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Exploring LSTM-CAMF: A New Approach for Context-Aware Collaborative Filtering

Errakha K.[1], Samih A.[2], Marzouk A.[1], Krari A.[3], Dfouf S.[4]

[1]*Computer, Networks, Mobility and Modeling Laboratory, Hassan First University*
[2]*Artificial Intelligence Research and Applications Laboratory, University Hassan First*
[3]*Laboratory of Research Watch for Emerging Technologies, Hassan First University, Settat, Morocco*
[4]*Faculty of Legal, Economic and Social Sciences, Mohammedia, Hassan II University*

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To produce more accurate recommendations, Context-Aware Recommender Systems (CARS) incorporate contextual elements during user interactions. However, a major challenge lies in the need for additional contextual data, which can hinder the performance of collaborative filtering techniques. In this research, we introduce an innovative approach for detecting contextual information in real time by integrating Long Short-Term Memory (LSTM) recurrent neural networks with Context-Aware Matrix Factorization (CAMF). This strategy is designed to dynamically adjust to changes in contextual conditions by modeling user relationships and their temporal evolution, ultimately aiming to boost recommendation accuracy. The effectiveness of the proposed method is evaluated using two standard performance metrics: Mean Absolute Error (MAE), NDCG (Normalized Discounted Cumulative Gain), MSE (Mean Squared Error) and Root Mean Square Error (RMSE).

Keywords: *CAMF; LSTM; RMSE; MAE; CARS.*
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1. Introduction

Recommender Systems (RS) have become indispensable in assisting users to sift through vast volumes of data and reduce the impact of information overload in the age of big data [1]. These systems generate personalized suggestions across various domains, such as e-commerce and digital media, by analyzing users' historical interactions. Yet, taking into account the situational context in which a recommendation is made is essential when users face numerous options. Context-Aware Recommender Systems (CARS) build upon conventional techniques by incorporating contextual variables; however, many existing models treat context as static, despite the dynamic nature of user preferences [2]. There remain significant challenges, especially in accurately capturing shifts in user behavior and adapting to evolving contextual factors. Our research directly tackles these issues. In this work, we introduce a hybrid recommendation model that merges the capabilities of Long Short-Term Memory (LSTM) networks with Context-Aware Matrix Factorization (CAMF). This integration is designed to address the shortcomings of existing methods by combining LSTM's strength in modeling sequential data with CAMF's ability to process contextual inputs. Through this synergy, the proposed approach aims to deliver more precise and contextually relevant recommendations. The remainder of the paper is organized as follows:

1. reviews related research;
2. outlines our proposed model and methodology;
3. presents the experimental setup and results;
4. concludes with insights and prospects for future research.

2. Related works

This section presents an overview of several Context-Aware Recommender Systems (CARS) introduced in the literature, selected according to the focus of each study and its scholarly impact, measured by citation count. The objective is to identify potential areas for enhancement. To structure the discussion, the section is divided into three distinct subsections. Section 2.1 deals with context-aware recommendation systems, while section 2.2 researches into use of long-term memory (LSTM) in recommender systems. Section 2.3 briefly describes and explores temporal dynamics in recommender systems.

2.1. Context-aware recommender systems (CARS)

The notion of context is inherently multifaceted and can vary significantly depending on the specific domain of application. Initially, this study defined context as encompassing physical locations, groups of individuals, nearby objects, and the temporal evolution of these elements [3]. Broadly speaking, context includes any additional information that can improve the precision of recommendations, and there is a general consensus that incorporating contextual elements enhances the personalization of recommender systems [4].

Context-Aware Recommender Systems (CARS) represent an advancement in recommendation technologies by integrating such contextual data to boost system performance [5]. A substantial body of research has been devoted to methods for embedding context – such as user activity, temporal aspects, spatial location, or even environmental conditions like weather – into recommendation algorithms [6]. By aligning recommendations with the user's situational conditions, CARS can deliver more relevant and adaptive suggestions [7–9].

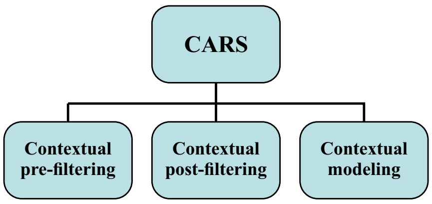

Fig. 1. Context-aware recommendation systems.

