Contextual-Boosted Deep Neural Collaborative Filtering Approach for Arabic Textual Documents Recommendation

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Abstract

The technological advancement and the expansion of using the internet has made it possible to communicate between people and machines. Many exchanged textual resources have been given simultaneously make users have difficulty in choosing the most appropriate items that will improve their knowledge. To deal with data sparsity problem, review-based recommendation systems have shown potential in a wide range of Natural Language Processing (NLP) tasks. Due to the high-dimensionality and the complex semantics of Arabic textual data, review-based approach is proposed for documents recommendation. Two parallel neural networks are introduced to learn items properties and users' behaviors. Indeed, contextualized word representation model is used. Then, Gated Recurrent Units (GRU) is attached for extracting high-level-semantic features. After that, a shared layer modeled complex interactions between the latent vectors of users and items to improve subsequently rating prediction. Experiments showed the superiority of our proposed model compared with state-of-the-art methods.

1 Introduction

Many technological advances have made it possible to communicate between peoples and machines (Slimi et al., 2022). The greatest benefit of delivering resources provided users with an opportunity to try a new learning style and explore its advantages (Hazar et al., 2022). With the increasing abundance of data over the internet, research on high-quality recommendation systems has gained interest in industry and academic. It has become very important for online platforms (e.g. e-commerce, music, books, social media, advertising, etc.) to provide the users what they need and like without wasting time searching (Dhelim et al., 2022).

Most early recommendation systems use Collaborative Filtering methods (CF) that focus on learning accurate representations of user preferences and item features. Previous models used numeric ratings given by users as inputs. However, they suffered from data sparsity problem (Duan et al., 2022). They had difficulties for learning representations and generating reliable recommendations for users or items with few ratings. Another drawback of CF is that it did not make full use of the available context information like item attributes or user profile to make thereafter recommendations. To alleviate these problems, the use of textual reviews has attracted growing attention. Users can explain their opinions underlying their given ratings. They contain valuable and rich information that cannot be obtained from ratings alone (Jian et al., 2022).

Most of reviews-based models have been focused on English language but not on Arabic. This is due to the richness of Arabic specificities (Meddeb et al., 2021a): a review can include different forms in the vocabulary or syntactic and semantic representations. For example, a word can have more than one lexical category in different contexts what changes the meaning of the sentence (Mahmoud and Zrigui, 2017). In this context, reviews-based recommendation models have attracted attention in different Natural Language Processing applications (e.g., product recommendation, information retrieval, social networks, etc.).

In this paper, contextual-boosted deep neural CF approach is proposed for Arabic textual documents recommendation. This model learns user and item representations simultaneously using two parallel networks. Each one is based on Arabic Bidirectional Encoder Representations from Transformers (AraBERT) for textual reviews embedding. It is efficient to extract meaningful features adaptable to arbitrary contexts that cannot be extracted from traditional word embedding like word2vec and GloVe. For more interpretability, Gated Recurrent Units (GRU) architecture is applied for modeling more semantics from reviews. Once user and item representations are learned, they are concatenated together in a shared hidden space and finally fed to multilayer perceptron (MLP) that is used as an interaction function for rating prediction.

This paper is organized as follows: Section 2 presents a literature review. Section 3 and 4 detail the components and experiments of the proposed approach. Finally, section 5 describes conclusions and future work.

2 Literature Review

Recommendation systems have become widely used for alleviating the overload of information available online. For example, videos recommendation (YouTube), films recommendation (Netflix), Music recommendation (Last.fm), and Books recommendation (Goodreads, Amazon, etc.) (Meddeb et al., 2021b). In this section, the related works to our research are presented.

2.1 CF-based recommendation

Collaborative filtering (CF) is a dominant state-of-the-art recommendation method in which peoples how share similar preferences in the past tend to have similar choices in the future (Meddeb et al., 2021c). The most successful CF methods were based on Matrix Factorization (MF). Using historical records (e.g., ratings, clicks, consumptions, etc.), their main idea is to construct an implicit semantic model representing users and items as vectors of latent factors (called embedding); and modeling thereafter user-item interactions using the inner product operation. Several recommendation methods have been employed MF models.

