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Advancing Context-Aware Recommender Systems: A Deep Context-Based Factorization Machines Approach

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Abstract: Context-aware recommender systems (CARS) aim to offer personalized recommendations by incorporating user contextual information through analysis. By analyzing these contextual cues, CARS can better understand the preferences and needs of users in different situations, thereby improving the relevance and effectiveness of the recommendations they provide. However, integrating contextual information into a recommendation system presents challenges due to the potential increase in the sparsity and dimensionality. Recent studies have demonstrated that representing user context as a latent vector can effectively address these kinds of issues. In fact, models such as Factorization Machines (FMs) have been widely used due to their effectiveness and their ability to tackle sparsity and to reduce feature space into a condensed latent space. Despite these advantages, FMs encounter limitations when dealing with higher-order feature interactions, since the model's design, primarily focused on second-order interactions. Furthermore, a significant drawback of FMs is their inability to distinguish between different contexts effectively. By utilizing a uniform latent space to model interactions across all features, FMs overlook the nuanced differences that distinct contexts bring to the interactions. This article introduces a CARS model called Deep Context-Based Factorization Machines (DeepCBFM). The DeepCBFM combines the power of deep learning with an extended version of Factorization Machines (FMs) to model non-linear feature interactions among user, item, and contextual dimensions. Additionally, it addresses specific shortcomings of FMs with the goal of enhancing recommendation accuracy. We implemented our method using two datasets that incorporate contextual information, each having distinct context dimensions. Experimental findings demonstrate that the DeepCBFM model surpasses baseline models, thereby validating its efficacy.

Keywords: Recommender systems, Context Aware Recommender Systems, Factorization Machines, Context-Based Factorization Machines, Deep Learning, DNNs

1. INTRODUCTION

In light of the vast and ever-expanding array of products and services available today, Recommender Systems (RS) have become indispensable across a range of sectors, including ecommerce, video content, cinema, travel, and, notably, the gaming industry. RS belong to the category of data filtering systems, and their primary function is to provide user-specific recommendations based on individual preferences [1]. The adoption of RSs offers two significant advantages: firstly, they streamline the user experience by minimizing the time and effort required to find desired items, and secondly, they contribute to increased company sales and revenue generation. Classical Recommender Systems primarily rely on just two key dimensions: the user dimension and the item dimension, to offer personalized recommendations. In the content-based approach [2], a more detailed strategy is employed. This method incorporates both item features and user profiles in the recommendation process. By analyzing the characteristics of items and the preferences and behavior of users, content-based systems provide recommendations that are tailored to individual users based on the content. Conversely, Collaborative filtering approaches [3] take a different route. They don't require detailed information about users or items. Instead, they depend on user ratings to assess preferences for specific items. However, these approaches have shortcomings because they overlook various factors that can impact a user's preferences, such as the contextual factor. For example, a father's movie preference may shift based on whether he's watching alone or with his kids, with context (like the presence of companions) influencing his choices.

Recommendation systems often face two primary challenges: sparsity and high dimensionality in the data. Sparsity arises when there are limited interactions or ratings between users and items, while high dimensionality results from the addition of contextual information, which effec-

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tively increases the number of dimensions in the dataset. Paradoxically, incorporating contextual data can exacerbate the sparsity issue by introducing more dimensions to the data, further complicating the recommendation process. Sparsity refers to the situation where there are significant missing data points in a dataset, while high dimensionality results from the addition of new features, which effectively increases the number of dimensions.

Factorization Machines FM [4] which is a supervised algorithm effectively resolves aforementioned problems and delivers impressive performance. This method involves the transformation of user-item dimensions into latent spaces, creating a low-dimensional representation of the data. The majority of research within the realm of CARSs [5] has been dedicated to improving and advancing Factorization Machines. One of the primary drawbacks of FM is its reliance on a fixed interaction function, often an inner product, to estimate high-order interactions between User and Item. This fixed function may not adequately capture the complexity and nuances of real-world user-item relationships. High-order interactions refer to interactions among three or more features. For example, in a movie recommendation system, a second-order interaction might consider how the genre and the director of a movie affect its rating. A high-order interaction could look at how the genre, director, user age and time of day together influence the rating. These interactions can provide more nuanced insights and improve the predictive performance of the model. However, capturing and utilizing these higher-order interactions effectively is challenging, primarily due to computational complexity, data sparsity, and the potential for model overfitting. The computational cost of explicitly modeling high-order interactions increases exponentially with the order of interaction. For an interaction of order n, a naive approach would require considering all n-way combinations of features, which becomes computationally infeasible for large n. This complexity is further compounded by the sparsity of datasets, where occurrences of higher-order feature combinations are rare, complicating the learning process. Moreover, as the model complexity rises with the inclusion of higher-order interactions, the risk of overfitting intensifies, particularly in scenarios where the available dataset is insufficient to train the model on a multitude of parameters, undermining the model's generalizability and effectiveness. All this can result in less accurate recommendations compared to more advanced techniques that can better model the complexities of user-item interactions. Moreover, FM employs a single latent vector even when dealing with features originating from distinct contextual dimensions or contexts. This can be a limitation of FM, since it tends to overlook the fact that features may exhibit distinct behavior when interacting with features from separate contexts. This lack of context-awareness can limit FM's ability to capture the nuanced interactions that occur between features across different contexts. The main contributions proposed by the present work are:

- New Context-Aware Recommender Model: The main contribution is the introduction of a new context-aware recommender model. This model combines Deep Neural Networks (DNNs) and Factorization Machines (FMs). This hybrid approach likely aims to capitalize on the strengths of both DNNs and FMs to enhance CARS performance. This approach considers additional information, like time, companion, location, etc., in order to provide personalized recommendations.
- Exploiting Deep Learning Techniques: The second contribution is the utilization of DNN to capture non-linear feature interactions. This is important because deep learning models are known for their capability to capture intricate patterns in data. By doing so, the proposed model can address some of the limitations associated with traditional Factorization Machines, which may struggle with modeling higher-order interactions.
- New Variant of FM for CARSs: The final contribution is the introduction of a new variant of Factorization Machines specifically adapted to Context Aware Recommender Systems (CARSs). This variant is designed to capture the differences between different contexts and also to capture low order feature interactions.

The remainder of this paper is organized as follows: Section 2 provides a review of related works. Section 3 presents the proposed model (Deep Context-Based Factorization Machines model). Section 4 analyses results. Finally, the last section presents a conclusion of the realized work.

2. RELATED WORKS

Recently, many studies have been presented to enhance the exactness and the efficiency of recommenders, either by improving FM, which is a reference algorithm, by exploiting the strengths of deep learning or by using new methods.

Cheng et al. [6] presented a Wide and deep learning model, that uses the wide linear model to memorize the interaction of features and deep learning DNNs for feature generalization. The model was evaluated using PlayStore, the outcomes demonstrate that the model increased the acquisitions of apps.

Guo et al. [7] presented a Deep FM algorithm, which merges the power of FMs and DNNs to improve recommendation performances with less manual feature engineering work. Both components of the model were trained jointly in order to gain in terms of performance and also to capture high order interactions.

Xiao et al. [8] presented an Attentional FM model, which captures the strengths of interactions between features using neural attention networks. The model tries to enhance FM by improving the interpretability and the representation ability of a FM algorithm.

Lian et al. [9] introduced the Compressed Interaction Network(CIN) and integrated it with DNN to develop a unified approach. This approach strives to autonomously acquire the interaction between features in a direct manner, thereby circumventing the need for feature engineering.

Song et al. [10] presented a CTR model using a self-attentive neural network called AutoInt. It learns automatically high order by allowing the interaction between features for relevance determination.

Yu et al. [11] presented a Input aware Factorization Machine to enhance FMs by considering the inputs influence on feature representations. The model uses neural networks to learn the input factors of each features in several instances. The model endeavors to augment predictive capability while preserving the linear complexity of the traditional FM.

Pan et al. [12] presented Field-weighted FM for recommendation in display advertising field. The model is an extension of FM that aims to capture the importance of interaction of different pairs of fields in reasonable complexity time.

Trigeorgis et al. [13] presented a deep MF to learn attribute representations. The model uses a semi Non-Negative Matrix Factorization algorithm to model representations of low dimensions.

Lara-Cabrera et al. [14] presented a collaborative filtering Recommender System that exploits DNNs and FMs to enhance recommendations precision. The method uses a deep learning paradigm not to capture high order features but to improve the MF model.

Ez-Zahout et al. [15] presented a hybrid movie Recommender System based on Matrix Factorization and KNN. The model provides recommendation to a user by calculating movies similarity and generating top k movies.

While prior research has demonstrated strong results in terms of accuracy, performance, and interpretability in recommendation systems, they have generally overlooked the significant influence of contextual factors on user behaviors. In response to this limitation, other researchers have made efforts to incorporate contextual data into the recommendation process with the aim of achieving improved outcomes, based on Matrix Factorization and Factorization Machines. For instance, Baltrunas et al. [16] proposed a CARS model based on Matrix Factorization. This model takes into account the interplay between contexts and ratings given to items by using extra additional parameters. One key benefit of this solution is its lower computational overhead, and it also offers the flexibility to depict the interaction between context and items at various levels of detail or granularity. In their work, Madani and Ez-zahout [17] proposed a CARS model that utilizes a BERT model for personalized NER. The model enables the automatic extraction of contextual information. Furthermore, the authors adapted traditional Factorization Machines to accommodate contextual information, enhancing their capability to provide accurate rating predictions.

Casillo et al. [18], presented a CARS that leverages embedded context likely involves integrating contextual data directly in recommendations to enhance the system's performance. In this work, instead of treating contextual information as an external or additional input to the recommendation model, the system incorporates this context within the model itself. Moreover, the method leverages matrix factorization's computational efficiency to address scalability issues. While Matrix Factorization and Factorization Machines offer advantages, they encounter challenges when it comes to capturing the intricacies of non-linear feature interactions in the learning process. Numerous researchers have endeavored to harness the capabilities of deep learning in crafting more intricate context-aware recommender models, aiming to address the complexities posed by non-linear problems in recommendation systems.

