



Research Paper

Hybrid Method of Recommender System to Decrement Cold Start and Sparse Data Issues

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Abstract

Background and Objectives: The primary purpose of recommender systems is to estimate the users' desires and provide a predicted list of items based on relevant data. Recommender systems that suggest items to users face two cold start and sparse data challenges.

Methods: This paper aims to propose a novel method to overcome such challenges in recommender systems. Singular value decomposition is a popular method to reduce sparse data in recommender systems by reducing dimensions. However, the basic singular value decomposition can only extract those feature vectors of users and items that may be recommended with lower recommendation precisions. Notably, using the similarity criteria between entities can reduce cold start to resolve the singular value decomposition problem by extracting more refined factor vectors. Besides, considering the context's dimensions as the third dimension of the matrix requires using another flexible algorithm, such as tensor factorization, which offers a viable solution to minimize the sparse data challenge. This study proposes TCSSVD, a novel method to resolve the challenges mentioned above in recommender systems. First, a two-level matrix is obtained using the similarity criteria between the user and the item to reduce the cold start challenge. In the second step, the contextual information is used by tensor in two-level singular value decomposition to reduce the challenge of sparse data.

Results: For reviewing the proposed method, these two data sets, IMDB and STS, were used because of applying user and item features and contextual information. The RMSE criterion (95% accuracy) was used to investigate the predictions' accuracy. However, since the user's rating of the item is particularly important in recommender systems, compared with other methods, such as tensor factorization, HOSVD, BPR, and CTLSVD, the TCSSVD method uses the following criteria: Precision, Recall, F1-score, and NDCG.

Conclusion: The findings indicated the positive effect of using the innovative similarity criteria on the extraction of user and item attributes to reduce the complications deriving from the cold start challenge. Also, the use of contextual information through the tensor in the TCSSVD method reduced the complications related to sparse data. The results improve the recommendation accuracy of the recommender systems.

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Introduction

The digital era has filled the lives of users with endless

lists of products and services. The number of products and services (items) in many cases is beyond what users

can handle. Also, the time spent rating every single option restricts users' selection. Recommender systems help users overcome such problems by collecting data from various sources to offer compatible items with their preferences or aims [45].

Recommender systems are classified into three types: collaborative filtering (CF), content filtering, and hybrid. The content-based method processes recommendations based on the similarity with users' previous preference. In other words, in that method, the existing items are compared with the previous items rated by the user to make recommendations. CF's underlying presumption is that users who agreed on something in the past tend to agree on it in the future. Therefore, CF searches for users with similar tastes and uses this information to generate predictions. A hybrid system is an accretion of CF and a content-based system [34].

CF techniques are generally divided into memory-based and model-based categories. Model-based approaches are first taught to apply the current information to be exerted later for estimating user ratings for new items. The singular value decomposition (SVD) algorithm is a popular matrix factorization (MF) technique. The decomposition of singular values creates a new space giving a new meaning to the relationship between users and items. Singular value decomposition (SVD) only considers the relationship between users and items to predict the likelihood of a user to like an item. However, it does not acquire more abstract features of the user and the item leading to the predictive rating's impreciseness. Therefore, to achieve a more precise predicted rating by exploiting more abstract features, we further decompose the user matrix and item matrix by SVD [10].

Tensor Factorization (TF) is an expanded version of MF, allowing preferable order tensor decomposition, and is used to determine the hidden parts within the data, which are represented as a multidimensional data structure [13].

The main challenges in the RS method are related to the cold start and sparse data. Sparse data is characterized by the low number of ratings for available items and the difficulty of finding a relationship between users and items [19], [40]. The factors related to cold start problems, including new users and new items, are significant issues hindering CF performance. In the case of a new user or a recently inactive user (consisting of ratings given to the items) in the system, the main challenge is to determine the item to the user. An item has zero ratings in the system when updated for the first time, hence the implausibility of item recommendation to the user [7].

The similarity criteria between users, items, and contextual dimensions are the solutions to the cold start

or sparse data challenges. CF techniques explain a similarity criterion to find an active user's neighbors or the items similar to the target item. The traditional similarity criteria, such as Pearson's correlation coefficient, cosine similarity, and their different types, are often used to calculate the similarity of a pair of users or between items [30]. Other popular metrics used in collaborative filterings, for instance, Bhattacharya Coefficient with correlation, NHSM, and PSS, are novel metrics [12]. The contextual dimensions in an RS consist of any information used to identify an entity. Villegas *et al.* divide the context into five categories: individual, location, time, activity, and relational contexts [52].

For the cold-start issue, recommender systems are designed based on the similarity criteria and MF methods. Similarly, to address the sparse data challenge, the MF method based on contextual information has been developed.

Our contributions are listed as follows:

- An MF method provides a similar measurement between users and items to use the existing data to resolve the cold start challenge in RS.
- The measurement of the proposed similarity between users and items in the RS framework is a generic method applicable to any recommendation domain. Here, the key idea is to use the available semantic features in users and items to make accuracy-improving recommendations.
- TCSSVD, as a MF method, that addresses the sparse data in an RS by the similarity matrix, similarity measurement of contextual information (individual, relational, activity, location, and time) as additional information, and feature tensor to improve the performance of recommendations.
- A set of experiments were conducted on IMDB and STS data sets to evaluate or justify the proposed method's contexts and users' similarity measures and recommend better items.

The remaining parts of this investigative article are ordered as follows: Second section discusses an overview of related works. The third section explains the proposed approach. Then, the fourth section describes TCSSVD. The fifth section provides a summary of the results and discussion. Finally, the last section deals with the conclusion and relevant recommendations for future research.

Related Works

This section surveys the techniques and challenges, the similarity criteria, contextual information, and hybrid methods associated with RSs. An RS is a set of information filtering tools that helps users in their information accessibility processes by prophecy and recommendations of items that can attract their attention [16].

Various techniques have been used in recommender systems: MF [10], KNN [58], neural network [24], decision tree [28], fuzzy [49], clustering [18], association rules [51], genetic [29], Bayesian [32], and graph [35].

Hoang Son conducted a comparative reading of the cold-start challenge in an RS [48] and proposed two solutions:

1. Investigating the recommender process by the MF and Bayesian methods [32] or using latent topical models like an MF [11], [36].

