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DEEP LEARNING-ASSISTED EXPLICIT AND IMPLICIT CONTEXT-BASED PERSONALIZED RECOMMENDER SYSTEM

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ABSTRACT

In the digital world, recommending the desired items to the users is still a challenging task with the unprecedented growth of the information on the Web. The recommender system plays a significant role in addressing the information overload problem in the abundance collection of the data. Recently, a context-aware recommender system has become a potential solution for providing personalized service to users. Several conventional recommendation researchers have considered contextual information in addition to the user-item-rating preferences. However, only a few recommendation research works have focused on effectively utilizing the explicit and implicit contextual information in the deep learning-based recommendations. Hence, to improve the recommendation quality, extracting the contextual user-item interaction and modeling the deep learninSg with latent context learning is essential. Thus, this work presents the DEep learning-assisted explicit and implicit COntext-based personalized Recommendation (DECOR) model to suggest the contextually desired as well as the popular items to the users. The proposed DECOR approach incorporates contextual preference extraction and deep learning-based personalized recommendation processes. Initially, it focuses on analyzing the users' explicit and implicit contexts and the items' contexts to improve the quality of the personalized recommendation. In essence, the proposed DECOR approach utilizes the explicit context of the rating, time, and location along with the implicit context from the users' reviews as the context vectors. Moreover, it enriches the individual users' rating with the items' popularity and generates the normalized rating score to facilitate the contextual and personalized recommendation. Secondly, the DECOR approach learns the contextual preferences of the users on the items with the assistance of the Long Short-Term Memory (LSTM) deep learning model. Thus, the proposed approach predicts the user preferences on the items with the knowledge of users' preference score and normalized rating score and several additional contextual factors and suggests the relevant items. Thus, the experimental results show that the DECOR approach significantly outperforms the existing recommendation model on the benchmark test dataset.

Keywords: *Recommender System, Explicit Context, Implicit Context, Deep Learning, Items' Context, and Personalized Recommendation*

1. INTRODUCTION

With the rapid evolution of Web data, the availability of digital information has been increased at an unprecedented rate. Traditional search engines provide tons of information for each query, which is not appropriate for the users to extract the relevant information from the massive suggestions. To overcome this constraint, the recommender system [1, 2] has emerged as the information filtering system with the advantage of providing personalized content or services to the users among the large volume of data. By analyzing the users' behaviors and preferences on the items, the recommender systems address the information overload problem in the disparate digital domains, including e-commerce, e-book, news, tourism, media, and entertainment recommendation [3]. With the growing and extensive interest in the recommender system, incorporating contextual information such as the time, location, and user activity in the recommendation decisions has gained significant attention among the researchers. The existing context-aware recommendation models [4] exploit predefined explicit contextual information to generate the recommendations. To provide

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personalized suggestions to the users, considering latent contexts of user interaction is crucial instead of depending only on the predefined contextual factors.

In the context-aware recommendation model, explicit contextual information is inadequate to recognize the contextual preferences of the users on the items [5]. To cope up with this, several researchers have focused on extracting the latent contexts from the users' activities particularly, their posted reviews, to improve the quality of the recommendations. Despite this, the recommendation models suggest the contextually preferred items to the users regardless of the items' significance in the real world. Consequently, it leads to the recommendation of the unpopular items or items with deficient quality when contemplating only the contextual preferences. Hence, it is essential to examine the explicit as well as the implicit contextual preferences of the users along with the potential knowledge of the items' context. Recent researchs [6] have shown that several recommender systems have adopted the supervised and unsupervised learning models to personalize the recommendation services across diversified users' preferences. To develop the recommender system with the implicit interaction analysis, different statistical, machine learning, and deep learning models have been widely utilized for improved recommendation quality [7]. With the increased complexity of the large-scale data, several recommendation approaches have been modeled the solutions with the deep learning model. However, capturing the personalized preferences for each user from a massive set of contextual vectors is still a major constraint even adopting the deep learning models for the recommender system [8, 9]. Hence, developing the context-aware recommender system without violating the users' satisfaction is crucial [10]. Thus, this work focuses on modeling the recommender system with the users' context, including the explicit and implicit contextual factors and the items' context with the assistance of the deep learning model.

The main contributions of this DEep learning-assisted explicit and implicit COntext-based personalized Recommendation (DECOR) work are discussed as follows.

This work presents the context-aware recommender system using the deep learning algorithm to generate the predictions from the predefined explicit and implicit contexts of the users and the items.

