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Influential Nodes Based Alleviation of User Cold-Start Problem in Recommendation System

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Abstract: The Cold-start problem considered as one of the most common limitations of Recommender Systems (RSs) which indicates to situation when a new user or items lastly combined to the system. We focus in this study on set of the users who did not receive attention by researchers about their preferences in future, so they often have been ignored. Highlight on their interests may improve the recommendation systems; we utilize the social relation information and social network analysis to alleviating the new user's problem by exploiting the preferences of influential nodes to recommend items for new users. So, the main contribution in this research is employing the influential nodes to alleviate the cold start problem. Top-M influential nodes have been assigned from the social communities using closeness and degree centrality measure and then suggest the most popular interest items of those nodes to new users. The performance of our approach has been applied using two data sets: Lastfm published by Group lens research and CiaoDVD published by LibRec research group. The experimental results show that exploiting influential nodes in cold start issue improve the recommendation system.

Key words: Cold start, influential nodes, centrality, social relations, recommendation system, cold-start problem

INTRODUCTION

In recommendation systems, there are some challenges, one of these challenges is called cold start problem which indicates to situation when a system has no any inferences for users or items because it has not yet collected sufficient information about them (Jahrer *et al*., 2010). The problem of cold start includes three kinds; new item problem, new user problem and new system problem (Ma *et al*., 2009). In such kinds, it is usually difficult to supply recommendation as in form of new user. Additionally, there is very lees acquaintance about user that is obtainable. For a new item, no ratings are usually obtainable. And thus collaborative filtering cannot make useful recommendations in case of new item as well as new user. For the new system, it is difficult to find the pattern (Adomavicius and Tuzhilin, 2005) as there is very less acquaintance about user and lastly added product or items.

In traditional RSs, most of the methods that are designed to alleviate the cold start problem integrate rating data with content data or in other forms, comprise aspects from content-based systems to the recommendation process (hybrid recommenders). More importantly, e.g., Dunham (2002) exploit acquaintance that is delivered by ontologies while Park *et al*. (2006) concentrate on simple filter bots (acting as pseudo-users who automatically rate items according to certain attributes).Additionally, There are exist non-content based methods, such as Ahn (2008) and Huang *et al*. (2004) who only use rating data: the former introduces a similarity measure which takes into account the proximity of the ratings, the rating impact and item popularity, while in the latter method the set of neighbours is extended by exploring transitive associations between the items and users.

In fact, One of the promising directions suggests that the incorporation of a trust network and interpersonal relations such as friend circle can significantly help alleviating the user cold start problem (Qian *et al*., 2014; Victor *et al*., 2011, 2008). In this study we try to benefit from trust network, social relationship among users and influential nodes in social communities to mitigate new user problem which affect the accuracy of recommendation systems.

Literature review

Related work: The most existing works use information, just as demographic data, click, browsing time and interaction with users to solve the cold start problem. In (Li *et al*., 2009), the new item problem has been solved using dynamic browsing tree model. The user browsing records in previous method have been transformed to dynamic browsing tree based on product categories of E-commerce website. New item will be chosen based on the matching degree between new item and dynamic

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browsing trees of all users. The authors in (Yin *et al*., 2009) use implicit information of new users and multi-attribute rating matrix to alleviate the cold start problem.

Hybrid approaches are another approach that be used for solving cold start problem. In (Leung *et al*., 2008), a novel hybrid recommendation approach has been presented to address this issue by applying cross-level association rules to integrate content information of items into collaborative filters. Another hybrid models have been developed in (Lam *et al*., 2008) and (Sun *et al*., 2011) based on the analysis of two probabilistic aspect models and both the ratings and content information respectively.

The social network analysis theory is also support the recommender systems. The social network-based recommender systems in terms of integration social network analysis theory with recommender systems to obtain Social Network-based Recommender Systems (SNRSs) as in (He and Chu, 2010; Victor *et al*., 2008). As for the work in (Perez *et al*., 2011), a model has been designed which assists users in finding people that belong to their social network.

Some researchers focus on how the recommender system deals with new user (cold start problem) by using social information as in (Sahebi and Cohen, 2011). In other words, other information such as the profile of user can be used to recommend relevant items for a new user in a system. Alleviating the cold start problem by computing the similarities between each pair of users and building user relation network based on similarity in their taste (Yujie *et al*., 2013), then communities or groups have been detected to obtain the candidate neighbours of new user from groups. Others like (Sedhain *et al*., 2014) enhanced the recommend relevant items of the new user by propose a neighborhood model depending on the information of the user's social network content such as Facebook friends and Facebook page likes.

Most of the previous researchs depend on the friends group or trust network for new users to avoid the cold start problem. In other hand, demographic information has been suggested as a way to fix that issue. In this research, the influential nodes of the friends' network have been taken in account to alleviate that problem. The motivation of proposed method is that the influential nodes may represent good candidates to recommend their preferences for the cold start users, especially for those who have few or no friends as well as no available demographic information.

