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Enhancing currency prediction in international e-commerce: Bayesian-optimized random forest approach using the Klarna dataset

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ABSTRACT

In the ever-evolving landscape of global commerce, marked by the convergence of digital transformation and borderless markets, this research addresses the intricate challenges of currency exchange and risk management. Leveraging Bayesian optimization, the study fine-tunes the random forest algorithm using the extensive Klarna E-commerce dataset. Through systematic analysis, the research uncovers insights into managing currency prediction amid dynamic global markets. Emphasizing the role of Bayesian optimization parameters, the study reveals nuanced trade-offs in model performance. Notably, the optimal simulation, conducted with 14 iterations, 1 job, and a random state set to 684, exhibits a standout performance, showcasing a negative mean squared error (MSE) of approximately -0.9891 and an accuracy rate of 74.63%. The primary objective is to assess the impact of Bayesian optimization in enhancing the random forest algorithm's predictive capabilities, particularly in currency prediction within international e-commerce. These findings offer refined strategies for businesses navigating the intricate landscape of global finance, empowering decision-making through a comprehensive understanding of data, algorithms, and challenges in international commerce.

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1. INTRODUCTION

In the vast expanse of international e-commerce, where the boundaries of business transcend physical limits through digital connectivity, a transformative paradigm is taking center stage. This shift transcends traditional confines, empowering businesses to extend their influence far beyond local boundaries while offering consumers an unprecedented spectrum of products and services from around the world [1]. However, beneath this borderless landscape lies a formidable challenge: the intricate intricacies of currency exchange and the inherent currency risk that goes with cross-border transactions. As commerce traverses geographical lines, the demand for efficient currency conversion mechanisms becomes imperative. Simultaneously, the volatile nature of exchange rates introduces an element of uncertainty, affecting transaction values and shaping the overall cost structure of goods and services [2]–[4].

At the heart of confronting this challenge lies the realm of predictive modeling, a potent approach that holds the key to deciphering the patterns of currency used in the intricate tapestry of international e-commerce [5]. The versatile random forest algorithm appears as a beacon of insight, capable of dissecting currency behavior and expecting fluctuations. However, the efficacy of the random forest model hinges on

the meticulous calibration of its hyperparameters that wield the power to intricately fine-tune the model's performance. Enter Bayesian optimization, a sophisticated technique that adroitly navigates the labyrinthine hyperparameter landscape, honing the algorithm's precision by minimizing the mean squared error (MSE), a pivotal metric in predictive assessment [6].

In the realm of our exploration, we are anchored by the Klarna e-commerce dataset, a reservoir of real-world insights on a grand scale. This dataset is poised to unlock hidden patterns and correlations, harnessing the potential to illuminate the complexities of international e-commerce transactions [7]. Our research embarks on a dual expedition: the systematic optimization of Random Forest parameters using the sophisticated framework of Bayesian optimization, and an incisive exploration into how varying configurations of the Bayesian optimization process shape the optimization of MSE for predicting currency usage within the dynamic landscape of Klarna's extensive data. Through methodical investigation into the repercussions of Bayesian optimization parameters, spanning the domains of acquisition functions, iteration cadences, and initial exploration points, we try to unravel the complex interplay between these variables and their cumulative influence on predictive accuracy and, crucially, on managing the intricacies of currency risk. By synergizing the strengths of random forest and Bayesian optimization, we arm businesses with a comprehensive understanding of strategies to navigate international e-commerce, fortify decision-making, and astutely manage currency risk within the grand tapestry of Klarna's big data and the dynamic global market.