For instance, Rosni Lumbantoruan et al. [10] introduced a model known as TopC-CAMF, developed in response to the increasing demand for personalized recommendation mechanisms. Unlike conventional approaches that depend on predefined contexts like time or place, TopC-CAMF derives individualized contextual cues from user-generated textual reviews. Leveraging matrix factorization techniques, the system identifies the most influential contextual factors for each user based on their review content, which in turn informs more accurate and user-specific recommendations. Similarly, Krishan Kant Yadav et al. [11] proposed a hybrid system that combines matrix factorization with neural networks to enhance both the accuracy and breadth of recommendations. Their model was tested across several datasets, with evaluation metrics such as RMSE indicating improved performance. The potential applications of this approach span various sectors, including online retail, social platforms, and digital entertainment. CARS expand on conventional recommender systems by incorporating dimensions like time, location, device, or user environment, transitioning from a traditional two-dimensional model (User – Item) to a multidimensional framework (User-Item-Context) [12]. Formally, the utility function in CARS can be represented as follows:

$$R\colon \mathcal{U} \times \mathcal{I} \times \mathcal{C} \to \text{Rating}, \qquad (1)$$

where U denotes the set of users, I the set of items, and C the set of contextual variables [13]. Adomavicius et al. [6] categorized context integration strategies into three main paradigms: pre-filtering, post-filtering, and contextual modeling, as depicted in Figure 1:

— Context-Based Pre-Filtering: In this strategy, contextual information is applied at the early stage of the recommendation process to filter data before it reaches the core algorithm. Within content-based recommendation systems, this typically involves generating multiple context-dependent profiles for both users and items. During recommendation generation, the system selects the most appropriate feature vector corresponding to the detected context. In collaborative filtering systems, pre-filtering consists of adapting the rating predictions by associating them with specific contextual dimensions [14].

- Context-Based Post-Filtering: This approach incorporates contextual information after the initial recommendation list has been generated. The main objective is to refine or reorder the output by selecting or prioritizing rating predictions based on the current context, thus enhancing the overall relevance of the recommendations [15].
- Contextual Modeling: In this paradigm, context is directly integrated into the core recommendation computation. For content-based systems, contextual variables influence the similarity calculations between users and items, thereby adapting recommendations to the user's situation. In collaborative filtering systems, heuristic-based methods are often employed in memory-based models, while advanced model-based approaches leverage techniques such as tensor factorization and context-enriched matrix factorization to capture context effects during training [15]. Among the most recognized models in this area is Context-Aware Matrix Factorization (CAMF), which extends traditional collaborative filtering by incorporating contextual dimensions to improve recommendation relevance. CAMF applies matrix and tensor factorization methods to decompose the user – item interaction matrix into latent features, while simultaneously modeling context as an additional input layer. Different versions of CAMF exist to represent diverse contextual influences. For instance, CAMF-C assigns a global weight to each context value independently of items, using separate parameters for each context factor. Alternatively, CAMF-CI links each context – item pair with specific parameters, enabling the model to capture how context affects the relevance of individual items [10]. The CAMF framework is particularly suited to multi-context scenarios, as it analyzes, extracts, and integrates contextual data to dynamically tailor recommendations. As a result, it produces more accurate and situationally appropriate predictions, offering significant advantages over traditional context-free models.

2.2. Long Short-Term Memory

Long Short-Term Memory (LSTM) is a specialized architecture within the family of Recurrent Neural Networks (RNNs), designed to effectively learn from and model sequential data that exhibit long-term dependencies. In the domain of recommender systems, LSTMs are particularly valuable for identifying temporal trends and behavioral patterns in user-item interactions, ultimately enabling more accurate and individualized recommendations. This deep learning model has demonstrated strong performance across a range of applications, including various text classification tasks [16]. The network takes as input a sequence of elements

$$X = (x_1, x_2, \ldots, x_n)$$

and outputs a corresponding sequence

$$Y = (y_1, y_2, \ldots, y_m)$$

with each output computed based on internal activations generated by the model's architecture [17]. A defining feature of LSTM networks is the presence of memory blocks within their hidden recurrent layers. These blocks include memory cells that maintain the network's internal state over time through self-recurrent connections, as well as gating mechanisms-multiplicative units that control how information is stored, updated, and retrieved [18]. In its foundational form, each memory block is equipped with two key gates: the input gate, which governs the extent to which incoming data affects the memory cell, and the output gate, which determines how much of the 'cell's content influences the network's output at each time step.

