A Complex Network Approach for Collaborative Recommendation

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Abstract

Collaborative filtering (CF) is the most widely used and successful approach for personalized service recommendations. Among the collaborative recommendation approaches, neighborhood based approaches enjoy a huge amount of popularity, due to their simplicity, justifiability, efficiency and stability. Neighborhood based collaborative filtering approach finds $K$ nearest neighbors to an active user or $K$ most similar rated items to the target item for recommendation. Traditional similarity measures use ratings of co-rated items to find similarity between a pair of users. Therefore, traditional similarity measures cannot compute effective neighbors in sparse dataset. In this paper, we propose a two-phase approach, which generates user-user and item-item networks using traditional similarity measures in the first phase. In the second phase, two hybrid approaches $\text{HB1, HB2}$, which utilize structural similarity of both the network for finding $K$ nearest neighbors and $K$ most similar items to a target items are introduced. To show effectiveness of the measures, we compared performances of neighborhood based CFs using state-of-the-art similarity measures with our proposed structural similarity measures based CFs. Recommendation results on a set of real data show that proposed measures based CFs outperform existing measures based CFs in various evaluation metrics.

Keyword- Collaborative filtering, neighborhood based CF, similarity measure, sparsity problem, structural similarity.
1 Introduction

In the era of information age, recommender systems (RS) has been established as an effective tool in various domains such as e-commerce, digital library, electronic media, on-line advertising, etc. [20][2][14][11]. The recommender systems provide personalized suggestions about products or services to individual user filtering through large product or item space. The most successful and widely accepted recommendation technique is collaborative filtering (CF), which utilizes only user-item interaction for providing recommendation unlike content based approach [13][17].

The CF technique is based on the intuition that users who has expressed similar interest earlier will have alike choice in future also. The approaches in CF can be classified into two major categories, viz.  **model based CF and neighborhood based CF**.

Model-based CF algorithms learn a model from the training data and subsequently, the model is utilized for recommendations [21][18][8]. Main advantage of the model-based approach is that it does not need to access whole rating data once model is built. Few model based approaches provide more accurate results than neighborhood based CF [12][6]. However, most of the electronic retailers such as Amazon, Netflix deployed neighborhood based recommender systems to help out their customers. This is due to the fact that neighborhood based approach is simple, intuitive and it does not have learning phase so it can provide immediate response to new user after receiving upon her feedback. Neighborhood based collaborative algorithms are further classified into two categories, viz. **user based** and **item based CF**.

The user based CF is based on a principle that an item might be interesting to an active user in future if a set of neighbors of the active user have appreciated the item. In item based CF, an item is recommended to an active user if she has appreciated similar items in past. **Neighborhood based CF recommendation** extracts user-user or item-item similarity generally using Pearson Correlation Coefficient(PCC)and its variants, slope-one predictor from user-item matrix to predict rating of user for new item [9]. Item based CF is preferred over user based CF if number of items is smaller in number compared to the number of users in the system.

Generally, neighborhood based CF uses a similarity measure for finding neighbors of an active user or finding similar items to the candidate item. Traditional similarity measures such as pearson correlation coefficient, cosine similarity and their variants are frequently used for computing similarity between a pair of users or between a pair of items [5]. In these measures, similarity between a pair of users is computed based on the ratings made by both users on the common items (co-rated item). Likewise, item similarity is computed using the ratings provided by users who rated both the items. However, correlation based measures perform poorly if there are no sufficient numbers of co-rated items in a given rating data. Therefore, correlation based measure and its variants are not suitable in a sparse data in which number of ratings by individual user is less and number of co-rated items is few or none [10].

In this paper, we propose a novel approach for computing similarity between a pair of users (items) in sparse data. In the proposed approach, a user-user (item-item) network is generated using pearson correlation (adjusted cosine) for computing similarity between a pair of users (items). Having generated the net-
works, we exploit the structures of the network for addressing few drawbacks of neighborhood based CF. Having generated the networks, we exploit the structures of the network for computing similarity in sparse data and predictions for an item which receives ratings from few users. The approach is tested on real rating datasets. The contributions in this paper are summarized as follow.