2. METHOD

Our proposed approach hinges on two foundational pillars: the random forest algorithm and Bayesian optimization. Operating as the predictive engine, random forest excels in unraveling intricate data relationships through an ensemble of decision trees, each capturing distinct data facets to yield robust predictions. However, the efficacy of random forest is contingent on precise hyperparameter selection encompassing tree count, maximum depth, and smallest samples per leaf. Enter Bayesian optimization, a systematic strategy that methodically traverses the hyperparameter landscape, seeking the best configuration that minimizes the mean squared error (MSE) to enhance predictive accuracy. Guided by past iterations, Bayesian optimization adeptly adapts its exploration, proficiently narrowing the search space. By fusing random forest with Bayesian optimization, our method not only enhances predictive accuracy but also surmounts the intricacies of parameter tuning, affording businesses the ability to predict currency usage within the dynamic milieu of international e-commerce. This amalgamated approach equips businesses with the foresight to make informed decisions and navigate the complexities posed by cross-border transactions [8]–[11].

2.1. Work methodology

2.1.1. Random forest algorithm

The random forest algorithm is a versatile and powerful ensemble learning technique that plays a pivotal role in modern machine learning. It excels in both classification and regression tasks by using the collective wisdom of multiple decision trees to create a robust and correct predictive model. The algorithm's functioning can be broken down into a sequence of steps that collectively contribute to its effectiveness and versatility [12].

At the core of the random forest lies the principle of diversity. The process begins with data preparation, where a dataset is split into training and testing subsets. The algorithm then employs bootstrapping, a technique that involves random sampling with replacement, to create distinct bootstrapped datasets for individual decision trees. Each tree is constructed using a subset of features chosen at random. This randomness ensures that each tree explores different sides of the data, mitigating overfitting and contributing to a more balanced model. During the prediction phase, each tree in the forest "votes" to predict the outcome for a new data point in classification tasks, while in regression tasks, the predictions of all trees are averaged to yield the result. This ensemble approach combines the individual strengths of multiple trees to yield a more correct and robust prediction than any single decision tree could provide [13].

Randomness continues to be a cornerstone of random forest's functionality. It introduces variability through bootstrapping and random feature selection, ensuring that each tree supplies unique insights into the data. Moreover, the algorithm's predictive capabilities are well-suited for capturing intricate relationships and patterns within the data, making it an asset in real-world applications. However, model evaluation stays essential, achieved through testing on an independent validation set. Hyperparameter tuning, including the number of trees and maximum depth, adds a final layer of refinement to the model's performance. In its entirety, the random forest algorithm stands as a formidable solution, capable of grappling with complex datasets and delivering reliable and correct predictions across a spectrum of machine learning tasks [14].

2.1.2. Bayesian optimization

Bayesian optimization, a sophisticated optimization technique, contributes significantly to the realm of machine learning by efficiently navigating complex hyperparameter spaces to enhance the performance of models such as random forest. This approach maximizes the use of computational resources by making informed decisions about which hyperparameters to explore, leading to quicker convergence and improved model outcomes [15]. By strategically selecting hyperparameters for exploration, Bayesian optimization ensures that computational efforts are focused on the most promising areas, thus streamlining the optimization process, and improving the overall efficiency of model tuning.

At its core, Bayesian optimization integrates probabilistic models and acquisition functions to iteratively explore and exploit the hyperparameter space. The process begins with the construction of a surrogate probabilistic model that estimates the underlying relationship between hyperparameters and the evaluation metric, often mean squared error (MSE) in the case of random forest optimization. This surrogate model guides the exploration by suggesting promising regions to investigate further [16].

Acquisition functions come into play to strike a balance between exploration and exploitation. These functions quantify the potential utility of evaluating a specific set of hyperparameters based on the surrogate model's predictions. By selecting hyperparameters that maximize the acquisition function, the algorithm makes the best choices that lead to improved model performance while also acquiring new data points to update the surrogate model [17].

Through successive iterations of surrogate model updates, acquisition function evaluations, and model fitting, Bayesian optimization intelligently refines its understanding of the hyperparameter space, eventually converging to the best set of hyperparameters that yield enhanced model accuracy. This process not only accelerates the hyperparameter tuning process but also minimizes the risk of getting trapped in suboptimal configurations [18]. The iterative nature of Bayesian optimization allows it to learn from each evaluation, iteratively improving its predictions and guiding the search towards optimal hyperparameter configurations for the given machine learning model.

