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# Stable Confident Rating Prediction in Collaborative Filtering

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***Abstract*****: *Stability of matrix factorization is estimated in terms of gradient descent estimation at each iteration which ultimately defines the stability of recommendations in collaborative filtering techniques. Also, stability is inversely proportional to total number of iterations used for estimating ratings. This gives rise to the need of the method which possesses better rating predictability within less number of iterations. The accuracy of rating prediction is found to be better when user to user trust score is estimated using similarity of individual rated items. The trust estimation is also prone to sparsity due to irregularity of ratings in large volume of data sets (big data). Based on the experimentation strategy and platform requirements, the method of trust evaluation is proposed in this positional paper. The Lyapunov stability solver functions can be used directly in obtaining solution for the trust score amongst users which can bring sufficient stability in learning stages of matrix factorization process and hence better performance in predicting the ratings of non-rated items. Here, the results obtained possess the sufficient gravity for consideration of predicted ratings which also keeps errors in prediction at lowest level for rated items. The papers are addressed from similar domain in related work section to compare proposed work in terms of novelty and performance. The results obtained are satisfactory, which are assessed in terms of mean absolute error (MAE).***

***Keywords: Lyapunov solver, Kronecker product, trust estimation, matrix factorization, collaborative filtering.***

## I. INTRODUCTION

The missing entry problem for non-rated items in collaborative filtering in recommendation system (RS) is based on relationship prediction strategy amongst the users who have given rating to some of the items. The non-rated items by the users are main under considerations in rating predictions to identify expected virtual response to the rating system and the way of recommendations to users to increase the response for missing entry (non-rated items) as a psychological effect under business improvement strategies. The sole response is based on computations involved in achieving psychological response balancing capacity of the system for respective users thereby considering ratings and predicting ratings for non-rated item sets.

Most of the users can be seen to have rated similar category items. Based on this ratings, earlier it was used to recommend only those and similar category items (only). But the current era of business strategies have changed the direction to improve response of all users to almost all available items in different categories. The example of movie viewing service can be considered in the case. The movies belonging to particular genre only are suggested with normal rate evaluation but non-rated movie as item suggestion is main task and that has to be performed with the help of deep learning strategies to increase response to other genres in RS. The set U of users who are to be suggested for genres, not rated by them, the set V of users who have rated to genres rated by U and also to genres not rated by U, are considered to estimate the relation between U and V. This involves solving the missing entry problem for predicting the rating for non-rated items of users in U. As a solution to this challenge, the variety of techniques are developed by various researchers in last decade and are used to predict their respective ratings for non-rated item sets. In this position paper, we have shown summarized work by focusing mostly on techniques which involve deep learning methods. The techniques mainly focus on relationship establishment amongst users based on their ratings with the help of matrix factorization and then prediction of ratings for non-rated items in RS. The relation establishment amongst users is best possible strategy that is considerable in RS. Matrix factorization method is mostly used method in collaborative filtering process.

## II. RELATED WORK

Matric Factorization [1] is explored with fusing the implicit trust scores to make rating guess as exact as possible for the MF on explicit trust scores. Here authors used social MF for implicit trust scores among users for the sake of improving the results of model based RS. In [2] authors contributed enhancements of the performances in terms of efficiency and effectiveness of MF methods. Here authors tried to calculate the weight based on popularity estimation of item for the missing data rather than using a common weight factor. Also, authors addressed the challenge, with designing an innovative learning process with element-wise Alternative Least Squares (eALS) for improving MF model. An exploration [3] of matrix factorization methods used in collaborative filtering is presented. Here author demonstrated different matrix factorization methods like SVD, PCA and PMF. Matrix factorization [4] is important to improve the prediction quality. Author used matrix factorization technique to find change in user preferences. Here author suggested the inclusion of user biases and item biases to enhance the superiority of MF. Combined method of collaborative filtering with deep learning [5] is presented.