- The DECOR approach enhances the individual users' rating on the items with the items' context in terms of the popularity or average rating score to avert the suggestion of deficient items to the users.
- By integrating the explicit features of the rating, time, and location with the implicit context from the reviews, the DECOR approach recognizes the user preferences instead of extracting the implicit context from the user texts alone.
- Finally, the DECOR approach predicts the preference score of each user on all the items based on the weighted average of the contextual preference score and the normalized rating score using the LSTM deep learning model.
- Thus, the experimental results illustrate that the DECOR approach suggests the contextually desired items to the users through the deep learning-based latent context analysis.

2. RELATED WORKS

This section reviews several conventional recommendation researchers from modeling the recommender system with the contextual factors and the deep learning models.

2.1 Context-Aware Recommendation Approaches

Knowledge-based probabilistic Collaborative Filtering recommendation model [11] applies both the semantic web technologies and the topic models such as the Latent Dirichlet Allocation (LDA). Also, it suggests the recommendations based on the users' context in terms of the check-ins in the foodservice place. The deep context-aware recommendation approach [12] analyzes the latent context of the sequences in a compressed space. By applying the LSTM encoder-decoder network, it inherently learns the non-linear interactions between the users, items, and contexts for the accurate recommendation. The personalized context-aware recommender model [13] utilizes both the user and item preferences with the splitting criteria to recommend the movies to the users. Initially, it splits a single item into two virtual items based on the context value and then splits a single user into two virtual users based on the context values to generate accurate recommendations. The research work [14] presents the context-aware collaborative filtering model and generates the context influence factors to derive the latent representation. It applies the biased matrix factorization and Bayesian Personalized Ranking (BPR) to perform the rating prediction and item recommendation tasks, respectively. The restaurant recommendation approach [15] analyzes the users' comments and recognizes the users' preferences on the food to suggest the desired restaurants to the users. Moreover, it performs the sentiment analysis to extract the opinion of the users on the food names and suggests the nearby restaurants to the users based on the analysis of the time, location, and feedback of all the users. Context-aware music recommender system [16] considers the context information as features to extract the implicit feedback as well as utilizes the content features including the User Content Profile (UCP) and User Genre Profile (UGP). It employs the matrix factorization method to recommend the music items based on the implicit feedback alone. The Explicit Context Model (ECM) [17] introduces the additional model parameters by designing the item ratings with the contextual factors. This context-aware matrix factorization improves the rating prediction accuracy, tested on music and places of interest recommendation applications. The collaborative filtering-based recommendation approach [17] applies the Pearson correlation to measure the user similarity for the restaurant recommendation. Also, it ranks the restaurants based on the restaurant ratings and the similarity score obtained from the Pearson correlation.

From the study of the context-aware recommendation research works, it is determined that the inclusion of implicit context information significantly improves the quality of the recommendation process in addition to the explicit context. Moreover, it is verified that additional factors such as the time and location of the user-item interactions are to be contemplated to build a personalized restaurant recommendation system with satisfactory recommendations.

2.2 Deep Learning-Based Recommendation Approaches

Implicit or Latent Context Model (LCM) [19] learns the rating bias from analyzing different latent context criteria for each item with the help of the AutoEncoder model, which extends the traditional matrix factorization method. It extracts the potential features from a rich set of sensor data to infer the hidden context of each user in an unsupervised manner. Neural Matrix Factorization (NeuMF) approach [20] learns the latent features of the users and the items regardless of the context information by adopting the multilayer perceptron model. With the advantage of the neural network, it endows the Neural Collaborative Filtering (NCF) with non-linearities. eXtreme Deep Factorization Machine (xDeepFM) model [18] learns both the implicit and explicit feature interactions without manual feature engineering. By integrating a Compressed Interaction Network (CIN) with the Deep Neural Network (DNN), it explicitly examines the high-order features at the vector-wise level and suggests the desired recommendations. The research work [19] learns the user-user and item-item correlations as the low-dimensional vectors through the deep feed-forward neural network. By providing the pre-trained local and global representational vectors of the user-item interactions to the neural network model, it recommends the relevant items to the users. Deep Hybrid Recommender System based on Auto-encoder (DHA-RS) approach [20] combines the neural collaborative filtering with the stacked denoising autoencoder and learns the user and item features from the additional information. In consequence, it assists in predicting the user preferences and recommends the items based on the implicit feedback of the users. Knowledge-Based Recommendation System (KBRS) [21] analyzes the psychological disturbances of the users with the help of sentiment analysis and ontologies. By detecting the depressive content from the text data using the Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Bi-directional Long Short-Term Memory (BLSTM), it recommends the emotional health service in terms of health plans and accurate diagnosis. DNNRec model [22] utilizes the side information of the users and items and learns the non-linear latent factors and embedding with the retaining of the matrix factorization benefits in the recommendation model. Moreover, it designs the deep learning model with the decaying weights and cyclical learning rates across epochs and optimizes error metrics-based prediction performance. Deep learning-based context-aware recommendation framework [23] presents a recommendation model for high-dimensional and dynamic feature space based on the structured, unstructured, and latent representation of the contextual information. By analyzing the contextual factors of the user activity, time, and location, it assists the context-aware rating prediction, classification of users' feedback, and top-k recommendation generation. The pre-