For more interpretability, Lee and Seung (2001) introduced Non-Negative Matrix Factorization model (NGMF), in which a non-negativity constraint was proposed based on Singular Value Decomposition (SVD). Such optimal estimation methods have demonstrated the existence of overfitting problem due to the sparsity of user-item interactions. To deal with this issue, probabilistic factor models have been proposed. Mnih and Salakhtdinov (2007) proposed Probabilistic Matrix Factorization (PMF) method. It scaled linearly with the number of observations and performed well. In the same idea, Fang et al. (2020) proposed a Bayesian Latent Factor Model (BLFM). Based on the observed user-item interactions, they introduced a constraint on latent factor, and established a likelihood function. However, the majority of MF based methods were sub-optimal for learning rich real world data and complicated user-item interactions. To address these issues, neural networks have been integrated into recommender architectures. He et al. (2017) proposed Neural Collaborative model (NCF). They replaced the inner product with Multilayer Perceptron (MLP) model. It was useful for learning meaningful user-item interactions granting a high degree of nonlinearity and flexibility. Similarly, Bai et al. (2017) proposed a Neighborhood-based NCF (NNCF), in which an MLP layer was placed above the concatenated user-item embedding. By cons, Zhang et al. (2017) and Wang et al. (2017) placed it above the element-wise product of user and item latent vectors. Recently, Chen et al. (2019) proposed a Joint NCF (J-NCF) approach. They adopted the rating to explore both user and item features. MLP layers were applied for extracting latent vectors of users and items and modeling thereafter the interactions between them.

Although CF techniques have shown good performances for many applications, the sparsity problem is considered as one of their significant challenges. It is not easy for them to recommend items with few ratings. To alleviate these issues, users' textual reviews are used as auxiliary information.

2.2 Deep learning-based review modeling

Textual reviews contain rich semantic information about users and items, in which opinion written by users can reveal some information on rating behavior, and also opinions written for items may contain indications on their features (Zheng et al., 2017). For instance, McAuley and Leskovec (2013) proposed Hidden Factors and Topics (HFT) model for understanding rating dimensions with review text. User reviews were modeled using matrix factorization. Indeed, the topic distribution of each review was produced by the latent factors of the corresponding item. In the same vein, King (2014) proposed a unified model called Ratings Meet Reviews (RMR). Content-based filtering with CF incorporated both ratings and reviews. Topic modeling techniques were applied to the review. The obtained topics were aligned with rating dimension to improve rating prediction. Bao et al. (2014) applied Latent Dirichlet Allocation (LDA) and NGMF for latent vectors extraction from ratings and reviews. Then, transform function predicted missing ratings. Saeed et al. (2021) demonstrated the superiority of LDA than Principal Component Analysis (PCA) for Arabic reviews modelling and sentiment classification.

Recently, deep learning modeled efficiently auxiliary review information, such as the textual descriptions of items and preferences of users. They have good capabilities in modeling semantic information by considering the context of words from reviews. The first deep model was proposed by Zheng et al. (2017). Two parallel Convolutional Neural Networks (CNN) represented items' features and users' behaviors from reviews. The use of CNN was helpful in transforming features to high-level abstraction from a stacked of convolution followed by pooling layers (Bellagha and Zrigui, 2021). A shared layer fused them and a FM captured user-item interactions. After that, Chen et al. (2018) proposed NARRE model similar to DeepCoNN, in which two parallel CNNs were used for users and items modeling. Rather than concatenating reviews to one long sequence the same way that DeepCoNN does, an attention mechanism learned the review usefulness. The obtained attention weights are integrated into user and item representations to enhance the embedding quality and the subsequent prediction accuracy. Both DeepCoNN and NARRE employed traditional word embedding.

Everyone has an imposed background from his mother tongue and will have his own difficulties wide different from any another one speaking another language (Trigui et al., 2022). Following the literature, the majority of previous recommender methods have been focused on English resources. In contrast, few works have been concentrated on Arabic language. It is one of the poorly endowed languages that must be treated specifically (Haffar et al., 2021):

- *Complex morphological language:* the existence of diacritics and stacked letters. Arabic is an inflectional, derivational and non-concatenative language. (Mahmoud et al., 2021a).
- *Agglutinative language:* lexical units of words vary in number and in bending according to the grammatical relationships within sentences. (Mahmoud et al., 2021b)
- *Ambiguous language:* words can have more than one sense that is dependent on the context of use (Meddeb et al., 2017). For example, the word "قبل" can be a verb (accept) or an adverb (before) or a noun in its plural form (kisses). (Sghaier and Zrigui, 2020)

3 Proposed Approach

This section details the proposed approach for Arabic textual documents recommendation. The overall model is illustrated in Fig. 1. It has two parallel networks to model user and item embedding that are thereafter concatenated for modeling user-item interactions and rating prediction.