Imran Ahmed et al. [19] introduced a recommendation framework that leverages a heterogeneous information network to establish relationships among patients, medical conditions, and pharmaceutical products. The system involves a multi-stage pipeline including data extraction, preprocessing, sentiment analysis, and classification using an LSTM model. See the architecture in Figure 2. User-generated content, drug feedback, and various contextual features are incorporated into the model to predict individual user responses. The integration of diverse data sources enhances the precision of context-aware recommendations. Moreover, the system utilizes shared insights and evaluations from individuals with similar medical conditions, employing feature engineering techniques to extract critical attributes.

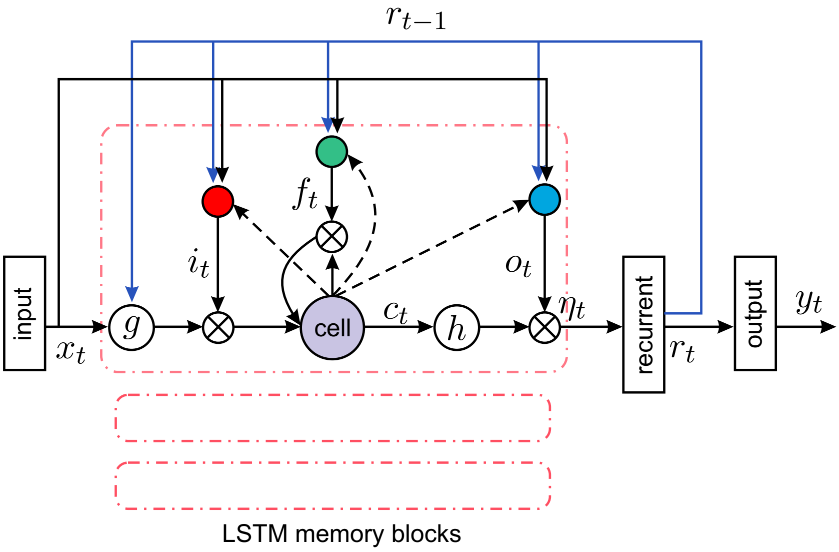

Fig. 2. LSTM memory blocks.

Chuanchuan Zhao et al. [20] proposed a novel recommendation method that combines deep bidirectional LSTM networks with a self-attention mechanism. This approach addresses challenges related to item representation, weight adjustment, and dual-directional preference modeling, ultimately capturing users' preferences more effectively. In another contribution, N. S. Kirutika et al. [21] developed a recommendation system tailored to social media environments using a hybrid LSTM-SVM classifier. This system was designed to differentiate between authentic and misleading information about the COVID-19 pandemic. Real-time Twitter data is collected, preprocessed, and transformed into binary feature vectors. The hybrid model, trained and evaluated using separate datasets, demonstrates superior performance over conventional methods across multiple metrics, including accuracy, sensitivity, and specificity.

Jie Wang et al. [22] presented a contextual citation recommendation system built on an end-to-end memory network framework. The model incorporates bidirectional short- and long-term memory (Bi-LSTM) layers to learn semantic representations of both article content and citation contexts. Additionally, it integrates author profiles and citation linkages into vectorized embeddings, and calculates contextual relevance using a multi-layer memory mechanism. Lastly, Wafa Shafqat et al. [2] proposed two deep learning-based models to enhance tourism recommendation systems. The first employs a context-enriched hierarchical architecture built on LSTM networks to forecast short-term tourist behavior. It utilizes environmental and situational variables, such as climate, weather conditions, and local risk levels, to provide personalized travel suggestions. The second model focuses on long-term travel preferences, integrating contextual inputs like user reviews, location ratings, geographic distance, and popularity scores to improve recommendation accuracy.

2.3. Review of recommendation system

Table 1 presents a detailed comparative analysis of a wide range of recommendation methodologies, along with the datasets employed for their validation and the performance metrics used in their evaluation. The methods span from conventional collaborative filtering models to more sophisticated deep learning-based techniques, such as LSTM. The datasets referenced are drawn from varied domains, including film, music, tourism, and e-commerce, reflecting the adaptability of these methods across applications. Evaluation measures include standard indicators like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), as well as more nuanced metrics such as Normalized Discounted Cumulative Gain (NDCG) and Mean Reciprocal Rank (MRR). In some instances, domain-specific metrics are applied, including sensitivity, specificity, and Cohen's kappa for classification accuracy, as well as training and validation loss for assessing deep learning model performance. This table offers a synthesized overview of contemporary approaches in recommendation systems research.