Jeong et al. [19] introduced a context-aware recommender system leveraging deep learning techniques. This approach considers contextual features to enhance recommendation accuracy. The model integrates a neural network and autoencoder, leveraging established deep learning architectures. Through this combination, the model effectively extracts distinctive features and forecasts scores during the input data restoration process. Notably, the proposed model exhibits versatility in accommodating diverse contextual information types.

Sattar and Bacciu [20] introduced a Context-Aware Graph Convolutional Matrix Completion method. This approach encompasses a comprehensive understanding of graph structures by integrating user preferences, contextual cues conveyed through edges. Through a graph encoder mechanism, it generates nuanced representations of users and items by taking into account contextual cues, inherent features, and user opinions. These representations are aggregated and fed into the decoder, which predicts ratings.

VU et al. [21] introduced an innovative strategy that leverages deep learning for the development of context aware multi criteria recommender systems. In their approach, DNN models play a pivotal role in predicting context aware multi criteria ratings and learning the aggregation function. The study effectively demonstrates the incorporation of contextual information into Multi Criteria Recommender Systems (MCRSs) through the application of DNN models. Specifically, they showcased the utility of DNN models in forecasting context aware multi criteria ratings and acquiring insights into the aggregation function.

Vaghari et al. [22]proposed a novel context-aware framework aimed at enhancing the precision of machine learning models in the identification of disease patterns. Their approach, characterized by the integration of multi-modal data sources, seeks to harness the synergistic effects of combining genetic, clinical, and environmental information. This comprehensive model not only improves diagnostic accuracy but also tailors therapeutic interventions to individual patient profiles, thereby advancing personalized medicine. However, the application of this model faces certain limitations, including the high computational cost associated with processing large multimodal datasets and the potential for biases inherent in incomplete or unrepresentative data. Addressing these challenges is crucial for ensuring the scalability and reliability of the framework in diverse clinical settings.

Vecchia et al. [23] proposed a groundbreaking model that leverages advanced computational techniques to enhance the accuracy of climate prediction models. Their approach, based on integrating satellite data with terrestrial observation networks, aims to fill critical gaps in meteorological data availability. This integration allows for a more com-

prehensive understanding of climatic patterns, facilitating better-informed decisions in climate-sensitive sectors such as agriculture and water resource management. However, the model also faces several limitations. One significant challenge is the potential for discrepancies and errors in satellite data, which can affect overall model accuracy. Additionally, the integration of heterogeneous data sources raises concerns about data compatibility and processing complexities. These challenges highlight the need for ongoing refinement of data integration techniques and the development of more robust error-correction algorithms to ensure the reliability and precision of climate forecasts.
Dilekh et al. [24] proposed a context-aware personalized recommendation system for smart homes, demonstrating the application of the FP-Growth algorithm and a Generalized Linear Model (GLM) to derive and utilize association rules for user behavior. Their study, which focused on a single-user scenario, highlighted the system's high accuracy and favorable precision/recall metrics, underscoring its effectiveness. Despite its achievements, the research acknowledged limitations, particularly its application within a single-user context, which may not fully capture the complexities of multi-user environments. Furthermore, the adaptability of the system to evolving user behaviors and the balance between personalization and privacy were not extensively tested. The integration of the system into broader smart home ecosystems and its interaction with various devices and platforms also remain areas for future exploration.
Previous research heavily relied on deep learning as the primary method for generating recommendations but failed to adequately address the challenges of sparsity and high dimensionality in real-world datasets. Unlike prior studies, our objective is to introduce a pioneering context-aware recommender system that specifically tackles the shortcomings of Factorization Machines (FMs) by harnessing the capabilities of Deep Neural Networks. Additionally, our aim is to unveil an evolved FM variant optimized for CARS. This refined FM version excels in capturing intricate feature interactions, spanning across both low and high orders. More detailed insights into the DeepCBFM model will be elaborated upon in the subsequent section.

3. PROPOSED MODEL

Our main goal is to develop an advanced recommender system that not only utilizes traditional user and item data but also integrates contextual information to gain a deeper understanding of user behaviors across diverse scenarios. This holistic approach enables us to deliver personalized recommendations tailored to individual user preferences and needs. In pursuit of this goal, we introduce the Deep Context-Based Factorization Machines Model (DeepCBFM), a fusion of Factorization Machines(FM) and deep learning techniques.
Illustrated in figure 1 is the model architecture comprising two simultaneous components: the primary CBFM component and the secondary deep component. The CBFM element expands upon Factorization Machines (FM) to capture second-order interactions, meanwhile the deep element

