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Developing an automated currency transactions forecasting process for global e-commerce and fintech companies

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Abstract. This paper introduces a groundbreaking automated forecasting process for global currency transactions, specifically designed for e-commerce and fintech companies. Traditional linear models, such as weekly moving averages, ARIMA, and SARIMA, have proven inadequate in capturing non-linearities and complex patterns within the data. To address these limitations, we propose an ensemble of diverse machine learning models. These models, characterized by varying lag periods, integrate regional holiday data, macroeconomic variables, and time-based variables. The proposed process exhibits high scalability, capable of simultaneously predicting forex currency transactions for multiple currencies. The implementation of this forecasting process empowers companies to manage currency exchange risk more effectively, enhance overall financial performance, and increase profits through consolidated transactions. Additionally, the automation of this process eliminates the need for manual forecasting, thereby boosting efficiency, accuracy, and employee morale. The findings of this study carry significant implications for the global e-commerce and fintech companies with operations in multiple currencies. They demonstrate the transformative potential of machine learning models in revolutionizing currency transaction forecasting and assisting in strategic decision-making for finance and treasury teams.

Keywords: Machine Learning Based Time Series Forecasting, Automated Currency Transaction Forecasting, Applied Machine Learning Workflow, Currency Exchange Risk.

1. Introduction

In the increasingly globalized marketplace, e-commerce and fintech companies operate across multiple currencies, making currency transactions an integral part of their business models. These transactions form the backbone of cross-border operations, influencing a company's financial performance, risk management strategies, and overall business stability. Hence, the ability to accurately forecast currency transactions is pivotal for these companies to navigate the complex and volatile landscape of international commerce.

However, the dynamic and intricate nature of currency markets, influenced by a plethora of factors such as macroeconomic indicators, geopolitical events, and market sentiment, makes accurate forecasting a challenging task. Traditional linear models often fall short in capturing the complex patterns and non-linear relationships inherent in currency transaction data.

To address this gap, this paper aims to develop an automated forecasting process that leverages an ensemble [1] [2] of machine learning models. These models, with their inherent capacity to handle high-dimensional, non-linear data [3], provide a promising avenue for accurately predicting global currency

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transactions. The framework proposed in this paper not only enables the end-to-end implementation of the forecasting process from conceptualization to implementation but also substantially improves the forecasting accuracy leading to improved financial performance and risk management for e-commerce and fintech companies with global operations.

2. Literature Review

Traditional forecasting methods have been extensively employed in predicting currency transactions, with weekly moving averages, Autoregressive Integrated Moving Average (ARIMA) [4], and Seasonal Autoregressive Integrated Moving Average (SARIMA) [5] models being prevalent. Weekly moving averages provide a simple and intuitive means of identifying trends by smoothing out short-term fluctuations. ARIMA, a more sophisticated model, uses past values and errors to forecast future trends, while SARIMA extends ARIMA by accounting for seasonality in data.

However, these linear models often encounter difficulties when grappling with the complex, non-linear nature of currency transaction data. Their inherent linear assumptions may lead to oversimplification of the underlying dynamics, resulting in potentially inaccurate predictions. Moreover, these models typically consider a single variable (past values of the currency transactions), ignoring multiple other factors that could influence currency transactions.

In contrast, machine learning models, with their ability to handle non-linear relationships and high-dimensional data, offer a promising alternative. These models can consider numerous variables simultaneously, offering more robust, accurate predictions. Machine learning algorithms such as tree-based models and deep learning models can capture complex patterns and non-linearity in the data.

Furthermore, the ensemble approach in machine learning, which combines multiple models, can leverage the strengths of individual models while mitigating their weaknesses. This approach has been proven to enhance predictive accuracy and robustness, making it a compelling choice for forecasting currency transactions in the complex, volatile environment of global e-commerce and fintech companies.

3. Research Methodology

3.1. Datasets

A comprehensive methodology was adopted for this study to ensure accurate forecasting. The process started with the collection and preprocessing of four types of data. The first was historical currency transactions data, which served as the primary source of information for the models. The second was regional holiday data for each currency, considering that holidays can significantly influence currency transactions. The third was macroeconomic variables, including interest rates, inflation rates and currency exchange rate versus the US Dollar, which are known to affect the local currency value. Lastly, various time-based features such as the day of the week, week of the year, and month of the year, quarter of the year variables were included to account for any potential seasonality in the data.