Table 1. Review of recommendation systems.

Ref.	Method	Dataset	Evaluation
[23]	PW-CAMF	STSTravel, InCarMusic	MAE, RMSE
[10]	TopC-CAMF	Beauty, Office, InCarMusic	RMSE, MAE, MSE, NDCG
[11]	MF-NN	MovieLens, Hindi Movie, Book Cross	MAE, RMSE, Coverage
[15]	CBMF	DePaulMovie, LDOS-CoMoDa, InCarMusic, Travel-STS	MAE, RMSE
[19]	LSTM	Dataset from www.Drugs.com	Training and validation loss
[20]	Bi-LSTM	MovieLens dataset	Recall, MAP, MRR, NDCG
[17]	LSTM-SVM Classifier	Twitter Dataset	Sensitivity, Specificity, Precision, Kappa

3. Proposed methodology

The proposed method integrates two powerful techniques to enhance the performance of context-aware recommendation systems: Long Short-Term Memory (LSTM) networks and Collaborative Aspect Matrix Factorization (CAMF). LSTM networks are a type of recurrent neural network (RNN) that are particularly effective at capturing and modeling temporal dynamics in data. They are designed to remember information for long periods, making them suitable for sequence prediction tasks. In this context, the LSTM model processes a sequence of data points over time to understand how user preferences evolve. CAMF is a matrix factorization technique that incorporates contextual information into the recommendation process. It models the interactions between users and items while considering additional contextual factors, such as user demographics or situational context.