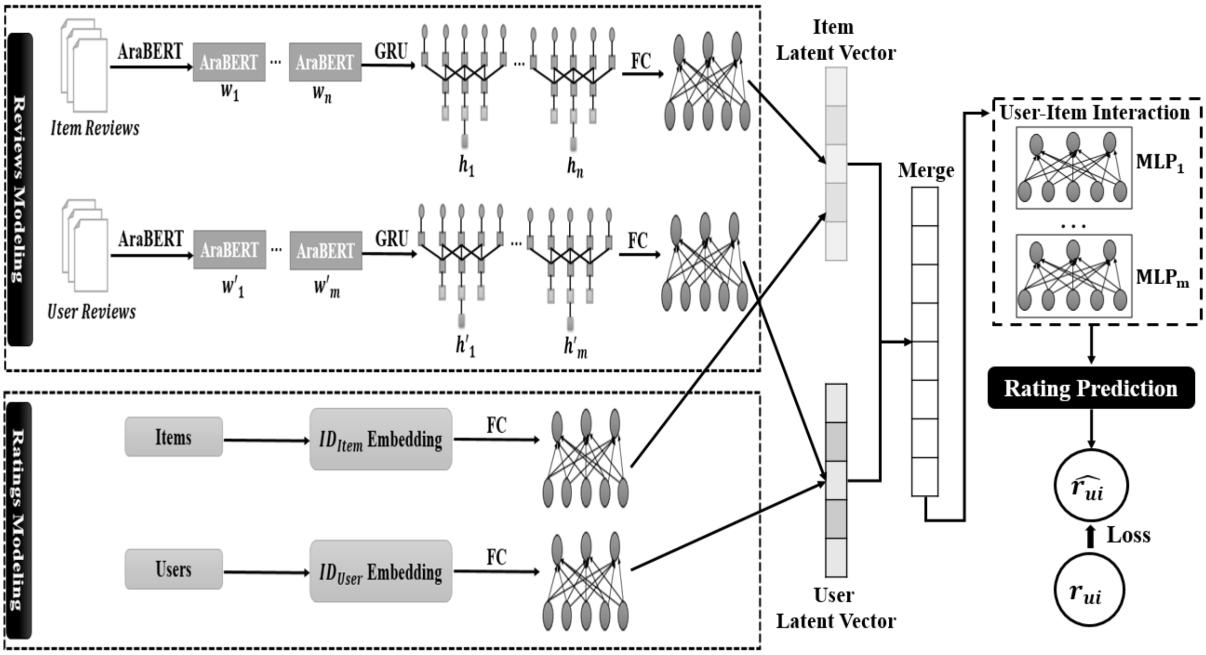

Fig. 1. Proposed architecture.

3.1 Rating Modeling Phase

Suppose that there are M users and N items denoted as $U = \{user_1, user_2, \ldots, user_M\}$ and $I = \{item_1, item_2, \ldots, item_N\}$. The user-item rating matrix R of dimension $N \times M$ is composed by the rating $r_{u,i}$ given by a user $user_u$ to an item $item_i$. For rating modelling, lookup function $\emptyset$ is applied to project the sparse representations into dense vectors using as inputs the identities of users $\{ID_1, ID_2, \ldots, ID_u\}$ and items $\{ID'_1, ID'_2, \ldots, ID'_i\}$, as follows in Eq. (1-2):

$$V^u_{1:M} = \emptyset(ID_1), \emptyset(ID_2), \ldots, \emptyset(ID_M) \quad (1)$$

$$V^i_{1:N} = \emptyset(ID'_1), \emptyset(ID'_2), \ldots, \emptyset(ID'_N) \quad (2)$$

Latent vectors of items $I_{Ratings}$ and users $U_{Ratings}$ are created through two fully connected layers according to the numerical ratings, as denoted in Eq. (3-4):

$$U_{Ratings} = ReLU(W.V^u_{1:M} + b_u) \quad (3)$$

$$I_{Ratings} = ReLU(W'.V^i_{1:N} + b_i) \quad (4)$$

3.2 Reviews Modeling Phase

Due to the sparseness and high-dimensionality of textual data, there are many difficulties for their NLP such as semantic diversity, metaphor expression and grammatical specificity. To solve these problems, reviews modelling process is proposed based on AraBERT and deep learning for rating prediction and Arabic textual documents recommendation. In this section, we will only illustrate the *user modeling process* because the same is also used for items with their inputs as the only difference. Indeed, each user or item is represented as a feature vector in K-dimensional latent factor space as follows: First, Arabic Bidirectional Encoder Representation from Transformers (AraBERT) represent the text with dynamic word vectors according to the context information. It can be adjusted according to the word meaning while the context information is fused. Then, Gated Recurrent Unit (GRU) extract the contextual features from the text.