2. Using the similarity criteria in the preferences of the user [55], demographic data [4], [54], social data [15], [16], etc.

Idrissi & Zellou. The SLR is utilized to analyze the existing partnerships and efforts using new tools and concepts to reduce the sparse data problem. RS involves two common ways to solve sparse data [26]:

1. Machine learning techniques (MF, TF) and few other computing techniques try alleviating the sparse data challenge [26].

2. The problem is to find the weights or the similarity criteria of different contextual information and use them to use in recommendation techniques [53]. Machine learning methods are efficient in reducing the sparse data challenge for RSs by asking users to rate random items when entering the systems [15].

MF can reveal latent features that exhibit the interactions between three different kinds of entities (users, items, and context) [36]. Ren et al. proposed the TGSC-PMF method based on MF for recommendation making following the user's favorite point of view deriving from spatial correlation to resolve the sparse data challenge using the data extracted from the site [42]. An approach has also been developed using a biased MF technique to predict rating and Bayesian Personalized Ranking (BPR). The stochastic gradient descent (SGD) based optimization method has been developed to learn context-related parameters and latent factors of users and items [32].

SVD is one of the most widely used MF techniques based on dimensionality reduction, mainly used to solve the sparse data challenge in an RS [34]. SVD combined with demographics improves the recommendation performance [54], semantic SVD++ [44] and imputation-SVD [58]. A new MF method called enhanced SVD (ESVD) has been proposed that includes the basic MF algorithms with rating repletion based on active learning [15].

Cui et al. used a two-level MF technique called CTLSVD, which divides the challenge into two U matrices with user characteristics and I-matrix property. It also filters out inappropriate items to solve the sparse data challenge. Then, they combined it with the context (time) dimension and created the CTLSVD matrix to

examine the time dynamics based on users' preferences for time-based item [10].

TF is an MF technique to reduce each tensor (multidimensional array) to smaller-dimension vectors. The tensor uses different contexts in the multi-faceted interactions of the user-item relationship in the recommendation process [6].

There are many algorithms with specific features for an RS [30]. The similarity criteria including Pearson Correlation Coefficient [41], Cosine [4], and Jaccard [37] are mostly used by recommendation systems. The similarity criteria to solve some cold start challenges, such as MIPFGWC-CS [48], NHSM [48], and RES [50]

Using MIPFGWC-CS, fuzzy geographic clustering aims to identify similar users based on the demographic characteristics of a cold start challenge [48].

NHSM is used to replace the Pearson coefficient or the cosine similarity criteria. This exploratory similarity criterion is composed of PSS features, incorporates the improved Jaccard into the user rating distinction in the design [48]. Inspired by a physical resonance phenomenon named RES, Tan et al. proposed a new similarity criterion to address the cold start challenge. By conducting mathematical modeling compatible with users' rating behaviors, RES estimates the distances between user beliefs and the Jaccard factor with co-relevant and non-relevant ratings [50]. Gongna et al. used the information related to users' demography and item grouping to improve prophecy accuracy. The recommender systems' method and item grouping based on the existing metadata and their latent factor vectors have been specified for one or several classes so that these classes have distinct group labels [14].

SHAN et al. expanded a nonlinearly mindful similarity model via locally attentive embedding. NASM has been developed based on a neural mindful item similarity (NAIS) model and performs significantly better [47].

Algorithms such as PSS [23], URP [33], O-CHSM [12] E-CHSM [12] are the most popular similarity criteria for reducing sparse data using contextual information [12].

The PSS algorithm considers three factors to determine the similarity in recommender systems, especially with the context information's entry. Proximity determines the agreement/disagreement between the two ratings and assigns penalties to disagreement. Then, the significance is determined based on item importance. Singularity exhibits the difference of two ratings from their average rating [23].

The URP algorithm specifically evaluates users who share similarities with items. Some users rate items as so high or so low. Users are prioritized based on the average variance of their given ratings to reflect users' behavior [33].

The E-CHSM algorithm uses skin metering instead of overlapping for field similarity. Proposing similarity measures suggests overcoming traditional and appropriate similarity measures for scattered data, especially knowledge-based data set. The skin criterion is a trait that gives a relatively large weight to the mismatch of traits with higher categories [12].

The O-CHSM algorithm considers the Bhattacharyya coefficient for global rankings, the NHSM ratios of standard ratings, global user behavior, and priorities. Also, it is readily incorporated into other measurements [12].

A recommended approach based on a prediction method uses the behavioral information extracted from the similarity criteria to classify users and reduce the cold start challenge [15]. The similarity criteria driven from social network data should be used to reduce cold start and sparse data in RSs [7], [8].

The demographic criteria are one of the similarity criteria, especially among users. Recommender systems [46] classify users based on their demographic information, such as age, gender, seasonality, occupation, nationality, and preference. The advantage of this technique is it helps resolve the cold start challenge [3].

Yang et al. proposed a meta feature-based unified framework (MERF) to make cold-start recommendations without the need for historical rating records, focusing only on item features. They proposed a Personalized Feature Preference (PFP) vector to characterize the item features' different importance to a user. They also proposed a parallel learning algorithm and an incremental updating algorithm for PFP to improve MERF efficiency [57].

The similarity-based contextual recommendation is incorporated into the sparse linear method and MF as two base algorithms [61]. Generally, MF algorithms reduce cold start by combining other methods with the similarity criteria. Wang et al. estimated a cold start challenge model based on MF for every decision tree node [54].

Karimi et al. proposed an MF method for challenging cold start in RSs, in which they first use the latent factors to find new users similar to the existing users. Then, they choose the highest-rated item among similar users. Thus, the new user can rate an item that users have already rated with similar behavior [20]. Braunhofer proposed a demographic, contextual MF (CAMF-CC) based on the demographic method (gender, age group, personality traits) to reduce the cold start challenge. The performance of this SPF pre-filtering algorithm shows better performance for contextual conditions [4].

Using SVD with other techniques and context similarity criteria methods reduces the sparse data challenge. Reddy et al. used the APPRO SVD algorithm

based on CF to reduce sparse data challenge. In fact, they used this method of Euclidean distance as a similarity criterion to find the KNN [43]. A normalization SVD technique to model user contention for a cold start challenge or their tendency based on the particularity of items was used in the KNN models. The proposed normalization technique was appraised using two data sets, Movie Lens and Group Lens [59].