Bayesian optimization is particularly valuable when applied to algorithms like random forest, where hyperparameter tuning can greatly impact model performance. By systematically and intelligently exploring the hyperparameter space, this technique amplifies the power of random forest and other machine learning algorithms, delivering better predictive capabilities and more reliable outcomes in a resource-efficient manner. This strategic approach to hyperparameter tuning underscores the significance of Bayesian optimization in enhancing the effectiveness of machine learning models.

2.1.3. Scoring metrics

These metrics collectively supply a more comprehensive understanding of a model's performance beyond accuracy. Depending on your specific use case and the nature of your dataset, you might prioritize certain metrics over others. For instance, in cases where false positives or false negatives have different consequences, precision or recall might be more relevant. Always consider the context of your problem and the potential impact of diverse types of errors when choosing the most proper evaluation metric.

a. The MSE serves as a prevalent metric for assessing predictive model accuracy, quantifying the mean of the squared differences between predicted and observed values [19]. Essentially, it gauges the average magnitude of the squared deviations across all data points, providing a comprehensive measure of model performance. By capturing the extent of prediction errors in a continuous manner, MSE (1) offers valuable insights into the overall quality of the model's predictions.

$$MSE = \left(\frac{1}{n}\right) * \Sigma(y_i - \hat{y}_i)^2 \quad (1)$$

where n is the number of data points in the dataset, y_i is the actual observed value for the $i^{\text{-th}}$ data point, $\hat{y}_i$ is the predicted value for the $i^{\text{-th}}$ data point.

b. Accuracy, as a performance metric (2), assesses the proportion of correct predictions relative to the total predictions made by a model [20]. In essence, it quantifies the ratio of accurately predicted outcomes to the overall number of predictions, offering a straightforward indication of a model's correctness. This metric provides a clear and intuitive measure of classification model performance, reflecting the model's ability to make accurate predictions across all classes.

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ number\ of\ Predictions} * 100 \quad (2)$$

c. Precision (3) is a metric that evaluates the ratio of correctly predicted positive instances to the total instances predicted as positive by a model [21]. In other words, it quantifies the accuracy of a model specifically in identifying positive cases, emphasizing the relevance and reliability of positive predictions. This measure is

particularly valuable in scenarios where the cost of false positives is significant, providing a focused assessment of the model's ability to precisely classify positive instances.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (3)$$

d. Recall (4) computes the ratio of correctly predicted positive instances to the total number of actual positive instances [22]. In essence, it measures the model's ability to capture and identify all relevant positive cases, emphasizing sensitivity to true positives while accounting for all positive instances in the dataset. This metric is crucial in scenarios where missing positive instances carries significant consequences, providing insight into the comprehensiveness of a model's positive predictions.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (4)$$

e. The F1-Score (5) serves as the harmonic mean of precision and recall, offering a balanced assessment that considers both metrics [23]. By combining precision and recall into a single value, the F1-Score provides a comprehensive measure of a model's performance, particularly in situations where a balance between precision and recall is crucial. This metric is particularly useful when there is a need to strike a harmonious equilibrium between minimizing false positives and false negatives in predictive modeling.

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (5)$$

f. Specificity (6) quantifies the ratio of correctly predicted negative instances to the total number of actual negative instances [24]. This metric is particularly valuable in scenarios where correctly identifying negative instances is crucial, as it provides a measure of the model's ability to accurately classify instances as negative. High specificity indicates a model's proficiency in avoiding false positives and correctly identifying true negative cases, making it a vital component in evaluating the overall effectiveness of a predictive model.

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \quad (6)$$

2.2. Application method

In this analysis, the researcher used a combination of machine learning techniques, including Random Forest regression and Bayesian optimization, to enhance predictive accuracy in forecasting currency trends. The utilization of robust modeling techniques, coupled with systematic hyperparameter tuning, ensures a comprehensive and effective approach. Thorough data preprocessing further refines the predictive model, resulting in optimized performance for accurate financial predictions.