AraBERT Representation Layer: Given an input set of user-written reviews $S^{user}_u = \{s_{u1}, s_{u2}, \ldots, s_{uj}\}$ where J is the total number of Arabic reviews from user u. S^{user}_u is fed to a pre-trained model that builds upon the transformer architecture. As our initial embedding model, we use $AraBERT$ of 4 encoder layers and 4 self-attention heads. It has 256 hidden dimensions, that are directly utilized later as the fixed embedding dimension. The parameters are fine-tuned during the training process of our model. Indeed, each review is tokenized into words. Because rating prediction is not a sentence pairing task, AraBERT model takes thereafter each review as a single textual segment composed of 256 tokens. The obtained sequences are then passed through a stack of transformer encoders to obtain their respective contextualized representations as follows in Eq. (5):

$$h_{[CLS],u} = \{h_{[CLS],u1}, h_{[CLS],u2}, \dots, h_{[CLS],uj}\} \quad (5)$$

Where: $h_{[CLS],u} \in R^{j\times 256}$.

In theory, any encoder layer may be selected to provide the hidden state of [CLS] as the review's representations. In this study, we select the 4th layer. Following Sun et al. (2019), they have illustrated that the predictive capability of this layer is the best among the others. The final user embedding $P_u \in R^{1\times 256}$ is generated by calculating the average of the [CLS] representations of the reviews written by a user u, as defined in Eq. (6):

$$p_u = \frac{1}{J}\sum_{t=1}^{J} h_{[CLS],ut} \quad (6)$$

Similarly, the item embedding $Q_i \in R^{1\times 256}$ is generated with the same manner from the item embedding network as defined in Eq. (7):

$$q_i = \frac{1}{J}\sum_{t=1}^{J} h_{[CLS],it} \quad (7)$$

To sum up, each user u's review set $S_u^{user} = \{s_{u1}, s_{u2}, \dots, s_{uj}\}$ and item i's review set $S_i^{item} = \{s_{i1}, s_{i2}, \dots, s_{ij}\}$ can be represented as comprehensive vectors $P_u^{user} = \{p_1, p_2, \dots, p_N\} \in R^{N\times 256}$ and $Q_i^{item} = \{q_1, q_2, \dots, q_m\} \in R^{M\times 256}$, respectively, where N and M are the total numbers of users and items.

Fine-Tuning Layer: The fine-tuning layer is proposed to focus on the effective information in the reviews used for recommendation. Following the literature, several recent NLP studies showed the relevance of RNN models for modeling sequential data and extracting hidden contextual states. Gated Recurrent Units (GRU) architecture is a different version of RNN widely used because of its time efficiency characteristics. Instead of LSTM-RNN, it has only two gates:

- The reset gate r_t jointly controls the calculation from the previous hidden state h_{t-1} to the current one h_t.
- The update gate z_t controls both the current input data and the previous memory information h_{t-1}. It determines how much h_{t-1} is passed to the next state.

GRU is characterized by fewer parameters, that can affect the same effect as LSTM while reducing the training time. Another advantage of using GRU is that its hidden layer uses long short-term memory and gated recurrent units to hold the long-term dependencies, which are inherent in the text regardless of lengths and occurrences. The specific gate unit is calculated as follows (Eq. 8-11):

$$z_t = ReLU(W_z.[h_{t-1}, x_t]) \quad (8)$$

$$r_t = ReLU(W_r.[h_{t-1}, x_t]) \quad (9)$$

$$\tilde{h}_t = tanh(W.[r_t \times h_{t-1}, x_t]) \quad (10)$$

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times \tilde{h}_t \quad (11)$$

Where: x_t is the input of GRU model and obtained by AraBERT pre-training language model; $W \in R^{m\times n}$ are the weight matrices of reset r_t and update z_t gates, n is the number of the hidden units; h_{t-1} is the previous hidden state; $\tilde{h}_t$ is the candidate hidden state; and the operator $\cdot$ denotes an element point-wise multiplication.