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filtering approach [24] is a deep learning-based recommender system model that combines the context-aware neural collaborative filtering and item-splitting method to incorporate contextual data. Recommendation Model based on Deep Representation Learning (RM-DRL) approach [25] incorporates information preprocessing and feature representation to generate the primitive feature vectors of the users and models the representation learning for the item features and the user features. By modeling the multi-layer CNN and Attention-Integrated Gated Recurrent Unit (AIGRU), it generates the semantic feature vector for the items and users, respectively. In consequence, it computes the preferences of the users on the items and recommends the desired items to the users.

The deep learning-based previous recommendation literature shows that the deep learning models require the most relevant features and preferences for the user-item interactions to suggest the desired recommendations. Also, it is verified that the selection of relevant contextual information is very important to ensure the usefulness of the recommendations due to the diverse nature of the contextual data.

3. PROBLEM STATEMENT

In the digital world, recommender system often encounters difficulty in suggesting the desired items to the users with users' satisfaction. Traditional recommendation models of collaborative and content-based filtering provide user-item interactions on different dimensions. In addition, context information-based recommendation becomes crucial to fulfilling the users' needs. Extracting the latent contextual information is challenging for the recommendation model with increased dynamicity among the users' preferences. Hence, modeling the latent contextual representation for the interrelationships among the users and items is critical. Hence, the memorization-enabled deep learning-based context-aware recommendation model is vital for dynamically changing users' opinions on the items. Instead of incorporating the explicit context information such as the time and location, analyzing several implicit contexts is essential from the users' review text, items' context, and other features. In addition, suggesting unpopular items to the users decreases the satisfaction level of the users. Thus, this work focuses on providing the different contexts as the input to the deep learning model to determine the users' preferences for the recommendation.

4. THE PROPOSED METHODOLOGY

With the target of designing a deep context-aware recommendation model, this work examines the relations between the users, items, and contexts. The DECOR approach incorporates two main processes, such as the contextual feature extraction for the users and the items and the user-item contextual relation-based deep recommendation. In the proposed methodology, contextual feature extraction involves the analysis of the explicit and implicit features of the users and the explicit context of the items. Moreover, the DECOR approach models the training knowledge with the contextual features of the users, items, and user-item relational score for the deep learning model to extract the preferences and suggest personalized recommendations to the users. The overall recommendation procedure composed of two main processes is illustrated in Figure 1.

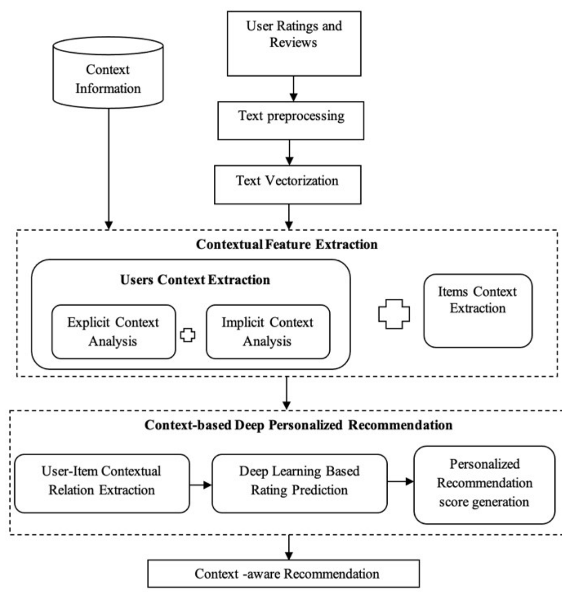

Figure 1: The Proposed DECOR Methodology

The proposed deep context-aware recommendation model adopts the different contextual knowledge and deep learning model to enhance the quality of the recommendation performance. Figure 2 depicts the exemplification of the proposed context-aware recommendation model.

