Context-Aware Collaborative Filtering Framework for Rating Prediction Based on Novel Similarity Estimation

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Abstract: Recommender systems are rapidly transforming the digital world into intelligent information hubs. The valuable context information associated with the users' prior transactions has played a vital role in determining the user preferences for items or rating prediction. It has been a hot research topic in collaborative filtering-based recommender systems for the last two decades. This paper presents a novel Context Based Rating Prediction (CBRP) model with a unique similarity scoring estimation method. The proposed algorithm computes a context score for each candidate user to construct a similarity pool for the given subject user-item pair and intuitively choose the highly influential users to forecast the item ratings. The context scoring strategy has an inherent capability to incorporate multiple conditional factors to filter down the most relevant recommendations. Compared with traditional similarity estimation methods, CBRP makes it possible for the full use of neighboring collaborators' choice on various conditions. We conduct experiments on three publicly available datasets to evaluate our proposed method with random user-item pairs and got considerable improvement in prediction accuracy over the standard evaluation measures. Also, we evaluate prediction accuracy for every user-item pair in the system and the results show that our proposed framework has outperformed existing methods.

Keywords: Recommender system, context-based similarity estimation, rating prediction, collaborative filtering.

1 Introduction

We are living in the age of information management that ultimately leads towards the age of recommendations. Therefore, machine learning based intelligent recommender system comes in front of searching techniques and significantly improves the user experience. Most of the commercial objectives are to target the right products or services for an

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individual consumer and this has introduced a new world full of challenges, i.e., personalized recommendations. Rating prediction acts as a core activity at the heart of any collaborative recommender system. It is a complete framework of methodologies used to predict user interests or opinions based on the relationship with other components of the system. For example, the movie recommendation on Netflix is based on the historic user interests or interests of homogeneous users. Similarly, a product recommendation on Amazon can be deduced by the users purchase history or through time and location context, even the purchase history of close friends also provide extensive information. Recommender systems are ubiquitous in the current digital world. The efficient generation of relevant recommendations in large-scale systems is a very complex task. In order to provide personalized recommendations, the algorithms need to capture varying interests and find mostly nonlinear dependencies between them. Enormous data sparsity and real-time requirement make such recommendations challenging in dynamic real-life situations. Context-aware recommender systems come up with an innovative utilization of dynamic context information such as user behavior, changing weather conditions, government policies, and cultural habits [Ali, Shao, Khan et al. (2019); Hou, Wei, Wang et al. (2018); Parent and Kim (2017)]. It has been proven that additional context information is highly supportive for most types of recommender systems and it boosts up the recommendation performance [Dridi, Zammali and Alsulimani (2020)]. The traditional recommender systems recommend items simply based on content similarity and collaborative filtering, neglecting the conditional usage of the items/services by the users, while in the real world, the conditional usage of items is a practical reality. In other words, it is important to automatically determine what kind of products are considered by which type of users, where (location) and when (time), while making recommendations. For example, people usually prefer to buy expensive products when some special event is approaching where this condition has lots of significance to whom someone is buying a gift for? Such conditional usage is considered under the context-aware recommender systems.

In this work, we introduce a novel context-based rating prediction approach that is based on a unique context scoring scheme. The proposed context scoring model incorporates different factors such as movie release year and ratings given by similar users in the system and a dynamic threshold level to consider a user in a similarity pool. The proposed context based rating prediction (CBRP) system has three inputs: the subject user, the subject item and a rating matrix, and it generates a list of context scores for highly influential users for the subject user over the subject item. In view of collaborative filtering, the generated context score can also be considered as a similarity measure for the given subject user-item pair. We demonstrate that the proposed similarity measure has improved the prediction accuracy by utilizing context information. In short, our contribution can be summarized as follows. We propose a novel similarity measure that can extract more accurate rating predictions compared with existing state-of-the-art methods. We exploit additional context information which is associated with user-item pairs and model the different impacts from varying context on user preferences when choosing different items. We design a unique context scoring strategy that has an inherent capability to incorporate multiple conditional factors to filter down the most relevant recommendations. Our additional experimental results demonstrated that it can act as an essential milestone for reliable Top-*N* recommendations. Then, we conduct extensive experiments on three publicly available datasets to evaluate our proposed model and obtain considerable improvements. Also, we evaluate prediction accuracy for every user-item pair, and experimental results show that our proposed method outperforms state-of-the-art techniques.