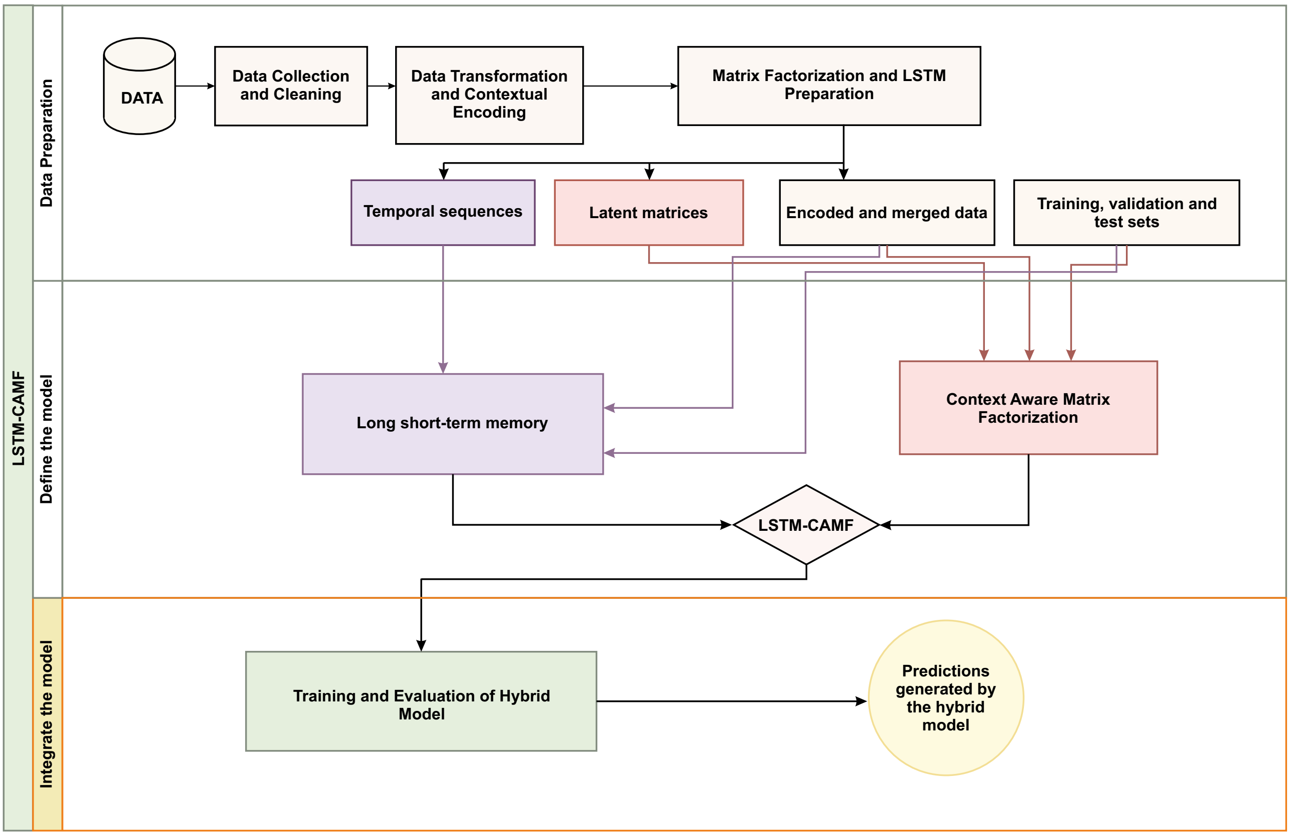

Fig. 3. The implementation steps of the hybrid approach.

The LSTM model is employed to capture temporal patterns in the data. It processes a sequence of input data points over time to generate an output that reflects the temporal characteristics of user behavior. This output from the LSTM represents the captured temporal features at each time step, which helps in understanding how user preferences change over time. CAMF leverages contextual features to improve the accuracy of recommendations. These features can include various types of information, such as metadata about the items, tags, genres, or user-specific information. By considering these contextual factors, CAMF provides more relevant recommendations that align better with the user's current context.

The integration of LSTM and CAMF is achieved by merging their respective outputs. The combined output Leverages the strengths of both approaches: LSTM ability to capture temporal patterns and CAMF ability to handle contextual interactions. This combined output is then used for the final prediction, providing a more Accurate and context-aware recommendation.

The hybrid model, which integrates the LSTM and CAMF outputs, is used to make the final recommendation. This approach improves the recommendation systems overall performance by capturing both temporal and contextual relationships in the data. By utilizing both LSTM and CAMF, the system can provide recommendations that are not only based on historical user behavior but also tailored to the current context, leading to more relevant and personalized recommendations. The LSTM-CAMF approach is based on temporal hybridism in user-product interaction using LSTM and CAMF collaborative matrix factorization. A description of the implementation steps is shown in Figure 3. Initially, the phase of collecting, cleaning, encoding and normalizing interactions, and then dividing the data into validation, training and test sets, is known as data preparation. Then, thanks to the recurrent layers, the LSTM model takes into account the passage of time, and in the CAMF model, the user-product matrix is factorized to learn latent representations. In the final phase, the two models are linked in a dense layer that merges temporal and collaboration information. These approaches are used to improve the performance of recommendations using both sequential and collaborative relationships.

4. Experimental evaluation

This section assesses the performance of our interactive recommendation approach through comprehensive experimentation using two publicly available real-world datasets. These experiments are designed to rigorously evaluate the system's ability to deliver accurate and context-aware recommendations.

4.1. Dataset

This sub-section describes the datasets analyzed. The datasets analyzed include InCarMusic and DePaulMovie. InCarMusic Dataset This dataset examines music preferences within in-car environments, documenting user preferences and behaviors associated with music selection and listening habits during automobile travel. There are 26 distinct contexts, including driving style, landscape, state of mind, sleep, traffic conditions, and weather and climate. The DePaulMovie Dataset comprises training and testing subsets focused on movie recommendations. User preferences, movie ratings, and contextual information that influence movie choices are included. The De Paul Movie Dataset is a collection of films that includes: A total of 5 043 ratings categorized as follows: 1 448 ratings presented without specific context. 3 595 contextual ratings (see Table 2).

Table 2. Description of dataset.

	InCarMusic	DePaulMovie	STSTravel
Users	42	97	249
Items	139	79	325
Context	8	3	14
Rating	4 012	5 043	2 534
scale	1–5	1–5	1–5

4.2. Accuracy evaluation metrics

To evaluate the predictive accuracy of the implemented algorithms, we employed standard performance metrics widely used in recommendation system research. The primary metrics selected were the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE), both of which quantify the deviation between predicted ratings and actual user feedback.