The limited research that addresses the evolutionary MF algorithm has concerning the similarity criteria is used to reduce both the challenges mentioned thus far. Codina et al. first used the SPF algorithm scattering S conditions and cosine similarity between vectors to reduce the cold start challenge, which uses context conditions according to implicit semantic relationships. It then uses the X_s training set to reduce sparse data to build local scoring [9]. Rafalides et al. first used the initial feedback learning tagging method followed by the item clustering methods, such as k-means and Tensor-based SVD, to reduce sparse data and cold start challenges [38]. Besides, social trust and SVD methods are used to resolve sparse data and cold start challenges [56].

Natarajan et al. proposed a new method to reduce the sparse data and the cold start challenges in CF. To the cold start challenge, RSs with Linked Open Data (LOD) model has been designed, and for sparse data challenge, the MF model based on SVD with Linked Open Data has been expanded. LOD similarity is a composition of improvised PCC and similarity PICSS used to detect semantically similar items of a target item to develop an item-factor vector in the SVD process. The experiments on Netflix and Movie Lens data sets represent the priority of the proposed techniques related to other available methods that improve the recommendation precision [34].

As mentioned earlier, the major challenges of recommending systems are the cold start and sparse data. CF and a content-filtering system should be used with demographic criteria to solve the cold start challenge [4]. The following measures should be taken to reduce sparse data: Personalized feature preference [57] Social trust [56] Linked open data [34]. Features of various context dimensions in context discussion such as using context composition [35] SVD matrix [8], [9], [56] items rated by users with similar relational context to new users by the MF [10], [20], [60].

Proposed approach

The proposed method, as shown in Fig. 1, is based on MF with a focus on the similarity criteria (users-items-contextual) and tensor concepts. Conversely, TCSSVD-based developed RSs take the semantic features of items or users and dimension context used to handle the cold

start and sparse data issues in RSs. Hence, the accuracy of the given suggestions is improved in RSs. Figure 1 illustrates an overview of the RS presented technique.

Table 1 shows the signs used to implement the proposed method. In the first step of the user demographic matrix, the properties of the item are designed.

In the second step, the user-item similarity matrix is obtained by comparing the user-item feature matrix with the user-item matrix. The user-item similarity matrix with the contextual information is created through the properties, and momentum stochastic gradient descent [17].

Table 1: Signs of TCSSVD algorithms

Symbol	Description	Symbol	Description
u	A user	R	User-item matrix
i	An item	τ	Latent features central tensor
c	A contextual condition	S	Latent features context matrix
x	Number of user demographic features	Y	User-item-context ratings tensor
y	Number of item characteristics features	b_u	The bias of user u
t	Number of user context features	b_i	The bias of item i
U	A set of users	b_c	The bias of context c
I	A set of items	μ	The average rating for all items
M	User matrix	ρ	Context weight measure
N	Item matrix	W	Similarity measure between users
D	User demographic feature matrix	V	Similarity measure between items
E	Item feature matrix	Z	Similarity measure between contexts
P	Latent matrix of user feature matrix	α	Learning rate
Q	Latent matrix of item feature matrix	β	Regularization parameter
F	User-item feature matrix	λ	Momentum
A	User-item similarity matrix	$\hat{r}_{u,i,c}$	The predicted rating that user u would give to item i with context

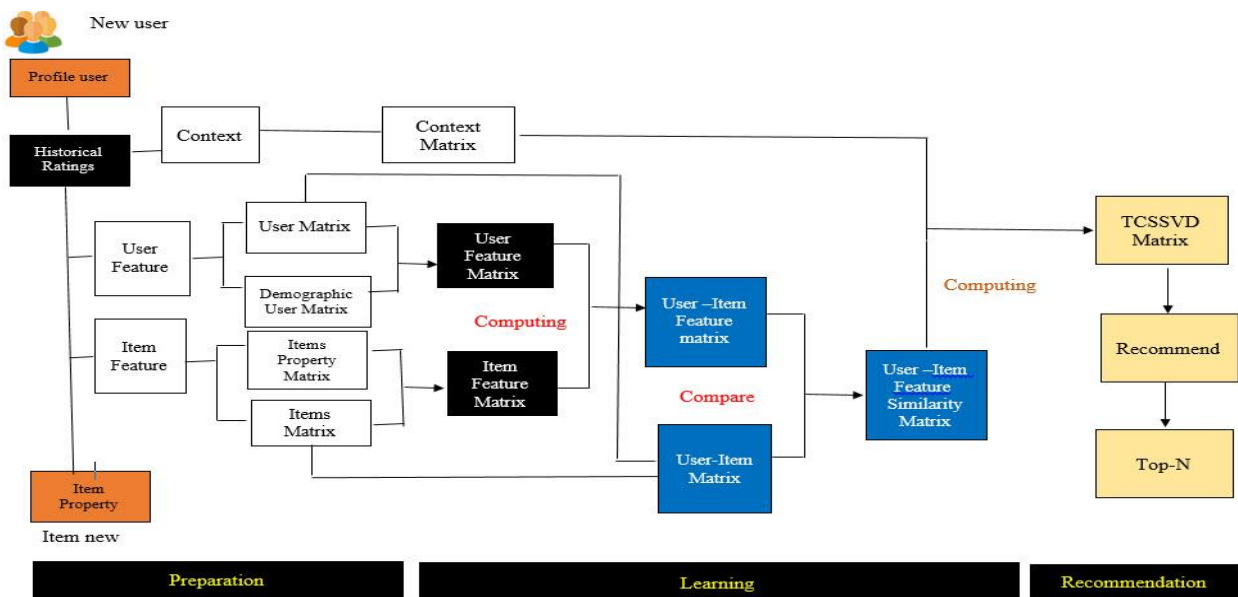


Fig. 1: The structure of proposed scheme.

TCSSVD method

As mentioned, the cold start challenge occurs when a new user enters a system or users who have been in the system for some time do not make any activity. However, new items that have recently entered the system also aggregate such challenges. SVD is a popular recommending algorithm. However, the original SVD can only extract the vector of users and items, preventing further feature refinement and damage recommendations accuracy. As mentioned above, this paper proposes an SVD-based similarity matrix that breaks down the user and item matrix into user demographics, item features, and contextual information to obtain a matrix from more refined features and improves result accuracy and user satisfaction. Users with sharing common features

generally decide based on each other's opinions.