The rest of the paper is organized as follows. Section 2 presents an overview of the existing work done in this domain during the last two decades. Section 3 specifies the preliminary concepts, notations, and symbols we formally use in the rest of this article. Section 4 illustrates the proposed context-based rating prediction framework and novel similarity estimation method. Section 5 presents the experimental details. Finally, Section 6 concludes the paper with possible future extensions of this research work.

2 Related work

Over the last two decades, researchers and practitioners have been broadly working to address the rating prediction problem [Phuong, Lien and Phuong (2019); Jiang, Chen, Jiang et al. (2019)]. The existing approaches are mostly based on the assumption that users with similar interests in the past must like similar items in the future [Sundermann, Domingues, Sinoara et al. (2019)]. Practically, this assumption is not valid, as in the real world, user preferences may change with time, location, mood, and through many other factors. Someone may get opposite inclination with its prior neighbors with different locations. Furthermore, through this track, the recommendation algorithm has to bear a lot of computational costs to capture the similarities and dissimilarities among millions of user-item pairs. In this regard, the context-based rating prediction models are free from the above discrepancies in the sense that they are mostly dynamic [Raza and Ding (2019)].

There have been many techniques to deal with rating prediction in recommender systems. The context-based collaborative filtering is one of the most deeply researched architectures in past years [Wang, de Vries and Reinders (2008)]. There also has been a growing interest in context-aware recommender systems over the past few years. A comprehensive study on context-based recommender systems with a multidimensional recommendation model, Adomavicius et al. [Adomavicius, Sankaranarayanan and Sen (2005)], extends the user-item interaction with contextual data. The proposed methodology is somehow similar to the OLAP-based models widely used in data warehousing applications. Besides, using a manual approach to deal with context relevance, there are some data mining and machine learning algorithms that help us to detect and model contexts automatically. In Adomavicius et al. [Adomavicius and Zhang (2012)], it is suggested that an expert should keep some contextual features as a candidate. Then, employing statistical methods, the most relevant context should be extracted, for example, performing a pairwise t-test among candidate features. Odic et al. [Odic, Tkalcic, Tasic et al. (2013)] integrated comprehensive literature on automatic context detection techniques for movie recommender systems. Karatzoglou et al. [Karatzoglou, Amatriain, Baltrunas et al. (2010)] proposed a tensor factorization based multiverse recommendation model. The model utilizes a different type of context as an additional dimension in the representation model of data in the form of data tensors. Another unique way to get the relevance of a context was given by Baltrunas et al. [Baltrunas, Ludwig, Peer et al. (2012)], in which some imaginary contextual preference model has been offered to users to observe this opinion.

Table 1: Basic notations

Notations	Descriptions
U, I	Set of total users, set of total items respectively
SU, SI	Subject User, Subject Item (whose rating we are going to predict)
Ls	List of all items subject user has rated
Sim (i, j)	Similarity between user i and j
k	Number of selected neighbors
r_{ij}	Rating range from $0 \leq r_{ij} \leq 5$ given by user (u_i) on item (i_j)
L_{sui}	List of user-item the subject user and other users have rated
L_{oui}	A refined sub-list of L_{sui} common with subject item.
CS_{uj}	Context score of a user (u_i) over a list of users j
L_{cs}	A dictionary of context scores for each candidate user
PR	Predicted Ratings

