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A Solution Towards to Detract Cold Start in Recommender Systems Dealing with Singular Value Decomposition

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Abstract. Recommender system based on collaborative filtering (CF) suffers from two basic problems known as cold start and sparse data. Appling metric similarity criteria through matrix factorization is one of the ways to reduce challenge of cold start. However, matrix factorization extract characteristics of user vectors & items, to reduce accuracy of recommendations. Therefore, SSVD two-level matrix design was designed to refine features of users and items through NHUSM similarity criteria, which used PSS and URP similarity criteria to increase accuracy to enhance the final recommendations to users. In addition to compare with common recommendation methods, SSVD is evaluated on two real data sets, IMDB and STS. Experimental results depict that proposed SSVD algorithm performs better than traditional methods of User-CF, Items-CF, and SVD recommendation in terms of precision, recall, F1-measure. Our detection emphasizes and accentuate the importance of cold start in recommender system and provide with insights on proposed solutions and limitations, which contributes to the development.

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Keywords: Recommender systems; Singular value decomposition; Cold start; SSVD; Similarity measure.

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1. Introduction

In recommended system (RS), there is a set of users and a set of items that each user rates a set of items by values. Suggestions mean predicting the rate for a user who has not rated the desired product, in this case. Moreover, RS of an item to a user is based on the points the user has already made [16]. Recommendation techniques come in two basics: collaborative filtering (CF) and content filtering.

CF techniques, the user expresses his opinion by scoring items in the system and shares user systems with the same scoring patterns and uses these like-minded users to calculate the forecast [3].CF techniques are generally divided into memory-based and model-based categories. Unlike memory-based methods that directly use stored points for estimation; Model-based techniques use these rates to learn a model that predicts unknown rates. In this technique, they try to build a model of the data and then perform the calculations only on the model. These models are used to predict real data [10].

The main idea in model-based techniques is to model user interactions and items with factors that reflect the hidden features of users and items in the system. This model is initially taught using the available information to be used in the next step to estimate user ratings for the new item. There are a variety of techniques to alleviating the cold start such

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as clustering, decision tree, Bayesian network, Markov, etc. to build model-based methods, especially matrix factorization (MF) model [10;18]. Singular value decomposition (SVD) is one of the most widely used methods in MF. In the SVD algorithm for analyzing the single values of the space, the relationship between users and items finds a new meaning [2].

CF methods use a similar standard to find the neighbors of an active user or to find similar items to the target item. Traditional similarity criteria such as Pearson correlation coefficient, cosine similarity and different types are often used to calculate the similarity of a pair of users or between a pair of items [13]. Traditional similarity criteria are not effective in solving cold start challenges, thus in recent years, similarity criteria such as PSS, URP have been used [11].

As mentioned, the main challenge in cold starter recommendation systems. A cold start is caused by a lack of user data and a history of ranking items, which is used as a mechanism to alleviating user’s preferences and make recommendations [7]. Therefore, two general objectives in the research are pursued:

- Methods to improve the determination of similarity criteria between new users or new items.
- Use of matrix factorization with new similarity criteria.

2.Related works

Highly similarity algorithms proposed in recommender systems including cosine similarity (COS), Pearson correlation (PC), PIP and BCF. The cosine similarity measure r_{UI} of the U user rate to item I, r_{VI} of the user's V to item of I and Í indicates the set of items that have a common rate between U and V.

However, cosine similarity suffers from the problem of common points between users. Also, despite significant differences in rates, the output of the similarity criterion will high[8].Pearson's similarity criterion examines two users or items in terms of how they are linearly related to each other, but ignores common points, despite paying attention to items with common points and their numerical value [4]. The PIP criterion considers three important factors called proximity, influence and popularity between the points in calculating the similarity criterion of the two items (user). It ignores commonalities [11].