Mean Absolute Error (MAE). The MAE measures the average size of the prediction errors, regardless of their direction. It is calculated as the average of the absolute differences between the predicted and actual valuations. Lower MAE values indicate better agreement between the predicted and actual valuations, suggesting better performance of the model in terms of prediction accuracy,

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| .$$

Root Mean Squared Error (RMSE). The RMSE gives the square root of the average of the squared differences between the predicted and actual classifications, penalizing large errors significantly. Lower RMSE values indicate better performance, meaning that the model predictions are closer to the actual classifications,

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}.$$

NDCG (Normalized Discounted Cumulative Gain). NDCG evaluates the ranking quality of recommendations by considering the position of relevant items. Highly relevant items ranked higher contribute more to the score. The score is normalized between 0 and 1,

$$\mathrm{DCG@}k = \sum_{i=1}^{k} \frac{2^{rel_i} - 1}{\log_2(i+1)},$$

$$\mathrm{NDCG@}k = \frac{\mathrm{DCG@}k}{\mathrm{IDCG@}k}.$$

MSE (Mean Squared Error.) MSE measures the average of the squared differences between the predicted values and the actual values. It penalizes larger errors more severely than smaller ones,

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

4.3. Evaluation methodology

We compare the LSTM-CAMF method with three state-of-the-art reference systems: TopC-CAMF [15] and PW-CAMF and CBMF. In this paper, we apply cross-validation five times and carefully adjust each reference systems.

We present experimental results for three recommendation models: based on two common evaluation metrics – mean absolute error (MAE) and root mean square error (RMSE). The evaluation was conducted on the INCARMUSIC dataset. The results are summarised in Table 3 below.

Table 3. Evaluation of LSTM-CAMF, TopC-CAMF, and PW-CAMF models based on MAE and RMSE (IncarMusic).

Metric	LSTM-CAMF	TopC-CAMF	CBMF	PW-CAMF
MAE	0.43	0.5074	1.2901	0.869
RMSE	0.61	0.6440	1.5207	1.092

Two additional performance measures are used to present the evaluation results for the LSTM-CAMF and TopC-CAMF models: Mean Square Error (MSE) and Normal Discounted Cumulative Gain (NDCG). These metrics provide an insight into the accuracy and the quality of the ranking of the recommendations produced by the models. The evaluation is performed on the INCARMUSIC dataset. The results are summarised in Table 4.

Table 4. Evaluation of LSTM-CAMF, TopC-CAMF models based on MSE and NDCG (INCARMUSIC).

Metric	LSTM-CAMF	TopC-CAMF
MSE	0.35	0.5074
NDCG	0.757	0.7216

In this section, we report the results of evaluating the LSTM-CAMF, PW-CAMF, and CBMF models based on the mean absolute error (MAE) and root mean square error (RMSE). These metrics provide an assessment of the prediction accuracy and the ability of the model to minimize the errors in the recommendations. The evaluation is performed on the STS Travel dataset. The results are summarized in Table 5.

Table 5. Evaluation of LSTM-CAMF, PW-CAMF, CBMF models based on MAE and RMSE (STS Travel).

Metric	LSTM-CAMF	PW-CAMF	CBMF
MAE	0.650	0.740	0.9284
RMSE	0.880	0.927	1.1126

Table 6. Evaluation of LSTM-CAMF, CBMF models based on MAE and RMSE.

Metric	LSTM-CAMF	CBMF
MAE	0.580	0.6591
RMSE	0.850	0.9186

The results of the evaluation of the LSTM-CAMF and CBMF models on the basis of mean absolute error (MAE) and root mean square error (RMSE). These measures assess the accuracy of the predicted classifications and the overall performance of the model. The evaluation is performed on the DePaulMovie dataset. The results are summarized in Table 6.

4.4. Experimental results and discussion

This section presents the experimental results of four different models, LSTM-CAMF, TopC-CAMF, PW-CAMF and CBMF, evaluated by different performance measures such as MAE, RMSE, MSE and NDCG on different datasets, INCARMUSIC, STS Travel and DePaulMovie. The results show that the performance of each model is comparable in terms of prediction accuracy and classification quality.

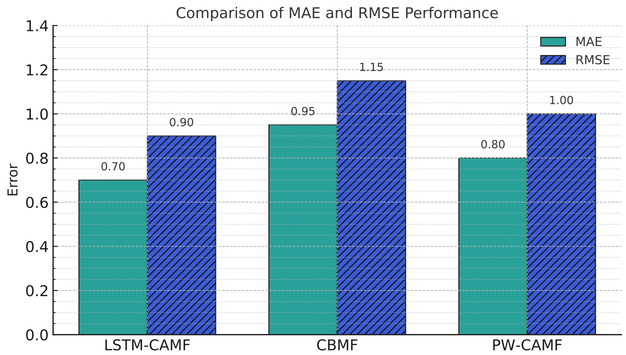

Fig. 4. LSTM-CAMF, TopC-CAMF, and PW-CAMF model evaluation using MAE and RMSE (INCARMUSIC).