Similarly, a contextual video recommendation was presented by Mei et al. [Mei, Yang, Hua et al. (2011)]. The authors proposed a contextual model based on multi-modal context relevance and user feedback. Chen et al. [Chen, Chen, Zheng et al. (2012)] proposed a model for tweet recommendation that incorporates contextual attributes to improve the recommendation quality. The proposed method outperforms by modeling contextual attributes. The contextual recommendation is also prevalent in route recommendation [Hu, Qin and Shao (2018)]. More recently, Jiang et al. [Jiang and Xu (2019)] utilized commodities data to improve the efficiency of a collaborative filtering algorithm. Similarly, Yuan et al. [Yuan and Mu (2019)] introduced a flexible approach capable of handling dynamic users' preferences for rating prediction. The proposed method used a pair of preferences to represent the whole preference of user over items. Then, these paired preferences are used to build up latent feature vector for user.

3 Preliminaries and notations

Before we introduce the details of our proposed CBRP model, we look at some basic concepts and primary notations. The CBRP system has three major inputs, i.e., the subject user *SU*, the subject item *SI* and a rating matrix *R*. The objective of the system is to predict the most accurate rating for the subject user over the subject item utilizing additional context information available in rating matrix *R*. More formally, let $U = \{u_1, u_2, u_3, u_4, \dots, u_N\}$ and $I = \{i_1, i_2, i_3, i_4, \dots, i_M\}$ be the set of users and items respectively. Then, the user-item rating matrix $R = [r_{ij}]_{N \times M}$ is a set of ratings such as each $r_{ij} \in \{0, 0.5, 1, 1.5, \dots, 5\}$, where the rating set given by the user u_i over item i_j, is from the rating range, i.e., $0 \leq r_{ij} \leq 5$. Practically, a large number of ratings are always missing from the given matrix *R*. The objective of a rating prediction system is to predict these missing ratings with the help of existing available ratings and effectively modeling the contextual information. Basic notations to describe different concepts and user-item lists with similar interests and preferences are presented in Tab. 1.

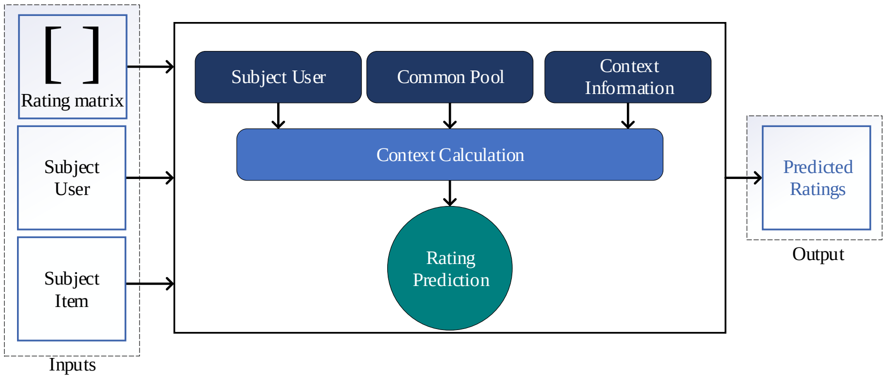

Figure 1: Basic structure of CBRP system

4 Proposed framework

We introduce a novel context-aware approach for rating prediction. As presented in Fig. 1, the proposed CBRP system has three inputs; the subject user *SU*, the subject item *SI*, and a rating matrix *R*. The objective of CBRP system is to predict an accurate rating for the subject user over the subject item utilizing additional context information. More formally, let $U = \{u_1, u_2, u_3, \ldots, u_N\}$ and $I = \{i_1, i_2, i_3 \ldots, i_M\}$ be the set of users and items respectively. Then, the user-item rating matrix $R = [r_{ij}]_{N\times M}$ is a set of ratings such as each $r_{ij} \in \{0, 0.5, 1, 1.5, \ldots, 5\}$ are the user ratings for a given item. Our objective is to predict an unseen rating *PR* of *SU* over *SI* in light of the user's preferences shown by *R*.