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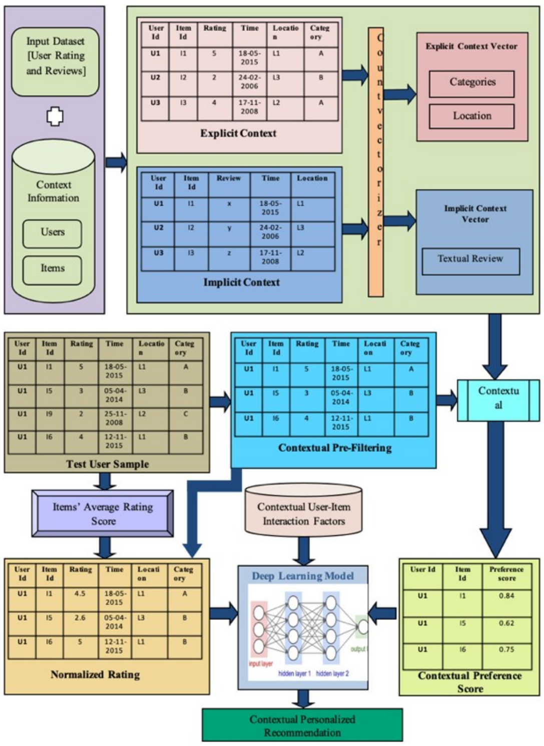

Figure 2: Process Flow of The DECOR Methodology

4.1 Contextual Preference Extraction

Knowledge-based probabilistic collaborative filtering Initially, the DECOR approach applies preprocessing and vectorization to examine the contextual features of the users and items for the preference extraction on user-item relations. The text preprocessing involves the cleaning of the noises such as the number conversion, abbreviation expansion, special characters removal, punctuation removal, stopwords removal, and upper case to lower case transformation. In subsequence to the preprocessing., the DECOR approach recognizes the explicitly available features regarding the users in the recommendation site and implicit feedback of the review along with the analysis of the explicit features of the items, including the received acclamation from other users.

4.1.1 Analyzing Explicit and Implicit Features

The DECOR approach focuses on extracting the contextual features of the users, including the explicit and the implicit features. The DECOR approach analyzes the explicitly available features of the time, location, and rating information of the user-item relations to extract the preference of the users on the items. The explicit context extraction is responsible for grasping the users' context in terms of the situations from a set of predefined contexts, requires an adequate source to train the user behaviors with the wide coverage of the contexts. Hence, the DECOR approach utilizes the explicit factors of the 'time' and 'location' during the user interactions on the items, which facilitates the recognition of the contextual preferences instead of determining the generalized preferences of the users for the recommendation. In the proposed methodology, implicit context extraction is responsible for extracting the hidden context patterns from the available large-scale data particularly, textual reviews posted by the users on the items. Moreover, the DECOR approach analyzes one of the explicit contexts of the rating with the combination of the temporal context and the knowledge extracted from the implicit context.

$$\mathrm{Context}_{i,j} = \begin{cases} R_{i,j} + T_{i,j} + L_{i,j} + Ca_{i,j} & ,\text{if } C = C_E \\ Rev_{i,j} & ,\text{if } C = C_I \end{cases} \quad (1)$$

According to Eq. (1), the DECOR approach utilizes the rating ($R_{i,j}$), time ($T_{i,j}$), location ($L_{i,j}$), and type or category of the item ($Ca_{i,j}$) are the explicit contexts and review ($Rev_{i,j}$) as the implicit context. The DECOR approach applies the contextual pre-filtering on the user preferences to discard the irrelevant or less interesting items during the item similarity score computation. Instead of characterizing the users' behaviors from their entire preference list, the DECOR approach filters the user preferences with top rating scores on recent timestamps to accurately recognize their recent preferences.

$$N(R_{i,j}) = \frac{\left[\alpha \times (R_{i,j}) + (1-\alpha) \times \left(\frac{\sum_{k=1}^{n} R_{k,j}}{n}\right)\right]}{2} \quad (2)$$

In addition to the extraction of the users' contexts, the DECOR approach utilizes the items' context, popularity, or average rating score to suggest the desired and best items as the recommendations to the users. To accomplish this, the DECOR approach estimates the normalized rating of the user on the items ($N(R_{i,j})$) with the items' context using Eq. (2). In Eq. (2), $R_{i,j}$ and $R_{k,j}$ refers to the rating of the ith user on the jth item and rating on the jth item by all kth users among 'n' number of users, respectively. 'α' denotes the weighted parameter, which prioritizes the individual user rating than the average rating received by the item with constant weight.

4.2. Deep Learning-Based Contextual Recommendation

In the subsequence of the contextual feature analysis, the DECOR approach designs the deep learning-based recommendation model with the contextual information acquired from the user-item interactions. By modelling the training data based on the users' and items' context, it learns the user preferences and suggests the desired items based on the recommendation score of the user on each item.