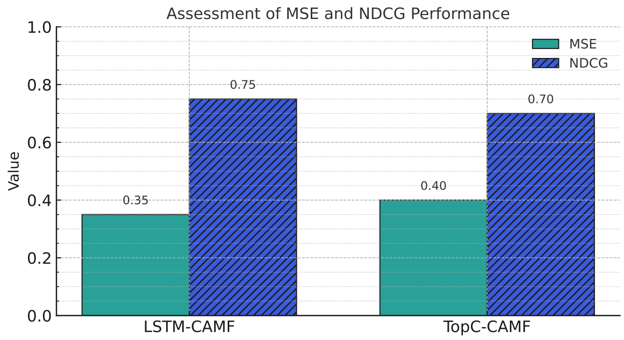

Fig. 5. Assessment of MSE and NDCG-Based models, TopC-CAMF, and LSTM-CAMF (INCARMUSIC).

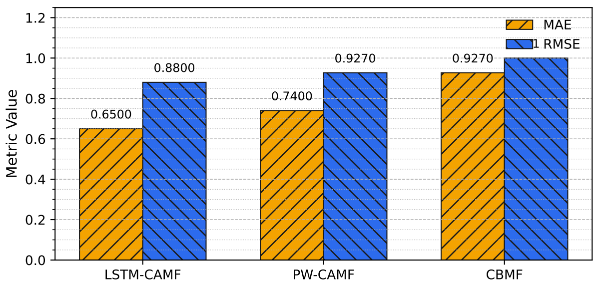

Fig. 6. Assessment of LSTM-CAMF, PW-CAMF, and CBMF models utilizing MAE and RMSE (STS Travel).

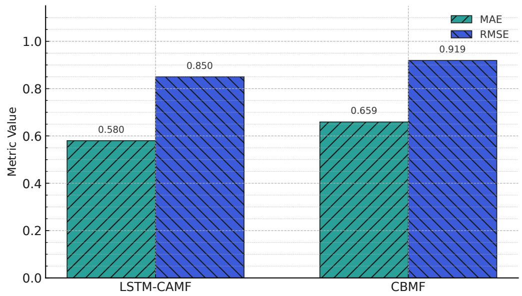

Fig. 7. Evaluation of LSTM-CAMF, CBMF models based on MAE and RMSE.

Across all datasets and evaluation metrics, LSTM-CAMF consistently outperforms the other models, exhibiting higher prediction accuracy and classification quality. In terms of MAE and RMSE, LSTM-CAMF performs the lowest in each case, indicating that it is the most accurate model in terms of minimizing prediction errors and handling large errors. LSTM-CAMF shows exceptional performance in the INCARMUSIC in Figures 4 and 5 and STS Travel datasets Figures 6 and 7, leading in both MAE (0.43 and 0.650) and RMSE (0.61 and 0.880). It significantly outperforms PW-CAMF and CBMF, which have higher error rates, with CBMF consistently performing worst in both metrics. LSTM-CAMF also excels in classification quality, as evidenced by its higher NDCG score (0.757) compared to TopC-CAMF (0.7216) on the INCARMUSIC dataset. This highlights the ability of LSTM-CAMF to classify relevant items more efficiently, leading to more useful recommendations. When comparing

LSTM-CAMF with CBMF on the DePaulMovie dataset, LSTM-CAMF again outperforms CBMF in both MAE (0.580 versus 0.6591) and RMSE (0.850 versus 0.9186), indicating that it is better at providing accurate recommendations and handling prediction errors. In summary, LSTM-CAMF shows excellent performance in all datasets and metrics evaluated. It consistently provides better prediction accuracy, error minimization and ranking quality compared to other models such as TopC-CAMF, PW-CAMF and CBMF. These results show that the combination of LSTM and CAMF structure for storing complex models of data is efficient, making LSTM-CAMF an effective choice for recommendation systems. Its performance can be further improved by optimizing and testing it on new datasets.