4.1 Basic motivations

Motivated by the concept of global boosting, we have introduced a novel framework for finding the most similar users. Unlike cosine or Pearson similarities, the proposed model considers both close and far neighbors with a unique scoring scheme that brings the highly similar neighbors closer to each other while the less similar users also remain in the race but with lesser impact. We aim at computing a context score for each candidate user by utilizing the exponent function. For this purpose, lets assumes that a user u_i has *s* similarity with user u_j. We want to maximize *s* if the rating difference of user u_i and user u_j is null and lower values. Formally, an exponential function is a function of the form $f(x) = ab^x$, where *b* is a positive real number and *x* is the exponent value. For a function of any real variable, the exponential property uniquely specifies that the growth rate is directly proportional to the real value number. The constant of proportionality of this relationship is the natural log of the base *b* such that:

$$\frac{d}{dx} b^x = b^x \log_e b \qquad (1)$$

For *b*=1 the function value is a constant and for constant the derivative is zero. Therefore, the constant *e*=2.71... has been associated as a unique standard for which the constant of proportionality is 1, and now the function's derivative can be specified as:

$$\frac{d}{dx}e^{x} = e^{x}log_{e}\,e = e^{x} \tag{2}$$

Algorithm 1: Proposed framework

Input: Subject User (*SU*), Subject Item (*SI*), Dataset rating matrix (*R*)

Output: Predicted Ratings (*PR*) for an *SU* over *SI*

```
Ls=ϕ, L_sui=ϕ, L_oui=ϕ
for each user ui∈R do
    if (ui = =SU)
        Ls=ui
    end-if
end-for
for each item li∈Ls do
    for each item lj∈R do
        if (li= =lj & lj≠SI)
            L_sui=lj
        end-if
    end-for
end-for
for each item ui∈R do
    if (ui= =SI)
        L_oui=ui
    end-if
end-for
CP=L_sui ∩ L_oui
L_cs={ϕ}:        //An empty dictionary to maintain each user's context score
for each user uj∈CP do
    CSuj=0
    for each item ij∈CP do
        CSuj=CSuj+exp(-(CP[uj]–CP[ij]))
    end-for
    L_cs={User[uj], CSuj}
end-for
L_cs=Sort (L_cs)
PR=Weighted mean (top-k user ratings in L_cs)
```

4.2 Context score

For our concerns, the similarity between users *u* and *v* is defined as the maximum context score obtained by user *u* over the rated items of user *v*, whereas, the context score is the core activity for similarity calculation. It is the impact of contextual factors on the overall relationship of users *u* and *v*. The detailed computation of context score is illustrated in Algorithm 1. Here, we attempt to portray the abstract view of similarity estimation between users *u* and *v* in Eq. (3) as follows:

$$sim(u, v) = Max\ (CS), while\ CS = \sum_{i=1}^{N} \frac{1}{e^{(Rating\ Diff\ of\ u,v)}} \tag{3}$$

N is the total number of similar items the user *v* has rated in common with the user *u*. The significance of the context score depends on the count of common items set as well as the maximum number of users with zero rating-difference. It is important to consider here that one zero rating-difference user has about two times more impact on a context score compared with the one with a 0.5 rating difference. Similarly, a one zero rating-difference user has about three times more impact to the one with a 1.0 rating difference. This impact exponentially reduces as the rating difference increases. In case a user has more than a 1.0 (threshold) rating difference, we will not consider it to be added in the similarity pool.

