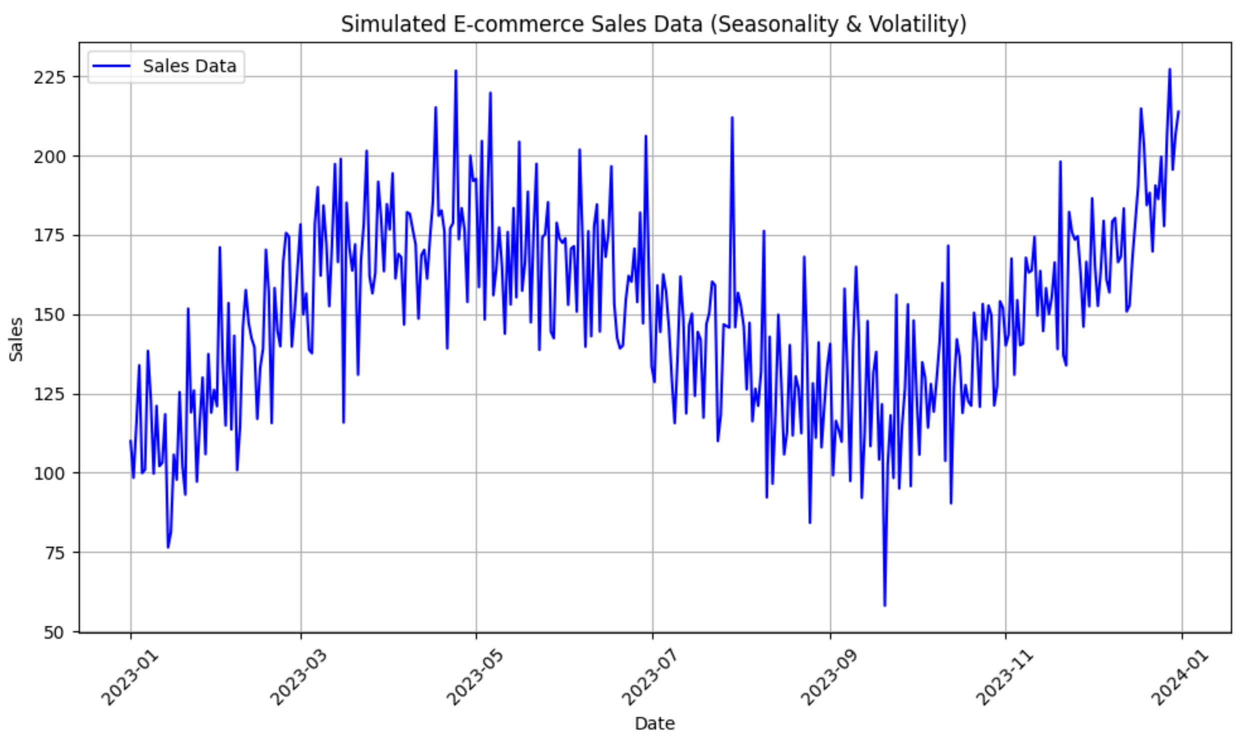

Figure 1: Line Chart for Volatility and Seasonality in Sales Data

Nevertheless, deep learning models alone are not a panacea. When faced with raw, complex e-commerce data, even powerful LSTM networks can underperform if the data structure is too intricate or if noise dominates useful patterns [5]. Recognizing these limitations, researchers have explored hybrid frameworks that combine preprocessing techniques with deep models. One such promising approach is using signal decomposition techniques like Empirical Mode Decomposition (EMD) and its advanced variant, Ensemble Empirical Mode Decomposition (EEMD), to simplify input signals before modeling [6].