The JMSD criterion is a combination of jacquard and squared (MSD) criteria. In fact, in order to calculate the amount of information, the number of items with a common rate with its exact rate, the number of items with a common rate with a different rate range and the amount of MSD calculates the rate of items with a common rate. The Jakard similarity criterion deals with the difference in rates provided by both pairs of users. This criterion is largely due to the overcoming of MSD and Jaccard problems. However, it suffers from local information problems and not using all the privileges [4].

Despite other similarity criteria, BCF takes advantage of all the benefits provided by users and thus uses a combination of local and global similarity criteria to calculate the similarity between users.I_U and I_V, respectively, are a set of products provided by a UV user and a rate that may not have been shared by any user who has been privileged by each user [15].

As mentioned, one of the most important challenges of the recommendation systems is the cold start challenge, and the common similarity criteria alone are not able to reduce this challenge, and new criteria have been proposed. Algorithms such as PSS, URP can be mentioned as the most popular similarity criteria used to reduce the start [11].

The PSS algorithm considers the result of three factors to determine the similarity in the recommendation systems. Proximity considers absolute difference between two ratings and assigns penalty to disagreement.Significance assumes that those ratings which are far off from the median are more significant.Singularity uses difference of two ratings from the mean of their rating vector.

The URP algorithm evaluates users similar to items in a specific way. Some user's rate items as very high and others rate items as low. Meanwhile, to reflect this ranking behavior of users, the priority of user ranking is determined based on the average variance of the rankings [11].

The E-CHSM algorithm uses skin metering instead of overlap for field similarity. Proposing similarity measures suggests overcoming traditional and appropriate similarity measures for scattered data, especially a set of knowledge-based data sets. The skin criterion is a trait that gives a relatively large weight to the mismatch of traits with the greater number of categories. The O-CHSM algorithm, the Bhattacharyya coefficient for global rankings and NHSM ratios of common ratings, considers global user behavior priorities and can be easily combined with other similarity measurements [11].

Most of the algorithms that respond better to different data have been algorithms that have used CF methods. There are many methods in CF and one of the most considered methods is the use of MF methods [10;18]. Appling MF methods along with similarity criteria is one of the solutions to reduce the cold start [13].

In order to solve the cold start challenge, the use of a content filtering and CF combination system using demographic criteria [5]. Criteria for similarity through MF [9] and Cluster labeling [14]. Nevertheless, attention to items rated by similar users with new users who have entered the system can be indicated by MF [2; 12].

3. Proposed method

The structure of the present study is based on the method presented in the criteria of similarity and use of MF based SVD. In order to reduce the challenge of cold start and improve the process of offering suggestions in recommender systems. In this method, initially a two-level matrix based on user, user feature, item and item feature is designed to determine the similarity (similarity criterion) with the users, called SSVD. Then, the new similarity criteria presented are used to determine the final proposals. Figure 1 shows a view of the method presented in the RS.

4. Analysis of the scheme

In this section, first, the improved SVD algorithm based on user similarity criteria and similarity of items called SVD was introduced. In the second step, a new similarity criterion was used to provide better recommendations.

4.1 *The SSVD algorithm*

Cold start challenges as mentioned when a new user enters a system or users who have been in the system for some time but have not done anything. On the other hand, there is a plan for a new item that has recently entered the system. SVD is a classic and popular algorithm for recommendation. However, the original SVD can only extract user vectors and items, which may make it impossible to refine more features and reduce the accuracy of the recommendations. Based on what has been said, an SVD-like similarity matrix called SSVD was proposed. The SSVD algorithm decomposes user and item matrices using user.

Demographic features and item properties to obtain a matrix of more refined features. This will make the results of the recommendations more accurate for users and more satisfying.

The user's demographic information matrices (user feature) and item properties (item feature) are converted into two matrices, D and F, respectively. In this case, the Pearson correlation was considered to be based on the similarity of the information through those users whose average number of x variables of demographic variable is greater than $(x/2)+1$; they have a minimum rate of similarity criteria. Also, items with an average number of y-criteria are similar to the characteristics of the item from $(y/2)+1$.

