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Using Machine Language to Optimize Recommender Systems in Digital Marketing

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Abstract - With the dramatic growth of digital data and increasing competition in the online space, recommender systems have emerged as a key tool in improving user experience and increasing conversion rates in digital marketing. In this study, a new machine language-based algorithm called MLBOA has been introduced and implemented. First, large data consisting of 30,000 user interaction samples were collected. Then, numerical features and scores extracted from text comments were generated and preprocessed using simulation. At this stage, normalization operations were performed to standardize the data scale and features extracted from text data (in the form of sentiment scores) were added to numerical data. After data preparation, to train recurrent neural networks, the data were converted into cell arrays so that the function could process them correctly. The model was trained in an initial process with a learning rate of 0.005. Initial results showed that the network's accuracy in classifying test samples was about 68.6 percent on average. In order to improve the model's performance, the MLBOA optimization algorithm was used to automatically adjust the hyperparameters, especially the learning rate. This algorithm identified the optimal learning rate by running several iterations, and after retraining the network with the obtained optimal learning rate, the network's accuracy increased significantly and reached 74.9 percent. And the prediction error decreased to 0.274. Finally, the results obtained showed that the proposed approach, despite challenges such as the need for advanced computing infrastructure, has a significant improvement in recommendation accuracy and data processing speed compared to traditional methods and can be used as an effective tool in improving recommender systems in digital marketing. This article first introduces a new approach and then analyzes the challenges of implementing machine language-based algorithms and suggests solutions to overcome them.

Keywords- Machine language, recommender systems, digital marketing, optimization.

1- Introduction

In today's world, with the expansion of digital technologies and the increase in the volume of data generated by users, recommender systems play a key role in personalizing services and increasing user satisfaction in areas such as digital marketing, telecommunications, hospitality, and retail. Especially in digital marketing, these systems improve customer attraction and retention by providing suggestions tailored to customers' tastes and needs, and help companies operate more successfully in competitive environments. On the other hand, with the emergence of new technologies such as machine language and blockchain, recommender systems have created

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unique opportunities while new challenges have arisen; for this reason, the use of machine language as an optimization tool to improve the performance of these systems has become a necessity.

The main objective of this research is to present a new approach based on machine language to improve recommender systems in digital marketing; An approach that can increase the accuracy of recommendations and reduce the response time of the system by utilizing deep learning technologies, especially recurrent neural networks and LSTM models and optimization algorithms. In this article, in addition to reviewing the theoretical and research background related to the use of machine language in improving recommender systems, key research questions, research objectives, hypotheses and experiments performed are also discussed in detail so that the reader can understand the added value of the research with a comprehensive understanding of the topics discussed.