Social recommender systems: Social media is the collective of online communications channels dedicated to interaction, content-sharing and collaboration. It is becoming one of the important parts of daily live . The popularity of social media leads to increase the people's social activities with their families, friends and colleagues which produces rich social relations. Social media has become is the environment in which people has affected on each other in their decisions. However, the events in the real life affect the activities on the Internet and vice versa, so the interaction among people is increased. In other words, the social media has enabled people to affect each other in their decisions (Panda *et al*., 2014).

Important to realize that the preference of user is influenced by his social relations such as friends logically, social correlation theories such as homophily and social influence can explain that case (Marsden and Friedkin, 1993).

The social networks become rich environment to improve recommendation system. Generally, the two main types of recommender systems: content-based and Collaborative-Filtering (CF) (Yang *et al*., 2014; Guo *et al*., 2012; Liu and Lee, 2010). The social recommender system based on memory use memory based CF models, where a missing rating for a given user can be obtained from the ratings of his neighbors. In traditional user-oriented methods, similarity measures are used to get the correlation among users, while memory based social recommender systems use both rating and social information to find the correlation among users. Social recommender systems include two phases: firstly, finding users who have socially relations to a given user; secondly, aggregating ratings from the users who obtained from the first step to estimate missing ratings (Tang *et al*., 2013).

In this research, we need to study the effect of social information on all users and how we can exploit social information and influential nodes to alleviate the user cold start's problem, hence only the social information has been used to find the users who have relations to a given user.

Social influence: Notion of influence is important and long studied (Business, fashion, voting trends, marketing, recommendation, etc.) (Rajaraman and Ullman, 2011), influence measuring is difficult (Involves human choices, societies, complex), one of the key factors to measure influence is interpersonal relationship among users.

The influential nodes in the network can be represented in social network analysis by different centrality metrics where the network centrality is a powerful tool in the analysis of large scale networks; it can determine the relative importance of a node in the network (Panda *et al*., 2014). Many influence models and centrality measures have been proposed to rank actors within a social network (Qian *et al*., 2012); the most common centrality measures: Degree, Betweenness and Closeness, etc (Saryyuce *et al*., 2013). Let G = (V, E) be a network modeled as a simple graph with n = |V| vertices and m = |E| edges, where each node is represented by a vertex in V and a node-node interaction is represented by an edge in E. The d_G (u, v) is used to denote the length of the shortest path between two nodes (u,v).

Degree centrality is measured for undirected and directed networks, the first one indicates to the direct links which node has. As for a directed network in-degree and out-degree centrality are usually used. In-degree centrality points to the number of connections ending at a node while the out-degree centrality indicates to the number of connections starting from a node (Panda *et al*., 2014). The betweenness can be defined as the number of times that a node lies on the shortest paths between any pair of nodes in the network graph (Panda *et al*., 2014). Finally, closeness indicates to node that is nearby to all other nodes in a network (directly or indirectly) is the inverse of the sum of the shortest distances between each node and every other node in the network. A node is considered important if he/she is relatively close to all other nodes (Saryyuce *et al*., 2013). The Closeness Centrality (CC) is defined as in Eq. 1 : (Wasserman and Faust, 1994):

$$CC(u) = \frac{1}{\sum_{v=1}^{n} d_C(u, v)} \tag{1}$$

PAM (Partitioning Around Medoid): One of the well-known partitioning clustering algorithms is k-means. It supposes a Euclidean space and also provides the number of the clusters. Possibly, trial and error can be used to infer the best value of k.

K-medoids is a basic method for clustering in PAM, where it is related to the k-means and medoid shift algorithms. However, k-means and k-medoids algorithms attempt to decrease the distance between points that grouped in one cluster and the point that designated as the center of that cluster.

In PAM algorithm the K objects are selected as medoids (centroids) of clusters , remaining objects of data are assigned to the closest cluster, where "closest" means closest to the medoid of the cluster.

Last step of PAM clustering is that swapping the current medoids with new random non-medoid objects provided that new cost is better than current cost. In this research the PAM algorithm used for create social communities from the friend's network to find the influential nodes for each community.

MATERIALS AND METHODS

Proposed method: The proposed method has been illustrated in the following steps:

Pre-processing: In this step, for the Lastfm dataset the binary user-item has been created where 1 represent listen an item by a user and 0 otherwise. For the CiaoDVD dataset, only the users who have ratings and at the same time belong to the trust network have been considered. The ratings network of Ciao DVD dataset includes 1:5 as a rating for products.

Create relation networks: Relation's network is created by the friend's and trustee's relations that are already available in the Lastfm and ciaoDVD datasets respectively.

Dividing users: To deal with cold start problem, the cold start users should be separated. Therefore, the users have been divided into two groups the first one for users that have number of friends greater than threshold (t) and second group (cold start group) for users that have number of friends less than or equal (t). For the first group, the user-oriented memory based social collaborative filtering has been used as a preferences prediction as follows:

$$P_u = i_n, \quad n = 1, 2, \ldots, N \tag{2}$$

Where,

P_u = The preferences prediction of a user
i's = The top
N = Popular items among the friends of user which have not been listened, watched or purchased before by that user

The items in list have been ranked according of their popularity (from most to least popularity) among friends or trustees.