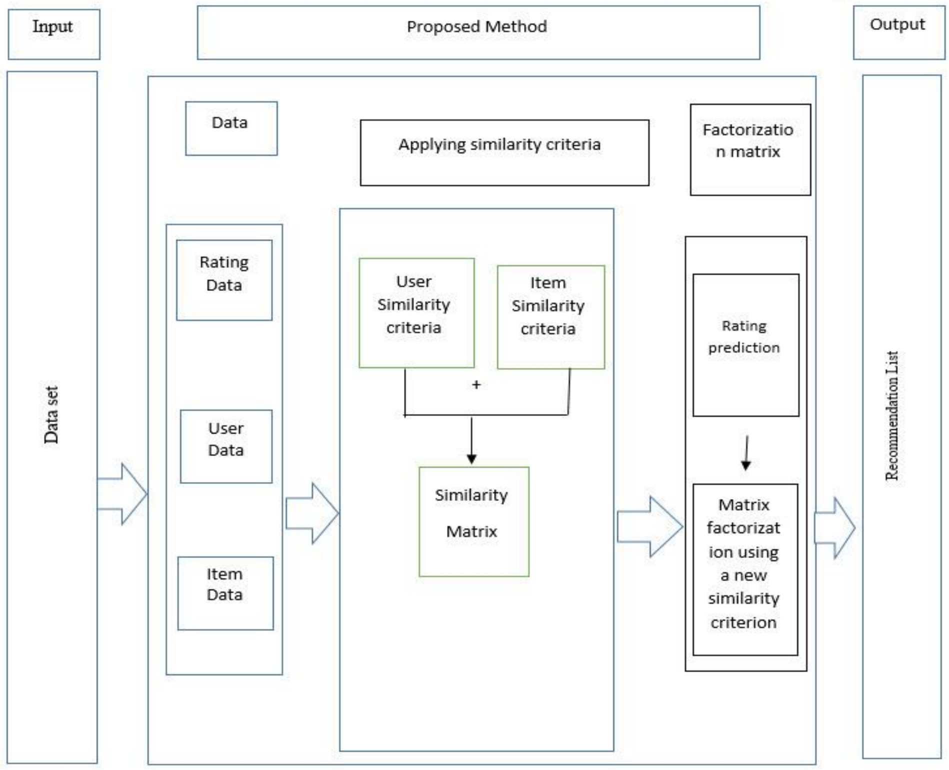

Figure 1. The Architecture of the proposed scheme.

To be specific, SSVD firstly divides the rating matrix into the user characteristics matrix U and the item characteristics matrix I by SVD, and then SSVD continues decomposing the User Demographic Factor and item feature factor obtained by SVD to extract the more refined factor matrix such as matrices M, K, N, L. The View of SSVD method is illustrated in Figure 1, on the basis of SVD, SSVD continues to extract the characteristic factor matrix, including U, D, I, F in the characteristics of users and items, where U, D, I and F are four orthogonal matrices of size $m \times k$, $k \times k$, $n \times k$ and $k \times k$, respectively. And k is the decreasing rank of the matrices U, D, I, F, which is obtained based on the main classification of items in each domain. Moreover, SSVD can acquire more abstract factors (such as features of the item, about the actor of the film; Demographic characteristics, age of the user).

The flowchart of SSVD method is illustrated in Figure 2, on the basis of SVD, SSVD continues to extract the characteristic factor matrix, including U, D, I, F in the characteristics of users and items, where U, D, I and F are four orthogonal matrices of size $m \times k$, $k \times k$, $n \times k$ and $k \times k$, respectively. And k is the decreasing rank of the matrices U, D, I, F, which is obtained based on the main classification of items in each domain. Moreover, SSVD can acquire more abstract factors (such as features of the item, about the actor of the film; demographic characteristics, age of the user).