- We propose a novel approach to utilize traditional similarity measures to generate user-user and item-item networks. The generated networks help in establishing transitive interaction between a pair of users, which is difficult to capture using traditional measures.

- The user based CF fails to predict rating of an item if it receives rating from few users (less than \( K \) users). Structure of the networks are exploited to address this problem by combining item based CF with the user based CF. Two algorithms termed as HB1 and HB2 are introduced for this purpose.

- We discuss the drawback of the use of F1 measure in recommendation scenario and introduce a new metric to evaluate qualitative performance of the collaborative filtering algorithms to capture the variation of rating provided by individual user.

- To show the effectiveness of the proposed approach in sparse dataset, we implemented neighborhood based CF using traditional similarity measures and neighborhood based CF using proposed approach.

The rest of the paper is organized as follows. The background and related research are discussed in Section 2. The proposed novel approach is introduced in Section 3. Experimental results and evaluation of the proposed approach are reported in Section 4. We conclude the paper in Section 5.

2 Background and related work

In this section, we discuss working principle of neighborhood based approach in detail and different similarity measures introduced in literature in-order to increase performance of recommendation systems over past decades.

2.1 Neighborhood-Based Approach

The neighborhood or memory based approach is introduced in the GroupLens Usenet article[19] recommender and has gained popularity due to its wide application in commercial domain [14][13][1]. This approach uses the entire rating dataset to generate a prediction for an item (product) or a list of recommended items for an active user. Let \( R = (r_{ui})^{M \times N} \) be a given rating matrix (dataset) in a CF based recommender system, where each entry \( r_{ui} \) represents a rating value made by \( u^{th} \) user \( U_u \) on \( i^{th} \) item \( I_i \). Generally, rating values are integers within a rating domain(RD), e.g 1-5 in MovieLens dataset. An entry \( r_{ui} = 0 \) indicates user \( U_u \) has not rated the item \( I_i \). The prediction task of neighborhood-based CF algorithm is to predict rating of the \( i^{th} \) item either using the neighborhood information of \( u^{th} \) user (user-based method) or using neighborhood information of \( i^{th} \) item (item-based method).
Neighborhood-based Prediction method can be divided into two parts User-based and Item-based. User based methods predicts based upon ratings of \(i^{th}\) item made by the neighbors of the \(u^{th}\) user. This method will computes similarity of the active user \(u\) to other users \(U_p, p = 1, 2...M, p \neq u\). Then \(K\) closest users are selected to form neighborhood of the active user. Finally, it predicts a rating \(\hat{r}_{ui}\) of the \(i^{th}\) item using the following equation.

\[
\hat{r}_{ui} = \bar{r}_u + \frac{\sum_{k=1}^{K} s(U_u, U_k)(r_{ki} - \bar{r}_k)}{\sum_{k=1}^{K} |s(U_u, U_k)|}
\]

where, \(\bar{r}_u\) is the average of the ratings made by user \(U_u\), \(s(U_u, U_k)\) denotes similarity value between user \(U_u\) and its \(k^{th}\) neighbor. \(\bar{r}_k\) is the average of ratings made by \(k^{th}\) neighbor of the user \(U_u\), and \(r_{ki}\) is the rating made by \(k^{th}\) neighbor on \(i^{th}\) item.

Item-based collaborative filtering has been deployed by world’s largest online retailer Amazon Inc. It computes similarity between target item \(I_i\) and all other items \(I_j, j = 1, ...N_i \neq j\) to find \(K\) most similar items. Finally, unknown rating \(\hat{r}_{ui}\) is predicted using the ratings on these \(K\) items made by the active user \(U_u\).

\[
\hat{r}_{ui} = \bar{r}_i + \frac{\sum_{k=1}^{K} s(I_i, I_k)(r_{uk} - \bar{r}_k)}{\sum_{k=1}^{K} |s(I_i, I_k)|}
\]

where, \(\bar{r}_i\) is the average of the ratings made by all users on items \(I_i\), \(s(I_i, I_k)\) denotes the similarity between the target item \(I_i\) and the \(k^{th}\) similar item, and \(r_{uk}\) is the rating made by the active user on the \(k^{th}\) similar item of \(I_i\).