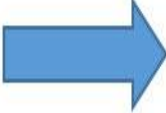
Therefore, this feature is used to solve the cold start challenge reduction for users who have recently logged in or have not shown any system performance. It is used to find similarities between users through the (1).

$$W(obj_a, obj_b) = \frac{\sum_{d=1}^x W_d(obj_{ad}, obj_{bd})}{x} \quad (1)$$

where d is the specific demographic feature of the user, and x is used to represent the total number of user demographic feature and obj_{ad} means the d -th attribute of the object obj_a . $obj_{bd} = obj_{ad}$ then the value of $W_d(obj_{ad}, obj_{bd})=1$; otherwise, it is 0.

With the assumption of 4 demographic variables, comparing four users based on the similarity criteria mentioned in (1) requires taking the following steps to construct the user's demographic feature matrix:

	D1	D2	D3	D4
U1	Denmark	Copenhagen	Man	30
U2	Denmark	Odense	Man	28
U3	Uk	London	Female	26
U4	France	Nice	Man	35



	D1	D2	D3	D4
D1	1	$\frac{2}{4}$	0	$\frac{1}{4}$
D2	$\frac{2}{4}$	1	0	$\frac{1}{4}$
D3	0	0	1	0
D4	$\frac{1}{4}$	$\frac{1}{4}$	0	1

Fig. 2: A view of the user demographic feature matrix.

However, new items that enter the system resemble the items within the system. Hence, the peculiarity of item features to suggest new items in these systems is one solution to overcome the cold start challenge.

Equation (2) is used to find the similarities between items.

$$V(obj_a, obj_b) = \frac{\sum_{e=1}^y V_e(obj_{ae}, obj_{be})}{y} \quad (2)$$

where e is a specific feature of the item, and y is used to represent the total number of specific feature item and obj_{ae} means the attribute of the object obj_a . If $obj_{be} = obj_{ae}$ then the value of $V_e(obj_{ae}, obj_{be})=1$; otherwise, it is 0.

The following steps should be taken to construct the item feature matrix to compare these nine items based on the similarity criteria mentioned in (2), with the assumption of 9 item-specific feature variables. The second step, which is created by multiplying the

two matrices of user properties (P) and item properties (Q), creates the user-item matrix of items (F). In the construction of the matrix of user-item (F) properties, a decrease in k rank is used to reduce the dimensions. Moreover, a matrix of single values is created based on a decrease rank. In fact, k is considered the minimum reduction rank of x and y .

$$F_{u,i} = p_{uk} \sigma_{kk} q_{ik}^T \quad (3)$$

This study used the PSS similarity measure to compare the user-item feature matrix (F) with the SVD matrix (R), which is made by multiplying the user-item matrix based on the user ratings. The three main elements of the PSS similarity measure, including proximity, significance, and singularity can be considered based on (4).

Proximity whether or not the two score ranks in the two matrices agree Importance, the degree of importance of the desired rank is in the two matrices.

	E1	E2	E3	E4	E5	E6	E7	E8	E9
I1	1378	61	862	18	7	2010	9	37	346
I2	309	1622	704	21	14	2003	9	37	493
I3	939	1562	1857	14	1	2010	9	37	98
I4	535	513	172	1	7	2003	9	37	158
I5	497	699	1622	3	1	2010	9	37	396
I6	1562	1404	127	21	8	2009	9	37	542
I7	660	513	1679	7	6	2002	9	37	253
I8	1840	98	127	17	10	2001	9	37	506
I9	366	1744	1504	7	1	2010	9	37	806



	I1	I2	I3	I4	I5	I6	I7	I8	I9
I1	1	$\frac{2}{9}$	$\frac{3}{9}$	$\frac{3}{9}$	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{3}{9}$
I2	$\frac{2}{9}$	1	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$
I3	$\frac{3}{9}$	$\frac{2}{9}$	1	$\frac{2}{9}$	$\frac{4}{9}$	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{4}{9}$
I4	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	1	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$
I5	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{4}{9}$	$\frac{2}{9}$	1	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{3}{9}$
I6	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{3}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	1	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{3}{9}$
I7	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	1	$\frac{2}{9}$	$\frac{3}{9}$
I8	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{2}{9}$	1	$\frac{2}{9}$
I9	$\frac{2}{9}$	$\frac{2}{9}$	$\frac{4}{9}$	$\frac{2}{9}$	$\frac{3}{9}$	$\frac{3}{9}$	$\frac{3}{9}$	$\frac{2}{9}$	1

Fig. 3: A view of the specific feature item matrix.

Uniquely, the difference in rank is the average of the ranking points in the two matrices. The PSS similarity measure is used to compare the two mentioned matrices and create a similarity SVD matrix. The similarity SVD matrix is obtainable from the more abstract factors (such as item features, lead actor, and user demographics). This way, the similarity matrix can reduce the problem of cold start in new users and items.

$$\begin{aligned}
 \text{Proximity}(f_{a,b} - r_{a,b}) &= 1 - \frac{1}{1 + \exp(-|f_{a,b} - r_{a,b}|)} \\
 \text{Significance}(f_{a,b} - r_{a,b}) &= \frac{1}{1 - \frac{1}{1 + \exp(-|f_{a,b} - f_{med}| * |r_{a,b} - r_{med}|)}} \\
 \text{Singularity}(f_{u,a} - r_{v,b}) &= \frac{1}{1 - \frac{1}{1 + \exp(-|((f_{u,a} - f_a) + (r_{v,b} - r_b))/2|)}}
 \end{aligned} \quad (4)$$

The similarity singular value decomposition matrix was able to somewhat reduce the cold start challenge; however, it still has a rating matrix obtained from those unrated points. In other words, the resulting matrix faces the sparse data challenge. The K cross-validation was based on the RMSE criterion to ensure all users' participation in rating items, to the extent that the obtained results were generalizable independent of the data. The RMSE measure in k repeats is less than the specific value of p , indicating that the item has not been rated by the user, hence the sparse data challenge.

Context dimensions in the SVD matrix features are used to reduce the challenge of sparse data, which were divided into five categories: relational, individual, activity, location, and time. The similarity measure (context weight performance) is used to calculate the contextual matrix.