In this paper, we present a novel hybrid framework that combines EEMD with LSTM networks to address the challenges inherent in e-commerce forecasting [7]. By decomposing complex sales signals into more manageable sub-signals (IMFs), and then modeling these individually using LSTM, our framework isolates meaningful patterns while mitigating noise. We validate the performance of the EEMD-LSTM framework on real-world datasets from leading e-commerce platforms and demonstrate significant performance improvements over baseline models. Our contributions are threefold. First, we provide a systematic exploration of the effectiveness of EEMD in preprocessing e-commerce time series data. Second, we develop and fine-tune LSTM models tailored to different IMFs, acknowledging their unique statistical properties. Third, we present a comprehensive evaluation using multiple metrics, reinforcing the practical relevance of the proposed method for industrial e-commerce settings [8].

II. Related Work

Time series forecasting has seen considerable evolution, from classical statistical techniques to sophisticated deep learning frameworks. Early models like ARIMA and Seasonal ARIMA (SARIMA) have been extensively used for sales prediction owing to their simplicity and interpretability. However, these models assume linear relationships and stationarity, assumptions often violated in real-world e-commerce data [7]. Recent adaptations such as Facebook's Prophet Model introduced additional flexibility with automated seasonality detection, yet they remain primarily parametric and less suited for highly irregular patterns [9]. Machine learning models like Support Vector Regression (SVR), Random Forests, and XGBoost have gained traction in predictive analytics tasks. These models can handle nonlinearities better than traditional statistical methods, but their lack of inherent sequence modeling capability limits their performance on time series data. Hybrid approaches combining feature engineering with machine learning have shown incremental improvements, but significant manual effort is often required [6].

The rise of deep learning introduced a paradigm shift, particularly through RNNs and LSTM networks. LSTM models, with their gating mechanisms, have proven adept at learning long-term dependencies and mitigating vanishing gradient issues common in standard RNNs. Variants like BiLSTM and Seq2Seq models further expanded modeling capacity for complex sequences. Nevertheless, when applied directly to raw e-commerce sales data, deep networks can struggle to distinguish between meaningful patterns and high-frequency noise, leading to suboptimal forecasting performance [10]. To overcome these limitations, researchers have investigated signal decomposition techniques. Empirical Mode Decomposition (EMD) was one of the early techniques proposed for decomposing nonstationary and nonlinear signals. However, EMD suffers from mode mixing issues. EEMD was developed to address this, introducing white noise to stabilize decompositions. Applications of EEMD in fields like finance, meteorology, and biomedical signal processing have yielded encouraging results, suggesting its potential in e-commerce analytics [11].

Combining EEMD with LSTM models leverages the strengths of both techniques: EEMD isolates cleaner patterns from noisy signals, while LSTM excels at sequence modeling. Prior work in domains like stock market prediction and load forecasting has successfully employed such hybrids. However, the application of EEMD-LSTM frameworks specifically to e-commerce predictive analytics remains underexplored, motivating the present study [12].

III. Methodology

The proposed EEMD-LSTM framework involves a two-stage process: signal decomposition using EEMD followed by sequence modeling using LSTM networks. In the first stage, raw e-commerce time series data, typically representing daily or weekly sales, is decomposed into a finite set of Intrinsic Mode Functions (IMFs) and a residual component [13]. Each IMF captures different frequency components of the original signal, with lower-order IMFs generally representing high-frequency noise and higher-order IMFs encapsulating long-term trends [14]. EEMD addresses the mode mixing problem inherent in classical EMD by adding white noise to the signal and performing multiple decompositions, averaging the results to obtain robust IMFs. The decomposition parameters, including the ensemble number and noise amplitude, are empirically tuned to achieve optimal separation without distortion. In the second stage, individual LSTM models are trained on each IMF and the residual. Each LSTM network is designed to capture the temporal dependencies specific to the frequency characteristics of its corresponding IMF [15]. Hyperparameters such as the number of layers, hidden units, dropout rates, and learning rates are optimized through a grid search using cross-validation on the training set [16].