Similarity computation is a vital step in the neighborhood based collaborative filtering. Many similarity measures have been introduced in various domains such as machine learning, information retrieval, statistics, etc. Researchers and practitioners in recommender system community used them directly or invented new similarity measure to suit the purpose. We discuss them briefly next.

### 2.2 Similarity Measures in CF

Traditional measures such as pearson correlation coefficient (PC), cosine similarity are frequently used in recommendation systems. The cosine similarity is very popular measure in information retrieval domain. To compute similarity between two users \(U\) and \(V\), they are considered as the two rating vectors of \(n\) dimensions, i.e., \(U, V \in \mathbb{N}_0^n\), where \(\mathbb{N}_0\) is the set of natural numbers including 0. Then, similarity value between two users is the cosine of the angle between \(U\) and \(V\). Cosine similarity is popular in item based CF. However, cosine similarity does not consider the different rating scales (ranges) provided by the individual user while computing similarity between a pair of items. Adjusted cosine similarity measure addresses this drawback by subtracting the corresponding user average from the rating of the item. It computes linear correlation between ratings of the two items.

Pearson correlation coefficient (PCC) is very popular measure in user-based collaborative filtering. The PCC measures how two users (items) are linearly related to each other. Having identified co-rated items between users \(U\) and \(V\), PCC computes correlation between them. The value of PCC ranges in \([-1, 1]\)
The value +1 indicates highly correlated and −1 indicates negatively correlated to each other. Likewise, similarity between two items $I$ and $J$ can also be computed using PCC. Constrained Pearson correlation coefficient (CPCC) is a variant of PCC in which an absolute reference (median in the rating scale) is used instead of corresponding user’s rating average. Jaccard only considers the number of common ratings between two users. The basic idea is that users are more similar if they have more common ratings. Though profoundly used PCC and its variants suffer from some serious drawbacks described in section 4.

PIP is the most popular (cited) measure after traditional similarity measures in RS. The PIP measure captures three important aspects (factors) namely, proximity, impact and popularity between a pair of ratings on the same item [4]. The proximity factor is the simple arithmetic difference between two ratings on an item with an option of imposing penalty if they disagree in ratings. The agreement (disagreement) is decided with respect to an absolute reference, i.e., median of the rating scale. The impact factor shows how strongly an item is preferred or disliked by users. It imposes penalty if ratings are not in the same side of the median. Popularity factor gives important to a rating which is far away from the item’s average rating. This factor captures global information of the concerned item. The PIP computes these three factors between each pair of co-rated items. PIP based CF outperforms correlation based CF in providing recommendations to the new users.

Haifeng Liu et al. introduced a new similarity measure called NHSM (new heuristic similarity model), which addresses the drawbacks of PIP based measure recently. They put an argument that PIP based measure unnecessarily penalizes more than once while computing proximity and impact factors. They adopted a non-linear function for computing three factors, namely, proximity, singularity, singularity in the same line of PIP based measure. Finally, these factors are combined with modified Jaccard similarity measure [15].

Koen Verstrepen and Bart Goethals proposed a method that unifies user- and item based similarity algorithms [22], but it is suitable for binary scale.

Before proposing our method, let us first analysis the problem with methods which use co-rated items through experiments on different datasets. These problems motivated us to formulate our proposed methods.

3 Proposed method for rating prediction

As mentioned earlier, we employ the well developed concept of similarities of nodes in a network for the prediction of entries of a rating matrix when a network is generated by using the given data. We propose to generate an user-user (resp. item-item) weighted network with node set as the set of users (resp. items) and the links in the network are defined by the PCC similarity of the users (resp. items) in the given data. Once the network is generated, a local similarity metric for nodes reveals insights about the connectivity structure of neighbors of a given node, and a global similarity metric provides the understanding of how a node is correlated with rest of the nodes in the network. Thus, a network approach to determine correlations between users or items provides a holistic outlook into the interpretation of a data.