Algorithm 1 presents the overall workflow of the proposed framework. Here, we have given *SU*, *SI* and the rating matrix *R* that contains the random ratings by the other users available in the dataset. Our objective is to predict the ratings of the subject user for the subject item. Initially, we have extracted a complete list L_s of the items the subject user has already rated other than the subject item. Likewise, we have extracted another list L_{sui} against each item in L_s that the other users in the system have rated. To construct the common interest items, we developed another list L_{oui} of other users rated subject items. By intersecting both lists, i.e., L_{sui} and L_{oui}, a common pool *CP* has been developed that contains user only rated common item with the subject user. Finally, we have calculated the similarity score *CS* for every user in *CP* against every item and maintain a dictionary of results entitled L_{cs}. L_{cs} is a list of similarity scores for each neighbor of the subject user for the subject item. The values in L_{cs} indicate the closeness of each member in term of maximum count of common items and the level of similar rating interest on other items. The maximum L_{cs} value indicates the higher similarity between the subject user and the user with a higher L_{cs} value. Realizing this fact, we pluck off the top-*k* (for the current work, *k*=5) values from the L_{cs} list and calculate the weighted mean of these user ratings (weighted with the number of close neighbors). In conclusion, the weighted average of top-*k* users in L_{cs} returned an initial dimension of the subject rating as per its collaborative context. Additionally, we have calculated the context score as per the release year by dynamically clustering each users' movie pool into multiple clusters based on its movie release year. This is another powerful indicator about users' choice of likeness by comparing it with the user's overall trend of rating movies.

5 Experiments

This section demonstrates the experimental details for evaluating the proposed framework. Also, it validates the performance of our method on selected datasets. We present a comparison followed by detailed results and discussions.

5.1 Datasets

We evaluate the proposed approach on three datasets made available by MovieLens and FilmTrust. The first one is called ML-100K, which contains 100,000 ratings of 943 users over 1,682 different movies. The second one is called ML-1M, which contains more than 1Million (1, 000, 209) ratings from 6,040 users over 3,952 movies [Adomavicius and Zhang (2012)]. In both datasets, each user has rated more than 20 movies on average and ratings are scaled from 1 to 5. Furthermore, movies are classified into 19 different classes or genres, and each movie belongs to one or more genres depending on their content and nature. Additionally, all movies have a unique release year value, and the density of user-item matrix in the ML-100K dataset is about 6.3%, and 4.45% in the ML-1M dataset [Adomavicius and Zhang (2012)]. FilmTrust is another widely used movie rating dataset. It was collected from a movie rating sharing website (FilmTrust). The dataset contains 1,508 users with 2,071 distinct movies and 35,497 ratings from different users [Guo, Zhang and Smith (2013)].

5.2 Comparison methods

To demonstrate the effectiveness of our proposed approach, we compared our prediction accuracy with other collaborative rating based prediction methods. We have chosen the partial singular value decomposition (PSVD) [Yuan and Mu (2019)], the user rating prediction (URP) [Kumar, Kumar and Thakur (2019)], the Koren stochastic gradient descent (KOR-SGD) [Koren (2010)], the Koren alternating least squares (KOR-ALS) [Koren (2010)], the cosine similarity and K-nearest neighbor (CosineKNN), the nonnegative matrix factorization (NMF), the probabilistic matrix factorization (PMF) and the singular value decomposition (SVD++). A description of these methods is given as follows:

-PSVD [Yuan and Mu (2019)]: PSVD is a flexible matrix factorization based approach capable of handling dynamic users' preferences for rating prediction. It used a pair of preferences to represent the whole preference of a user over items. Then, these paired preferences are used to build up latent feature vector for representing user rating behavior.

-URP [Kumar, Kumar and Thakur (2019)]: User rating prediction (URP) is a recently proposed rating prediction method that mainly depends on the highly-rated items. It utilized the idea of adoptive collaborative filtering.

-KOR-SGD [Koren (2010)]: The well-known stochastic gradient descent (SGD) is basically an optimization method. It is fast and widely used in collaborative filtering based rating prediction methods.

-KOR-ALS [Koren (2010)]: Alternating least squares (ALS) is another method which calculates the rating predictions through a different way.

-CosineKNN: The cosine similarity and K-nearest neighbor method measures the similarity between two user vectors by calculating the cosine of the angle between them.

-NMF: Nonnegative matrix factorization (NMF) is one of the most widely used baseline technique for comparing recommender system performance. It has wide range of uses from rating prediction to topic modeling.

-PMF: Probabilistic matrix factorization (PMF) takes advantage of probability models for matrix factorization.