For each of these categories, the standard dimensionality (ω) is considered for the search. If the user approves the criterion, the weight is one; otherwise, it is 0. Equation (5) is used to find the similarities between contexts.

$$Z(obj_a, obj_b) = \frac{\sum_{c=1}^t \omega Z_c(obj_{ac}, obj_{bc})}{t} \quad (5)$$

where c is a specific context of the user, and t is used to represent the total number of specific context feature and obj_{ac} means the c -the attribute of the object obj_a . If $obj_{bc} = obj_{ac}$ then the value of $Z_c(obj_{ac}, obj_{bc}) = 1$; otherwise, it is 0.

The following steps should be taken to construct the latent context matrix to compare these five context variables based on the similarity measure mentioned in (5), with the assumption of 5 users. Finally, a tensor MF was formed in an SVD matrix called TCSSVD. Besides, tensors are used in the matrix to minimize calculations and optimize the results, leading the three-dimensional matrices to have a higher performance and presentation of more suitable items to users. Regarding that, (6) calculates the actual value of r_{uic} . The approximate rate of user u to item i in field c is the actual value of r_{uic} . In (7), r_{uic} shows the predicted rate of i item selected by u user in c context. In this equation, μ is the mean score for all items, including b_u , b_i , and b_c , respectively, the average deviation of user u from the mean of the total rate the mean deviation of items i from the mean of the total rate, and the mean deviation of the mean of the c context. The study used the learning rate α and the regulatory parameter β to update the mean deviation of the items, users, and contexts. In (8), the error measure

is obtained from the difference between the actual value of r_{uic} and the prediction rate $\hat{r}_{uic}$. In (9), the study used

momentum stochastic gradient descent (MSGD) [39] through the coefficient of momentum (λ).



	U1	U2	U3	U4	U5
C1	Happy	positive	only	holiday	3repetitions
C2	Fear	Neutral	Family	Weekend	-1
C3	Surprised	-1	Weekend	Partner	2repetitions
C4	-1	Negative	-1	Official	-1
C5	Angry	-1	only	Official	-1

	C1	C2	C3	C4	C5
C1	1	0	0	0	$\frac{1}{5}$
C2	0	1	0	0	0
C3	0	0	1	0	0
C4	0	0	0	1	$\frac{1}{5}$
C5	$\frac{1}{5}$	0	0	$\frac{1}{5}$	1

Fig. 4: View of the context matrix

$$r_{uic} = \sum_{k=1}^K P_{uk} Q_{ik} S_{ck} \quad (6)$$

$$\begin{aligned} \hat{r}_{uic} &= \mu + b_u + b_i + b_c + \sum_{k=1}^K P_{uk} Q_{ik} S_{ck} \\ b_u &= b_u + \alpha \cdot (e_{ui} - \beta \cdot b_u) \\ b_i &= b_i + \alpha \cdot (e_{ui} - \beta \cdot b_i) \\ b_c &= b_c + \alpha \cdot (e_{ui} - \beta \cdot b_c) \end{aligned} \quad (7)$$

$$e_{uic} = r_{uic} - \hat{r}_{uic} \quad (8)$$

$$\begin{aligned} P_u &= \lambda \cdot P_u + \alpha \cdot (e_{ui} \cdot Q_i S_c - \beta \cdot P_u) \\ Q_i &= \lambda \cdot Q_i + \alpha \cdot (e_{ui} \cdot P_u S_c - \beta \cdot Q_i) \\ S_c &= \lambda \cdot S_c + \alpha \cdot (e_{ui} \cdot P_u Q_i - \beta \cdot S_c) \end{aligned} \quad (9)$$

In the training process of the method presented in the TCSSVD matrix, the available parameters can be calculated by minimizing possible connections and errors using Fresenius norms based on (10):

$$L = \frac{1}{2} (e_{uic})^2 + \frac{\beta}{2} (\|P_u\|^2 + \|Q_i\|^2 + \|S_c\|^2 + b_u^2 + b_i^2 + b_c^2) \quad (10)$$

The New Heuristic Context Similarity Measure (NHCSM) method is used to calculate proposal based on (11) to estimate the similarity measure between k, the initial item, proposal, and the n item. Table 2 shows the pseudo-code of the TCSSVD algorithm.

$$\begin{aligned} Sim(a, b)^{NHCSM} &= \\ Sim(a, b)^{UDP} * Sim(a, b)^{IFP} * Sim(a, b)^{PSS} * Sim(a, b)^{CWP} \end{aligned} \quad (11)$$

Table 2: The pseudo-code of TCSSVD algorithm

Algorithm: Tensor Context Similarity Matrix Algorithm (TCSSVD)

Input: target users $\mathbf{u}_{target}$, new user, new item, rating matrix r , k , top- n
Output: The n recommended item for target users $\mathbf{u}_{target}$

Compute the average rating(μ)
initialize $b_u, b_i, b_c, e_{uic}, \hat{r}_{uic}$
Initialize matrices P, Q, S
While $RMSE < \rho$
 for each user u do
 Use (1) Calculate $\mathbf{W}$ (**new user ,user**)
 for each item i do
 Use (2) Calculate $\mathbf{V}$ (**new item ,item**)
 for each context c do
 Use (5) Calculate $\mathbf{Z}$ (**context new entity ,context other entity**)
 if $r(u, i, c) \neq 0$
 Use (7) predict rating
 Compute e_{uic}
 Use (9) update the matrices P, Q, S
 end if
 end for
 end for
 end for
 calculate RMSE
end while
Predict unknown rating based on (7)

Select the k recommended item to the target users $\mathbf{u}_{target}$
Calculate the similarity between r_{uic} **and the** k recommended item using (11)
Select the k recommended item final to the target users $\mathbf{u}_{target}$
Select the n recommended item in the K items recommend to the target users $\mathbf{u}_{target}$

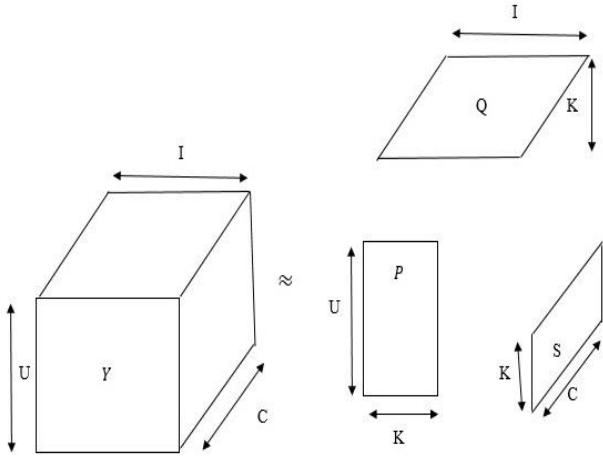


Fig. 5: A view of the TCSSVD matrix.