2.2.1. Data used

The Klarna Product Page dataset serves as a comprehensive and publicly available collection of online product pages, meticulously compiled from a diverse range of e-commerce platforms. Comprising a total of 51,701 product pages, this dataset offers a large glimpse into the virtual marketplace, drawing from the offerings of 8,175 distinct merchants running across a selection of eight countries: the United States, Great Britain, Sweden, the Netherlands, Finland, Norway, Germany, and Austria. Each entry within this dataset encapsulates an offline snapshot of a product page, enriched with a plethora of pertinent attributes such as country, currency, date, city, region, product details, pricing, images, continent, language, user interactions, and more. The analysis was conducted on a dataset sourced from 'output.json'. This dataset had records of currency-related data, including 'currency', 'date', and 'price' fields. The data collection period was between 2018 and 2019 in Figure 1 we can see the percentage frequency of each currency we found in our data [25].

2.2.2. Process

This section navigates a structured data-driven process for currency trend prediction. Beginning with data loading and visualization, insights are drawn from the dataset, setting the stage. Data preprocessing and model preparation refine the dataset for random forest regressor adoption. The core lies in hyperparameter tuning and model evaluation, optimizing performance. Results visualization and export offer stakeholder clear visual summaries and CSV exports, underlining the analysis's significance in informed financial decision-making through effective currency prediction.