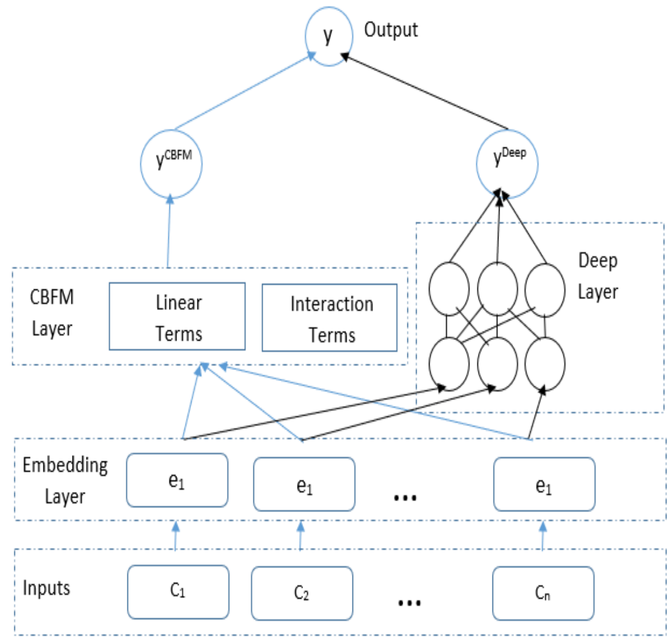

Figure 1. The architecture of the DeepCBFM

focuses on modeling higher-order feature interactions. Both elements utilize common input and embedding layers, and the model's ultimate prediction results from the combined outputs of these two components. This section provides a comprehensive breakdown of each component within the proposed model.

A. CBFM component

In previous works, Linear regression (LR) model has been widely employed in ratings prediction [25][26]. To predict ratings LR uses a linear combination of features as shown in the equation below:

$$y_{LR} = w_0 + \sum_{i=1}^{d} w_i x_i \tag{1}$$

However, the LR model does not perform well since it does not consider the interaction between features, which is crucial. Poly2 models [27] tackle this problem by adding order-2 feature interactions to the above equation, which gives as a result:

$$y_{Poly2} = w_0 + \sum_{i=1}^{d} w_i x_i + \sum_{i=1}^{d} \sum_{j=i+1}^{d} x_i x_j w_{h(i,j)} \tag{2}$$

However, it is clear that this method suffers from some drawbacks. For instance, the interaction parameters of features can be trained only when these features appear in the same record, which means that unseen features will have insignificant predictions. The FM model outperforms Poly2 especially when the model deals with sparse data.

FM calculates interactions between two features via the dot product of their corresponding latent vectors. FM equation is stated as:

$$y_{FM}(x) = w_0 + \sum_{i=1}^{d} w_i x_i + \sum_{i=1}^{d} \sum_{j=i+1}^{d} < v_i, v_j > x_i x_j \quad (3)$$

FM can train embedding vector $v_i(v_j)$ even if it never or rarely appeared in the data. To learn the effect of latent between features, FM uses only one latent vector even for features from different contexts. For instance, when computing interactions among three contexts (Day, Companion, and Mood), FM utilizes the same embedding vector for Monday to capture its latent effects when paired with $Companion < v_{Monday}, v_{Son} >$ and also with $Mood < v_{Monday}, v_{Happy} >$, despite these contexts being distinct. This approach overlooks the nuanced behavior of features when they interact across different contexts. To verify this observation, we utilize ANOVA, a statistical method developed by Ronald Fisher in the early 20th century. ANOVA is employed to detect and showcase potential similarities or differences in specific aspects within a studied population through variance analysis. The formula of ANOVA is defined as follow:

$$F = \frac{Meansumofsquaresduetotreatment}{Meansumofsquaresduetoerror} \quad (4)$$

We do not use ANOVA method to verify the existence of relationship between two features, but simply to capture the difference of features interaction strength. We conduct this experiment on DePaulMovie dataset [28]. Figure 2 shows the obtained results from the interaction of three contexts namely Time, Location and Companion using ANOVA two-way. This statistical tool helps us to compute the interaction strength between two contexts (C_i, C_j) and an outcome Y.

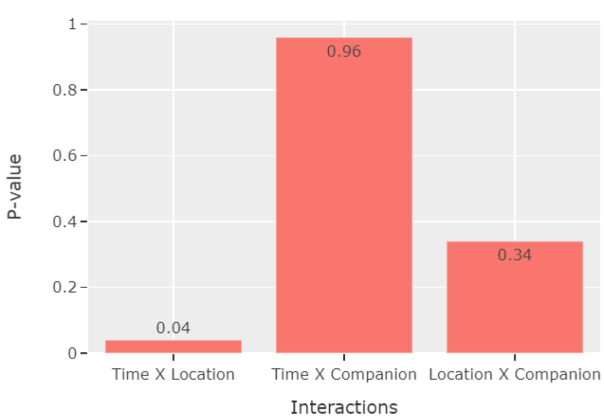

Figure 2. Interaction between contexts

As we can see, the interaction between features is expressed in P value, when the P value is under 0,05 it means that the interaction is significant, otherwise, there is no significant interaction between features. For the first interaction between Time and Location the P value achieves 0.04 which means inferior to 0.05 so Therefore, the interaction effect between these two contexts is considered significant. For the second interaction (Time, Companion) and the third interaction (Location, Companion), the obtained values are higher than 0.05 which means that, there is no significant interaction between these two pairs of contexts. The primary conclusion drawn from this experiment is that variables exhibit varying interaction patterns when paired with variables from distinct contexts. Addressing the limitations of FM highlighted earlier, we introduce an enhanced version termed CBFM. This extension of FM incorporates extra weights to discern variations between contexts and to distinguish the latent vectors of a feature when it interacts with other features from different contexts. Within our model, the primary goal of the CBFM component is to capture second order feature interactions while accommodating contextual differences. The equation of CBFM is stated as:

$$y_{CBFM}(x) = w_0 + \sum_{i=1}^{d} w_i x_i + \sum_{i=1}^{d} \sum_{j=i+1}^{d} < v_i w_{c(i)}, v_j w_{c(j)} > x_i x_j \quad (5)$$

Where w_0 and w are respectively the bais term and weights of feature vectors, v_i, v_j the latent vectors of $feature_i$,$feature_j$, $w_{c(i)}$, $w_{c(j)} \in \mathbf{R}$ are weights to capture the importance between $context(i)$ and $context(j)$.