4.2.1 Users' and Items' Context-Based Knowledge Modelling

The DECOR approach adopts the deep learning model for learning the normalized rating score and the context vectors, including the implicit context as the review, explicit context as the category or type, and explicit context as the location. In the proposed methodology, context vectors are modelled from different contextual factors implicitly and explicitly. By jointly considering the review, category, and location, the DÉCOR approach computes the preference score of the user on all the items, influences the deep-learning based recommendation. Eq. (3) computes the preference score of the ith user on the jth item based on the combination of weighted similarity scores of the reviews ($S(Rev_{r1,r2})_{i,j}$), category of the user-item interaction ($S(Ca_{c1,c2})_{i,j}$) and location of the user-item interactions ($S(L_{l1,l2})_{i,j}$) with the assistance of the correlation distance.

$$P_{i,j} = \alpha_1 \times \sum_{r=1}^{|Re|} \left(\frac{S(Rev_{r1,r2})_{i,j}}{|Re|} \right) + \alpha_2 \times \sum_{c=1}^{|Ca|} \left(\frac{S(Ca_{c1,c2})_{i,j}}{|Ca|} \right) + \alpha_3 \times \sum_{l=1}^{|L|} \left(\frac{S(L_{l1,l2})_{i,j}}{|L|} \right) \quad (3)$$

In Eq. (3), α_1, , α_2 and α_3 refers to the constant weighted parameters with the different weighted priorities of 0.4, 0.35, and 0.25, respectively. 'Re', 'Ca', and 'L' denotes the total number of reviews posted ith user, the total number of categories or types of items preferred by the ith user, and the total number of nearby locations preferred by the ith user, respectively. In consequence, the DECOR approach learns the preference score of each user on all the items in the recommendation site from the training knowledge of the user-item interactions and predicts the users' preferences on the items with the help of the deep learning model.

4.2.2 Personalized Recommendation Using Deep Learning

With the increased advantage of the deep neural networks, the DECOR approach designs the recommender system with the LSTM deep learning model. To accurately generate the personalized recommendation score for each user, the DECOR approach learns the latent features of the user-item contextual interactions and predicts the recommendation score using the deep learning model. By providing the extracted contextual preferences in the form of the users' preference score ($P_{i,j}$) and the normalized rating score ($N(R_{i,j})$), the DECOR approach contextually learns the desired patterns of the users on the items along with several additional contextual features.

$$Rec\_Prob(i,j) = \begin{cases} 1, & (P_{i,j} \;\&\&\; N(R_{i,j})) == High \\ 0, & Otherwise \end{cases} \quad (4)$$

Eq. (4) describes the recommendation probability score for the i^{th} user on the j^{th} item based on the contextual users' preference score and the user and the items' context-based normalized rating score. If both the preference score and normalized rating score are high than other items, the DECOR approach assigns that the recommendation probability for the i^{th} user on the j^{th} item as '1'; otherwise, the deep learning model based proposed recommender system ignores the items for the generation of the personalized recommendation list. In addition to these two contextual factors, the DECOR approach considers several additional contextual features while providing the training knowledge to the deep learning model to contextually generate the recommendation score of a particular user on all the items. The recommendation decision-making not only relies on the contextual preference score and the normalized rating score also utilizes the knowledge of potential contextual features to strengthen the personalized recommendation decision. Thus, the DECOR approach effectively suggests the desired items to the users with the recommendation score predicted from the LSTM deep learning model.

5. EXPERIMENTAL EVALUATION

This section describes the implementation requirements and their results from the testing of the proposed DECOR approach existing ECM [17], LCM [19], NeuMF [20], and Collaborative Filtering-based Restaurant Recommendation System (CORR) approach [18] on the benchmark test dataset of Yelp dataset.

5.1 Experimental Setup

The experimental model implements the recommendation algorithm on Ubuntu 16.04 64-bit machine with a 3GHz Intel CPU and 16GB memory. It conducts the experiments of the proposed and existing recommendation algorithms using the Python programming language. It runs the python libraries with the python version 3.6.8 to implement the deep learning model with the assistance of the numpy, pandas, nltk processing, sklearn preprocessing, and sklearn metrics.

5.2 Dataset Description

The experimental framework utilizes the dataset from Yelp's Dataset Challenge [26] that consists of user data, reviews, and business data to test the personalized, contextual recommendation model. The Yelp dataset contains 1100k reviews generated by 190k users on 42k businesses in five cities of Edinburgh, Las Vegas, Madison, Phoenix, and Waterloo, gathered from 2005 to 2015. Among five files in the Yelp dataset, the experimental model utilizes the users' review and business JSON files to test the recommendation model. From the users' review file, 'user_id', 'business_id', 'review_id', 'star', 'date', and 'text' attributes are utilized for the evaluation. Whereas 'business_id', 'address', 'city', 'stars', 'review_count', 'is_open', and 'categories' are utilized from the business file for the evaluation.