-SVD++: The main idea of SVD++ is to mix up the strengths of the standard singular value decomposition method and additional users' preferences. User preferences for each item are modeled against different properties of items.

5.3 Measures

To estimate the prediction performance of a recommender system, root mean squared error (RMSE) [Li and Mu (2019)] and mean absolute error (MAE) [Herlocker, Konstan and Terveen (2004)] are the two most commonly used accuracy measures. Basically, RMSE and MAE are used to evaluate the prediction accuracy, while precision and recall are used to evaluate the quality of Top-*N* recommendation [Zhang, Gong, Lee et al. (2016)]. We adopt RMSE and MAE as we are mainly concerned with prediction accuracy. RMSE reflects the degree of deviation between the estimated ratings and actual ratings. It penalizes large deviation more heavily by squaring the errors before summing them. Formally, RMSE is defined in Eq. (4).

$$RMSE = \sqrt{\frac{\sum_{ui \in N}(PR_{ui} - AR_{ui})^2}{|N|}} \tag{4}$$

$$MAE = \frac{1}{N} \sum_{ui \in N} |PR_{ui} - AR_{ui}| \tag{5}$$

Here, PR_{ui} represents the predicted ratings of u over i, where AR_{ui} represents the actual ratings. Finally, we can get the RMSE score by dividing the squared sum of the difference between predicted rating and actual rating of total user-item pairs and taking the square root after dividing this sum with the total number. In Eq. (5), we have formally defined MAE, which estimates the average absolute deviation between the predicted ratings and actual ratings for each user-item pair. Same with RMSE, the lower value of MAE reflects the higher level of system accuracy.

5.4 Experiment settings

Our initial experiments on three datasets are based on predicting rating accuracy for a number of random user-item pairs against all the rated items in the system. For this purpose, we randomly selected 200 users-item pairs and estimated their ratings through the proposed rating prediction method. For each selected user-item pair, we chose the top five high context score candidate users. Then, we predicted ratings for every user-item pair in the system for the same context score settings described previously and kept its RMSE and MAE accordingly. Results for randomly selected user-item pairs are demonstrated in Tab. 2.

5.5 Results and discussions

The prediction accuracy of a single user-item pair could not be claimed as the overall accuracy of the whole system. Therefore, we have evaluated the CBRP method in two phases. In the first phase, we randomly selected 200 user-item pairs from each dataset (i.e., Movie Lens 100K, 1M, and FilmTrust) and kept RMSE and MAE values through our proposed rating prediction model. This experiment has been performed five times independently. Tab. 2 presents the resulting values against each iteration. Also, it demonstrates that the proposed method CBRP has outperformed other methods. The corresponding values of performance measures on the given datasets for each pass have been categorically presented. For more illustration, the last column of the table has been designed to show the percentage improvements in prediction accuracy. In the second phase, we have calculated the mean RMSE and MAE scores on CBRP, the selective methods and the three additional baselines, i.e., NMF, PMF and SVD++ rating prediction methods. Fig. 2 presents a graphical representation of the improvements made by CBRP on 200 random samples over the dataset MovieLens' 100K. It is clearly demonstrated in Fig. 2 that our proposed CBRP model achieved the best performance against all existing methods on MovieLens' 100K dataset. On average, we have achieved 8.8% improvement in RMSE and 11% improvement in MAE for the user-items pairs. Fig. 3 presents RMSE and MAE values on dataset MovieLens' 1M.

