Machine learning models for predicting daily profitability in Mauritanian digital banking operations: a case study

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ABSTRACT

This article presents a case study on predicting daily profitability in Mauritanian digital banking operations using machine learning models. We utilized a dataset containing detailed information on daily operations to assess predictive models and predict profitability. The study assesses various machine learning models like logistic regression (LR), support vector machine (SVM), K-nearest neighbors (KNN), and multi-layer perceptron classifier (MLPClassifier), in order to identify the most precise model for predicting daily profitability. A systematic approach guides the analysis of banking transactions by performing detailed preprocessing operations, which include type conversions, feature selection, and missing value management. The dataset receives systematic partitioning into three parts for training, validation, and testing to establish model reliability. LR had a recall rate of 99% and an F1-score of 99%, SVM had a recall rate of 53% and an F1-score of 54%, KNN had a recall rate of 96% and an F1-score of 95%, and MLPClassifier had a recall rate of 94% and an F1-score of 97%. The findings show that the LR model performed better than the other models in terms of both recall and F1-score. Future research will investigate both deep learning approaches and hybrid models to enhance prediction accuracy.

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1. INTRODUCTION

In the banking sector, it's crucial to predict daily profits for better financial planning and strategic decision-making using machine learning technology to analyze data in real time and detect trends to minimize risks and maximize earnings for a competitive edge among banks, as per various studies showcasing its effectiveness in predicting banking performance and profitability [1]. In an instance highlighted in a study mentioned by researchers [2], different machine learning models were evaluated for their applicability in assessing banking profitability within the sector forecasting realm. Furthermore, a research piece compared machine learning techniques for anticipating potential bank failures and stressed the importance of accurate predictive modeling in the banking industry [3].

Noteworthy advancements have been observed in Mauritania's banking sector, where the Popular Bank of Mauritania (BPM), in collaboration with Comviafa, launched Bankily, the country's first digital banking service, back in January 2020. This project was designed to make it easier for people to open bank accounts and improve access to money transfer and payment services, for both those with bank accounts and those without them in Mauritania. In addition to that effort by institutions like the National Bank of Mauritania (BNM), BAMIS Bank, the Mauritanian Investment Bank (BMI) and the Islamic Bank of Mauritania (BIM) they have all introduced their own digital banking services, which have rapidly advanced the digital banking sector. These advancements underscore how important machine learning and digital transformation are in boosting the profitability and competitiveness of banks. Rapid developments in machine learning, driven by improvements in computing power and the availability of datasets, have significantly impacted a range of industries, with an effect on the banking sector. Empowering banking experts to make informed decisions through precise property assessments and financial forecasting [4], [5].

In this context, the Mauritanian Investment Bank operates its digital bank, Sedad Bank, to implement advanced technologies that develop solutions for its operational challenges. The main goal of this initiative is to develop predictive models that predict the daily profitability of banking operations. This research, included in this strategic dynamic, presents a method based on machine learning models to identify factors of daily profitability and predict the profitability for better bank planning and management capabilities. In this study, the scope is to validate and contrast four machine learning models used: logistic regression (LR), Support vector machine (SVM), K-nearest neighbors (KNN), and multi-layer perceptron (MLP) classifier to forecast profitability. The daily profits are influenced by elements like the type of transactions, their amounts, as well as bank commission and agency commission, along with TOF tax payments.

To evaluate how well these models work in practice, we used the Sedad Bank daily operation dataset and analyzed performance measures such as precision, recall, F1-score, and the confusion matrix. Our paper is structured as follows: we start with a review of the related work in Section 2. Then move on to outlining the methodology in Section 3 before presenting the results and discussing the findings in Section 4 and concluding the study in Section 5.

2. RELATED WORK

The banking sector is being transformed by artificial intelligence (AI), changing how operations are carried out and boosting customer interactions while also strengthening risk management practices significantly. By integrating AI into their systems and processes, financial institutions can improve efficiency, provide personalized customer experiences and enhance security measures.