3.2. Process Workflow

Figure 1 presents the comprehensive end-to-end workflow for the entire process, from data collection to the implementation of an automated machine learning-based solution for daily business operations. The methodology harnesses the power of machine learning and the depth of multi-dimensional data to establish a robust, automated forecasting process. By fusing multiple models and a diverse range of data sources, the process is strategically designed to capture the intricate patterns and non-linearities inherent in currency transaction data, thereby achieving exceptional forecasting accuracy.

The data underwent thorough preprocessing, including cleaning, handling missing data, normalization and encoding categorical data to ensure the quality and consistency of the data fed into the models. Next, an ensemble of multiple machine learning models was chosen, each tailored to effectively manage varying lag periods. These models were trained using a subset of the preprocessed data, and their performance was validated using a separate validation dataset. The Mean Absolute Error (MAE)

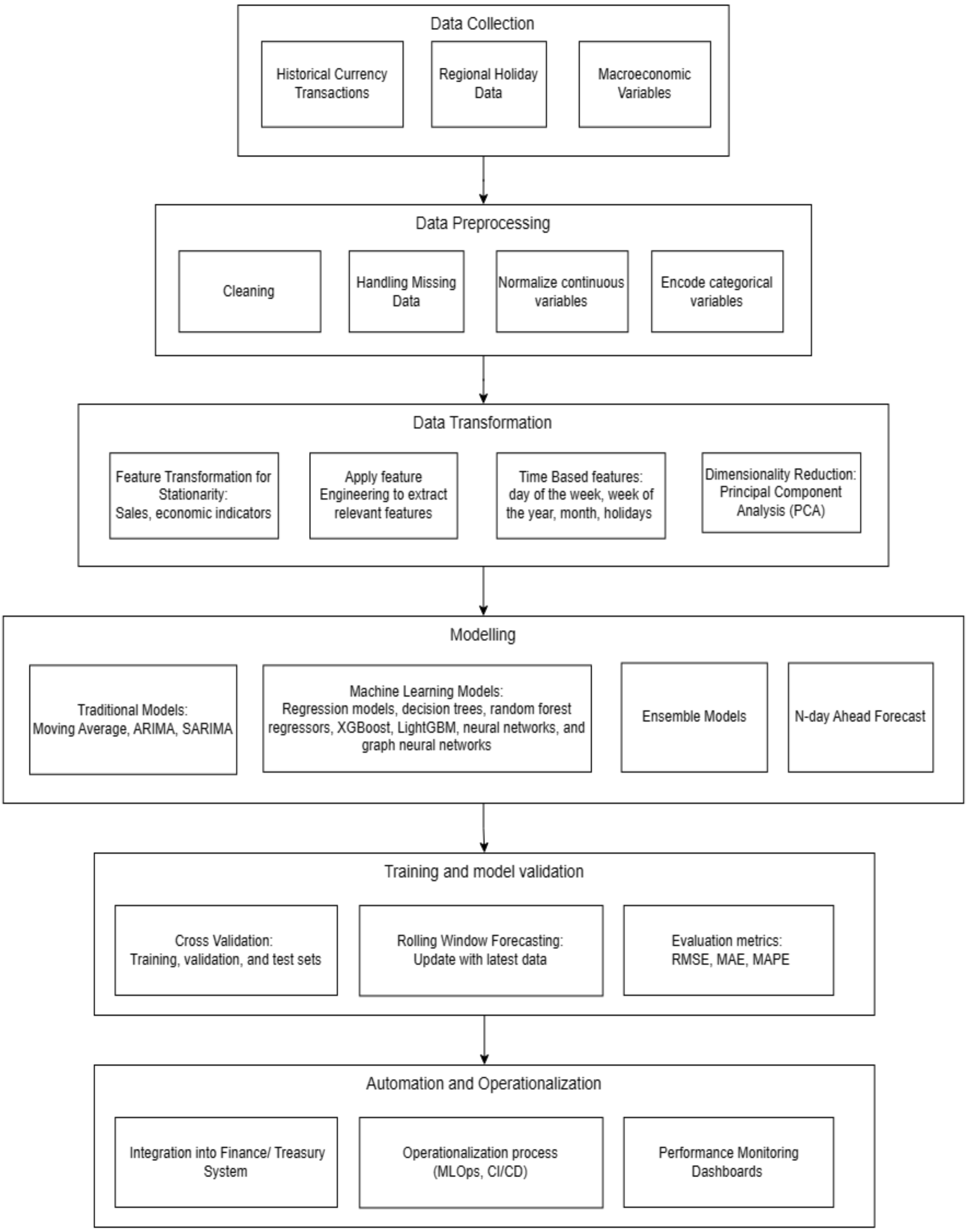

Figure 1. An Automated Currency Transaction Forecasting Process for Global E-commerce and Fintech Companies: From Data Collection to Automation and Monitoring
NB: RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error)