Table 2: Results of randomly selected 200 user-item pairs on each selected dataset (acronyms DS is used for dataset, P for the number of passes and % Imp. denotes percentage improvement)

DS	P	CBRP		CosineKNN		KOR-ALS		KOR-SGD		URP		% Imp.	
		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Ml-100K	1	**0.7733**	**0.5810**	0.8233	0.6480	0.9208	0.7323	1.2193	0.9889	1.1985	0.8562	6%	10%
	2	**0.7969**	**0.6210**	0.8344	0.6625	0.9411	0.7547	1.2237	0.9688	1.2030	0.8721	4%	6%
	3	**0.8013**	**0.6303**	0.8497	0.6683	0.9471	0.7405	1.2964	1.0515	1.2008	0.8642	6%	6%
	4	**0.8062**	**0.6114**	0.9089	0.7302	0.9510	0.7484	1.3849	1.0718	1.3145	0.9356	11%	16%
	5	**0.8100**	**0.6261**	0.9722	0.7501	0.9851	0.7975	1.3901	1.1133	1.4256	0.9691	17%	17%
Ml-1M	1	**0.7697**	**0.6060**	0.8562	0.6816	0.9227	0.7497	1.1460	0.9069	1.0653	0.8965	10%	11%
	2	**0.7697**	**0.6060**	0.8656	0.6846	0.9537	0.7185	1.1947	0.9229	1.2969	0.9216	11%	11%
	3	**0.8343**	**0.6800**	0.8815	0.6749	0.9574	0.7407	1.2351	0.9688	1.5018	1.0156	5%	1%
	4	**0.8392**	**0.6690**	0.8864	0.6919	0.9903	0.7780	1.2551	0.9659	1.1684	0.9458	5%	3%
	5	**0.8516**	**0.6840**	0.9029	0.7203	1.0319	0.8067	1.3466	1.1054	1.2672	0.9176	6%	5%
FilmTrust	1	**0.7194**	**0.4298**	0.8498	1.4864	0.7808	0.5268	1.1229	0.8980	1.2433	1.1102	8%	18%
	2	**0.7423**	**0.4388**	0.8764	0.6787	0.8074	0.5232	1.1495	0.9246	1.4635	1.3304	8%	16%
	3	**0.7431**	**0.4390**	0.9831	1.4163	0.8509	0.4659	1.2562	1.0313	1.3643	1.2312	13%	6%
	4	**0.7761**	**0.4816**	0.9974	1.2130	0.8606	0.4893	1.2705	1.0456	1.3500	1.2169	10%	2%
	5	0.8798	0.5255	1.0966	0.9955	**0.8097**	**0.4802**	1.3697	1.1448	1.2168	1.0837	-8%	-9%

A similar improvement trend has been observed in Fig. 3 with 7.4% and 6.2% respectively for MovieLens' 1M dataset. Finally, Fig. 4 illustrates the performance of CBRP on FilmTrust's dataset which is slightly lower, but on average we achieved 6.2% and 6.6% reduced error rates. Overall, it can be seen that CBRP is apparently superior to other methods in term of RMSE and MAE. Fig. 5 portrays that the average prediction accuracy for every user-item pair is considerably lower than the other methods.

6 Conclusion

We have introduced a novel context-based rating prediction approach that is based on a unique context scoring scheme. The proposed method incorporates different contextual factors such as rating timestamp, ratings given by similar users in the system and a dynamic threshold level to consider a user in similarity pool or not. The proposed framework has three inputs; the subject user, the subject item and a rating matrix, and it generates a list of context scores for highly influential users for the subject user over the subject item. Our experimental results proved that the proposed similarity measure with valuable context information has improved the prediction accuracy that ultimately leads towards better Top-*N* recommendations as well. In future, the research can further be extended by incorporating more contextual conditions and it could be a key milestone for reliable recommendations.