Further, in order to reduce sparsity in the data for rating prediction, we introduce the concept of intermediate rating for an item by an user who has not
rated the corresponding item. Thus, we use both the user-user and item-item network structural similarities to propose new metrics for rating prediction.

### 3.1 Network generation and structural similarities

Let $\mathcal{U}$ and $\mathcal{I}$ denote the set of users and items respectively of a given data set. The adjacency matrix $A = [A_{ij}]$ for the user-user (resp. item-item) weighted network is defined by $A_{ij} = \text{PCC}(i, j)$ where $i, j$ denote users (resp. items) and $\text{PCC}(i, j)$ denotes the PCC similarity between $i$th and $j$th nodes. Thus, in the user-user (resp. item-item) network, the users (resp. items) are represented by nodes and links between any two nodes are assigned with weight $\text{PCC}(i, j)$ if $\text{PCC}(i, j) \neq 0$ otherwise the nodes are not linked. The size of the user-user (resp. item-item) network is given by $|\mathcal{U}|$ (resp. $|\mathcal{I}|$) where $|X|$ denotes the cardinality of a set $X$.

In this paper, we consider the following structural similarities for the user-user or item-item network. Let $A$ denote the adjacency matrix associated a network $G$. For a node $i$ of $G$, let $\gamma(i)$ denote the set of neighbors of $i$.

- **Common Neighbors (CN)**: The CN similarity of two distinct nodes $i$ and $j$ is defined by
  \[ s_{ij}^{\text{CN}} = |\gamma(i) \cap \gamma(j)|. \]
  It is obvious that $s_{ij}^{\text{CN}} = [A^2]_{ij}$, the number of different paths with length 2 connecting $i$ and $j$. So, more the number of common neighbors between two nodes, more is the value $s_{ij}^{\text{CN}}$ between them.

- **Jaccard Similarity**:
  This index was proposed by Jaccard over a hundred years ago, and is defined as
  \[ s_{ij}^{\text{Jaccard}} = \frac{|\gamma(i) \cap \gamma(j)|}{|\gamma(i) \cup \gamma(j)|} \]
  for any two distinct nodes $i$ and $j$ in the network.

- **Katz Similarity**: The Katz similarity of two distinct nodes $i, j$ is defined by
  \[ s_{ij}^{\text{Katz}} = \sum_{l=1}^{\infty} \beta^l \cdot |\text{paths} < l >_{ij} | = \beta A_{ij} + \beta^2 [A^2]_{ij} + \beta^3 [A^3]_{ij} + \ldots, \tag{3} \]
  where $\text{paths} < l >_{ij}$ denotes the set of all paths with length $l$ connecting $i$ and $j$, $[A^p]_{ij}$ denotes the $ij$th entry of the matrix $A^p$, $p$ is a positive integer and $0 < \beta$ is a free parameter (i.e., the damping factor) controlling the path weights. Obviously, a very small $\beta$ yields a measurement close to CN, because the long paths contribute very little. The Katz similarity matrix can be written as
  \[ S_{ij}^{\text{Katz}} = (I - \beta A)^{-1} - I \]
  where $\beta$ is less than the reciprocal of the largest eigenvalue of matrix $A$. Thus, Katz similarity of two nodes is more if the number of paths of shorter length between them is more.