5.3 Evaluation Metrics

To exemplify the quality of the personalized recommendation algorithm, the experimental model utilizes four different performance metrics. The experimental model evaluates the recommendation performance through precision and recall metrics and rating prediction performance through the RMSE and MAE metrics. To validate the performance of the recommendation accuracy, the experimental model matches the recommended items with the items regarding the attributes of the 'is-open' and 'average rating of the item'. Moreover, the performance of the recommendation list is evaluated by the Hit Rate and Normalized Discounted Cumulative Gain (NDCG) metrics. The evaluation metrics are described as follows.

Precision: It is the ratio between the number of correctly recommended relevant items and the number of recommended items.

Recall: It is the ratio between the number of correctly recommended relevant items and the total number of items to be recommended.

Root Mean Square Error (RMSE): RMSE measures the square root of the average squared difference between the actual preference score and the predicted preference score of the rating prediction model.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(R_j - R_j'\right)^2} \qquad (5)$$

Mean Absolute Error (MAE): MAE is the absolute difference between the actual and predicted scores of the rating prediction model.

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}\left|R_j - R_j'\right| \qquad (6)$$

Where, 'Rj', 'Rj'', and 'n' refers to the actual rating of jth item, predicted rating of jth item, and the total number of items, respectively.

Hit Rate: It measures any of the top-n recommended items in the test of a particular user. The average of all the users is referred to as the hit rate.

$$\text{Hit Rate} = \begin{cases} 1, & \text{if item in top} - \text{n list exists in the test set} \\ 0, & \text{Otherwise} \end{cases} \qquad (7)$$

$$\text{Hit Rate@n} = \frac{\sum_{i=1}^{n} \text{Hit Rate}}{n} \qquad (8)$$

Normalized Discounted Cumulative Gain (NDCG): It is the measure of ranking of the test item in the top-n recommendation list. If the NDCG@n is high, the ranking is better for the average of all the users.

$$\text{NDCG} = \begin{cases} \frac{\log 2}{\log(k+1)}, & \text{if the item in the top} - \text{n list is ranked at kth position} \\ 0, & \text{Otherwise} \end{cases} \qquad (9)$$

$$\text{NDCG@n} = \frac{\sum_{i=1}^{n} \text{NDCG}}{n} \qquad (10)$$

5.4 Experimental Results

To accurately establish the advantage and prospect of the recommendation algorithm in the personalized recommendation model, it conducts a comparative evaluation between the proposed and existing recommendation models.

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5.4.1 Precision

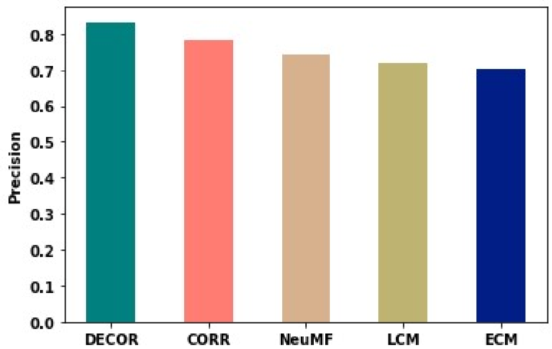

Figure 3: Comparative Performance of Precision

Figure 3 shows the performance of the proposed DECOR and existing CORR approach for the different number of user-item interaction samples in the Yelp dataset. The precision value of the proposed DECOR approach significantly increases by 4.8% than the existing CORR approach. The preference extraction accomplishes it from the explicit context of the rating, time, and location and the implicit context of the review in the DECOR approach. In contrast, the existing CORR approach considers the users' rating information as the explicit context in the collaborative filtering model, which fails to recognize the latent context in the user-item interactions and misleads the recommendation of contextually relevant items. Hence, the existing CORR approach obtains only 78.5% of precision in validating the performance of the relevant item recommendation quality. Compared to the NeuMF and LCM models, the ECM model achieves only 3.7% and 1.3% minimal precision value due to the lack of learning the user behaviors by the neural network model even when considering the contextual preferences.

5.4.2 Recall

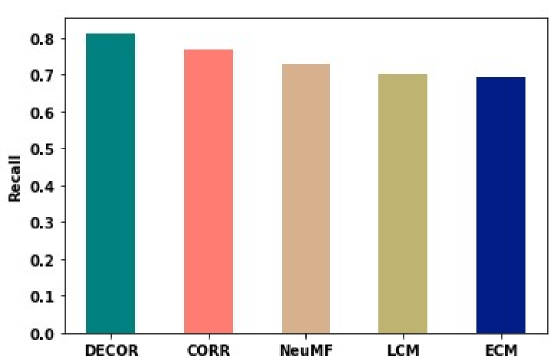

Figure 4: Comparative Performance of Recall

The recall of the proposed DECOR and existing CORR approaches are illustrated in Figure 4. The recommendation performance of the DECOR approach yields 4.3% higher than the existing CORR approach due to the existing recommendation approach applying the Pearson correlation to extract the similar users' preferences for the recommendation. Consequently, the rating-based user similarity alone is inadequate for generating the personalized recommendation list for each user. Moreover, the proposed DECOR approach focuses on recognizing the latent contexts behind the user-item interactions from the predefined explicit contexts and the implicit context hidden in the users' reviews. As a result, the DECOR approach achieves 81.2% of recall, whereas the existing CORR approach obtains 76.9% of recall for the different number of user-item interaction samples. The recall of the LCM and ECM models obtained 70.2% and 69.4%, and the DECOR approach achieved 11% and 11.8% higher recall than the LCM and ECM models by utilizing the combined knowledge of explicit and implicit features for the user preference extraction.