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Here author precisely discovered hidden factors to improve matrix factorization. In [6] authors have demonstrated the importance of matrix factorization for prediction of rating. Here author proposed matrix factorization based on confidence score. Author stated that, by combining the accuracy and the confidence improves recommendation quality. In [7] authors implemented modification in non-negative matrix factorization. Here author tried to achieve high convergence with low complexity. This method handles sparsity of the matrices. In [8] authors considered side information in matrix factorization to improve prediction performance. Author analyzed stability of the method. Fresh matrix factorization [9] technique using improved singular value decomposition is introduced. Here author used basic matrix factorization method for finding missing entries. In [10] authors developed a technique for calculating rating deviations using matrix factorization.

Sparsity issue [11] in ratings matrices in collaborative filtering is addressed using matrix factorization. Authors have mentioned the objective function which learns hidden features in matrix factorization. The non-rated items ratings are predicted using inner product of latent factors. MAE based results are shown which show better performance. In [12] authors have displayed method using content based matrix factorization to increase the prediction accuracy of ratings for non-rated items. The content-boosted algorithm is shown. The work contribution is in terms of content awareness consideration compared to other systems.

Bayesian Probabilistic Matrix Factorization (BPMF) method [13] with parallel processing technique is enlightened. The distributed task in Gibbs sampling basis is used for parallel processing architecture. Compared to other systems, authors have shown task scheduling in multi node computations in distributed processing environment. The results are in terms of computational time consumed basis. In [14] authors have illustrated Bayesian non negative matrix factorization technique along with clustering method to improve the performance evaluated using MAE results for Recommender Systems. The sensitivity of clustering techniques to sparsity of ratings matrices is addressed to establish clustering using KMEansLogPowerPlus method during matrix factorization process to improve the results. Authors likewise offer a unique pre-clustering procedure adjusted to the planned probabilistic method along with evaluation results for different hidden factors during matrix factorization. Results are also considered on the basis of improved BNMF computation time over the typical matrix factorization, which is an extra up gradation in the pre-clustering algorithm developed by authors.

Stability examination [15] of matrix factorization process using Lyapunov functions based stability inspection is demonstrated. The classical matrix factorization techniques are usually unstable in terms of predictability for multi iterations execution scenarios is the outcome of the authors' experimentations and examinations.

In summarized view, collaborative filtering is the most appropriate method for generating recommendations. Based on existing literature exploration, collaborative filtering can be best implemented using matrix factorization. Combining trust based techniques with matrix factorization will give better results. Clustering used prior to factorization is responsible to have pre labelled relationship establishment amongst user sets in supervised training techniques in matrix factorization process. The latent feature consideration is dependent on information available other than ratings, along with availability of context information for predicting relations amongst users. Also, to keep number of iterations at minimum level, the stability examination of objective function is very important while performing matrix factorization in collaborative filtering based RS. Defining objective function in matrix factorization process is challenging task for predicting stable relationship amongst users.

## III. RATING PREDICTION MODEL

Hisashi Kashima et al [24], have given objective function for the link prediction between any two users in the network. The idea is well elaborated and possess stability due to Lyapunov based function solver. We extend this link prediction model to trust estimation in rating prediction with modifications in processing.

The relation estimation for the rating prediction problem can be defined as a job to predict a relation existence between a random pair of users. Multiple relation may exist amongst users based on ratings given to variety of item sets. In this positional paper, we consider a more common task of predicting multiple relations based on similar ratings structure among the pairs of users based on ratings given to respective item sets.

Consider two sets of users as,

$$U: = \{u_1, u_2, \ldots, u_M\} \quad \ldots(1)$$

Such that, intersection of U and V will provide users with similar items ratings

$$V: = \{v_1, v_2, \ldots , V_N\}, \quad \ldots(2)$$

Who have rated similar items to that by set U and also additionally rated that are not rated by set U. Some of U and V are identical in accordance with ratings given to items. Let the set of rated and not rated items by user in U and V be,

$$Z: = \{z_1, z_2, \ldots, z_T\}. \quad \ldots(3)$$

Depending on application type U and V will contain sets where some of them will have similar items rated. It should be noted that, U, V and Z will have M, N and T as triplet basis respectively. Considering an example of movie rating dataset in which U, V are user sets and item sets respectively and Z are set of ratings respectively. The rating relation based on $z_i$ and $z_j$ between two users $u_i$ and $v_j$ indicates that a user $u_i$ have rated $z_i$ which is similar to $z_j$. Also, in another example of users belonging to same type, the relationship within the members, the members which are also in U and V, and Z is a set of association (relation) types within the members, for example, Z := {ratings to similar genres of movie}.