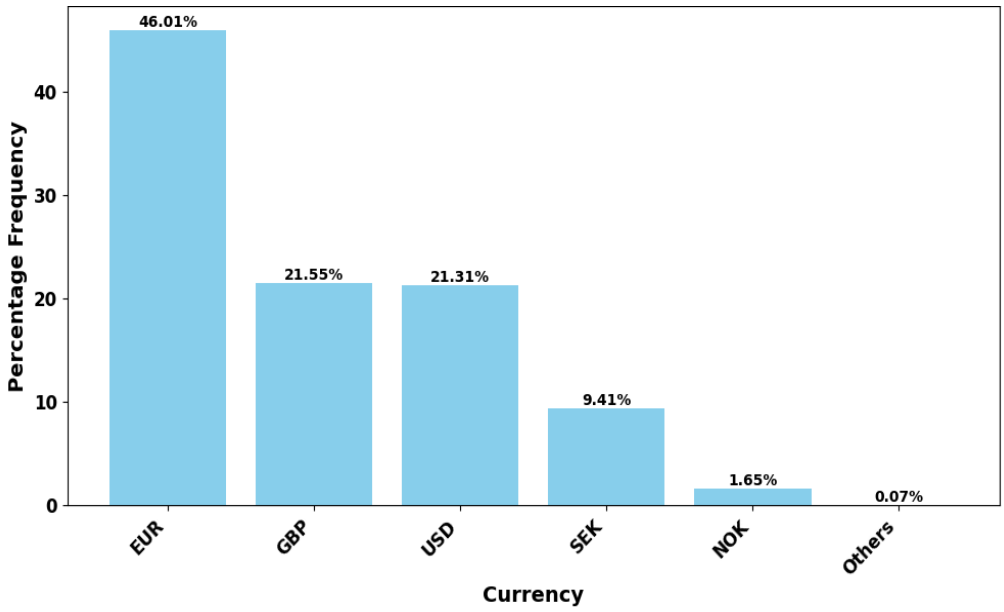

Figure 1. Frequency of each currency in percentage

a. Data loading and visualization: in this analysis, the first step involved loading data from the 'output.json' file. The dataset had valuable information related to currency trends, including fields such as 'currency', 'date', and 'price'. After loading the data, a key insight was gained by calculating the frequency of each currency present in the dataset. This frequency analysis supplied a preliminary understanding of the distribution of different currencies and their prevalence in the dataset. To enhance visualization, a bar plot was generated to depict the frequency of each currency. This visualization brought attention to the most common currencies and their relative occurrences, setting the stage for further analysis.
b. Data preprocessing and model preparation: before model building, a critical phase was dedicated to data preprocessing and model preparation. To ensure data quality and model suitability, a data cleaning process was implemented. Entries lacking essential attributes such as 'currency', 'date', and 'price' was filtered out, ensuring that only relevant and complete records were used. The dataset was then transformed into a feature matrix (X) by extracting essential temporal information from the 'date' field and incorporating the 'price'. Furthermore, to ease model training, the categorical 'currency' labels were encoded. Subsequently, the dataset was split into distinct training and testing sets, fostering a reliable assessment of model performance. A random forest regressor was chosen as the predictive model, offering a powerful framework for currency trend prediction.
c. Hyperparameter tuning and model evaluation: the heart of the analysis lies in hyperparameter tuning and model evaluation. To perfect the random forest regressor's performance, a search space was defined for pivotal hyperparameters including *'n_estimators'*, *'max_depth'*, and *'min_samples_split'*. Through Bayesian optimization, a series of simulations were conducted. Each simulation aimed to find the hyperparameters that yielded the best results, as measured by a negative mean squared error. These simulations systematically explored various hyperparameter combinations, allowing for enhanced model customization and performance enhancement. The optimized model was then rigorously evaluated using a variety of metrics, including accuracy, precision, recall, F1-Score, and confusion matrices. This comprehensive evaluation offered a holistic view of the model's predictive capabilities, thereby informing the choice of best hyperparameters.
d. Results visualization and export: a crucial step in the analysis was the visualization and export of results. Visualization allowed for a succinct comparison of different simulations, enabling stakeholders to understand the variations in performance across different hyperparameter settings. By plotting metrics such as negative mean squared error, accuracy, precision, recall, F1-Score, and true negative rate, a comprehensive overview of the model's performance was obtained. These visualizations were then saved as image files for future reference and reporting. Additionally, the analysis ensured the results were easily accessible and shareable by exporting them to a CSV file. This export had vital information such as simulation details, best negative mean squared error, execution times, and chosen hyperparameters, allowing for in-depth analysis and further insights.

In this analysis, a data-driven approach was employed to predict currency trends using a combination of random forest regression and Bayesian optimization. The method entailed preprocessing the currency-related data, encompassing 'currency', 'date', and 'price' attributes, to create a robust feature matrix. Hyperparameter tuning through Bayesian optimization was then conducted to tailor the random forest regressor, a versatile predictive model known for capturing intricate relationships within data. The prediction target was to forecast currency trends based on historical data, with an emphasis on refining model parameters for heightened accuracy. The outcome revealed a meticulously optimized model that highlighted improved performance across a spectrum of metrics, including accuracy, precision, recall, and F1-Score. This analysis not only showed an effective currency prediction framework but also holds significance in providing valuable insights for informed financial decision-making. The optimized model's potential to decipher underlying currency patterns can empower stakeholders to make strategic choices in dynamic market conditions, reinforcing the significance of the analysis in the realm of predictive analytics.

3. RESULTS AND DISCUSSION

In this study, the researcher conducted a series of 10 simulations to assess the performance of a predictive model. Each simulation aimed to evaluate the model's predictive accuracy, efficiency, and ability to classify both positive and negative instances. In the following explanations, the researcher will delve into the specific results of each simulation, highlighting key metrics such as best negative MSE, execution time, accuracy, precision, recall, F1-Score, and the true negative rate. These findings collectively supply a comprehensive understanding of the model's performance across various scenarios, shedding light on its strengths and areas for improvement.