5.4.3 RMSE

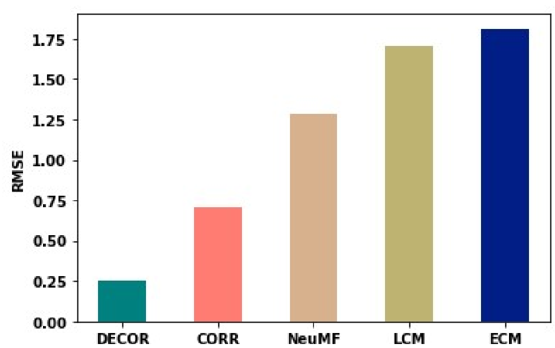

Figure 5: Comparative Performance of RMSE

Moreover, the proposed DECOR approach focuses on recognizing the latent contexts behind the user-item interactions from the predefined explicit contexts and the implicit context hidden in Figure 5 shows the RMSE of the proposed DECOR and existing CORR approaches for the different number of user-item-rating samples that vary for the user-item interactions. The DECOR approach obtains 0.2498 as RMSE value but, the existing CORR approach yields 0.7103 as the RMSE value while testing on the part of the samples from the restaurant dataset. The DECOR approach significantly reduces the prediction error value by learning the users' and the items' context from the rating, reviews, and additional contextual factors.

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Even though the existing CORR approach utilizes the restaurant-based weighted rating for the recommendation decision, the lack of contextual preference analysis leads to a higher RMSE value. In addition, only similar users' preference-based recommendation in the CORR approach leverages the irrelevant suggestion of the desired items to the users. Consequently, it results in the recommendation performance with a 0.46 higher RMSE value than the proposed DECOR approach. Moreover, the RMSE value of the NeuMF model outperforms the LCM-based recommendation model by 0.423 minimal RMSE due to the advantage of the neural network-based training and contextual factors analysis in the NeuMF instead of extracting the user preferences by the unsupervised model in LCM.

5.4.4 MAE

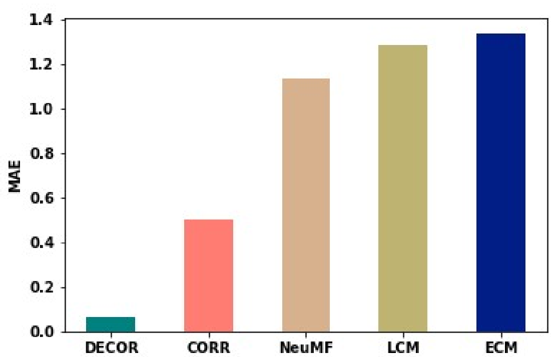

Figure 6: Comparative Performance of MAE

The MAE performance of the proposed DECOR and the existing CORR approaches are depicted in Figure 6 when testing the Yelp restaurant recommendation dataset. The DECOR approach yields 0.442 minimal MAE performance than the CORR approach even the existing approach recommends the items with the combination of the collaborative filtering and the Pearson correlation measurement. The existing CORR approach lacks to adopt the deep learning model for the learning of the latent contextual user-item interactions, which leads to the recommendation of the items within the coverage of the neighborhood users' preferences. With the significance of the normalized user rating and contextual preference score and additional contextual factors in the training knowledge, the proposed DECOR approach strengthens the recommendation decision-making and thus, achieves only 0.0624 as the MAE value during the evaluation of the rating prediction. In addition, the influence of the neural network in the accurate recommendation is proved by the results of the NeuMF and LCM models compared to the ECM model based recommendation. As a result, NeuMF and LCM achieve only 0.203 and 0.051 minimal MAE values than the ECM model.