Recent studies have shown that AI driven advancements are making an impact across industries like finance, with examples including the use of Blockchain for secure authentication in process mining as well as employing advanced predictive models based on IoT technology and remote sensing for precision agriculture [6]-[8]. The change is driven by the expansion of data volume, the urgent necessity to cut down on expenses as well as the growing desire for tailored and easily accessible banking solutions.

In this segment of our study material, we delve into published works on AI implementations in the banking sector, highlighting how machine learning plays a role in empowering banks to make use of extensive data reservoirs to deliver swifter and more accurate services that are highly personalized. Through the application of algorithms, organizations can enhance their operations and foresee customer requirements ahead of time [9]-[14].

Research conducted by Catalini *et al.* [15] shows that machine learning models created to imitate judgement perform better than those created for financial gain purposes. Their research emphasizes two points: (i); models that imitate decision making skills perform well in new situations, indicating that investment choices could be mirrored. (ii); models focused on maximizing success rates outshine models mimicking humans when evaluating candidates not included in the data pool, suggesting that human evaluators might miss out on promising opportunities. Discrepancies, in models often stem from intuition, can result in overlooking the intricacies of applications at times. This indicates the function of AI in managing information and making decisions in data settings.

A study by Jewandah [16] examined how AI impacted leading banks in India during 2018. It found that, despite the changes brought about by AI technology, along with blockchain and cloud computing in the banking sector, tangible acceptance is still constrained, stressing the ongoing importance of human interaction. Indian financial institutions are looking into incorporating AI technologies to boost productivity and improve customer satisfaction.

A study by Andrew [17], Andrew delved into the influence of AI in industries, with a special emphasis on automation techniques like robotics and machine learning applications. He emphasized the importance of selecting and providing data thoughtfully for AI deployment, to grasp connections between variables that have already brought about substantial industry transformations and hold the potential for more groundbreaking advancements.

Thim and Seah [18] delved into real world AI uses in the world by focusing on neural networks (NN). They looked at how heuristic neural networks could be combined with Markowitzs Efficient Frontier in portfolio theory to improve portfolio construction and maximize investment returns. Kashiwagi [19] highlighted the renewed interest in AI, driven by advancements in learning, suggested that financial institutions should embrace AI more effectively through approaches like open innovation to unlock its full capabilities.

Expanding on the findings from our review of related word, in this area revealed a gap that led us to focus on a groundbreaking study in Mauritania, the first of its kind, looking into the operations of Sedad Bank's digital services platform. The main goal is to create a model that can estimate profits by making use of available data and applying various machine learning methods. Taking into account the type of data involved in this research and the importance of balancing simplicity, with accuracy and reliability in our analysis, we have chosen four used machine learning models for this study.

In this article, we will compare four machine learning models used to forecast daily profits in the realm of digital banking in Mauritania: LR, SVM, KNN, and MLPClassifier. The research will make use of the Sedad Bank Daily Operation Dataset as a resource for examining the variables impacting profitability and creating prediction models.

3. METHODOLOGY

In this part of our paper, we explore how to forecast profits by utilizing machine learning techniques. We opted for four models: LR, SVM, KNN, and MLPClassifier. For this task, our evaluation of the models was based on the Sedad Bank daily dataset, comprising 71 543 samples and 16 features. In Figure 1, we illustrate the approach we used outlining the steps taken and providing explanations in this section.