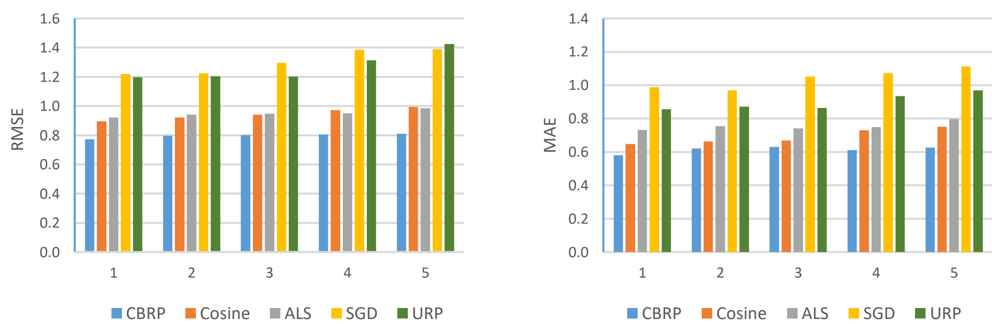

Figure 2: RMSE and MAE values on MovieLens 100K dataset

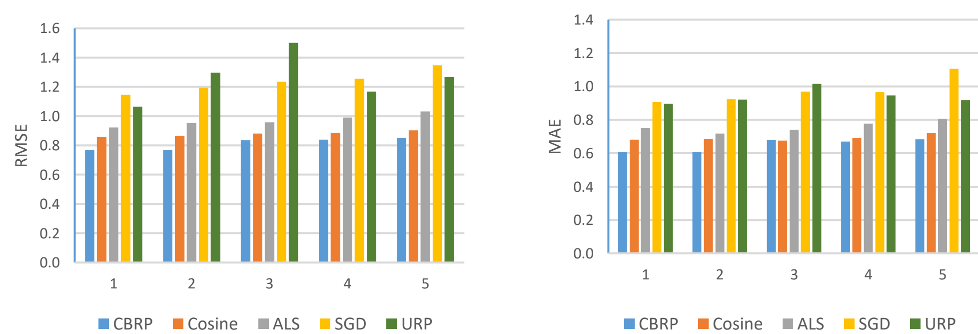

Figure 3: RMSE and MAE values on MovieLens 1M dataset

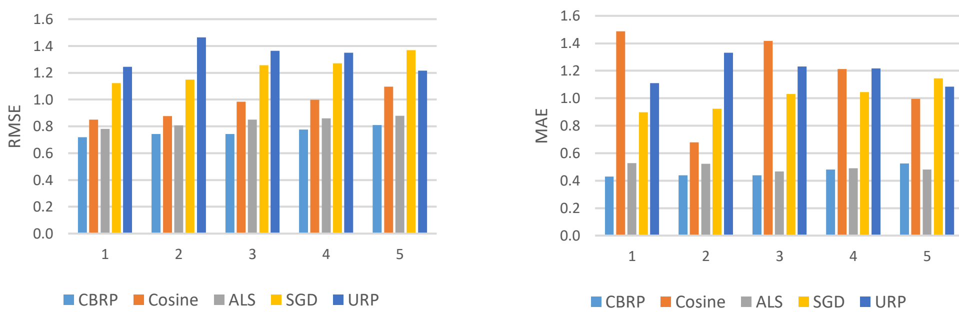

Figure 4: RMSE and MAE values on FilmTrust dataset

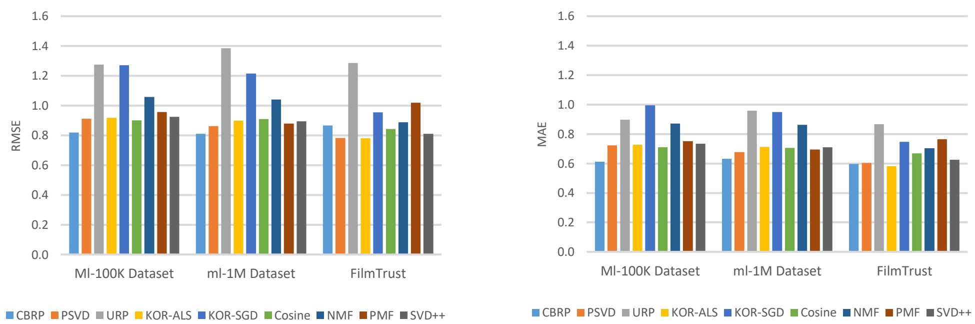

Figure 5: Results of average prediction accuracy for every user-item pair

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