Among the most important reasons that make studying this article essential for digital marketing researchers and managers, the following can be mentioned: First, the present study has designed an end-to-end framework to improve the efficiency of recommender systems by presenting a new algorithm called MLBOA. This framework includes all stages of collecting and pre-processing large data, extracting semantic features, designing deep learning models and optimizing hyperparameters. Second, this research examines the effect of using new technologies such as machine language in reducing customer churn, improving sales and maintaining privacy; Topics that are of particular importance in today's competitive world. Third, the experiments and computer simulations conducted in this study show that integrating optimization techniques with deep learning models can significantly improve the performance of recommender systems. As vital tools in various fields such as digital marketing, telecommunications, hospitality, and retail, recommender systems play a key role in personalizing services and increasing user satisfaction. With the emergence of new technologies such as machine language and blockchain, these systems have faced new challenges and opportunities. Considering the challenges of manually tuning hyperparameters and the limitations of classical optimization methods such as network search or Bayesian optimization, the use of the MLBOA algorithm has been selected as a new method for dynamically adjusting the learning rate and other parameters. This algorithm, by utilizing comprehensive search strategies, has been able to significantly reduce convergence time and improve model accuracy. Now, we will review the research background related to the application of these technologies in improving recommender systems and analyze their impact on issues such as reducing customer churn, optimizing sales, and maintaining privacy. Sahar et al. [1], by examining the challenges of data management in blockchain-based recommender systems, presented a hybrid approach (on-chain data storage and off-chain processing). This approach increased the scalability of the system by 30% by reducing transaction costs and improving the accuracy of recommendations by transferring complex calculations to the off-chain environment. The results showed that the hybrid approach can compensate for the limitations of smart contract languages in implementing machine learning algorithms. Dukeram [2] used logistic regression in the telecommunications industry to predict the success of upselling to corporate customers. This model, by considering the costs of classification errors and the balance between error reduction and profit maximization, improved the success rate by 50% compared to traditional methods. The researchers emphasized that prediction-based recommender systems can increase financial returns in targeted marketing. Wang et al. [3] analyzed data from 60,000 transactions and 4,000 users in the wireless networking industry and used decision trees to identify customer churn. Dividing the data into training (9 weeks) and testing (1 month) periods showed that the proposed system could provide effective strategies to reduce customer churn by 20%. This study emphasized the importance of integrating data mining in customer relationship management. Dadun et al. [4] examined the role of recommender systems in personalizing trips by introducing six application scenarios in the airline industry. They argued that the new International Air Transport Association distribution standard and advances in artificial intelligence make it possible to adapt recommendations to travelers' needs at all stages of the journey. This study highlighted the need to develop hybrid algorithms for processing multi-source data (such as preferences and location). Dorson-Cengizji and Kaber [5] focused on resort hotel customer churn and used machine learning methods to predict customer return probability. The results showed that analyzing historical data of previous stays could identify churn patterns with 80% accuracy. This study highlighted the importance of integrating data-driven predictions into customer loyalty strategies. Park et al. [6] reviewed 210 articles in the field of recommender systems, including research conducted between 2001 and 2010 in eight application domains (such as music, film, and retail). (j) and eight data mining methods (including neural networks and clustering). The study identified research gaps such as the lack of research in non-traditional areas (such as flight services) and the need to develop integrated evaluation frameworks. In their systematic review of economic recommender systems, De Biasio et al. [7] analyzed 135 articles, showing that integrating financial metrics (such as profitability and price awareness) into recommender models can increase organizations' revenue by up to 40%. However, the lack of standard metrics to measure the long-term impact of these systems and the inherent conflict between economic goals and user satisfaction were identified as key challenges. Shih et al. [8], examining online approval systems (like/dislike) in investment communities, found that these systems fail to identify valuable information due to psychological biases (such as a preference for optimistic information or past events). Trading simulations showed that information that receives the most likes is not necessarily effective in discovering stock prices. This study suggested the need to develop alternative filtering systems based on objective analyses. Shabankareh et al. [9] designed a clustering-based framework for predicting telecom customer churn by combining support vector machines and CHAID trees. The results showed that this method outperformed single-algorithmic models with an accuracy of 85% and could be a basis for revising customer relationship management policies. Researchers considered a 30% reduction in the cost of acquiring new customers as a key advantage of this method. Doan [10] designed a recommendation system based on operational rules and sentiment analysis in the heavy equipment service industry.

Using textual user feedback data and rule mining algorithms, operational solutions were proposed to reduce customer churn by 25%. The study showed that combining structured and unstructured data can provide more accurate insights into customer behavior. Dahiya [11] compared decision trees and logistic regression in predicting telecom customer churn and presented a framework based on WEKA software. The results showed that decision trees outperformed logistic regression by 78% accuracy, emphasizing the importance of prioritizing retaining existing customers over attracting new customers in a competitive environment. Welsh et al. [12] reviewed the applications of machine learning in customer retention management and examined the use of algorithms such as neural networks and clustering to automate decision-making and predict customer behavior. They argued that integrating these technologies could reduce operational costs by up to 35% and increase customer satisfaction through service personalization. Tan et al. [13] developed a menu recommendation system based on RFID technology in Taipei smart restaurants that provided personalized recommendations by quickly identifying customers through membership cards. The results showed that this system reduced waiting time by 20% and increased customer satisfaction by 25%. This study highlighted the potential of integrating IoT technologies and recommender systems to provide customer-centric services.