In the SSVD algorithm, which is obtained by multiplying the four matrices U, D, I, F. Multiplying matrices I and F indicates the priority of the item and in order to reduce the challenge of cold start for new items. The results obtained through similar users and similar items according to the similarity criteria of the results obtained in order to fill the R rating matrix. Table 1 shows the signs of the SSVD algorithm.

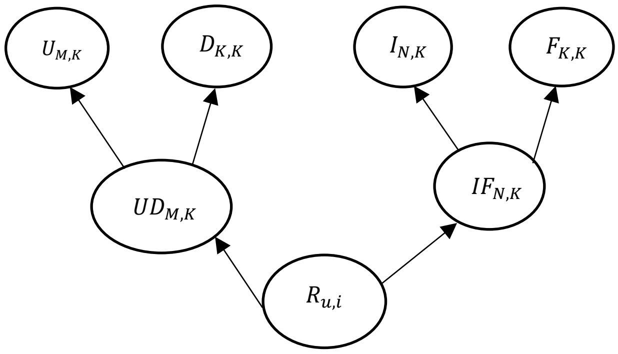

Figure 2. The view of the SSVD method.

Table 1. Signs of SSVD algorithms.

Symbol	Description
u	A user
i	An item
$r\hat{}_{u,i}$	The predicted rating that user u would give to item i
U	A set of users
I	A set of items
D	A set of Demographic users
F	A set of feature items
μ	Average rating for all items
b_u	The bias of user u
b_i	The bias of item i
α	Learning Rate
β	Regularization parameter
λ	Momentum
R	Rating Matrix

As shown in (1), the $r_{u,i}$ rating matrix is obtained at this stage of the product U, D, I, F. In (2) μ Average rating for all items, b_u and b_i denote the deviation of the rating of user u from the average of the total ratings and the deviation of the rating of item i from the average of the total ratings, respectively. We need to learn the matrix parameters to fill the R rating matrix, especially for new users or new items. In order to update, the momentum stochastic gradient descent [17] was used. The values of the parameters are shown in (3).

$$r_{ui} = D.(IF)^T \tag{1}$$

$$\hat{r}_{ui} = \mu + b_u + b_i + UD.(IF)^T \tag{2}$$

$$\begin{aligned} e_{ui} &= r_{ui} - \hat{r}_{ui} \\ b_u &\longleftarrow b_u + \alpha\,.(e_{ui} - \beta.b_u) \\ b_i &\longleftarrow b_i + \alpha\,.(e_{ui} - \beta.b_i) \\ U &\longleftarrow \lambda.U + \alpha\,.(e_{ui}.D.IF - \beta.U) \\ D &\longleftarrow \lambda.D + \alpha\,.(e_{ui}.U.IF - \beta.D) \end{aligned} \tag{3}$$

$$I \longleftarrow \lambda.I + \alpha\,.(e_{ui}.UD.F - \beta.I)$$
$$F \longleftarrow \lambda.F + \alpha\,.(e_{ui}.UD.I - \beta.F)$$
$$UD \longleftarrow \lambda.UD + \alpha\,.(e_{ui}.IF - \beta.UD)$$
$$IF \longleftarrow \lambda.IF + \alpha\,.(e_{ui}.UD - \beta.IF)$$

4.2 *NHUSM similarity criterion*

New Heuristic User Similarity Measure (NHUSM) similarity criterion, which is actually a combination of PSS and URP and field performance criterion that includes 4 factors (Proximity, Significance, Singularity, and user performance). In formula (4). the formula for calculating the similarity criterion is shown

- Proximity: Determines whether the two ranks agree or disagree which based on the absolute difference between the two ranks.
- Significance: which is considered for those users according to the importance of the item.
- Singularity: Indicates the difference between two ranks of their average rate.
- User Performance:User Ranking Behavior, Priority of User Ranking, which is determined based on the mean variance of rankings.