Consider a triplet presented by ($u_i$, $v_j$, $z_k$) is single type relation between users.

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In triplet based technique, obtaining solution for the multiple type relation is equivalent to obtaining single type relation for a given triplet, as also mentioned in [24]. Hence, third order tensor M x N x T can be used for representing triplet with single-type (mono) relationship set, given as,

$$[S]_{ijk} := s_{ijk} \qquad \ldots(4)$$

The variable $s_{ijk}$ indicates a relationship level for the triplet $(u_i, v_j, z_k) \in U \times V \times Z$, The relation strength obtained in this strategy, can be used to predict the rating in trust based rating prediction. The generalized principal can be followed that, a large value of relationship strength can lead to consider the high confidence of better value of rating while predicting, and a smaller value leads to consider the high confidence of the less value of rating for prediction.

Now, consider alternative M x N x T tensor with third-order $S^*$ which signifies the observed ratings for the items. In case of supervised learning based strategy, $S^*$ is considered as the target values for a learning phase using dataset of training.

The clustering method in supervised learning plays most important role while labelling particular user sets with respect to ratings sets available for training purpose. The K-means clustering based method can solve the problem of clustering. But as large data examination is involved in RS, K-means is supposed to be sensitive to sparseness of the datasets. As indicated in [14] the KMEansLogPowerPlus based clustering method can be used to solve the issue and better clustering based on ratings to have relationship triplets while performing supervised training.

The items based clustering is done using prediction of particular user being in cluster given by equation in [14], as,

$$P_i \in C = \sum_{c \in C} dist(i,c) + \log\left(\frac{|I_c|}{|I_i|} + 1\right) \qquad \ldots(5)$$

Where c denotes the cluster number. Let there be set of triplets having rated and non-rated items based relations denoted by E. For obtaining elements of $S^*$, we can use the conditional assignment in which $[S^*]$ will possess the values equal to $S^*$ in case where all i, j, k will belong to E and equal to 0 for otherwise. In this, $S^*_{ijk}$ represents a set of positive value if there is a relationship in $(u_i, v_j, z_k)$, and to negative value if there is no relationship in $(u_i, v_j, z_k)$.

When there is no rating given by the user for particular item we fill that value with zero that is for (i, j, k) does not belong to E, $[S^*]_{i,j,k}$ is occupied with zero. Hence, we recommend set $s^*_{ijk}$ as, equal to ratio of E to $E^+$ if there is relation in $(u_i, v_j, z_k)$ and equal to ratio of -E to $E^-$ if no relation in $(u_i, v_j, z_k)$. In this we consider, $|E^+|$ and $|E^-|$ as the statistics of triplets with respect to relationship and without relationships, correspondingly. Along these lines of setting the target values relates to the Fisher discriminant in the case that we utilize the squared loss function [16].

*A. Objective function*

Since there exist an issue in semi supervised learning scenarios in the relation based rating forecasting, we can make use of label propagation as in [17, 18], which is one of the best in class of semi-supervised learning strategies. The label propagation technique can be utilized when two users that are like each other may have a similar label. Label forecasting can be summed up to relation prediction, since the relation prediction issue can be viewed as an errand of foreseeing labels for (user, user, ratings) triplets. Applying the label propagation technique to triplets, we can anticipate trust quality with respect to the label of the triplets.

Changing the label propagation standard, we can express the triplet rendition standard as two similar (user, user, ratings) triplets are probably going to have a similar relationship strength. As per this relation propagation standard, we characterize the objective to limit as the function of controlled parameters (σ, μ) times the summation of similarity matrix elements with respect to squared value of difference of elements in S. The objective function for finding the relation amongst users will be similar to objective function mentioned in [24].