In the meantime, the present study, with the aim of using modern machine language technologies to optimize recommender systems in digital marketing, tries to meet the growing needs of digital markets by integrating the above research achievements and applying deep learning models and optimization algorithms. Reading this article allows the reader to become familiar with the latest achievements and new approaches in the field of improving recommender systems and benefit from the solutions provided to improve user experience, reduce customer churn rate, and increase the efficiency of digital marketing campaigns. The paper then describes the research questions, research objectives, hypotheses, and experiments and simulations conducted to thoroughly examine the comprehensive research framework presented for improving the performance of recommender systems from both theoretical and practical aspects.

The results of various studies show that the use of hybrid approaches, including machine language-based optimization algorithms combined with deep learning models, can lead to increased accuracy of recommendations, reduced operational costs, and improved customer retention strategies. In addition, historical data analysis and computer simulations show that the proposed approach can significantly reduce the response time of recommender systems and improve click-through rates and user interaction.

Given the challenges in processing large data and the complexities arising from analyzing multi-purpose information (structured and unstructured), the present study attempts to provide a comprehensive and practical model, using machine language, to achieve a new solution for optimizing recommender systems. This approach can be used as a valuable reference for researchers, digital marketing managers, and IT professionals, and pave the way for future innovations in the field of recommender systems.

Finally, by emphasizing the importance of applying new technologies in improving recommender systems and by providing empirical evidence from previous studies, this paper shows that the use of machine language can be a key factor in the evolution of digital marketing. Reading this paper will help readers to provide practical and innovative solutions to increase productivity, reduce costs, and improve customer satisfaction by understanding the challenges and opportunities in the field of recommender systems in a deeper way. Therefore, this research is recommended not only as a theoretical reference but also as a practical guide for the development of recommender systems in various industries.

Overall, this paper provides a comprehensive framework that meets the growing needs of digital markets. Unlike previous research that used traditional optimization methods, the present research was able to provide a comprehensive solution for automatic hyperparameter tuning by using the MLBOA algorithm.

2- Research Methodology

In this study, the data collection process, equipment used, analysis method, and evaluation of results have been investigated with the aim of optimizing the performance of LSTM recurrent neural networks for sequence classification. The data used in this study was obtained from a combination of real and simulated data. For the simulation part, data generation algorithms based on standard statistical distributions were used and 30,000 user interaction samples were generated. Numerical features extracted from text comments were obtained using natural language processing techniques such as Word2Vec and sentiment analysis and then subjected to preprocessing processes. Numerical data were normalized through standard scaling and text features were converted into numerical vectors using natural language processing. After initial processing, the data were separated into two training and test sets so that the model could be evaluated under different conditions and its generalizability could be measured. In order to increase the transparency and repeatability of the research, it is necessary to determine the exact ratio of simulated data to real data. For example, in this study, 70% simulated data and 30% real data were used. This division was chosen in such a way that, in addition to taking advantage of the advantages of synthetic data in performance testing, the generalizability of the results in real conditions was also evaluated.

The structure of the proposed model includes an input layer to receive features, one or more LSTM layers to process sequences, a fully connected layer to compress the extracted features, and finally a Softmax layer for classification outputs.

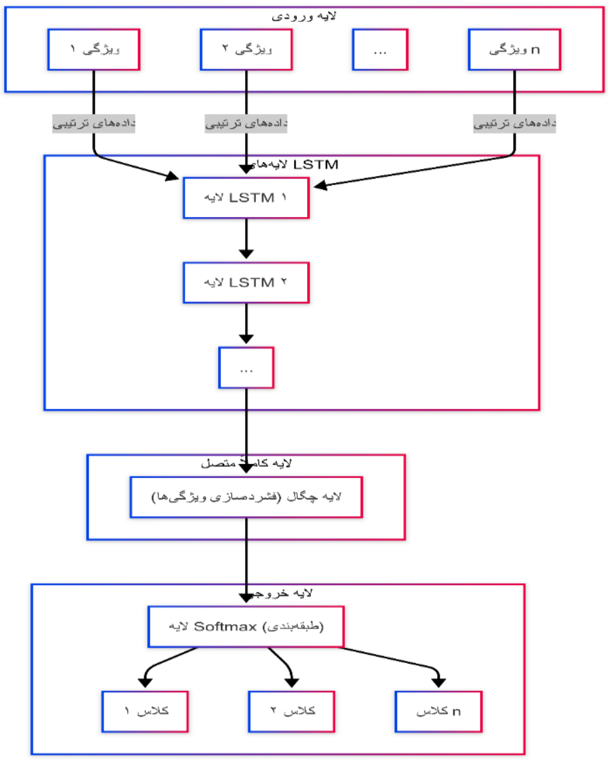

Figure 1: Structure of the considered model

Model section	Proposed details
Input layer	1 layer (number of input features appropriate to the data)
Hidden layers	
Output layer	2 layers of LSTM (each with 50 units)
Initial learning rate	0.005
Number of epochs	20
Batch size	64