Let $\lambda_1$ be largest eigenvalue of two nodes is more if the number of paths of shorter length between them is more. Let $\lambda_1$ be largest eigenvalue of $A$ in magnitude. We have set $\beta = \frac{0.85}{\lambda_1}$. This value of $\beta$ is used as damping factor of Google’s Page-Rank sorting algorithm.
Using the above mentioned similarity indices for users and items, one could predict the rating \( r_{ui} \) of \( I_i \)th item by user \( U_u \) as \( \hat{r}_{ui} \) by using the formulae (1) and (2).

| Dataset  | Purpose | \(|U|\) | \(|I|\) | #Ratings | \(|U|/|I|\) | \( \kappa \) | RD |
|----------|---------|--------|--------|----------|-------------|--------|-----|
| Movielens | Movie   | 6040   | 3706   | 1 M      | 1.6298      | 4.46   | [1-5]|
| Yahoo    | Music   | 15400  | 1000   | 0.3 M    | 15.4        | 2.024  | [1-5]|
| Netflix   | Movie   | 4141   | 9318   | 1M       | 0.4444      | 2.64   | [1-5]|

Table 1: Description of the datasets used in the experiments.

### 3.2 Network based hybrid approach for rating prediction

In this section, we introduce two new methods for rating prediction using both user-user and item-item networks constructed by the given data as mentioned above. Note that, in spite of significant advancement of calculation of user-user or item-item similarity in the network approach, the curse of sparsity hinders a finer prediction of ratings. For instance, if only a few users rated a particular item, network similarity of users suffer from accuracy keeping in mind that we can only use similarity of users who have rated a particular item \( I_i \) to which rating is to be predicted for an user \( U_u \). For the prediction of \( r_{ui} \), the rating of user \( U_u \) for the item \( I_i \), the \( K \)-neighbors problem \[10\] is concerned with the existence of minimum \( K \) number users who rated the item \( i \). Thus, in order to get rid of \( K \)-neighbors problem, we introduce the idea of intermediate rating (IR\(_k\)) as follows.

Let \( N_u \) be the number of users who have rated an item \( I_i \) and \( N_u < K \). Then, at first, we determine \( K - N_u \) users \( U_{i1}^*, U_{i2}^*, \ldots, U_{iK-N_u}^* \) best similar to \( U_u \). For these users, we predict rating of user \( U_{ik}^* \), \( k = 1 : K - N_u \) for the item \( I_i \) using item based similarity as

\[
IR_k = \bar{r}_i + \frac{\sum_{j=1}^{K^I} s(I_i, I_j)(r_{U_{ik}^*j} - \bar{r}_j)}{\sum_{j=1}^{K^I} |s(I_i, I_j)|}
\]  

(4)

where \( K^I \) is number of items whose similarities we have to use for prediction of \( IR_k \) and \( s(I_i, I_j) = s_{ij}^{Jaccard} \). For our present work we have set \( K^I = 10 \), but if similar user \( U_{ik}^* \) has rated less than 10 items we have used similarity of that many items for intermediate prediction.

Nevertheless, the \( K \)-neighbors problem can also be avoided for prediction of \( r_{ui} \) by selecting best \( K \) users similar to \( U_u \) without considering whether they have rated the item \( I_i \). If they have rated the item \( I_i \) then we use those ratings for prediction, else the value of \( IR_k \) can be used for the same.

Now, we propose the following formulae for prediction of \( r_{ui} \).
\textbf{4 Experimental Evaluation}

We conducted experiments on three real datasets, namely, Movielens (ML), Yahoo (YH) and Netflix (NF). Detailed description is given in Table 1. We utilized these datasets in two different ways to show the efficiency of our approaches on original dataset (Experiment 1 setup) as well as in sparse scenarios (Experiment 2 setup). We apply user-based method on Movielens and Netflix data sets and item-based method on Yahoo dataset as items are quite less compared to users in YH dataset.

\textbf{4.1 Experiment 1 Setup}

This setup is to show how the predictions differ for different users (items) based on the numbers of ratings a user made (an item received). We divided each dataset into 4 parts as described in (Table 2).

1. **U20-25 (I20-25):** The \textbf{U20-25} is a group of users who have rated number of items between 20-25. There are total 491 users in ML dataset.
Likewise, \( I_{20-25} \) is set of items which are rated by number of users between 20-25. There are only three (3) items in YH. So, this set consists of very sparse user (item) vectors. We see the effect of data sparsity on prediction for these users (items). Neighborhood selection is done from whole dataset.