The output of the GRU model is transmitted to a fully connected layer to model the final latent vectors of reviews written by users $U_{Reviews}$ and those written for items $I_{Reviews}$ as follows in Eq. (12-13):

$$U_{Reviews} = ReLU(W_u.h_t^{(l)} + b_u) \quad (12)$$

$$I_{Reviews} = ReLU(W_i.h_t^{(l)} + b_i) \quad (13)$$

Where: $W \in R^{f\times k}$ is the weight matrix, $b \in R^k$ is the bias term, ReLU is the Rectified Linear Unit activation function.

3.3 Heterogeneous Information Merge Phase

The final representations of users' preferences included the latent vectors of user-item ratings and user reviews, as defined in Eq. (14):

$$F_u = [U_{Ratings}, U_{Reviews}] \quad (14)$$

The final representation of items' features is composed by the latent vectors of item reviews and ratings, as defined in Eq. (15):

$$F_i = [I_{Ratings}, I_{Reviews}] \quad (15)$$

3.4 Rating Prediction Phase

User-Item Interaction Modeling: The final feature vectors of the users $F_u \in R^D$ and items $F_i \in R^D$ are concatenated by applying the dot product operation as defined in Eq. (16). For learning the interactions between user and item representations and modelling the CF effect, an affinity score $\widehat{rate}_{u,i}$ is defined as user u's preference for item i as denoted in Eq. (19). To do this, Multi-Layer Perceptron (MLP) model is applied on top of the concatenated user-item embedding to provide further flexibility and non-linearity as defined in Eq. (17-19).

$$h_o = F_u \odot F_i \quad (16)$$
$$h_1 = ReLU(W_1.h_o + b_1) \quad (17)$$
$$\dots$$
$$h_L = ReLU(W_L.h_{L-1} + b_L) \quad (18)$$
$$\widehat{rate}_{u,i} = W_{L+1}h_L + b_L \quad (19)$$

Where : h_0 is the concatenated user-item embedding in the shared hidden space; h_L is the L[th] MLP layer, W_L is the weight matrix, b_L is the bias vector, ReLU is the activation function and $\widehat{rate}_{u,i}$ denotes the predicted rating that user u gives to item i. In our model, three layered MLP were useful to learn efficiently more abstractive features.

Learning: For training, the Mean Squared Error (MSE) is used as the loss function. To optimize the performance of our model, MSE is minimized between the output score $\widehat{rate}_{u,i}$ from our model and the real score $rate_{u,i}$. It is defined as follows in Eq. (20):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(rate_{u,i} - \widehat{rate}_{u,i})^2 \quad (20)$$

Where: N refers to the training samples, $rate_{u,i}$ is the ground-truth rating given by user u to item i, and $\widehat{rate}_{u,i}$ is the predicted rating.

4 Experiments

4.1 Dataset

The experiments are conducted on Books Reviews in Arabic Dataset BRAD1.0. It consists of 4,993 Arabic books of different genres (historic, religion, health…) collected from the Goodreads web site; 76,530 users and 510,600 user-item interactions composed by reviews and ratings in the range of [1,5], as illustrated in the following Table 1:

Number of users	Number of books	Number of user-item interactions	
		Number of ratings	Number of reviews
76,530	4,993	510,600	510,600

Table 1: BRAD1.0 dataset

4.2 Parameters settings

This section represents the parameters of our proposed models. Table 2 depicts the configurations of AraBERT[1], GRU and MLP models, for textual reviews embedding and user-item interaction modeling:

Model	Parameter	Value
AraBERT	Hidden layers	4
	Attention heads	4
	Hidden size	256
	Dropout	0.1
	Optimizer	Adam
	Epochs	20
	Activation function	ReLU
GRU	Hidden units	256, 128, 64
	Activation function	ReLU
	Epochs	20
	Batch size	128
	Dropout rate	0.2
MLP	Latent factors	16
	Activation function	ReLU
	Hidden layers	128, 64, 8
	Batch size	256
	Droput rate	0.5

Table 2: Parameters configurations

4.3 Evaluation Metric

Root Mean Squared Error (RMSE) is used as an evaluation metric. It is the most used for rating prediction and recommendation systems.

Given N user-item ratings, the RMSE score is defined as follows in Eq. (21):

$$RMSE = \sqrt{\frac{1}{N}\sum_{u,i}(rate_{u,i} - \widehat{rate}_{u,i})^2} \quad (21)$$

4.4 Baselines

As depicted in Table 3, we compare our model with several competitive baselines, including CF- and deep learning-based methods, using reviews and ratings:

- **PMF (Probabilistic Matrix Factorization):** is based on a Gaussian distribution to model the latent factors for users and items.
- **SVD ++ (Singular Value Decomposition):** extends SVD with neighborhood method. The item-item similarity using a novel set of item factors.
- **J-NCF (Joint-Neural Collaborative Filtering):** coupled deep features learning and deep interactions modeling with a rating matrix. This was due by using MLP model.
- **DeepCoNN (Deep Cooperative Neural Network):** utilizes deep learning to

[1]https://github.com/aub-mind/arabert/tree/master/arabert

jointly model user and item from textual reviews.