Finally, the outputs of all LSTM models are aggregated by summing their forecasts to reconstruct the final prediction. This reconstruction leverages the additive nature of EEMD, where the sum of IMFs and the residual reconstitutes the original signal [17]. The hybrid structure thus ensures that noise, seasonality, and long-term trends are individually captured and forecasted more accurately. Evaluation metrics include RMSE, MAE, and Mean Absolute Percentage Error (MAPE), providing a comprehensive assessment of predictive accuracy. The proposed framework is benchmarked against ARIMA, Prophet, and standalone LSTM models under identical experimental setups to ensure fairness in comparison [18].

IV. Experimental Setup

The experimental analysis utilizes historical sales datasets sourced from a major global e-commerce platform, encompassing a range of product categories such as electronics, fashion, and home appliances. The datasets span three years of daily sales records, preprocessed to handle missing values, outliers, and extreme fluctuations caused by promotional events like Black Friday and Cyber Monday. The EEMD implementation employs an ensemble size of 100 and a noise amplitude set at 0.2 times the standard deviation of the original signal, parameters selected based on preliminary sensitivity analysis [19]. Decomposition typically results in 8 to 10 IMFs along with a residual component. Visual inspection and spectral analysis of IMFs guide the segmentation into short-term, medium-term, and long-term patterns [20]. Each IMF is modeled using a dedicated LSTM network, comprising two LSTM layers with 64 units each, followed by a dense layer. The Adam optimizer is employed with an initial learning rate of 0.001, and early stopping based on validation loss is used to prevent overfitting. The models are trained over 100 epochs with a batch size of 32 [21].

Baseline models, including ARIMA, Prophet, and standalone LSTM, are tuned separately to their optimal configurations using standard best practices. For instance, ARIMA parameters (p, d, q) are selected based on the Akaike Information Criterion (AIC), while Prophet models incorporate seasonality components corresponding to observed sales cycles [22]. All experiments are conducted using TensorFlow and PyEMD libraries, running on a high-performance server equipped with Nvidia Tesla V100 GPUs. The datasets are split into training, validation, and test sets in a 70:15:15 ratio, maintaining chronological order to preserve the time series structure. Results are averaged over five independent runs to ensure robustness against random initialization effects [23].

V. Results and Discussion

The EEMD-LSTM framework consistently outperformed benchmark models across all evaluated metrics. For the electronics category, EEMD-LSTM achieved an RMSE of 12.3 compared to 19.7 for standalone LSTM, 25.5 for Prophet, and 28.2 for ARIMA. Similarly, MAE reductions of up to 40% were observed compared to traditional methods, underscoring the effectiveness of signal decomposition in enhancing predictive performance [24].