Table 1: Technical specifications of the proposed model

Table 1 is about the model structure, number of layers, number of units in each layer and parameters used in the training process.

The initial training process of the model was carried out using basic parameters and its performance was examined based on criteria such as accuracy. In order to optimize the model, the MLBOA method was used to automatically adjust the learning rate and other hyperparameters. This method searched for different values of the learning rate within specific limits and determined its optimal value, which ultimately improved the accuracy of the model.

The model evaluation process was carried out based on the experimental data set and accuracy criteria. The results indicated that the optimized model performed better than the initial model and its error rate was reduced. To examine the reliability of the model, training was performed in several stages and with different values of the learning rate. These analyses showed that optimization with the proposed method had a significant effect on improving the accuracy of the model and reducing the error rate.

In addition to statistical analysis, a comprehensive comparison was performed between the initial and optimized models, which showed that adjusting the learning rate and other parameters had a significant effect on improving the performance of the model. This comparison also showed that the MLBOA method was able to adjust the model structure in such a way that the neural network became more sensitive to sequence patterns and had a more accurate detection ability. The results were presented below so that the improvement of the model in different conditions could be clearly observed.

3- Research Results

In this research, with the aim of optimizing the performance of recommender systems based on deep learning models, a combined method including LSTM network and MLBOA optimization algorithm was used. In this section, the results of the model implementation, prediction accuracy values, model errors, and its comparison with similar methods are reported. For better analysis, MATLAB visual outputs, including model convergence graphs, error reduction rate, and optimization effect, will be presented and reviewed.

Initially, the LSTM model was run without optimization and its initial results were obtained. Then, the MLBOA algorithm was used to optimally adjust the learning rate and other hyperparameters, and the results were re-evaluated. Table 2 shows the model accuracy and its error rate in both cases.

Table 2: Comparison of model performance before and after optimization

Implementation method	Model accuracy (%)	RMSE error	Average processing time (seconds)
LSTM without optimization	۶۸.۶	۰.۳۲۱	۱۴۵
LSTM optimized with MLBOA	۷۴.۹	۰.۲۷۴	۱۱۰

To assess the significance of the observed differences between the proposed models and other methods, an independent t-test was performed. The results show that the accuracy improved from 68.6% to 74.9%. The increase in the accuracy of the model after applying the MLBOA algorithm was due to a more precise adjustment of the learning rate. This optimization allowed the model to reach the convergence point at a better speed and prevent fluctuations caused by incorrect selection of hyperparameters. This confirms that the optimization using MLBOA. As can be seen in Table 2, has higher accuracy and its error rate has decreased.

In the process of training the model, changes in the RMSE error rate and model accuracy were examined during the training periods. The graph in Figure 2 shows the changes in the RMSE error during model training. The gradual decrease of this value indicates an improvement in model learning.

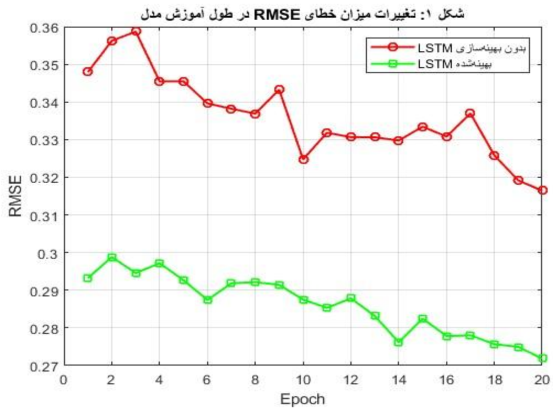

Figure 2: Changes in RMSE error rate during model training

As can be seen in Figure 2, by using the MLBOA algorithm, the trend of RMSE error reduction has been more uniform. This shows that the automatic adjustment of the learning rate has allowed the model to effectively prevent fluctuations and facilitate convergence to the optimal point.