This can be rewritten here and denoted as,

Objective Function (S) = σ (summation of
W $(S_{ijk} - S_{lmn})^2$ +0.5*Summation of
$(S_{ijk} - S^*_{ijk})^2 + \mu$ ( Summation of $(s_{ijk})^2$) …(6)

Where W is similarity matrix. Hence, using (6), tensor H can be defined as,

$$[H]_{i,j,k} = \begin{cases} 1 & if\ (i,j,k) \in E, \\ \sqrt{\mu} & otherwise \end{cases} \qquad \ldots(7)$$

As we have considered ratings to similar items based relationship prediction, we can also calculate similarity matrices P, Q from the elements of U, V and Z, respectively. For the sake of illustration purpose we consider first those matrices with non-negative values and also symmetric. In the example of movie recommendation of (user, item, rating) relationship prediction, P signifies likenesses among the users, in which $(i, \ell)^{th}$ element $[P]_{i,\ell}$ indicates the likeness between the $i^{th}$ user $u_i$ and the $\ell^{th}$ user $v_\ell$.

Relationship prediction can be done by obtaining similarity matrix in triplet-wise manner. The Kronecker product similarity method is used to calculate W as given in [24]. Therefore,

$$W := Q \otimes P \qquad \ldots(8)$$

Where, ⊗ is the Kronecker product and element-wise,

$$w_{ij,\ell m} := [P]_{i,\ell} \otimes [Q]_{j,m} \qquad \ldots(9)$$

The Kronecker product here is nothing but obtained rating matrix in matrix factorization. The main stability issue in matrix factorization is tackled here using equation (9) and its further solution in similar way to [24]. In this way, the product of the similarities is ultimately the Kronecker product similarity. This is an augmentation of the pair-wise similarity utilized in kernel function techniques [19-21] to triplets. The similarity obtained by Kronecker product relates to inner product matrices of triplet feature spaces of kernel matrices P and Q which are in their feature spaces respectively. Hence,

$$L := D_V \otimes D_U - Q \otimes P$$

Where, $D_U$ is a diagonal matrix based on Kronecker product similarity, hence element wise,


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$$[D_u]_{i,i} := \Sigma_j [P]_{i,j} \qquad \ldots(10)$$

In same manner $D_v$ can be obtained. To control the complexity for high and excessive dimensions of Kronecker product, the Kronecker sum similarity is deduced. The Kronecker sum similarity the effective consideration is done only when there are more than 60% chances of similarity between two triplets. Hence, we write,

$$W := Q \oplus P$$
$$= (I_N \otimes Q \otimes I_M) + (I_M \otimes I_N \otimes P) \qquad \ldots(11)$$

Taking the Laplace transform we can write,

$$L = L_V \oplus L_U, \qquad \ldots(12)$$

Where,

$$L_U := D_U - P \qquad \ldots(13)$$

And similarly $L_V$.

Kronecker sum provides positive value of the score compared to non-zero value (may contain negative) from Kronecker product which is more noteworthy. For rating prediction based on relationship amongst users, we follow matrix factorization process. The matrix factorization using singular value decomposition is easiest process we consider at this stage to obtain the final solution for Kronecker product based equations. Typically, the system of linear equations is solved using the method of conjugate gradient [22]. The gradient descend method is best possible matrix factorization process which is capable of keeping mean square error at lowest possible values thereby estimating error at each matrix shuffling stage for the said number of iterations with respect to predicted rating of rated items.

We consider vectored notations for in process values of algorithm for respective notations in all equations earlier. We can estimate the relation between users as,

$$(\sigma L + I_{MN}) \text{ vec } (S) = \text{vec } (S^*) \qquad \ldots(14)$$

Where $I_{MN}$ = diagonal (vec (H)), that is diagonal matrix of vector H. Also here $\mu = 1$.

As W is Kronecker product similarity,

$$(\sigma D_V \otimes D_U - \sigma Q \otimes P + I_{MN}) \text{ vec } (S) = \text{vec } (S^*) \qquad \ldots(15)$$

Hence relationship matrix becomes,

$$\sigma DUSDV - \sigma PSQ + S = S* \qquad \ldots(16)$$

The equation (16) obtained here is generalized Sylvester equation [23]. This Sylvester equation obtained can be solved using Lyapunov function. This final equation is used to estimate the prediction and hence shows the stability in the prediction with respect to training data.

### *B. Formulating the prediction of rating*

The S* obtained in equation (16) gives the trust amongst the users which can be considered to calculate the rating for non-rated item for particular user in ratings matrix. In general, the rating prediction depends on the trust within the neighbors for respective ratings on a particular item j for user i in U will be determined as follows,

$$r_{i,j} = \sum_{k \in TN_i} t_{i,k}\, r_{k,j} \;/ \sum_{k \in TN_i} t_{i,k} \qquad \ldots(17)$$

Where, $t_{i,k} = S^*$, k is k$^{th}$ user in U, also user i and item j.