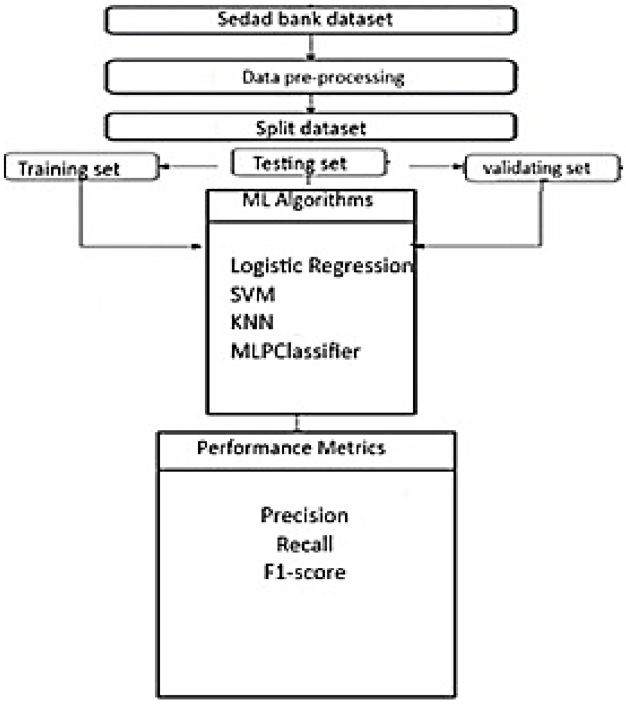

Figure 1. Process of our methodology

3.1. Sedad bank daily operation dataset

Sedad Bank is a digital bank in Mauritania that provides customers with the ability to manage their accounts, perform transfers, pay bills, and utilize other banking services. Its daily operation dataset is represented by a CSV file containing all daily transactions, includes details about the activities of banks and can be used to study what factors impact their profits and create models to predicting transactions profitability accurately. In Table 1 are listed all the characteristics of the dataset along with their explanations and the types of data they represent.

Table 1. Dataset description

Field name	Description	Data type
Date	Date of the transaction	Object
Tran code	Transaction code	Object
Tran type	Type of transaction	Int 64
Sender account	Account of sender	Object
Sender name	Name of sender	Object
Recipient account	Account of recipient	Object
Recipient name	Name of recipient	Object
Agency	Name of agency	Object
Bank account	Account of bank	Object
Bank name	Name of bank	Object
Amount	Amount of transaction	Float 64
Bank commission	Commission of bank	Float 64
Agency commission	Commission of agency	Float 64
TOF	Bank's deducted rate	Float 64
Reason	Transaction reason	Object
Profitability label	0: profitable 1: non-profitable	Int 64

Before building the model, it's important to examine the dataset to grasp its layout and features thoroughly. Regarding this matter, a correlation matrix (depicted in Figure 2) was created to evaluate the connections between attributes. Correlation values range from +1 to -1, reflecting the strength and direction of associations between variables:

- A positive correlation indicates a direct relationship.
- A negative correlation signifies an inverse relationship.
- A zero correlation suggests no relationship between variables.