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and the Mean Absolute Percentage Error (MAPE) metrics were utilized to evaluate model performance against the benchmark models. The training-validation process was carried out iteratively, fine-tuning the models to achieve optimal performance. For the performance evaluation metrics, MAE and MAPE were chosen over RMSE due to their effective handling of extreme errors. This decision was prompted by the observation of spikes in errors on certain days, such as holidays, which could significantly impact the accuracy assessment. Considering that RMSE tends to penalize these errors more severely, MAE and MAPE were deemed more suitable as evaluation metrics in this specific context.

The final model's performance was determined based on a test set comprising the most recent year's data. To ensure that the model has access to the latest data for prediction, rolling window forecasts were implemented across the training, validation, and test periods. This approach further enhances the model's reliability and forecasting accuracy. Additionally, macroeconomic variables were integrated into the models to account for their influence on currency transactions. This integration was carefully designed to enable accurate n-day ahead forecasts. By incorporating these variables, the models could react dynamically to changes in the economic environment, further enhancing the accuracy of the predictions.

3.3. Machine Learning Model Architecture

Figure 2 illustrates the architecture of the machine learning model used in this study. The architecture is designed to handle a diverse set of over 20 forex currency pairs. The model recognizes the varying significance of lag values for each currency and period, thus necessitating a generalized approach.

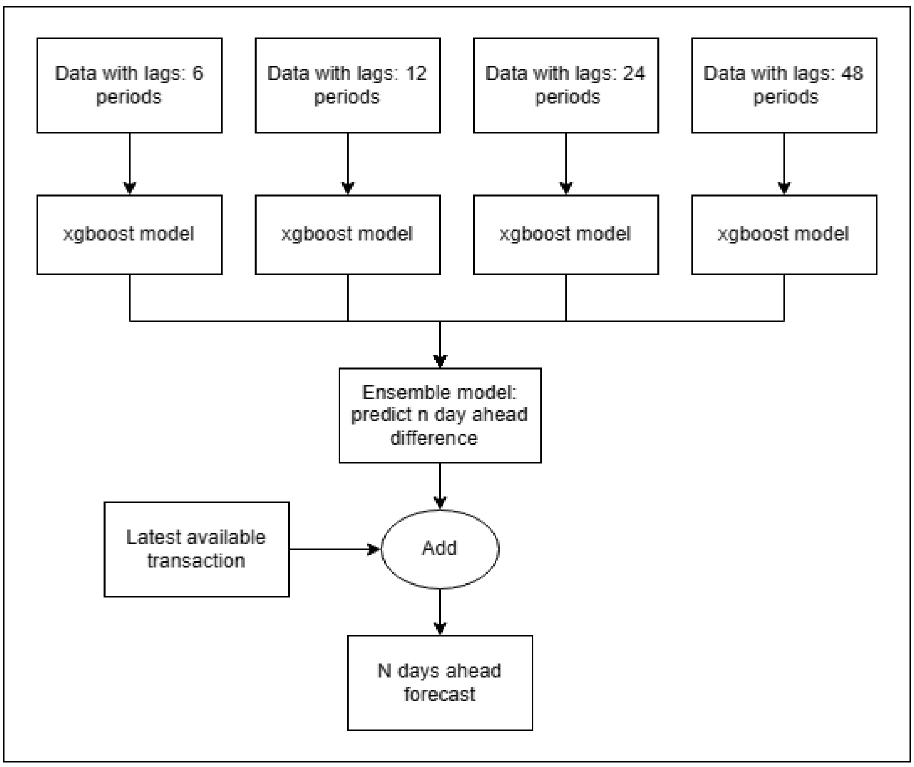

Figure 2. Machine learning model architecture for forecasting n-day ahead currency transactions volume

The architecture consists of an ensemble of machine learning models, each trained on different lagged inputs. Four distinct branches are established for each lagged value, specifically designed to capture the patterns at 1 week (6 business days) and multiples of 6, such as 12, 24, and 48 days. Each pipeline with different lag values undergoes a selection process to choose the most accurate model. XGBoost emerged as the most accurate model compared to benchmark models such as weekly moving average, ARIMA,

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and SARIMA, as well as various machine learning models including linear regression with lasso and ridge regularization, decision tree, random forest, gradient boosted tree, support vector machine, and two-layered artificial neural networks across all currencies and periods over a 1-year validation period, achieving the highest accuracy based on the lowest MAE and Mean Absolute Percentage Error (MAPE) metric in over 95% of cases. Hence, XGBoost was selected for each training branch.