Models	Features		
	Ratings	Reviews	Deep learning
PMF	×	-	-
SVD++	×	-	-
J-NCF	×	-	×
DeepCoNN	-	×	×
Our model	×	×	×

Table 3: Features of state-of-the-art methods

4.5 Discussion

Using BRAD1.0 dataset, several observations can be made from the rating prediction results of our model compared to the state-of-the-art methods as illustrated in Table 4:

Methods	RMSE
PMF	1.355
SVD++	1.215
J-NCF	1.050
DeepCoNN	0.905
Our model	0.855

Table 4: Experimental results of baselines

As illustrated in J-NCF model, user-item interactions modeled efficiently in a non-linear way, which is the limitation of traditional CF methods based on the dot product. It achieved 1.050 RMSE higher than PMF (1.355 RMSE) and SVD++ (1.215 RMSE).

Reviews-based methods like DeepCoNN performed better than classic CF models (PMF, SVD and J-NCF) that only consider the rating matrix as the input. It obtained 0.905 RMSE. This demonstrated the usefulness of review information. It was complementary to ratings specially to improve the representation quality of latent factors of user preferences and item features, and thereafter rating perdition.

Although review information was useful in recommendation, the performance could vary depending on how it was modeled. Indeed, the application of CNN was efficient for modeling reviews and extracting latent vectors of users and items.

Although that it did not need to manually label features, their performance was not satisfactory for analyzing the specificities of an ambiguous language like Arabic. To deal with this, we proposed a contextual-boosted deep neural collaborative filtering approach for Arabic textual documents recommendation. As shown in Fig.2, our proposed approach consistently outperformed all the cited baseline methods achieving 0.855 RMSE for the following reasons:

The model used the advanced AraBERT language model. It modeled efficiently deep semantics of words and dynamically generated high-quality of word vectors unlike traditional language models (e.g., GloVe and word2vec).

Then, GRU was useful to solve the related dependencies of long sentences by considering the context information.

Finally, experiments demonstrated the superiority of our model regarding the dimensionality of the user and item vectors and the hidden layers' number of MLP while fixing the other parameters: the width of embedding layer (K=16) and the number of hidden layers (3-MLP) improved the recommendation performance achieving 0.855 RMSE.

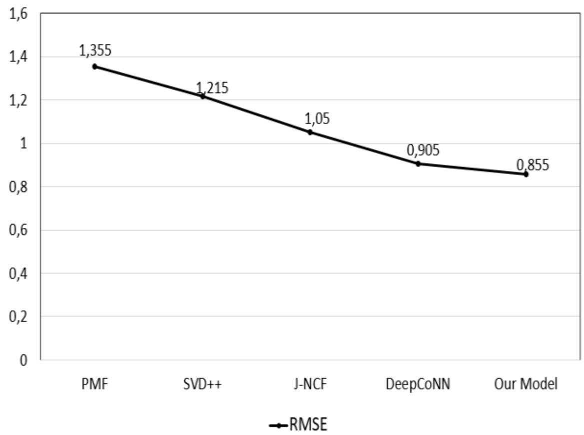

Fig. 2. State-of-the-art comparisons according to RMSE scores

5 Conclusion and Future Work

A contextual-boosted deep neural collaborative filtering approach for Arabic textual documents recommendation is proposed. It combined ratings and textual reviews seeing their complementary to improve the representation quality of latent factors of user preferences and item features.

The pre-trained AraBERT language model was useful to mine the deep semantics of Arabic words and dynamically generate high-quality vectors. Then, GRU modeled efficiently the related dependencies of long sentences by considering the context information. After that, MLP helped to model complex user-item interactions and improve rating prediction. Our proposed model is validated by experiments realized on BRAD1.0 dataset. They consistently outperformed other state-of-the-art methods namely PMF, SVD++ and J-NCF.

In linguistics, both of the previous and the succeeding words influence the current word semantic. For this reason, bidirectional recurrent neural network will be adopted in the future to learn long term dependencies in both forward and backward directions to improve the user-item textual information modeling process.

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