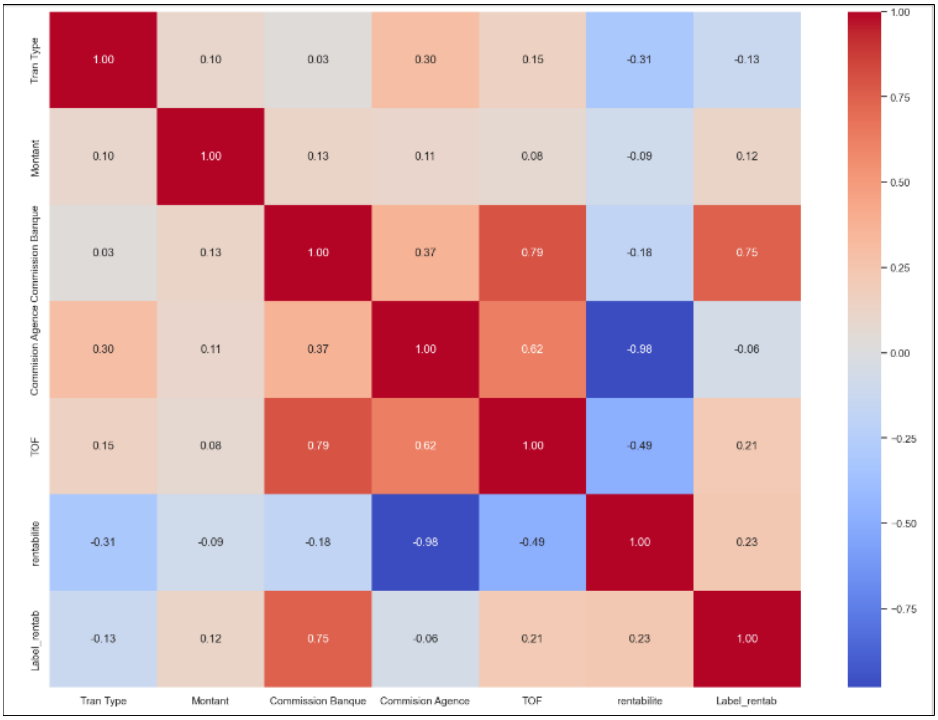

Figure 2. Correlation matrix

3.2. Data pre-processing

The pre-processing steps involve several key transformations to prepare the dataset for analysis. First, field types must be adjusted specifically; 'Sender Account' and 'Bank Account' should be converted from the Float64 data type to the object data type. Similarly, fields like 'Tran Type' and 'Profitability Label' should be converted from categorical data type to int64. Next, unnecessary columns that do not contribute to predicting profitability are removed to streamline the dataset. Handling missing data is also crucial; this typically entails removing rows with missing values to uphold data integrity. Finally, the dataset is divided into training, testing, and validation sets to ensure optimal model performance and reliability [20].

3.3. Dataset splits

We split data into training sets, validation and test sets to assess how well a model performs on data it hasn't seen before. This helps prevent overfitting and guarantees the model works effectively in real world scenarios. In our situation, we divided the data into 80% for training and 20% for testing when using LR. For the SVM and KNN models, we split the data into 80% for training and 20% for testing and using cross validation to adjust SVM hyperparameters and improve neighbor quality for KNN model. Lastly, for MLPClassifier we used the ratio of 70%/15%/15% to monitor performance and avoid overfitting issues.

3.4. Machine learning models

3.4.1. Logistic regression

LR is a linear model mainly employed for tasks related to classification. It uses a logistic function to predict the likelihood of a binary result. The model uses a linear combination of input features to compute probabilities, which are then converted into a range of 0 to 1 with a sigmoid function. LR is highly regarded for its simplicity and ease of understanding, which makes it successful for data that can be separated linearly. Nevertheless, it might face challenges with intricate connections or extensive datasets containing numerous characteristics.

3.4.2. Support vector machine

SVM is a flexible algorithm that can be applied to perform classification as well as regression tasks. It operates by determining the hyperplane that most effectively separates the data into separate classes. In linear scenarios, the hyperplane is simple, but in non-linear scenarios, SVM uses kernel functions to transform the data into a higher-dimensional space where a linear division is possible. This method enables SVM to effectively manage intricate data structures. SVM shows strong performance in high-dimensional spaces and is highly effective when there is a distinct separation between classes. Nevertheless, it may encounter difficulties when dealing with noisy data and might not function effectively when there are significantly more features than samples.

3.4.3. K-nearest neighbors

KNN is a model that relies on instances to perform tasks in classification and regression. In classification, KNN assigns a data point to a class by analyzing the most common class among its 'k' closest neighbors in the feature space. In regression, a value is predicted by averaging the values of the 'k' closest neighbors. The algorithms is highly appreciated for its simplicity and ease of use, as it does not need a dedicated training phase and instead functions as a "lazy learner." Nevertheless, KNN may experience slowness with big datasets and is affected by the selection of 'k' and the distance metric utilized. Moreover, irrelevant features can have a negative impact on the performance of KNN.

3.4.4. MLP classifier

The MLPClassifier, also known as MLPClassifier, is a neural network model specifically made for classification purposes. It is organized with numerous layers of nodes, or neurons, with each layer being connected to the next layer in its entirety. Activation functions are utilized by the network to add non-linearity to the model, while backpropagation is used to modify the weights throughout training. This structure allows the MLPClassifier to capture intricate, nonlinear connections and adjust to diverse data sets. Nevertheless, it frequently requires extensive datasets and substantial computational resources, may be less understandable than alternative models, and is influenced by hyperparameter tuning.