2. \( U_{100-149} \) (\( I_{100-149} \)): \( U_{100-149} \) is the set of users who have rated a significant number of items in ML and Netflix datasets. Similarly, \( I_{100-149} \) is set of items which are rated by number of users between 100 and 149. There are such 243 items in YH. So, this set consists of users (items) which have significant ratings.

3. \( U_{GE150} \) (\( I_{GE150} \)): \( U_{GE150} \) is set of users who have rated more than 149 number of items. Similarly, \( I_{GE150} \) is set of items which are rated by more than 149 number of users.

4. \( U_{GE20} \) (\( I_{GE20} \)): This set consists of user (item) vectors from whole dataset.

To compare prediction performance for different category we randomly select 150 users (items) from each category. If total number of users (items) in a set is less than 150, we select all of them in that category. For each user, we randomly delete 15 ratings. Deleting more than 15 entries for test purpose will mostly result in void or very sparse vector (only 1 or 2 ratings). We predict these deleted ratings using state of art methods and methods proposed in this paper.

### 4.2 Experiment Setup 2

Main objective of the experiment setup 2 is to show the performance of our network based similarity measures on sparse datasets made from original datasets. We removed 75 % ratings from each user (item) to make them sparse dataset. It may be noted that during sparsifying process all ratings of few items (users) are deleted fully. Description of these sparse datasets is given in Table 3.

| Dataset | Purpose | \(|U|\) | \(|I|\) | \#Ratings(RT) | \(|U|/|I|\) | \(\kappa = \frac{2|I|+|U|-1}{|U||I|}\) |
|---------|---------|--------|--------|---------------|---------|-----------------|
| Movielens | Movie | 6040 | 3517 | 0.25 M | 1.71 | 1.18 |
| Yahoo | Music | 15082 | 1000 | 0.08 M | 15.08 | 0.51 |
| Netflix | Movie | 4141 | 8094 | 0.25 M | 0.51 | 0.69 |

Table 3: Description of the Sparse datasets used in the experiments.
4.3 Metrics

We use various evaluation metrics to compare the accuracy of the results obtained by our network based CF and other neighborhood based CFs. Two popular quantitative metrics (Root Mean Squared Error and Mean Absolute Error) and one popular qualitative metric (F1 measure) are used. For the shake of readability, we discuss them briefly. Finally, we introduce a new qualitative measure termed as Best Common Rated Item (BCRI) to address the drawback of the F1 measure in recommendation scenario.

1. Root Mean Squared Error (RMSE): Let $X_u = [e_{u1}, e_{u2}, e_{u3}, \ldots, e_{um}]$ be the error vector for $m$ rating prediction of a user $U_u$. A smaller value indicates a better accuracy. Root Mean Square Error (RMSE) for a user
**Figure 4: BCRI in Movilens**

is computed as follows.

\[ RMSE = \sqrt[2]{\sum_{i=1}^{m} e_{ui}^2} \]

2. **Mean Absolute Error (MAE):** Mean Absolute Error measures average absolute error over \( m \) predictions for a user \( U_u \). It is computed as follows.

\[ MAE = \frac{\sum_{i=1}^{m} |e_{ui}|}{m} \]

3. **F1 Measure:** Many recommender systems provide a list of items \( L_r \) to an active user instead of predicting ratings. There are two popular metrics to evaluate quality of a RS in this scenario: (i) **Precision**, which is the fraction of items in \( L_r \) that are relevant and (ii) **Recall**, which is the fraction of total relevant items that are in the recommended list \( L_r \). A list of relevant items \( L_{rev} \) to a user is the set of items on which she made high ratings (i.e, \( \geq 4 \) in MovieLens dataset) in the test set. Therefore, **Precision** and **Recall** can be written as follows.

\[ Precision = \frac{|L_r \cap L_{rev}|}{|L_r|} \] and \[ Recall = \frac{|L_r \cap L_{rev}|}{|L_{rev}|} \]