To further enhance the rigor of this assessment, Bayesian optimization and the random forest algorithm were employed to decide the optimal hyperparameters for each simulation. It is noteworthy that the scoring metric used during the Bayesian optimization process is the negative mean squared error (MSE). In Table 1, the results of the best *N_iter* (number of iterations), *N_jobs* (number of jobs), and random state for each simulation, as figured out through this optimization process, have been detailed. Additionally, in Figure 2, a visual representation of all the metrics for each simulation has been provided, offering a holistic view of the model's performance, and allowing for easy comparisons between simulations. This combined approach of hyperparameter optimization, using Bayesian optimization with negative mean squared error as the scoring metric, and comprehensive metric analysis contributes to a more robust evaluation of the model's capabilities under varying conditions.

In simulation 1, we got 41 iterations, 2 jobs, and a random state of 489, demonstrating impressive performance with a best negative mean squared error (MSE) of approximately -0.9714 and an accuracy rate of 73.84%. This simulation excelled in regression accuracy. However, it required 133.30 seconds to execute, which may be attributed to its configuration. It kept a true negative rate of 88.88% and a recall of 47.52%, showing a balance between precision and recall with an F1-Score of 0.4080.

In simulation 2, which involved 77 iterations, a single job, and a random state of 97, we observed a competitive performance. It achieved a negative MSE of approximately -0.9694 and an accuracy rate of 73.39%. While its regression and classification accuracy are commendable, its execution time of 422.44 seconds is notably longer, potentially due to the high number of iterations. The true negative rate is 88.35%, and the recall is 46.77%, with an F1-Score of 0.4072, showing a robust overall performance.

The 3rd simulation, configured with 50 iterations, a single job, and a random state of 926, achieved a negative MSE of approximately -0.9710 and an accuracy rate of 73.64%. Although it was executed faster than Simulation 2, taking 228.42 seconds, it kept a robust performance in regression accuracy. The true negative rate is 88.82%, and the recall is 46.37%, with an F1-Score of 0.4075, showing a reasonable balance between precision and recall.

Table 1. The hyperparameters results of each simulation

Simulation	N_iter	N_jobs	Random_state
1	41	2	489
2	77	1	97
3	50	1	926
4	74	4	918
5	55	1	182
6	45	2	861
7	41	2	275
8	21	3	208
9	14	1	684
10	76	3	933