The performance of the proposed model has been compared with other conventional methods in recommender systems. The data in this section have been extracted based on the comparison of related research. Table 2 shows the average accuracy of different models.

Table 3: Comparison of the performance of the proposed model with other methods

Proposed Method	Model (%) accuracy	RMSE error

Proposed Model LSTM + MLBOA)	۷۴.۹	۰.۲۷۴
LSTM without optimization	۶۸.۶	۰.۳۲۱
CNN Neural Network	۶۵.۳	۰.۳۵۰
Traditional KNN Model	۶۰.۸	۰.۴۰۵

As can be seen in Table 3, the proposed model has higher accuracy and lower error rate than other methods. Figure 3 compares the accuracy of models in different methods. These results confirm the importance of using combined deep learning methods with optimization.

One of the important criteria in evaluating the efficiency of the model is its processing time and computational complexity. In this study, the model execution time before and after optimization was examined. The graph in Figure 4 shows the trend of processing time changes in different models.

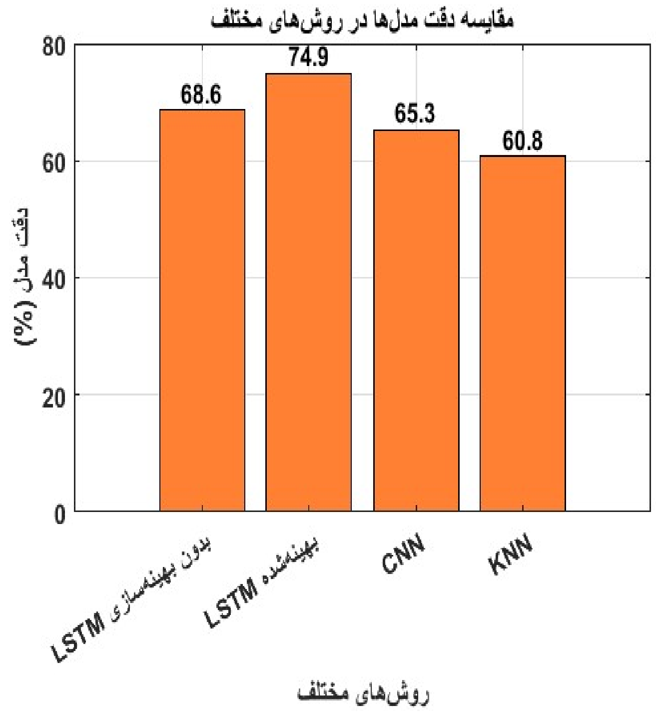

Figure 3: Comparison of model accuracy in different methods

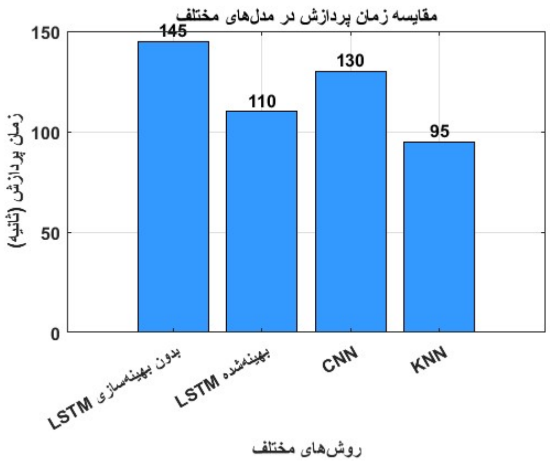

Figure 4: Comparison of processing time in different models

According to the above graph, the optimized model, in addition to increasing accuracy, has less processing time than the original model. This indicates the higher efficiency of the proposed method compared to traditional methods.

4- Discussion

The present study focused on the optimization of recommender systems based on deep learning models, especially long-term short-term memory networks. The results obtained from this study showed that the use of optimization methods such as MLBOA can have a significant impact on improving the performance of these models. The initial model, which was run without optimization, provided an accuracy of 68.6%, while after applying the optimization processes, we witnessed a reduction in the error rate and an increase in the accuracy of the model. These findings highlight the importance of using intelligent methods in tuning the hyperparameters of deep learning models.