However, there is always a trade-off between these two measures. For instance, increasing the number of items in \( L_r \) increases **Recall** but decreases **Precision**. Therefore, we use a measure which combines both called **F1** measure in our experiments.

\[ F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \]

4. **Best Common Rated items:** The F1 measure is very popular among information retrieval community. However, it is not suitable measure in the following scenario. There are users who are very lenient in giving ratings, e.g, **Tom** has given minimum rating value of 4 to items. On the
other hand, there are users who are very strict on giving ratings, e.g. Siddle has given at maximum rating value 2 to items. For strict users, it is difficult to find $L_{rev}$ the set of items on which she made high ratings (i.e., $\geq 4$) as such ratings are not present. Also if no predicted rating is $\geq 4$, we cannot compute $L_r$. To measure performances in such scenario, we introduce a new metric termed as Best Common Rated Items (BCRI). It determines whether best actual rated entries are also best predicted entries or not.

Let $BAI = \{ba_1, ba_2, ba_3, ba_4, ba_5\}$ be the set of top $t$ best rated items by a user and $BPI$ be the set of top $t$ best predicted items for the user. $BCR$ is computed as follows.

$$BCRI = BAI \cap BPI$$
4.4 Experimental Results and Analysis

In experiment setup 1, from each subset we selected users or items and predicted deleted ratings using all other users or items in the corresponding rating dataset. As we know traditional similarity measures use ratings of only co-rated items in case of user-based CF, whereas, they use ratings of common users in case of item-based CF. Therefore, in many situation we cannot find similarity between a pair of users (items). This is reflected in figure [1]. In figure [1] we get many times NaNs during similarity computations specifically while computing similarity for users in the first group $U_{20-25}$. It can be noted that if similarity come out to be NaN, we can not use it for prediction purpose. This shows that sparsity is a big issue in computing similarity using traditional similarity measures.

For Yahoo dataset we use item-based method as number of items is quite less than number of users. In this dataset, when we select items from $IGE_{20}$ for computing similarity, we find many NaNs (8460) for 150 items. Similar trends are found for other groups of items.

Similarly in Netflix data set, When we select users from $UGE_{20}$ total number of NaNs during similarity calculation for 150 users is 35816 and when we select users from $U_{20-25}$ it is 14535(for 6 users), where as for $U_{100-149}$, $UGE_{150}$, the numbers are significantly less, i.e 12881, 2932 respectively.

So we can see that few co-rated entries are hindrance in determining similarities between a pair of user or items. We use structural similarity measures to get rid of this problem.

We begin analyzing results of the experiments with Movielens dataset. Results of experiment setup 1 on Movielens is shown in Figure [2]- [4]. In general RMSE, MAE decrease, while BCRI increases with increase of nearest neighbors. The state-of-the-art similarity measure NHSM performs better than PIP in RMSE (Figure [2]), MAE (Figure [3]), BCRI. However, for large value of K PIP outperforms NHSM and other traditional measures in RMSE, MAE. From Figure [2]- [4] it is found that structural similarities based CFs outperforms PCC measure based as well as state of art similarities based CFs in each metric. Hybrid methods outperforms all other similarity measures in RSME, MAE. However, for small value of K Jaccard similarity obtained from network outperforms hybrid methods in BCRI. The HB1 is best. Among different categories, pre-
Results of experiment setup 2 on sparse Movielens subset are shown in figure 5-7. In figure 5, it can be noted that traditional similarity measure PCC performs poorly compared to the state of the art similarity measures. Recently proposed NHSM outperforms PIP measures in RMSE. However, all structural similarities computed from proposed network of users outperform PIP, NHSM and PCC measures in RMSE. Hybrid techniques are found to be outperforming other structural similarity measures derived from the network. In Figure 6, MAE of the CFs are plotted over increasing value of K. Similar trends are noted here also. Structural similarly measures based CFs outperform PCC and NHSM and PIP measures. Two hybrid techniques which are proposed to remove K-neighbor problem is found to be better than other structural similarity measures. The first hybrid approach makes least MAE as low as 0.82 at the value of K = 150.