B. Deep component

To model nonlinear feature interactions, we present a feed forward neural network [7]. In the initial phase of the deep component, sparse input features are converted into dense vectors through an embedding process. The original input vector is often characterized by high sparsity and dimensionality, encompassing a variety of data types (both categorical and continuous), and organized by contextual groupings like time, weather, and more. This scenario necessitates the use of an embedding layer to condense the input vector into a compact, dense form, facilitating its introduction to the first hidden layer for further processing. It's important to highlight that FM and deep components utilize shared feature embeddings due to two primary considerations: Firstly, by using the same embeddings, both the FM and deep components operate on a unified representation of the input features. This ensures consistency in how features are interpreted across different parts of the model, facilitating a more cohesive learning process. Embeddings capture the essence of each feature in a lower-dimensional space, preserving semantic relationships between features. When these embeddings are shared, it ensures that both the FM component, which excels at capturing second-order interactions, and the deep component, which models complex, non-linear relationships, base their computations on the same foundational understanding of the data.
Secondly, sharing embeddings between components simplifies the overall architecture of the model. Instead of having separate mechanisms for translating raw features into a format suitable for each component, the model centralizes this function in the embedding layer. This not only reduces

the number of parameters that the model needs to learn, saving computational resources but also streamlines the training process, as there is a single source of truth for feature representations. These embedding vectors are then concatenated to form a single, dense vector $s^{(0)}$, which serves as the input to the neural network. This vector effectively represents your original input data in a dense, lower-dimensional space, preserving important information while reducing dimensionality.

$$s^{(0)} = [e_1, e_2, e_3, ..., e_l] \quad (6)$$

l is the contexts' number, e_i embedding feature of i^{th} feature. The concatenated embeddings are fed into a feed-forward neural network. This network consists of multiple layers, each designed to capture increasingly complex patterns and interactions among the input features.

$$s^{(j)} = f(W^{(j)} s^{(j-1)} + b^{(j)}) \quad (7)$$

f is the activation function, j is layer depth, $W_{(j)}$ the weight of jth layer, $b_{(j)}$ the bias at the j^{th} layer and $s^{(j)}$ the j^{th} layer output. let $y^{(DNN)}$ be the deep layer output, the final prediction of DeepCBFM model is:

$$y = \sigma(y^{(CBFM)} + y^{(DNN)}) \quad (8)$$

Where σ is the sigmoid function.

4. Results and discussion

A. Datasets

To evaluate the DeepCBFM, two datasets provided by CARSKit [28] are used: The first is the DePaulMovie dataset encompasses a total of 5044 movie ratings, of which 1449 are non-contextual, and 3595 are contextual, based on specific viewing circumstances. This dataset distinguishes between three primary contextual dimensions: Location (with options of Home or Cinema), Companion (choices include Alone, Family, or Friends), and Time (categorized into Weekend or Weekday). These contextual factors enable a nuanced analysis of user preferences, tailored to specific viewing environments and social settings, thereby providing insights into how different contexts influence movie watching experiences. The second is the InCarMusic dataset comprises 4012 ratings collected from 43 users across 138 distinct music items, with 1004 ratings categorized as non-contextual and 3010 as contextual, reflecting the user's environment and situation during music listening. It features seven diverse contextual dimensions: Driving style (Relaxed or Sport driving), Landscape (Coastline, Countryside, Mountains, or Urban), Mood (Active, Happy, Lazy, or Sad), Natural phenomena (Afternoon, Daytime, Morning, or Night), Road type (City, Highway, or Serpentine), Sleepiness (Awake or Sleepy), and Weather (Cloudy, Rainy, Snowing, or Sunny). These dimensions allow for a detailed exploration of how various driving contexts affect music preferences, facilitating a deeper understanding of user behavior and preferences in different driving scenarios. In recommender systems (RS), data is typically structured as a rating matrix, with users represented by columns, items by rows, and observed ratings populating the matrix cells. Due to the incomplete nature of user ratings across all items, this matrix often exhibits significant sparsity. For context-aware recommendations that incorporate multiple dimensions, data is represented using tensors instead of matrices. However, the Factorization Machines (FM) model requires data to be formatted as Sparse Feature Vectors, also known as One Hot Encoding, a method predominantly used in deep neural network modeling.
To manage and manipulate the data effectively, we utilize the Pandas library [29], which provides robust tools for data analysis, cleaning, exploration, and manipulation. The Sparse Feature Vector representation converts the recommendation data into a series of tuples (x, y), where 'x' is a real-valued feature vector and 'y' the observed rating, enabling the function f(x) = y. This format reframes the recommendation challenge as a standard machine learning prediction problem, allowing for the straightforward application of conventional machine learning algorithms to the data. Additionally, the Sparse Feature Vector format readily accommodates extra contextual dimensions, enhancing the model's capability to handle complex, multi-dimensional datasets effectively.
Table I illustrates more detail about the two datasets.