$$\text{Proximity}(r_{u.a} - r_{v.b}) = 1 - \frac{1}{1+exp\,(-|r_{u.a}-r_{v.b}|)}, \tag{4}$$
$$\text{Significance}(r_{u.a} - r_{v.b}) = 1 - \frac{1}{1+exp(-|r_{u.a}-r_{med}|*|r_{v.b}-r_{med}|)},$$
$$\text{Singularity}\big(r_{u,a} - r_{v,b}\big) = 1 - \frac{1}{1+exp(-|((r_{u,a}-r_a)+(r_{v,b}-r_b))/2|)},$$
$$\text{Sim}(u, v) = 1 - \frac{1}{1+exp(-|\mu_u-\mu_v|*|\sigma_u - \sigma_b|)},$$

where μ_u and σ_u are the mean rating and the standard variance of user u, respectively. I_u Represents the set of ratings of user u. The operator $*$ means the common ratings between two users. $r_{u.b}$ is the rating of user u on item b. r_{med} is the median value in the rating scale.

5. Experiments and results

Implemented code of the method presented on two databases in IMDB and STS Kaggle Simulation Data Science. In this section, both the IMDB and STS data sets are used to evaluate performance of proposed algorithms. Anaconda software used to analyze data. Therefore, SSVD method is compared with three common Users-CF, Items-CF and SVD algorithms in three common evaluation criteria: precision, recall and F1-measure.

5.1 *Dataset*

The details of these two IMDB [1] and STS [6] datasets are given in Table 2. We divide the dataset into a training set and a test set by randomly putting 20% of the ratings for each user in a held-out test set. The remainder constitutes the training set. Conclusion.

Table 2. Details of IMDB and STS dataset.

Data set	IMDB	STS
Users	1088	1625
Items	2455	498
Ratings	20759	12675

5.2 *Performance evaluation*

Each data set is divided into training sets and test sets. The parameters in the SSVD algorithm are taught through scoring for items by new users or new items for users in the training set. In order to evaluate the performance of the proposed method, it is compared with three recommendation algorithms Users-CF, Items-CF and SVD. The results of the proposed method are also evaluated with the usual criteria of MAE, RMSE, Precision, Recall and F1-measure.

5.3 *Comparison of methods*

In this section, the proposed method is compared with Users-CF, Items-CF and SVD algorithms in IMDB and STS data sets, respectively. Our experiment uses the ratings of 1 to 5 for ranking. This is while in calculating the retrieval value and recommendation accuracy only items that have a 4 or higher rating are selected. The performance of different recommendation methods in the IMDB and STS data collection are shown in respectively. The results of Tables 3 and 4 show that no matter what method is used the STS collection is better than the IMDB collection which shows the extensive effects of cold start on recommendation accuracy. The Item-CF method has a better performance in comparison with the User-CF method because this method uses information item with the help of implicit and explicit item features. The SVD method has a better performance than the Item-CF method, because of using user and item attribute matrixes, using the SVD matrix, and then using the vector data in RS. But the SSVD method that uses the attributes of the SSVD matrix in the case of the user and item attribute matrixes, the two-level SVD matrix, and also the user and item feature dimensions; has a better performance in comparison to the SVD modeling method that only uses the relationship dimension.

Table 3. Comparison of methods in IMDB data set.

	MAE	**RMSE**	**Recall**	**Precision**	**F1-measure**
User-CF	0.473	0.631	0.211	0.342	0.258
Item-CF	0.446	0.618	0.213	0.348	0.269
SVD	0.410	0.605	0.215	0.357	0.270
SSVD	0.402	0.593	0.227	0.379	0.280

Table 4. Comparison of methods in STS data set.

	MAE	**RMSE**	**Recall**	**Precision**	**F1-measure**
User-CF	0.503	0.631	0.181	0.285	0.220
Item-CF	0.487	0.617	0.191	0.290	0.227
SVD	0.471	0.609	0.192	0.295	0.228
SSVD	0.457	0.603	0.202	0.315	0.232

The IMDB data set, which includes 20759 rankings for 2455 movie visit by 1088 users. Figures 3 to 5 show on IMDB data set the results of the precision, recall and F1-measure according to the number of films recommended. The results indicate that the performance of the proposed method has improved compared to Users-CF, Items-CF and SVD. However, as the values increase with increasing number of recommendations, the criteria for precision, recall and F1-measure evaluation are reduced. We also conduct some experiments on the STS data set, which includes 12,675 rankings for 498 travel packages by 1,625 users. Figures 6 to 8 depict in the STS data set, show that precision, recall, and F1-measure are reduced by increasing the number of recommendations.