Results and Discussion

In this section, IMDB and STS data sets are used to evaluate the proposed method's performance. We compare the TF, HOSVD, BPR, and CTLSVD methods with Precision, Recall, F1-score, and NDCG.

A. Datasets

To create and appraise RS's efficiency, data set with all the related contextual information play an essential role [21].

The LDOS-CoMoDa [27] data set has various contextual attributes, like emotions and mood [26]. The IMDB data set includes information collected from the survey where the respondents have explicitly answered such dynamic contexts [4], [9], [11], [25], [60].

The created database is taken from the LDOS-CoMoDa database and the CIL group database is taken from a rich data set of videos suggested by IMDB, including the order number, user number, item number, and the level of the user's interest in the item. The suggested numbers range from 1 to 5. This data set including 1088 users and 2455 items and a total of more than 20759 have been examined. In fact, it is time for the user to use the item [1]. The context dimension consists of twelve variables, including time, day type, season, location, weather, social endEmo, dominantEmo, mood, physical, decision, and interaction.

The database created by STS [4], [5] is taken from a tourism-related android mobile app in Italy [22] and includes the user number, users' demographics, the item number, item characteristics, and the user's level of interest in the item (an offer ranging from 1 to 5). This data set covers 1625 users and 498 items and a total of more than 12675. The contextual information consists of 14 variables, including time, the available, season, daytime, mood, weather, emotional stability, temperature, budget, agreeableness, openness to experience, transport, companion, distance, and goal

travel [5]. The original data set was split into two subsets for appraising different approaches: an 80% share was allocated to the train data set, and the remaining 20% was allocated to the test data set. The data set used in the training set is intended for calculating.

Table 3: Details of IMDB and STS data set

Data set	IMDB	STS
Users	1088	1625
Movies	2455	498
Context	12	14
Ratings	20759	12675

B. Evaluation Metrics

Evaluation measures are used in RS to evaluate the accuracy and efficiency of the methods used. The evaluation measure calculates mean squared error (MSE), mean absolute error (MAE), and K cross-validation errors between the actual rating of an item and the predicted rating in the RS [7].

K cross-validation determines the generalizability and independence of analysis results on a data set compared with the educational data [14], [31], [60].

For there to be no users who have not rated an item, hence the K cross-validation based on the root mean square error (RMSE) measure to the extent that the results presented can be generalized and independent of the data.

$$RMSE = \sqrt{\frac{\sum_{u,i} (R_{u,i} - \hat{R}_{u,i})^2}{|R|}} \quad (12)$$

R contains the actual rating values, $\hat{R}$ consist of predicted ratings and $|R|$ is the cardinality of the rating matrix. Quality evaluation deals with measuring the recommendations to determine the level of system learning, including precision, recall, and f-score, and normalized discounted cumulative gain (NDCG) [25].

This study recovered the Top-N recommendations as a ranked list of current offers to users. Therefore, the mentioned system learning levels were used to appraise the proposed approach's quality and effective recommendation [7].

Recall measure ratio of the number of recommendations is exactly the number of interest items to the user. Recall is defined as in (13) [25], [34], [43].

$$Recall = \frac{\text{correct prediction}}{\text{total relevant items}} \quad (13)$$

The precision determines the correct recommendations' ratio to the provided recommendations [25], [34], [43]. Precision is defined as

in (14).

$$\text{Precision} = \frac{\text{correct predictions}}{\text{total predictions}} \quad (14)$$

The F-score measure can be described as a harmonic average of the precision and recall [25], [34], [43].

F-score is defined in (15).

$$\text{F-score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (15)$$

The normalized discounted cumulative gain was measured to evaluate the quality of recommendations to determine the amount of learning in an RS. A higher NDCG value for a list of recommended items indicates a higher rank of the list's related items. NDCG@N measures the relationship of Top-N results and is defined in (16) [9], [58].

$$\text{NDCG} = \frac{\text{DCG@N}}{\text{idcg@N}} \quad (16)$$

DCG@N : Value of the ideal ranking list.

$$\text{idcg} = \text{rel}_1 + \sum_{i=2}^{\text{pos}} \frac{\text{rel}_i}{\log_2^2} \quad (17)$$

pos : Situation up to which the relationship is accumulated.

rel_i : Recommendation relationship at situation i

The simulations were conducted using Python on a computer equipped with a 3.2 GHz Intel Core i7 processor and 12GB of Ram.

The following Python libraries were used for analyzing the anaconda software collection: NumPy, Panda, and Tensor Flow.

C. Comparisons Methods

The study's method was compared with HOSVD, BPR, TF, and CTLSVD methods for efficiency improvement.

- TF assumes that the rating tensor from users, items, and types of context can be factorized into a product of three low-rank matrices [55].
- The most well-known TF uses the tensor matrix kernel for the decomposition of individual values and its conversion to the HOSVD [5].
- Bayesian Personalized Ranking (BPR) with SGD based optimization procedure applies to sparse data challenge alleviation. The rating prediction is generated by sorting the target user's preference scores to candidate items, which are calculated as the user's inner product of latent factors, and the items with contextual information are considered in this method [31].
- CTLSVD algorithm decomposes the user, and the item features matrices again to obtain a more refined feature matrix. CTLSVD combines the contextual information with the TLSVD algorithm [10].

D. Results

The proposed TCSSVD was compared with the TF, HOSVD, BPR, and CTLSVD methods for performance validity check to evaluate the expressed methods based on the evaluation criteria precision, Recall, F1-score, and NDCG.

As reported in Table 4, the proposed approach performed better than the HOSVD, BPR, TF, and CTLSVD methods.

Since the contextual information can potentially reduce the sparse data, the contextual information is one of the influential factors in the evaluated methods.