Steps:

1. Generate the ratings matrix from available data by filling zero for non-rated items.
2. Calculate trust amongst users using Sylvester equation (16)
3. Calculate the rating for particular non rated items using equation (17)
4. Estimate the error amongst rated and predicted matrix for respective rating of rated items.

## IV. EXPERIMENTAL RESULTS

The method based on KMEansLogPowerPlus clustering method as shown in [14] is used to compare our results. The clustering based method provides the missing ratings for the users based on the membership with respective cluster where cluster plays important role of providing relationship amongst users based on its distance from centroid. The more the distance less will be the rating predicted and also maximum rating expected in that particular cluster. The factored matrices are used to estimate the clusters in each iteration as indicated in [14].

In the proposed system we have used MEansLogPowerPlus clustering method as given in [14] for identifying the users among which relation estimation is feasible. The synthetic example input matrix is shown in figure 1. The zero indicated items are non-rated items for respective users. Predicting the value for zero is main objective in this process. The colored regions indicate the clusters obtained from clustering process. The prosed system is evaluated using dataset obtained from movie-lens for dataset of 1 million users.

| | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 | I10 | I11 | I12 | Cluster |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| U1 | 0 | 4 | 5 | 0 | 0 | 4 | 0 | 0 | 1 | 0 | 4 | 0 | 0 |
| U2 | 5 | 5 | 5 | 0 | 5 | 0 | 0 | 1 | 0 | 0 | 0 | 4 | 0 |
| U3 | 4 | 4 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| U4 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 5 | 0 | 1 |
| U5 | 2 | 0 | 0 | 2 | 0 | 2 | 0 | 0 | 2 | 0 | 0 | 4 | 1 |
| U6 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| U7 | 1 | 0 | 0 | 0 | 0 | 0 | 4 | 4 | 5 | 0 | 0 | 0 | 2 |
| U8 | 0 | 2 | 0 | 0 | 4 | 0 | 5 | 5 | 5 | 4 | 5 | 0 | 2 |
| U9 | 0 | 0 | 0 | 5 | 0 | 0 | 4 | 0 | 4 | 0 | 0 | 0 | 2 |
| U10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 2 | 3 |
| U11 | 1 | 0 | 1 | 0 | 4 | 0 | 0 | 1 | 0 | 2 | 1 | 0 | 3 |
| U12 | 0 | 1 | 0 | 0 | 0 | 5 | 0 | 0 | 2 | 2 | 2 | 1 | 3 |

**Fig. 1 Example Input ratings matrix along with clustering (colored shades)**

The example of predicted ratings for respective group of relation established among users is shown in figure 2 highlighted with gray colored background of rating value. The predicted rating is obtained by using equations (16) and (17). The resulting predictions are similar to that obtained in [14], but the advantage is that, predictions here are showing that, specific maximum predicted rating is similar to maximum rating given by other members of same clusters. This shows the maximum confidence depends on strength of relation between the pair of users. The results are further obtained in terms of mean absolute error (MAE) for different values of cluster K, in matrix factorization process.

Figure 3 shows the mean squared error examination of proposed system and graphical differentiation with method given in [14]. The results are showing good level of performance.

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| | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 | I10 | I11 | I12 | Cluster |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| U1 | 4 | 4 | 5 | 0 | 0 | 4 | 0 | 0 | 1 | 0 | 4 | 0 | 0 |
| U2 | 5 | 5 | 5 | 0 | 5 | 0 | 0 | 1 | 0 | 0 | 0 | 4 | 0 |
| U3 | 4 | 4 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| U4 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 5 | 0 | 1 |
| U5 | 2 | 0 | 0 | 2 | 1 | 2 | 0 | 0 | 2 | 0 | 0 | 4 | 1 |
| U6 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| U7 | 1 | 0 | 0 | 0 | 0 | 0 | 4 | 4 | 5 | 0 | 0 | 0 | 2 |
| U8 | 0 | 2 | 0 | 0 | 4 | 0 | 5 | 5 | 5 | 4 | 5 | 0 | 2 |
| U9 | 0 | 0 | 0 | 5 | 0 | 0 | 4 | 4 | 4 | 0 | 0 | 0 | 2 |
| U10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 2 | 3 |
| U11 | 1 | 0 | 1 | 0 | 4 | 0 | 0 | 1 | 0 | 2 | 1 | 2 | 3 |
| U12 | 0 | 1 | 0 | 0 | 0 | 5 | 0 | 0 | 2 | 2 | 2 | 1 | 3 |