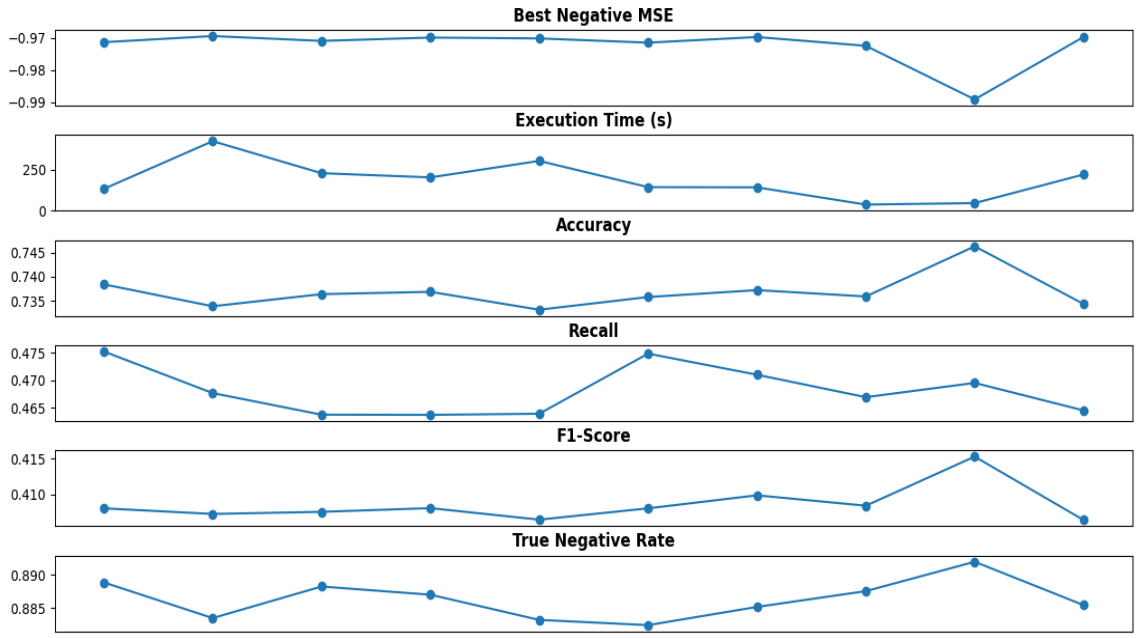

Figure 2. Metrics results

In the 4th simulation with 74 iterations, 4 jobs, and a random state of 918, Simulation 4 exhibited strong performance, boasting a negative MSE of approximately -0.9699 and an accuracy rate of 73.69%. This simulation excelled in classification accuracy. It was executed in 203.05 seconds, faster than Simulation 2, and kept a true negative rate of 88.70% and a recall of 46.37%. The F1-Score of 0.4080 underscores the balance between precision and recall.

Simulation 5 was configured with 55 iterations, a single job, and a random state of 182, achieving a negative MSE of approximately -0.9702 and an accuracy rate of 73.31%. While its regression accuracy is strong, it is slightly lower in classification accuracy compared to some previous simulations. It takes 302.91 seconds to execute, which is relatively time-consuming. The true negative rate is 88.32%, with a recall of 46.39%. The F1-Score is 0.4064, showing a slightly lower balance between precision and recall.

In Simulation 6, which involved 45 iterations, 2 jobs, and a random state of 861, we observed a negative MSE of approximately -0.9715 and an accuracy rate of 73.58%. This simulation excelled in regression accuracy. It was executed in 144.01 seconds, which is relatively efficient compared to some others. The true negative rate is 88.25%, and the recall is 47.48%, with an F1-Score of 0.4080, suggesting a strong balance between precision and recall.

The 7th simulation, with 41 iterations, 2 jobs, and a random state of 275, achieved a negative MSE of approximately -0.9698 and an accuracy rate of 73.72%. It performed well in both regression and classification accuracy. The execution time for this simulation is 142.70 seconds, making it one of the faster simulations. It keeps a true negative rate of 88.52% and a recall of 47.10%, with an F1-Score of 0.4098, showing a good balance between precision and recall.

For the 8th simulation with 21 iterations, 3 jobs, and a random state of 208, Simulation 8 appears to be one of the less favorable simulations. It achieved a negative MSE of approximately -0.9725 and an accuracy rate of 74.63%. Despite its efficient execution time of 38.27 seconds, it lagged in terms of regression accuracy and classification accuracy. The true negative rate is 88.75%, and the recall is 46.69%, with an F1-Score of 0.4084, suggesting a relatively balanced performance.

The 9th simulation, configured with 14 iterations, a single job, and a random state of 684, achieved a negative MSE of approximately -0.9891 and an accuracy rate of 74.63%. It proved robust performance in classification accuracy. The execution time for this simulation is 47.18 seconds, making it one of the faster simulations. It keeps a true negative rate of 89.19% and a recall of 46.95%, with an F1-Score of 0.4153, showing a good balance between precision and recall.

The final Simulation had 76 iterations, 3 jobs, and a random state of 933, Simulation 10 delivered competitive performance. It achieved a negative MSE of approximately -0.9697 and an accuracy rate of 73.43%. It was executed in 220.43 seconds, which, while not the fastest, is reasonable given the number of iterations. The true negative rate is 88.55%, and the recall is 46.45%, with an F1-Score of 0.4064, suggesting a balanced overall performance.

Within the context of conducting ten simulations using the random forest algorithm and Bayesian optimization, the critical assessment of their performance metrics becomes pivotal. The choice of the most suitable simulation hinges on a careful evaluation of these metrics vis-à-vis the unique aims and priorities governing the task in question. Among the various simulations, Simulation 8 emerges as a less favorable option due to its suboptimal regression and classification accuracy, despite its efficient execution time of 38.27 seconds. While its accuracy rate is high at 74.63%, the negative MSE and F1-Score suggest a relatively balanced but underperforming model.