TF methods poorly correlate with contextual information. Also, disregarding the similarity criteria between users and items can reduce suggestions' accuracy.

In HOSVD, the tensors are utilized in TF, but the multidimensional decomposition can use this method over the TF method.

The BPR method was used to learn the related parameters and latent factors of users, items, and contexts. The learning rate was used to estimate the recommendations' accuracy compared to the TF and HOSVD method in the data set IMDB and STS.

CTLSVD method decomposes the user feature matrix and the item feature matrix by SVD and adds the contextual information.

The same use of feature matrix and the item characteristic make the proposed method superior to the TF, HOSVD, and BPR methods by entering contextual information. The better performance of TCSSVD compared to CTLSVD relies on using the similarity criteria between users - items - contexts and the possibility of comparing the similarity matrix. Figure 6 and Fig. 7 represent the methods with precision, recall, and F-score criteria on IMDB and STS data sets, respectively.

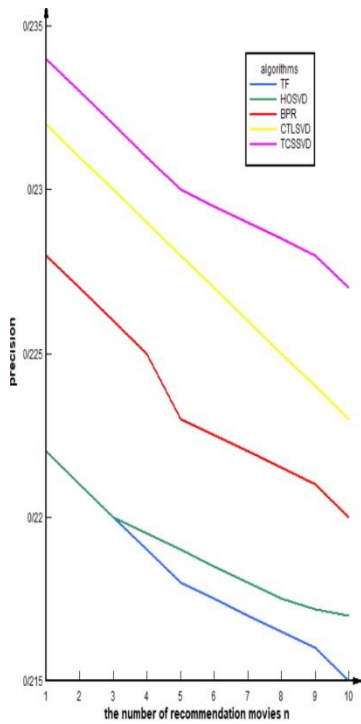
In all settings, the TCSSVD method outperforms other methods, demonstrating the advantage of the direct effect of contextual information on latent factors to learn context-aware latent representations. The latent factors are extracted in the users, and items and contextual information are considered. However, this observation shows that TF, HOSVD, BPR, and CTLSVD methods apply to reduce sparse data, but the TCSSVD approach can overcome the sparse data and cold start challenges.

The implicit ratings are evaluated to the Top-N predicted by different sequential approaches to calculating the NDCG of the recommendations.

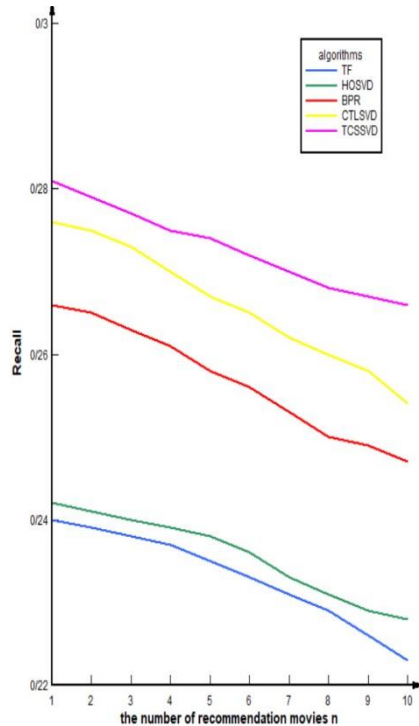
Figure 8 demonstrates the ranking effectiveness of the sequence recommendation approaches in terms of NDCG. Results indicate that the evaluated TF, HOSVD, BPR, and CTLSVD approaches predicted more relevant recommendations.

Table 4: Performance comparison

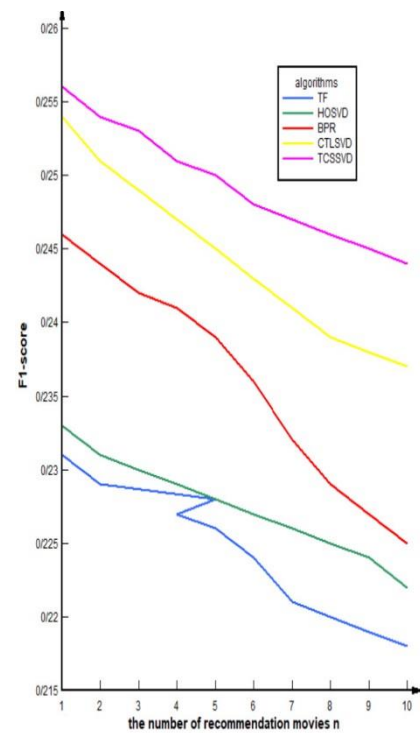
Method	Top	IMDB			STS		
		Precision	Recall	F-score	Precision	Recall	F-score
CSSVD	2	0.233	0.261	0.246	0.361	0.325	0.342
	5	0.230	0.264	0.245	0.353	0.331	0.341
	10	0.227	0.271	0.247	0.342	0.336	0.339
CTLSVD	2	0.231	0.257	0.243	0.331	0.307	0.318
	5	0.228	0.262	0.242	0.323	0.315	0.319
	10	0.223	0.269	0.244	0.318	0.321	0.320
BPR	2	0.227	0.246	0.236	0.313	0.266	0.287
	5	0.223	0.251	0.237	0.306	0.271	0.288
	10	0.220	0.256	0.236	0.295	0.278	0.286
HOSVD	2	0.222	0.233	0.227	0.297	0.256	0.274
	5	0.219	0.238	0.229	0.293	0.259	0.275
	10	0.217	0.241	0.228	0.289	0.264	0.276
TF	2	0.221	0.232	0.226	0.295	0.252	0.271
	5	0.218	0.234	0.225	0.291	0.258	0.274
	10	0.215	0.239	0.226	0.287	0.262	0.273



a) Precision



b) Recall



c) F-score

Fig. 6: The precision, recall and F-score of TF, HOSVD, BPR, CTLSVD and TCSSVD number of recommendations (IMDB).