5.4.5 Hit Rate

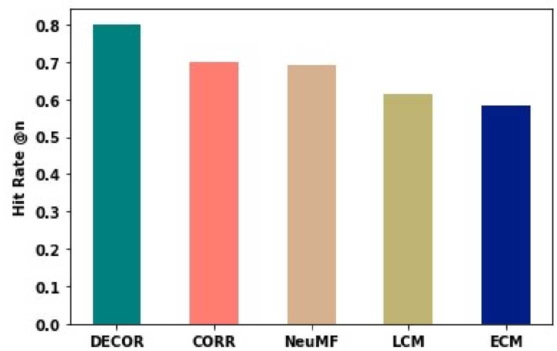

Figure 6: Comparative Performance of Hit Rate

The hit rate performance of the proposed DECOR with the baseline CORR, NeuMF, LCM, and ECM approaches is illustrated in Figure 7. The proposed DECOR approach utilizes the contextual knowledge in different perspectives and yields 0.801 of hit rate@n in which n=5. In the same scenario, the baseline CORR approach accomplishes only 0.699 of hit rate value regardless of the contextual preference score measurement. In addition, the baseline NeuMF, LCM, and ECM models obtain 0.693, 0.614, and 0.582, respectively. The proposed DECOR approach addresses the shortcomings in the recommendation of contextually preferred items by analyzing both the explicit and implicit features. Hence, the DECOR approach outperforms the existing explicit and implicit matrix factorization-based recommendation models of ECM and LCM by 0.219 and 0.187, respectively.

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5.4.6 NDCG

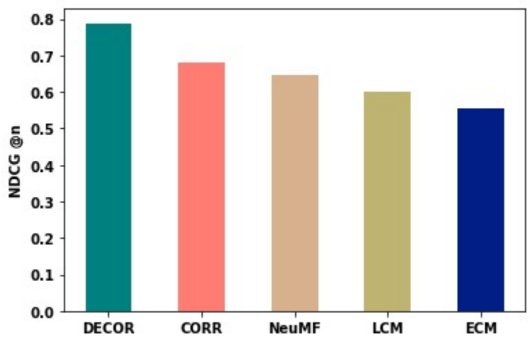

Figure 7: Comparative Performance of NDCG

Figure 8 shows the NDCG performance of the proposed DECOR and the existing CORR, NewMF, LCM, and ECM approaches. The proposed DECOR approach effectively achieves the NDCG value by 0.788 when n=5. At the same time, the existing CORR approach and NeuMF approach obtain the performance of the NDCG as 0.681 and 0.645, respectively. The existing recommendation models of CORR and NeuMF models lack to consider the contextual factors even though neural networks recognize the user-item interactions for the recommendation. By only analyzing the explicit or implicit features, the recommendation model suggests the undesired items with the different ranking order of items for each user. The existing ECM and LCM models obtain only 0.556 and 0.661 NDCG values in the top-5 recommendation list, whereas the proposed DECOR approach yields 0.788 NDCG. Moreover, the proposed DECOR approach yields 0.107 higher NDCG than the baseline NeuMF model, which is accomplished by the contextual features based on user preference probability computation and recommendation.

To summarize, the DECOR is more effective in improving the quality of the recommendations than the comparative recommendation models even when there are massive users with diverse preferences. Moreover, the proposed recommendation model has good flexibility with the influence of the changing factors of the explicit contexts, such as the category, time, and location of the user-item interactions. The impact on the recommendation is higher even when there is a lack of rating or review information with the evidence of investigating the additional contextual factors based on preference extraction.

6. CONCLUSION

This paper presented the deep learning-based context-aware personalized recommendation model, namely the DECOR approach. The proposed DECOR approach has comprised contextual preference extraction and deep learning-based personalized recommendation. By utilizing the explicit and implicit contexts of the users and the items, the DECOR approach has recognized the contextual preferences of the users on the items. Moreover, to recommend the relevant and popular or the best items to the users, it has enriched the individual users' rating with the items' average rating, termed as the normalized rating. The proposed DECOR approach has exploited the implicit context of the reviews and explicit context of the categories and location to compute the preference score and predicted the recommendation score on the items based on the normalized rating and the preference score along with the additional contextual factors. Thus, the experimental results illustrate that the proposed DECOR approach significantly outperforms the existing CORR approach with a 4.3% higher recall in the recommendation performance and 0.442 minimal MAE in the rating prediction performance while testing on the Yelp restaurant dataset. score along with the additional contextual factors. Thus, the experimental results illustrate that the proposed DECOR approach significantly outperforms the existing CORR approach with a 4.3% higher recall in the recommendation performance and 0.442 minimal MAE in the rating prediction performance while testing on the Yelp restaurant dataset. The main strength of this work is the generalizability and versatility of the recommendation by examining the higher-level relationship between the user-item interactions from the aspect of the item categories and the location of the user. Moreover, the preference score generation by the normalized rating and contextual factors greatly ensures the customized recommendation of desired as well as the popular restaurants to the users. However, this work fails to tune the learning model parameters concerning the contextually modeled input and lacks to enhance the learning pattern of the training knowledge in the deep learning model.

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