5. Conclusion and future directions

In this study, our hybrid CAMF-LSTM model demonstrated promising results in predicting user ratings for music items, outperforming the CBMF method in several key performance metrics. Specifically, our model achieved an MAE of 0.43 and an RMSE of 0.61 for the INCARMUSIC dataset, outperforming CBMF, which had an MAE of 1.29 and an RMSE of 1.5207. Furthermore, our model showed superior performance on the DePaulMovie dataset, where it again surpassed CBMF in both MAE (0.580 vs. 0.6591) and RMSE (0.850 vs. 0.9186). These results highlight the effectiveness of integrating the LSTM architecture with the CAMF framework, demonstrating improved prediction accuracy compared to traditional methods. The performance analysis of LSTM-CAMF across various datasets consistently revealed its ability to minimize prediction errors (as indicated by its lower MAE and RMSE) and enhance ranking quality (with higher NDCG values compared to TopC-CAMF and PW-CAMF). In particular, LSTM-CAMF showed its superiority in handling large prediction errors, making it a robust model for recommendation systems. However, while the results are promising, there is still potential for further improvement in the model's performance. Several avenues for future work can be explored to refine and enhance the model: Hyperparameter Optimization: Further hyperparameter tuning and optimization could be conducted to explore the hyperparameter space more thoroughly. Finding the optimal combination of parameters may lead to a more accurate model that better generalizes to unseen data. Incorporating Additional Contextual Data: Another direction for improvement is to incorporate more contextual information that could enhance the model's understanding of user preferences. By integrating external data sources, such as user demographics, behavior patterns, or temporal factors, the model can make more informed predictions and improve recommendation quality. Exploring Advanced Deep Learning Architectures: Moving forward, experimenting with more advanced deep learning models, such as Large Language Models (LLMs) or Transformers, could help capture more complex relationships between users, items, and contextual data. These architectures have shown great success in various domains, including natural language processing and recommender systems, and could further improve the robustness and accuracy of the CAMF-LSTM model. Cross-Domain Recommendations: Exploring cross-domain recommendation techniques could be another area for future research. By applying the model to different datasets and domains, it may be possible to enhance the model's generalizability and adaptability to various contexts, such as movies, books, or even e-commerce platforms. Hybrid Approaches: Combining LSTM with other types of models, such as collaborative filtering, content-based filtering, or reinforcement learning, could lead to a more comprehensive solution that leverages the strengths of each approach. Hybrid models are known to perform better in capturing the diverse aspects of recommendation tasks. By pursuing these directions, it is possible to enhance the performance of the CAMF-LSTM model and develop more accurate, efficient, and context-aware recommendation systems. This will contribute to building more personalized and effective recommendation engines across various domains, ultimately improving user satisfaction and engagement.

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Дослідження LSTM-CAMF: новий підхід до контекстно-залежної колаборативної фільтрації

Ерраха К.[1], Саміх А.[2], Марзук А.[1], Крарі А.[3], Дфуф С.[4]

[1] *Лабораторія комп'ютерів, мереж, мобільності та моделювання, Перший університет Хассана*
[2] *Лабораторія досліджень та застосувань штучного інтелекту, Перший університет Хассана*
[3] *Лабораторія дослідницького спостереження за новими технологіями, Перший університет Хассана, Сеттат, Марокко*
[4] *Факультет юридичних, економічних та соціальних наук, Мохаммедія, Університет Хасана II*

Для створення точніших рекомендацій контекстно-залежні рекомендаційні системи (CARS) включають контекстні елементи під час взаємодії з користувачами. Однак, основна проблема полягає в потребі додаткових контекстних даних, що може перешкоджати роботі методів колаборативної фільтрації. У цьому дослідженні подано інноваційний підхід до виявлення контекстної інформації в режимі реального часу шляхом інтеграції рекурентних нейронних мереж з довгостроковою пам'яттю (LSTM) з контекстно-залежною матричною факторизацією (CAMF). Ця стратегія розроблена для динамічного пристосування до змін у контекстуальних умовах шляхом моделювання відносин між користувачами та їхньої часової еволюції, зрештою, з метою підвищення точності рекомендацій. Ефективність запропонованого методу оцінюється за допомогою двох стандартних показників ефективності: середня абсолютна помилка (MAE), NDCG (нормований дисконтований кумулятивний приріст), MSE (середньоквадратична помилка) та середньоквадратична помилка (RMSE).

Ключові слова: *CAMF; LSTM, RMSE; MAE; CARS.*