(a)

| | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 | I10 | I11 | I12 | Cluster |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| U1 | 5 | 4 | 5 | 0 | 0 | 4 | 0 | 0 | 1 | 0 | 4 | 0 | 0 |
| U2 | 5 | 5 | 5 | 0 | 5 | 0 | 0 | 1 | 0 | 0 | 0 | 4 | 0 |
| U3 | 4 | 4 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| U4 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 5 | 0 | 1 |
| U5 | 2 | 0 | 0 | 2 | 2 | 2 | 0 | 0 | 2 | 0 | 0 | 4 | 1 |
| U6 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| U7 | 1 | 0 | 0 | 0 | 0 | 0 | 4 | 4 | 5 | 0 | 0 | 0 | 2 |
| U8 | 0 | 2 | 0 | 0 | 4 | 0 | 5 | 5 | 5 | 4 | 5 | 0 | 2 |
| U9 | 0 | 0 | 0 | 5 | 0 | 0 | 4 | 5 | 4 | 0 | 0 | 0 | 2 |
| U10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 2 | 3 |
| U11 | 1 | 0 | 1 | 0 | 4 | 0 | 0 | 1 | 0 | 2 | 1 | 3 | 3 |
| U12 | 0 | 1 | 0 | 0 | 0 | 5 | 0 | 0 | 2 | 2 | 2 | 1 | 3 |

(b)

**Fig. 2 Predicted rating for specific items using (a) Proposed method; (b) Method used in [14].**

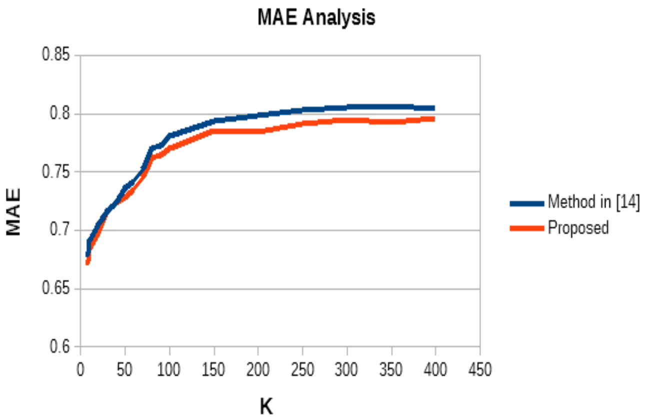


Fig. 3 MAE examination of movie-lens dataset using proposed method and differentiation with method in [14]

## V. CONCLUSION

In this paper, we have evaluated the results along with pre-clustering process as mentioned in [14]. The prediction of rating for non-rated items is dependent on the rating by same cluster members and level of trust amongst them. Earlier the direct probability calculation methods were used to estimate the trust. These were dependent on the distance of member from centroid of the cluster. The cluster centroids are randomly chosen at the start and remaining centroids are chosen based on distance. There was randomness involved in initial phase of rating prediction and hence less stability.

The method based on Lyapunov function solver for Sylvester general equation is obtained in this work. This provides strength for the estimated trust. This trust is the relation between the users. Hence, the predicted rating have sufficient grounds for consideration. The importance of trust consideration is addressed to predict accurate rating. This way the ratings obtained have sufficient grounds for consideration.

This paper contributes in modification of model for link prediction as given in [24] for the trust estimation. The clustering before processing, the modification in consideration of Kronecker product for matrix factorization for shuffling and updating P and Q factors of the matrix and then getting stable trust score at the end of all iterations is our main contribution against method in [24].

This method provides sufficient confidence for collaborative filtering. Hence, the trust based rating recommendation will increase satisfaction of users.

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