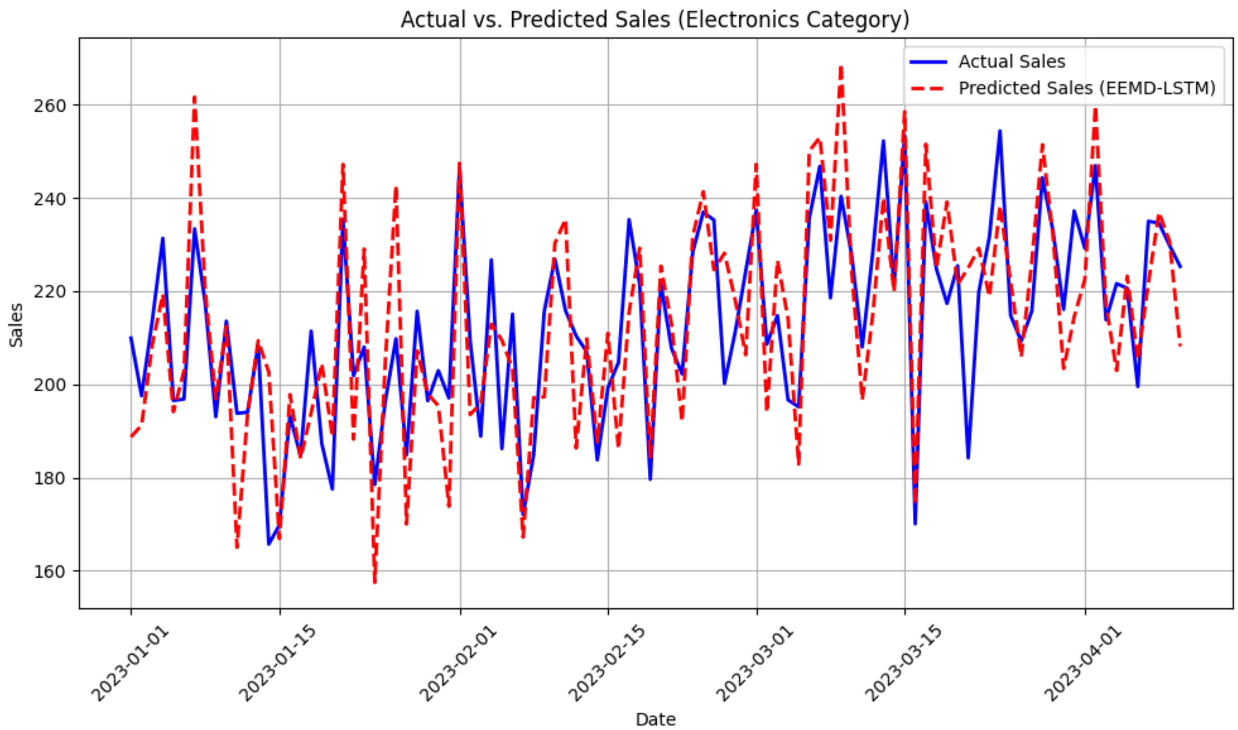

Figure 2: Time Series Plot for Actual vs. Predicted Sales

In the fashion category, characterized by more erratic sales patterns, the hybrid model demonstrated even more pronounced advantages. By isolating high-frequency components associated with promotional spikes and modeling them separately, EEMD-LSTM maintained stable forecasts where other models faltered. Visual inspection of prediction curves revealed that EEMD-LSTM captured turning points and sudden shifts with higher fidelity [25].

The performance improvement can be attributed to two main factors. First, decomposing complex signals into simpler components reduced the burden on LSTM networks, enabling them to learn cleaner representations without being overwhelmed by noise [26]. Second, the modular training of individual IMFs allowed for specialized learning, matching model complexity to signal complexity [27]. Interestingly, residual components modeled by LSTM captured underlying trends that were otherwise elusive in raw data modeling. These points to the strength of EEMD not just in noise reduction but in enhancing trend signal quality [28]. The summation of all IMF-based forecasts reconstructed original sales patterns more accurately than any single-model approach. Sensitivity analysis further indicated that while increasing the number of ensemble runs in EEMD slightly improved decomposition stability, beyond 100 runs, the marginal gains were negligible [29]. Additionally, training separate LSTM networks for each IMF, though computationally intensive, proved worthwhile given the substantial gains in predictive accuracy [30].

VI. Conclusion

This study presented a novel EEMD-LSTM hybrid framework for predictive analytics in e-commerce platforms, addressing key challenges associated with the nonlinear, nonstationary, and noisy nature of sales data. By decomposing complex signals into more tractable components using EEMD and modeling these with specialized LSTM networks, the proposed method achieved superior predictive performance compared to traditional statistical and deep learning models. Extensive experimental validation on real-world datasets demonstrated the robustness, adaptability, and effectiveness of the framework, establishing it as a promising solution for improving sales forecasting accuracy in dynamic e-commerce environments. Future work could explore adaptive decomposition techniques and ensemble learning strategies to further enhance forecasting capabilities, ensuring that e-commerce businesses remain agile and data-driven in an increasingly competitive digital marketplace.

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