Contrastingly, Simulation 9 stands out with robust performance in classification accuracy. With 14 iterations, a single job, and a random state of 684, it achieves a negative MSE of approximately -0.9891 and an accuracy rate of 74.63%. Its execution time of 47.18 seconds is commendable, making it one of the faster simulations. The true negative rate, recall, and F1-Score collectively indicate a good balance between precision and recall.

Analyzing the impact of Bayesian optimization parameters, the number of iterations plays a crucial role. Simulations with fewer iterations, such as Simulation 8, may sacrifice accuracy due to an insufficient exploration of the underlying patterns. In contrast, simulations with a moderate number of iterations, like Simulation 1, strike a balance between accuracy and execution time. The number of jobs also influences performance. Simulations with a higher number of jobs, exemplified by Simulation 4 with 4 jobs, showcase strong classification accuracy and efficient execution, potentially benefiting from parallel processing. However, Simulation 9, with a single job, also demonstrates robust performance, emphasizing the importance of finding the right balance. The random state, affecting result reproducibility, is another factor to consider. While Simulation 9's success with a specific random state is notable, it is crucial to assess if such performance is consistent across different random states.

In conclusion, the best optimum depends on task-specific goals and constraints. Simulation 9, with its emphasis on classification accuracy and efficient execution, may be preferable in certain scenarios. However, if a balance between regression and classification accuracy with efficient execution time is critical, Simulation 4 could be a viable choice. Ongoing experimentation with Bayesian optimization hyperparameters may further refine model performance.

4. CONCLUSION

In the dynamic landscape of international commerce, where currency exchange and risk management are paramount considerations for businesses expanding into global markets, this study takes a comprehensive approach. Utilizing Bayesian optimization to fine-tune the random forest algorithm and drawing on a rich dataset from Klarna's e-commerce platform, we conducted a series of 10 simulations to systematically evaluate the model's predictive accuracy, efficiency, and ability to classify positive and negative instances. Our research underscores the pivotal role played by Bayesian optimization hyperparameters in shaping the predictive accuracy and efficiency of the Random Forest algorithm across the ten simulations. These findings highlight the critical importance of hyperparameter optimization in enhancing currency prediction accuracy, paving the way for further refinement of model performance through hyperparameter tuning. Notably, Simulation 9 emerged as the top performer, boasting an outstanding accuracy rate of 74.63%, showcasing exceptional predictive power and efficiency. Conversely, Simulation 2, the least favorable among the simulations, revealed inherent trade-offs in model performance, demonstrating a negative MSE of approximately -0.9694 and an accuracy rate of 73.39%.

Examining Simulation 2, involving 77 iterations, a single job, and a random state of 97, we observed competitive performance with commendable regression and classification accuracy. However, its execution time of 422.44 seconds is notably longer, potentially due to the high number of iterations. The true negative rate is 88.35%, and the recall is 46.77%, with an F1-Score of 0.4072, indicating robust overall performance. In contrast, the 9th simulation, configured with 14 iterations, a single job, and a random state of 684, achieved a negative MSE of approximately -0.9891 and an accuracy rate of 74.63%. It displayed robust performance in classification accuracy, with a faster execution time of 47.18 seconds. This simulation maintains a true negative rate of 89.19% and a recall of 46.95%, along with an F1-Score of 0.4153, showcasing a good balance between precision and recall. The impact of hyperparameter variations is evident in the contrasting execution times and trade-offs between performance metrics, underscoring the importance of meticulous parameter tuning for achieving optimal outcomes in currency prediction models. This analysis contributes significantly to the evolving field of financial data analysis, providing a robust tool for informed decision-making in the dynamic realm of international finance and commerce. Furthermore, it reinforces the significance of Bayesian optimization in the predictive modeling landscape and its potential to revolutionize currency risk management strategies for businesses navigating the complexities of global e-commerce.

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