6. Conclusions

Cold start is one of the most common challenges in recommender systems. Using similarity criteria Matrix factorization has strategies to reduce cold start it has been suggested. In the presented method, a two-level matrix item called SSVD is created through the user characteristics. The SSVD matrix uses NHUSM-like resemblance criteria, which are derived from the PSS and URP similarity criteria, to determine final offers to users. The proposed method helps to suggest new cases for new users and items. In a way, it reduces the challenge of cold start. On the other hand, the NHUSM similarity criterion leads to increased accuracy and performance of the proposed method against traditional Users-CF,

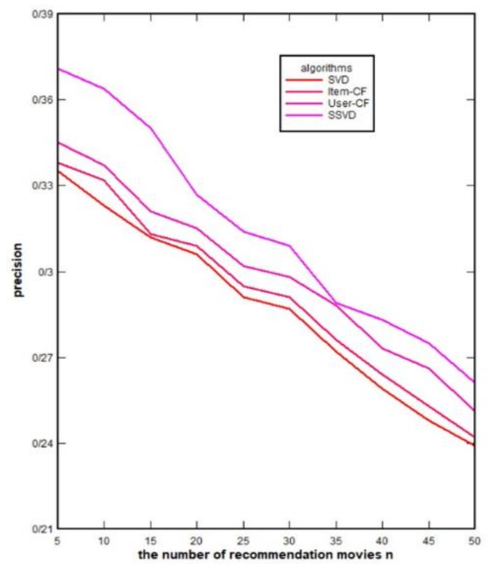

Figure 3. The precision of Users-CF, Items-CF and SVD algorithms the number of recommendations (IMDB).

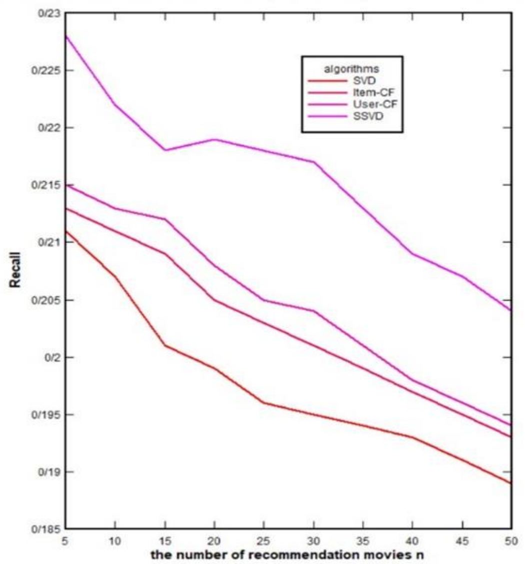

Figure 4. The Recall of Users-CF, Items-CF and SVD algorithms the number of recommendations (IMDB).

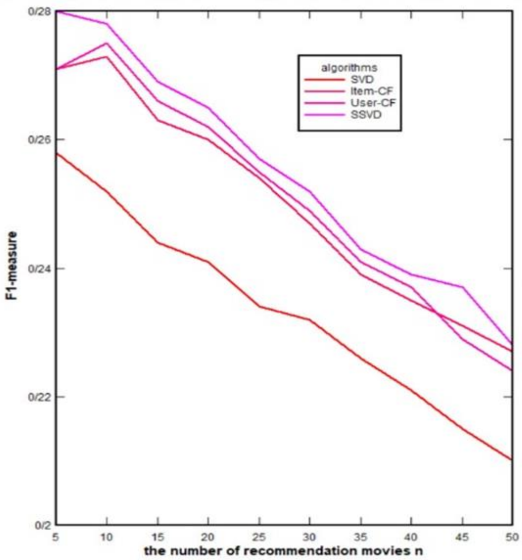

Figure 5. The F1-measure of Users-CF, Items-CF and SVD algorithms the number of recommendations (IMDB).