TABLE I. Statistics about the two datasets.

	DePaulMovie	**InCarMusic**
Users	124	43
Items	80	138
Ratings	5044	4014
Dimensions	4	7
Sparsity	94%	99%

B. Evaluation Measures

To measure DeepCBFM performance the RMSE and R-Squared are used: Root Mean Squared Error (RMSE) is one of the largest used metrics for regression problems. It is the MSE square root which is calculated as the squared differences between actual the target values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{m}(y_j - \hat{y})} \quad (9)$$

y_j is the real value and $\hat{y}_j$ is the target value.

R-squared (R^2) is a statistical measure that shows how close the data are to the regression line.

$$R^2 = 1 - \frac{Sumsquaredregression}{Totalsumofsquares} = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad (10)$$

Where SSR is the sum square of the difference between real and predicted variables, SST is the total of sum squares and $\bar{y}$ is the mean of all values.

C. Performance Comparisons

To confirm the effectiveness of CBFM and DeepCBFM, we select four baseline models:

FM [4]: Factorization Machines are a well-known method in Collaborative Filtering recommendation systems. They work by processing the rating matrix and converting it into a pair of low-rank matrices through a transformational procedure.

CBMF [18]: It is an extension of Matrix Factorization adapted with contextual information.

CANCF [30]: It is a hybrid approach that adapts and repurposes a prefiltering method for integrating context.

CAMCRS [21]: It employs deep learning models to predict ratings while considering contextual factors and simultaneously learns how to aggregate this information effectively.

D. Results of the Experiments

For the development environment, we use TensorFlow [31] to implement the model, installed on a computer using Windows 10 with 16GB of RAM. The implementation is inspired from [32]. Each dataset is splitted to train data (80%) and testing data (20%). The optimization method used is Adam, we fix the learning rate to 0.00001. we use a mini-batch of 4096. To avoid the overfitting problem, we use L2 regularization. We fine-tune two parameters to extract the best performance of DeepCBFM. The first parameter is the embedding size, as shown in figure 3, we observe that the RMSE reaches its lowest value when the size is 32, because a large size brings a better representation capacity to the model. Secondly, we analyze the dropout parameter, which is used to prevent the overfitting.

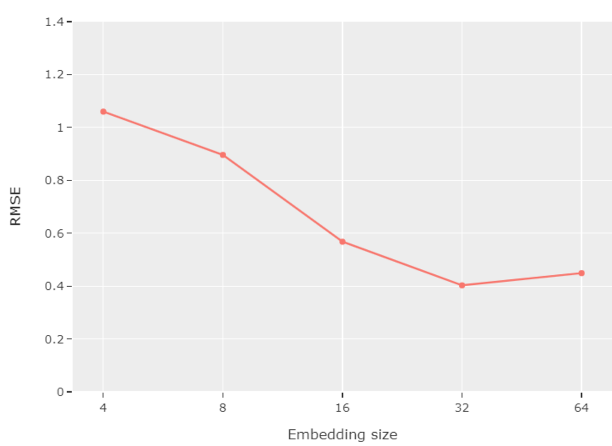

Figure 3. RMSE results of CBFM under the embedding size parameter.

As illustrated in figure 4, the dropout is set to a value between 0 and 0.9 with a jump of 0.1 each time. The results show that the DeepCBFM reaches the lowest RMSE value as the dropout equals 0.3, which justify the usefulness of the dropout. As mentioned earlier, we conducted a comparative analysis of The DeepCBFM against four models, utilizing 2 distinct datasets. Outcomes from both datasets were evaluated based on RMSE and R² metrics. Additionally, a specific focus was placed on assessing the effectiveness of the CBFM component in comparison to other methodologies, with a particular emphasis on the FM algorithm.

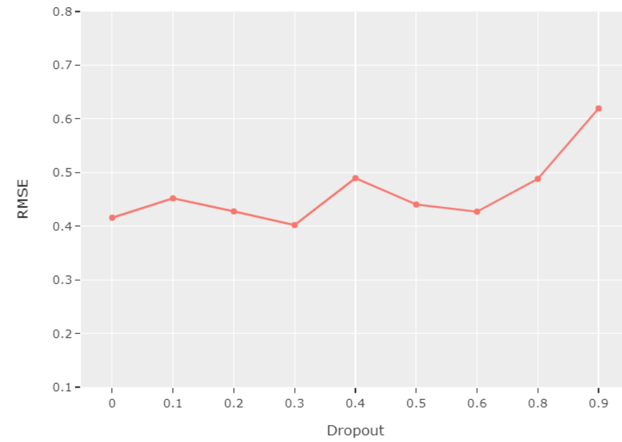

Figure 4. RMSE results of CBFM under the dropout parameter.

The RMSE and R-squared results depicted in Figures 5 and 5 offer valuable insights into the performance and predictive capability of different models on the DePaulMovie dataset. Firstly, the DeepCBFM model's attainment of the lowest RMSE value of 0.4027 suggests that its predictions are closest to the actual ratings compared to other models evaluated. This signifies the model's superior ability to minimize prediction errors and provide more accurate estimations of movie ratings.