The final forecast is generated by ensembling the outputs of the four XGBoost pipelines, yielding the n-day ahead difference forecast. This difference is then added to the most recently available data, providing the final n-day ahead forecast. This architecture allows for a robust and accurate forecasting system, able to handle the intricate nature of global currency transactions. The ensemble of machine learning models, once trained and validated, was transformed into an automated forecasting process. The process was developed to run autonomously, requiring minimal human intervention, and was designed to be adaptable, dynamically updating its predictions based on the latest data. This automated forecasting process was then integrated into the existing finance or treasury system of the company. The integration was seamless, ensuring that the new forecasting process worked in synergy with the existing system, leveraging its capabilities while enhancing its performance.

4. Results and Discussions

The implementation of the automated forecasting process yielded significant results. Its performance outshone traditional linear models, displaying impressive accuracy in predicting global currency transactions. The machine learning models' ability to consider multiple variables and their non-linear relationships resulted in forecasts that closely mirrored actual transaction data.

For businesses, this accurate forecasting had a profound impact. It enhanced the management of currency exchange risk, as businesses could make more informed decisions regarding their cross-border transactions. Moreover, it improved the companies' overall financial performance, reducing losses from unpredicted currency fluctuations. Importantly, the forecasting process resulted in increased revenue from better rates through consolidated transactions, directly contributing to the companies' bottom line. The model also demonstrated its relevance in dealing with significant calendar events, such as holidays. By incorporating regional holiday data and time-based variables, the forecasting process accurately predicted transaction patterns during these periods, further showcasing its robustness and adaptability.

One of the most significant impacts of this integration was the elimination of manual forecasting. With the automated process taking over, the need for employees to perform repetitive, time-consuming forecasting tasks was removed. This shift led to improved efficiency and accuracy, as the machine learning models could process vast amounts of data and identify patterns far beyond human capability. Furthermore, the removal of manual forecasting boosted employee morale, as they could now focus on more strategic, value-adding tasks. Beyond efficiency and morale, the automation also had a positive impact on employees' work-life balance. With the forecasting process being handled automatically, employees no longer needed to work during holidays or weekends, leading to a healthier work-life balance and increased job satisfaction.

While the methodology and model presented provide promising results, they are not without limitations. For instance, the model's performance might vary with extreme market volatility. Future work could focus on incorporating more dynamic real-time data sources and exploring more advanced machine learning techniques, such as deep learning or reinforcement learning based models that can further enhance the robustness and accuracy of the forecasting process.

5. Conclusion

The study introduced a innovative automated forecasting process for global currency transactions, integral to e-commerce and fintech companies. Recognizing the shortcomings of traditional linear models, such as weekly moving averages, ARIMA, and SARIMA, in capturing complex patterns and non-linearities in data, the study proposed a sophisticated ensemble of machine learning models.

The models, characterized by varying lag periods, efficiently factored in regional holiday data, macroeconomic variables, and time-based variables to enhance the accuracy of forecasts.

The methodology involved meticulous data collection and preprocessing, followed by the selection and training of the ensemble models. The models were then operationalized to produce n-day ahead forecasts, considering the dynamic macroeconomic variables. The ensemble models were then developed into an autonomous forecasting process and seamlessly integrated into the existing finance or treasury systems. This integration eliminated the need for manual forecasting, thereby improving efficiency, accuracy, and employee morale. It also positively impacted the employees' work-life balance, eliminating the need for working during holidays or weekends. Moreover, the implementation of the forecasting process offered significant benefits to the business' financial performance. It improved the management of currency exchange risk and enhanced the overall financial performance of the companies, resulting in increased revenue. The process also demonstrated its robustness by efficiently handling significant calendar events, such as holidays.

Despite a few limitations, the study represents a substantial advancement in the currency transaction forecasting. Future work can focus on incorporating more dynamic data sources and exploring advanced machine learning techniques to further improve the forecasting process's robustness and accuracy. The findings hold significant implications for global e-commerce and fintech companies, establishing the potential of machine learning models in revolutionizing currency transaction forecasting and supporting strategic decision-making.

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