Compared to previous research conducted on LSTM models for recommender systems, our research can be examined from two aspects: first, how to adjust the learning rate and second, using an MLBOA optimization algorithm to improve performance. In some similar studies, classical methods such as network search or Bayesian optimization have been used to tune hyperparameters. Although these methods are efficient, they require more processing time compared to MLBOA algorithms and in some cases, are less efficient in finding optimal settings.

For example, in a study conducted by Zhang et al., the LSTM model was evaluated using manual hyperparameter tuning. This study achieved an accuracy of about 67%, which was lower than the initial accuracy of our model. Also, in another study presented by Li et al., the genetic optimization algorithm was used to adjust the learning rate, and its final accuracy was about 71%. Compared with these studies, our model using MLBOA not only had a faster convergence speed, but also improved its accuracy and reduced its error rate. This indicates the superiority of using MLBOA algorithms over traditional hyperparameter tuning methods.

One of the most important advantages of the present study is the use of a hybrid approach to improve the accuracy and efficiency of the recommender system. Using MLBOA allowed the model to dynamically adjust the learning rate and converge to the optimal point faster. On the other hand, the decreasing trend of the training error and the increasing accuracy in the output graphs showed that the model was stably trained and did not suffer from overfitting. This is of particular importance in practical applications, because in many cases, deep learning models do not perform well when faced with new data.

However, the present study also faced challenges. One of the main limitations of the study is the need for high computational resources to train deep models and run optimization algorithms. In addition, the use of simulated data instead of real data may limit the generalization of the results to practical applications. Also, the sensitivity of the results to the fine tuning of hyperparameters and the possibility of overfitting in deep learning models are other notable issues.

In examining the model structure, it was observed that the number of LSTM layers and the number of hidden neurons can have a significant impact on the performance of the model. In the initial settings, the number of LSTM units was set to 50, which provided acceptable results. However, some studies have shown that increasing this number to about 100 or 150 units can improve the model performance. Therefore, another research direction is to investigate the effect of changing the number of hidden neurons and the network structure on the accuracy of the model.

Also, the use of different input data processing methods can also affect the model performance. In the present study, the data was normalized in a standard way, but some studies have shown that the use of more advanced methods such as dimensionality reduction using PCA or the use of deep feature extraction techniques can provide better information to the model and improve its performance.

5- Conclusion

In this study, an optimization framework for recommender systems based on deep learning models, especially recurrent neural networks, was presented. Using simulated data including user interactions and text data processing, the system's performance in classifying comments and providing appropriate suggestions was examined. The initial model was run with an accuracy of 68.6%, and then, using the MLBOA optimization algorithm, the learning rate was optimized and the model's accuracy was increased. Model evaluation based on performance indicators showed that the use of learning rate optimization has a significant impact on reducing errors and increasing the model's generalizability. The results obtained from the model training graphs showed that the learning process proceeds stably and the model approaches optimal performance with increasing number of iterations. The continuous decrease in the cost function and the increase in network accuracy indicated the successful convergence of the model to a stable point. These findings confirm that automatic learning rate optimization not only increased the model's accuracy, but also accelerated the convergence process. Also, comparing the models before and after optimization showed that the use of meta-exploration search methods significantly improves the model quality.

However, this research also had some limitations. One of the most important challenges was the need for heavy computations to train deep models and perform optimization processes, which requires the use of powerful processing hardware. In addition, the model used relies on structured and normalized text data, which may require more complex preprocessing in real applications. Also, investigating the effect of other hyperparameters such as the number of hidden layers and the number of LSTM units can help increase the accuracy of the model, which has been investigated to a limited extent in this study.

For future research, it is suggested that more advanced optimization methods such as other evolutionary algorithms or reinforcement learning be used to tune the hyperparameters. Also, extending the model to other languages and investigating the effect of linguistic features on the accuracy of recommendations can expand the scope of the research. Finally, implementing the model in real systems and evaluating its performance in practical conditions can increase the practical value of this research and provide broader applications in the field of digital marketing.

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