Additionally, the observed favorable outcomes of the Context-based Factorization Machines (CBFM) component in contrast to the conventional Factorization Machines (FM) approach highlight the significance of considering contextual information in recommendation systems. Contextual factors such as user preferences and item characteristics play a crucial role in enhancing predictive accuracy, as evidenced by the improved performance of the CBFM component. Moving to the R-squared metric, which measures the goodness of fit of the models, the DeepCBFM model's superiority becomes even more pronounced. By surpassing both the CBMF and FM models in terms of R-squared, the DeepCBFM model demonstrates its ability to explain a larger proportion of the variability in the ratings. This implies that the DeepCBFM model captures more nuanced patterns and underlying relationships within the data, leading to better predictions of movie ratings. The substantial margins by which the DeepCBFM model outperforms the

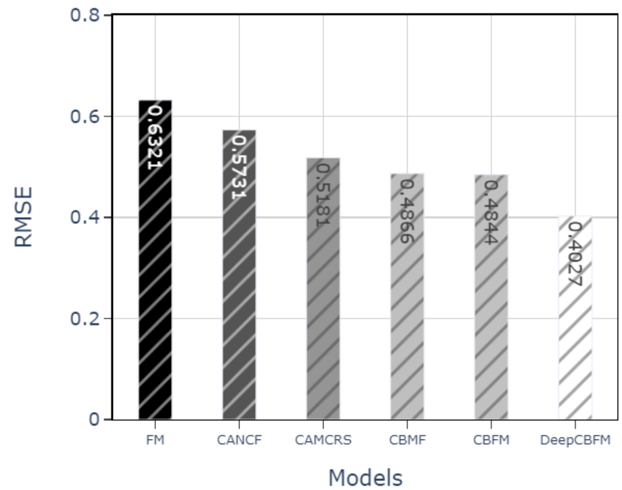

Figure 5. RMSE results obtained for DePaulMovie dataset.

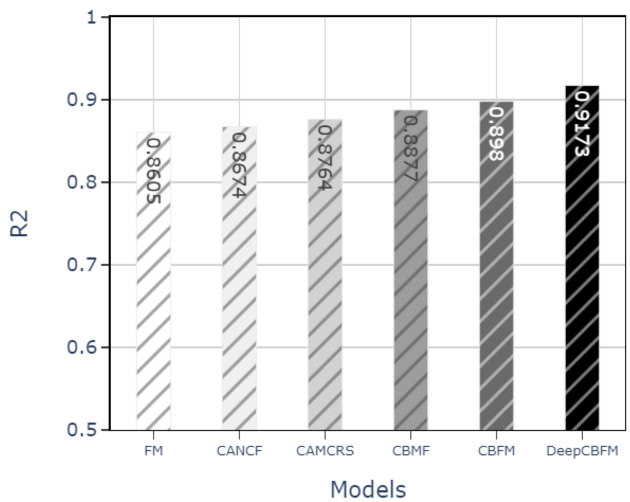

Figure 6. R² results obtained for DePaulMovie dataset.

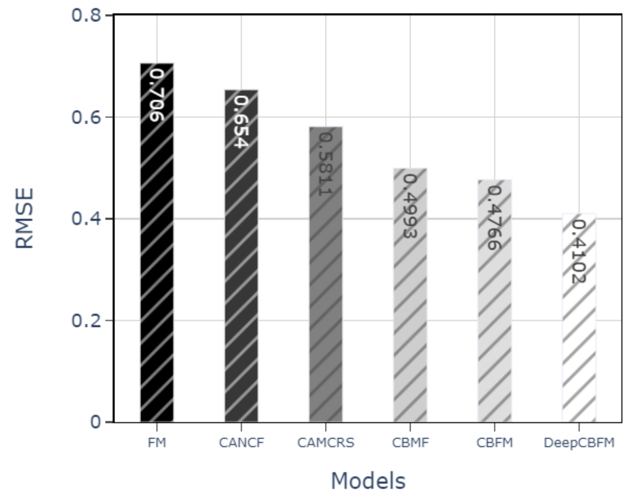

Figure 7. RMSE results obtained for InCarMusic dataset.

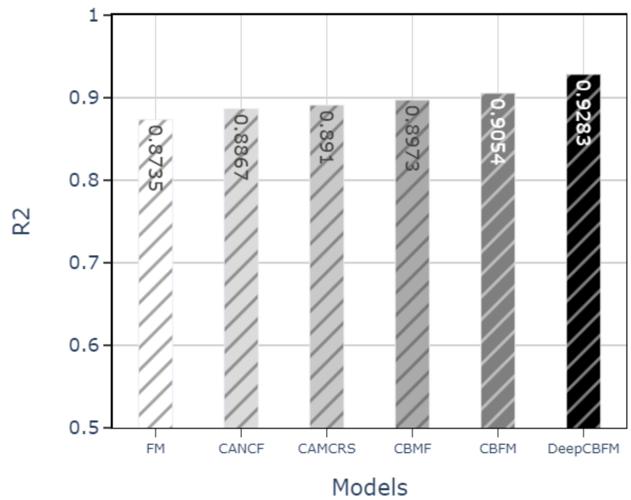

Figure 8. R² results obtained for InCarMusic dataset.