3.5. Performance measures

The performance of our models is evaluated by the confusion matrix. It outlines the predictions of the model using a sample of data. True positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) represent the primary results of the confusion matrix. The results are utilized in determining different metrics such as F1-score, recall, and precision, giving a thorough evaluation of the model's performance [21]-[23].

$$Accuracy = (TP + TN)/(TP + TN + FP + FN \tag{1}$$

$$Precision = TP / (TP + FP) \tag{2}$$

$$Recall = TP / (TP + FN) \quad (3)$$

$$F1 - score = (2\ x\ Precision\ x\ Recall) / (Precision + Recall) \quad (4)$$

4. RESULTS AND DISCUSSION

This research focuses on a topic that hasn't been studed in Mauritania before; therefore, we can't directly compare our findings to existing studies in the field. In this section, we will describe and talk about our results in detail. We tested the models on a computer running Windows 10 with a processor clocked at 2.40 GHz and 8 GB of RAM. The experiments were conducted using the Anaconda software, accessible for everyone to use. The model was created in Python, with tools from Scikit Learn library being used for implementation purposes. The metrics used to evaluate the models are outlined in Table 2.

Table 2. Results of different models on Sedad Bank daily operations dataset

Measures/Models	LR	SVM	KNN	MLP classifier
Precision (%)	99	77	94	99
Recall (%)	99	53	96	94
F1-score (%)	99	54	95	97

The results acquired from this study will be examined in this section. Figure 3 shows that LR and MLPClassifier had a precision rate of 99%, SVM had 77%, and KNN had 94%. The results indicate that the precision of the LR model and MLPClassifier outperformed the other models. The recall, also known as the true positive rate, is a widely used measure in machine learning for model assessment. Remember the recall percentages for LR, SVM, K-NK, and MLPClassifier shown in Figure 4: 99%, 53%, 96%, and 94% respectively. The Recall values obtained show that the Log Regression model is better than other models. The F1-score is a useful metric for evaluating a model's performance as it takes into account both precision and recall. The F1-score percentages for LR, SVM, KNN, and MLPClassifier in Figure 5 are 99%, 54%, 95%, and 97%, respectively. The findings demonstrate that the LR model surpasses other models in terms of F1-score values.

Based on the analysis discussed earlier, the following conclusions can be made:

- When it comes to predicting daily profitability, LR outperforms SVM, KNN, and MLPClassifier.
- SVM is the worst model to predict the daily profitability.

The upcoming research will explore machine learning and deep learning algorithms mentioned in studies on decision making methods and predictive analysis [24]. By integrating a methodology that includes learning models like CNN LSTM networks, as demonstrated in recent research on sketch recognition [25], we may improve the predictive accuracy for intricate financial datasets. Moreover, utilizing algorithms that prioritize data for analysis could enhance the accuracy of predictions [26]. Finally, we aim to combine these four models to enhance the capabilities.