The plot in figure 7 shows the efficiency of our structural similarity (extracted from network) based CFs over others measures based CFs. The F1 measure is used to show the capability of an approach to retrieve relevant items in a user’s recommended list. It is found that hybrid approach including other structural similarly outperform PCC, PIP and NHSM measures in F1 measures. This facts justifies our claim that hybrid approaches with network can address the problem of data sparsity. It can be noted that sparsity of the ML subset is 98.82% (Table 3).

Results of experiment setup 1 on Yahoo dataset is shown in figure 8-10. In general RMSE, MAE decreases, while BCRI increases with K-Neighbors. NHSM performs better than PIP in RMSE, MAE, BCRI but for large value of K, PIP performs better in RMSE, MAE than NHSM. It is observed that
Figure 9: MAE in Yahoo

Figure 10: BCRI in Yahoo
structural similarities outperforms PCC and state of art similarities in RMSE, MAE. Hybrid methods along with other structural measures outperform PIP, NHSM, PCC similarity measures in RMSE, MAE and BCRI metrics. Among the proposed measures, HB1 is best in all metrics. It can be noted that we applied item-based CF on Yahoo dataset.

To show the efficiency of the proposed network approach, we compare the performance of item-based CFs on Yahoo dataset and results are reported in figure 11-13. In Figure 11 and Figure 12, predictive metrics RMSE and MAE of different similarity measures based CFs are plotted over the value of K. In the both plots, it is found that structural similarity obtained from item network can provide better RMSE and MAE values compared to PCC, PIP and recently
introduced NHSM measure. In figure 13, F1 measures of different structural similarity based CFs, PCC based CF and PIP and NHSM based CFs are shown in increasing value of $K$. PCC based CF is worst performer in F1 measure. The PIP measure based CF outperforms NHSM measure. All similarity extracted from item-item network are found to be outperforming traditional PCC, PIP and recently introduced NHSM measure. The hybrid techniques are found to be suitable in this highly sparse dataset. It can be noted that network approach is equally successful in item-based CF.
Figure 15: MAE in Netflix

Figure 16: BCRI in Netflix

Figure 17: RMSE in Sparse NF
Figure 18: MAE in Sparse NF

Figure 19: F1 in Sparse NF
Results of experiment setup 1 on Netflix is shown in figure 14-16. NHSM performs better than PIP for smaller values of $K$ in RMSE, MAE, BCRI metrics. However, PIP outperforms NHSM in large value of $K$. We see that structural similarities outperform PCC and state of art similarities in RMSE, MAE and BCRI measures. Hybrid methods outperform all other similarity measures in RSME, MAE and BCRI metrics. The HB1 is best in all metrics.

Experimental results of experiment setup 2 on sparse Netflix data set is shown in figure 17-19. Similar trends are noted. Structural similarities based CF outperform PCC, PIP and NHSM based CFs in MAE, RMSE and $F_1$ measure on highly sparse Netflix subset. For smaller value of $K$, NHSM performs better than CN. However, with suitable number of nearest neighbors, hybrid methods perform better than other similarity measures in RMSE, MAE and $F_1$ metrics. The HB1 is the best in all metrics even on sparse datasets.

5 Conclusion

In this work, we proposed a new outlook to deal with the problem of collaborative recommendation by gainfully using the concept of structural similarity of nodes in a complex network after generating user-user and item-item networks based on the given data. We showed that, the curse of sparsity and K-neighbors problem can be delicately handled in this approach. Thus, we proposed CFs based on structural similarity measures of the user-user and item-item networks individually. Moreover, we introduced two methods which we call hybrid methods using both user-user and item-item networks for CF. We verified the effectiveness of these measures by comparing its performances with that of neighborhood based CFs using state-of-the-art similarity measures when applied to a set of real data. The comparison results established that the proposed measures based CFs and hybrid methods outperform existing similarity measures based CFs in various evaluation metrics.

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