CBMF and FM models in R-squared further underscore its effectiveness in modeling the complex dynamics of movie preferences. Consistent with the findings from the initial dataset, the outcomes from the Music dataset (figure 7 and 8) reaffirm the ranking of performance among all models. Notably, the FM model exhibits a decline in results, attributed to the dataset's inherent high contextual dimensions. Additionally, noteworthy observations include the close similarity in results between CBMF and CBFM models. This similarity can be attributed to their shared design focus on capturing low-order feature interactions.

Overall, these results not only highlight the superior performance of the DeepCBFM model but also emphasize the importance of incorporating contextual information and leveraging advanced modeling techniques, such as deep learning architectures, in recommendation systems. By doing so, recommendation models can better capture the diverse and intricate factors influencing user preferences, thereby enhancing the accuracy and effectiveness of movie recommendations for users.

E. Discussion

This research introduces an innovative methodology that integrates deep learning with a specialized version of Factorization Machine (FM), named DeepCBFM, designed specifically to enhance the performance of recommendation systems. Traditional methods have frequently struggled to fully comprehend and utilize the complex dynamics of contextual information and its profound influence on user preferences. Our approach marks a significant departure from these traditional methods, as it not only incorporates but also excels in parsing the nuanced interactions among features across diverse contexts. This ability to discern how features behave differently when interacting within various contextual frameworks is critical because it allows for more tailored and accurate recommendations. The results from our study underscore that merging deep learning techniques with factorization machines leads to a substantial improvement in managing datasets characterized by rich contextual dimensions. This enhancement is particularly noticeable when contrasting the performance of the DeepCBFM model with that of traditional FM methods. Such comparisons highlight the limitations of older models in dealing with the complexities inherent in contemporary recommendation systems environments. Furthermore, the comparison between the CBMF and CBFM models reveals a significant insight; while these models perform similarly in terms of low-order feature interactions, it is the high-order interactions, which are more complex and less apparent, captured by the DeepCBFM that are critical for achieving a higher level of accuracy.

Our investigation provides a comprehensive evaluation of the model's performance across two distinct datasets. However, the question of generalizability remains, given that the findings might be influenced by the unique characteristics of the datasets used. Future studies should therefore expand the scope of research to include a broader array of datasets, which vary not only in size but also in the complexity of contextual information they present. This expansion is essential to validate and possibly enhance the efficacy of the DeepCBFM model across different settings and applications.The demonstrated resilience of the DeepCBFM model in handling high contextual dimensions opens up new avenues for research, particularly in improving recommendation systems. Upcoming studies could look into integrating additional contextual factors, such as temporal and geographical data, or applying cutting-edge deep learning architectures like neural attention mechanisms or generative adversarial networks, which could further refine the model's predictive accuracy. The strong empirical support obtained from analyzing the DePaulMovie and InCarMusic datasets highlights the superior predictive capability of the DeepCBFM model over both traditional FMs and the more recent CBMF model.

This advancement is of paramount importance in the realm of recommendation systems, where the ability to accurately predict user preferences amidst complex contextual dimensions can dramatically enhance user satisfaction and engagement. Our findings suggest a significant paradigm shift towards integrating sophisticated deep learning components into recommendation models, aiming to harness the full spectrum of feature interactions. This shift could potentially lead to revolutionary improvements in how recommendation systems understand and cater to user needs, ultimately enhancing the overall effectiveness and user experience provided by these systems.

5. Conclusions and Future Work

This research presents DeepCBFM, a sophisticated neural network framework built upon Factorization Machines, specifically engineered for Context-Aware Recommender Systems (CARSs). DeepCBFM is designed to address the limitations of traditional baseline models and offers a more adaptable approach to efficiently modeling contextual data. The model excels in two key areas: firstly, it adeptly manages the variable behaviors of features as they interact with other features from diverse contexts; secondly, it captures high-order feature interactions and addresses nonlinear challenges through advanced deep learning techniques. Our experimental evaluation of DeepCBFM, utilizing two real-world datasets—DePaulMovie and InCarMusic—demonstrates that our model not only improves prediction accuracy but also outperforms other state-of-the-art models. However, our findings also highlight areas for potential future research and development. One such area involves the higher time complexity observed in our model compared to baseline models, suggesting a need for further optimization to enhance computational efficiency and scalability, particularly as we extend the application to larger and more complex datasets. This brings us to another critical point of future exploration: dataset specificity. The current application of our model may exhibit limited generalizability across different domains or more extensive datasets with varied contextual dynamics.

Future work will need to focus on validating and possibly refining DeepCBFM across a broader spectrum of datasets to ensure its effectiveness and applicability in diverse settings. Another promising direction for future research stems from the challenges associated with acquiring and integrating contextual information from real-world applications. To address this, we plan to investigate alternative sources of contextual data, including unstructured data sources, and develop efficient methods for their extraction and utilization. This exploration aims to enrich the contextual understanding of the model, thereby enhancing its predictive precision and relevance in real-life scenarios.

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