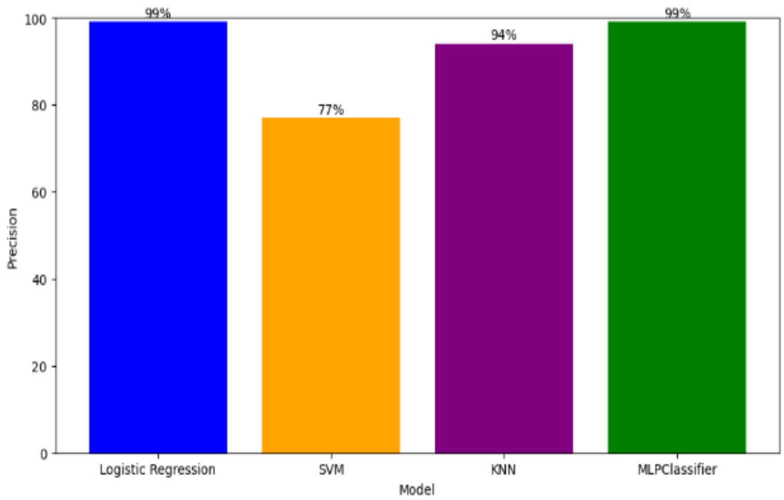

Figure 3. Precision

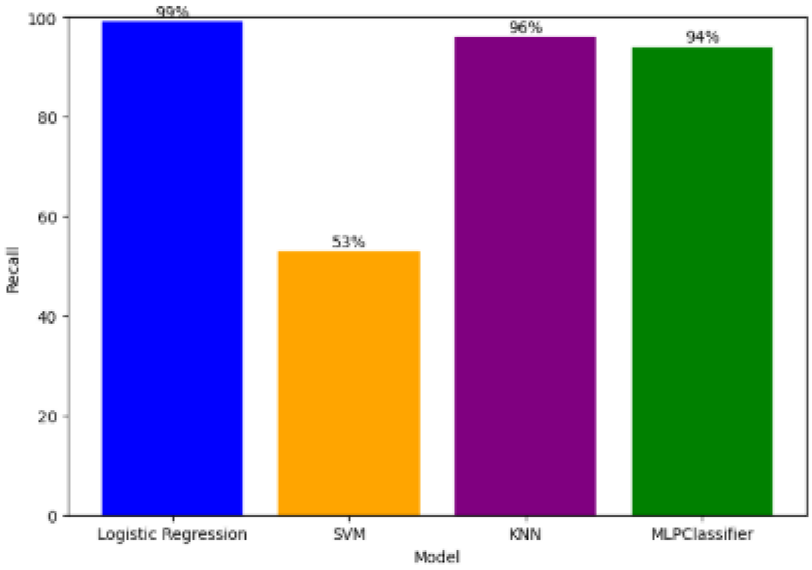

Figure 4. Recall

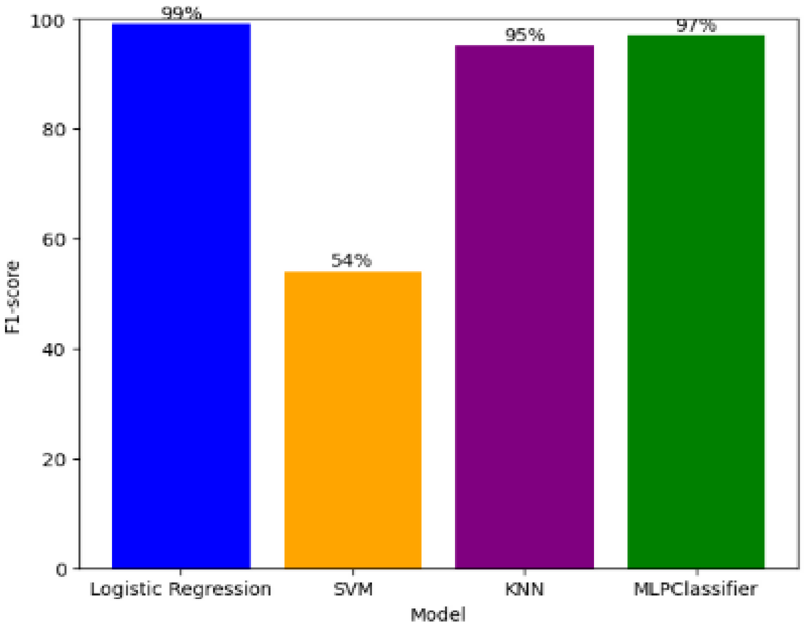

Figure 5. F1-score

5. CONCLUSION

Prediction is a well-established research area within the banking industry. To this, we used predictive models such as LR, SVM, KNN, and MLPClassifier to identify profitable operations and enhance banking strategies. In this context, this paper presents a proposed methode utilizing these models. Key metrics such as precision, recall, and F1-score were used to evaluate the performance of the model through a confusion matrix. The findings show that LR is the top-performing model in predicting daily profitability, with precision, recall, and an F1-score all at 99%, demonstrating the efficacy of LR in profitability prediction tasks. We aim to expand our research scope by assessing transactions over durations such as weekly, monthly and yearly datasets to gauge how effective the algorithms are in settings.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Mohamedou Cheikh Tourad		✓		✓	✓				✓	✓		✓	✓	
Ahmad Outfarouin		✓				✓				✓				
Nema Sidi Mohamed Mawloud		✓								✓				
Mohamedade Farouk Nanne		✓			✓	✓		✓	✓			✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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