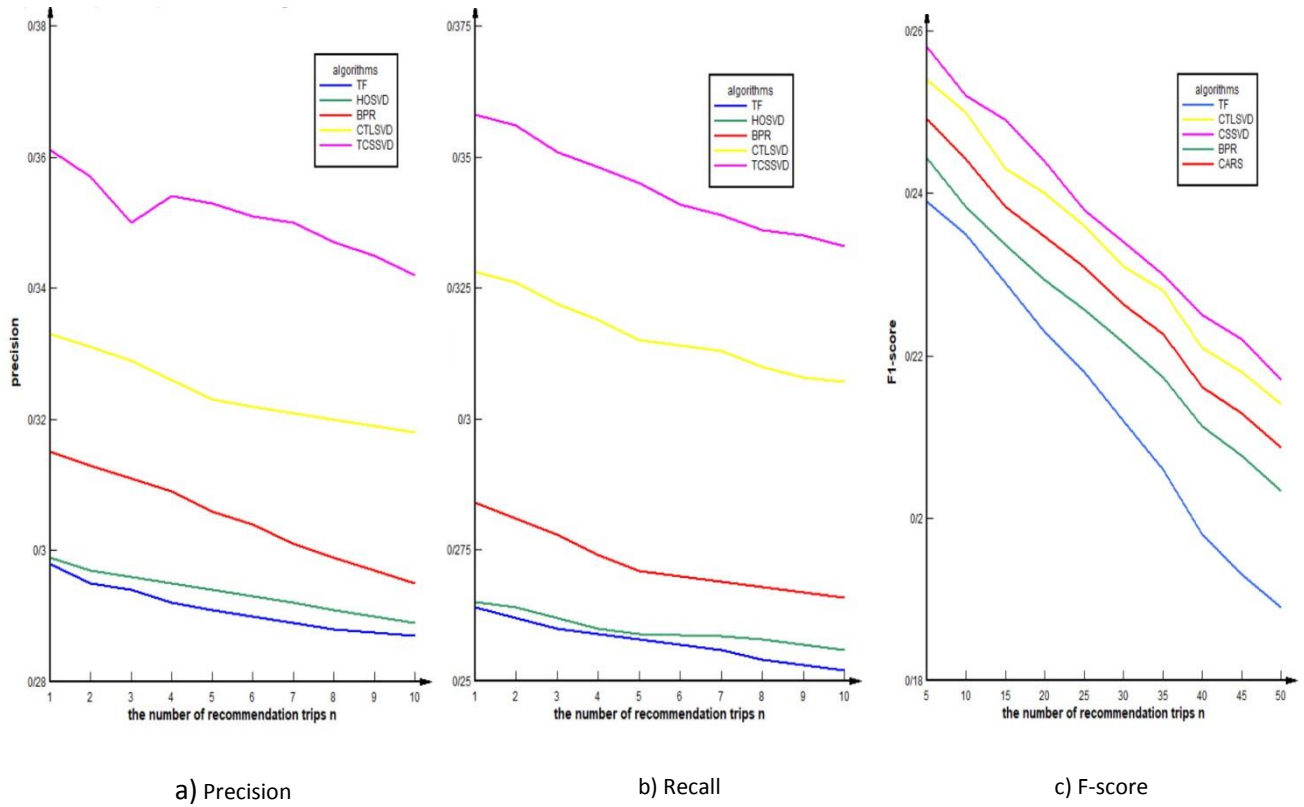


Fig. 7: The precision, Recall and F-score of TF, HOSVD, BPR, CTLSVD and TCSSVD number of recommendations (STS).

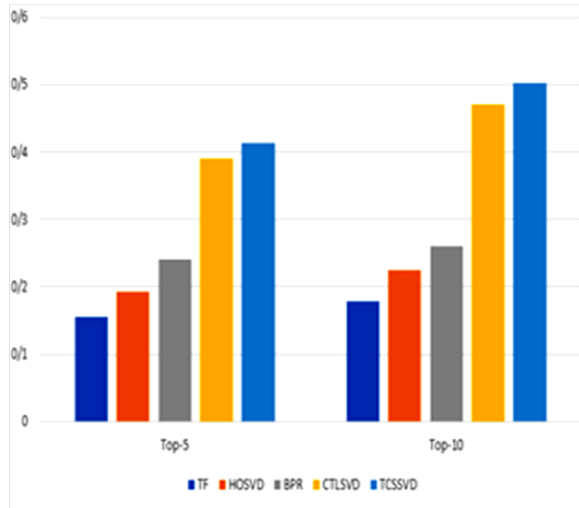


Fig. 8: NDCG measure for different approaches against the top number of recommendations.

Conclusion

This paper proposes a new technique that utilizes a similarity singular value decomposition matrix after reducing the cold start challenge using demographic and item features.

TCSSVD matrix was created using the tensor and contextual information and understanding the dimensions to reduce items not rated for users, also known as the sparse data.

Firstly, users' measured demographics and item property features were used to design the user-item feature matrix besides the PSS similarity measure to create a user-item similarity matrix to reduce the cold start challenge.

Finally, using the resulting matrix of a three-dimensional matrix to reduce calculations and higher convergence speed led to the utilization of the tensor property and the momentum stochastic gradient descent.

Based on results, the proposed technique resulted in an improvement, compared with the TF [6], [55], HOSVD [5], [36], BPR [31], [32] and CTLSVD methods [10].

In future work, we can use other machine learning techniques, such as neural network and LSTM techniques combined with the similarity, LOD, social data, and context criteria, to further improve the recommendations' performance.

Author Contributions

K. Vahidy Rodpysh, S.J. Mirabedini and T. Baniroostam conceived of the presented idea. K. Vahidy Rodpysh developed the theory and performed the computations. S.J. Mirabedini and T. Baniroostam verified the analytical methods. S.J. Mirabedini encouraged K. Vahidy Rodpysh to investigate and supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

Abbreviation

<i>RS</i>	Recommender Systems
<i>SVD</i>	Singular Value Decomposition
<i>CF</i>	Collaborative Filtering
<i>TF</i>	Tensor Factorization
<i>MF</i>	Matrix Factorization
<i>HOSVD</i>	Higher-Order Singular Value Decomposition
<i>LOD</i>	Linked Open Data
<i>BPR</i>	Bayesian Personalized Ranking
<i>SGD</i>	Stochastic Gradient Descent
<i>MSGD</i>	Momentum Stochastic Gradient Descent
<i>NDCG</i>	Normalized Discounted Cumulative Gain
<i>MSE</i>	Mean Squared Error
<i>MAE</i>	Mean Absolute Error

RMSE

Root Mean Square Error

NHCSM

New Heuristic Context Similarity Measure

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