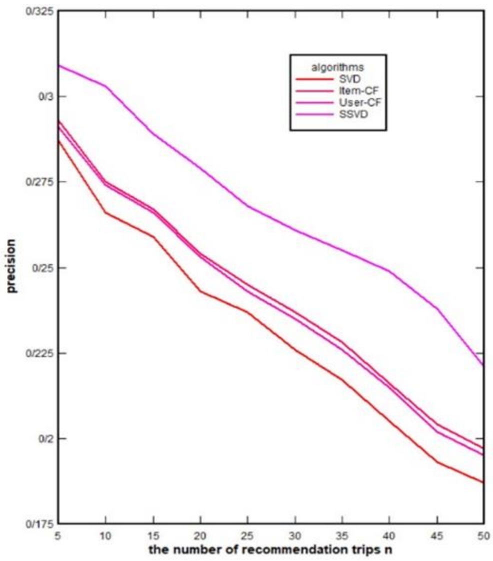

Figure 6. The precision of Users-CF, Items-CF and SVD algorithms the number of recommendations (STS).

Items- methods. CF and SVD show. In the next step, we can use multi-state methods to solve the data solitude challenge in addition to the cold start challenge; As a result, it leads to a more accurate recommendation system. Reading opportunities include the use of new similarity metrics and the need to use feature dimensions, a variety of available techniques or powerful initiatives such as machine learning techniques to help users gain more access to items with personal requirement and interests, which leads to improving the efficiency and accuracy of RS.

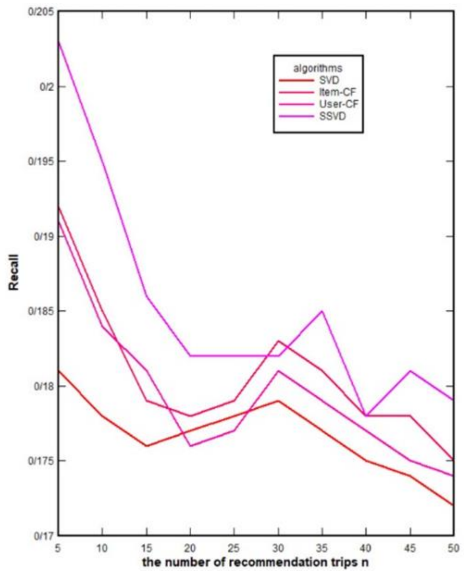

Figure 7. The recall of Users-CF, Items-CF and SVD algorithms the number of recommendations (STS).

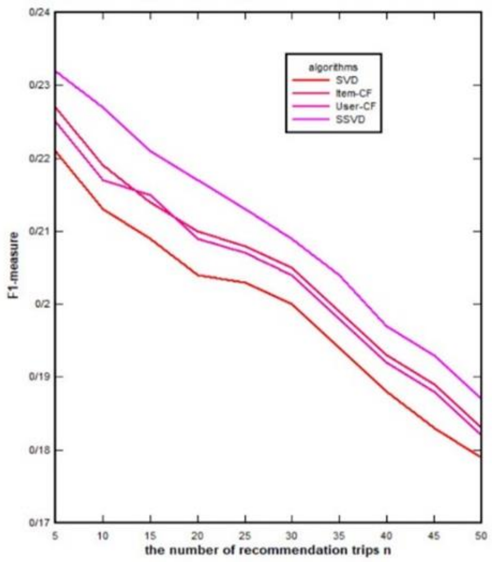

Figure 8. The F1-measure of Users-CF, Items-CF and SVD algorithms the number of recommendations (STS).

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