Assigned the influential nodes: The friend's network is divided into sets of social communities by using PAM (Partitioning Around Medoid) clustering algorithm to find the influential nodes for each community. For the Lastfm dataset, the closeness and degree centrality measures have been applied to find a certain number of the influential nodes in a community. Firstly we select top-K of nodes with best closeness centrality then the nodes that have a highest degree are selected to obtain the top-M influential nodes. The value M has been selected by try and error; however, it is changed when the size of

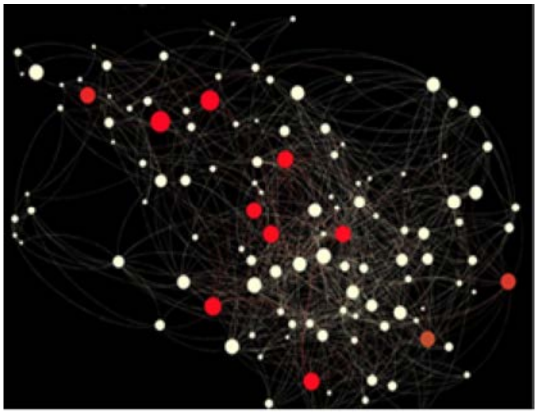

Fig. 1: Visualization of part of lastfm dataset to showing the influential nodes (larger red colored nodes are most influential nodes based on closeness and degree measure)

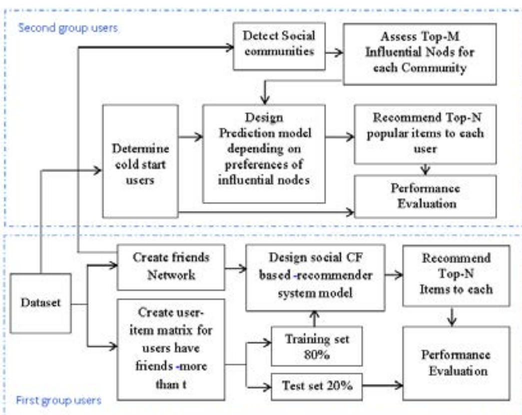

Fig. 2: Proposed system

the friend's network and the community changed. Figure 1 shows the influential nodes visualization using gephi open source software as illustrated the largest red nodes represent the influential nodes. For the CiaoDVD dataset the trustees that have a highest number of trustors have been considered as influential nodes. For the CiaoDVD dataset the trustees that have a highest number of trustors have been considered as influential nodes.

Preferences prediction: For each new user of the cold start group (the second group), the preferences have been predicted depending on the preferences of influential nodes in a community that the new user belong to.
So, the preferences are predicted as follows:

$$P_{uc} = i_n\text{-}inf_m,\ n= 1,2,\ldots.N \text{ and } m=1,2,\ldots.M \quad (3)$$

Where:

P_{uc} = The preferences of cold start user
i_n-inf's = The top
N = Popular items among the M influential nodes which have not been known before by that user as mentioned before regarding the first group, the ranking of items in recommendation list for each user is according to their popularity among all items. A Fig. 2 shows the block diagram of the proposed system

Performance evaluation: The recall@N measure is used to evaluate the performance of the proposed method at recommendation list with length N, because when the ratings are binary type and no dislike ratings are available, the recall measure is appropriate (for such dataset (Lastfm) (Kantor *et al*., 2011; Kayes *et al*., 2012; Hu *et al*., 2008) , The recall@N defined as (Fig. 2).

$$\text{Recall @ N} = \frac{\text{No. of items the user likes in top} - \text{N}}{\text{Total number of items the user likes}} \quad (4)$$

Also the coverage measure is applied to compute the ratio of new users who have benefited from the recommendations. Arguably, the system can be improved if recommends at least one item for a new user correctly.

$$\text{coverage} = \frac{\text{number of new users that truly reached}}{\text{Total number of new users}} \quad (5)$$

RESULTS AND DISCUSSION

Experimental results: The performance of proposed system has been evaluated on real world music dataset hetrec2011-Lastfm-2k (Lastfm) and CiaoDVD dataset. Table 1 and 2 show description of Lastfm and CiaoDVD datasets, respectively. The connectivity among nodes in

Table1 : Lastfm description

Users	1892
Artists(items)	17632
User listened artist relations	92834
User-user friend relations	25434
Users that have ≤2 friends	416
Users that have ≤3 friends	598
Users that have ≤4 friends	883
Sparsity	99.7

Table2 : CiaoDVD description

Variables	Value
Users (trustors and trustees)	2433
Trustors	920
Movies (items)	13066
User-movie ratings	34437
Trustor-trustee relations	22484
Trustors that have ≤2 trustee	171
Trustors that have ≤3 trustee	218
Trustors that have ≤4 trustee	249
Sparsity	99.9

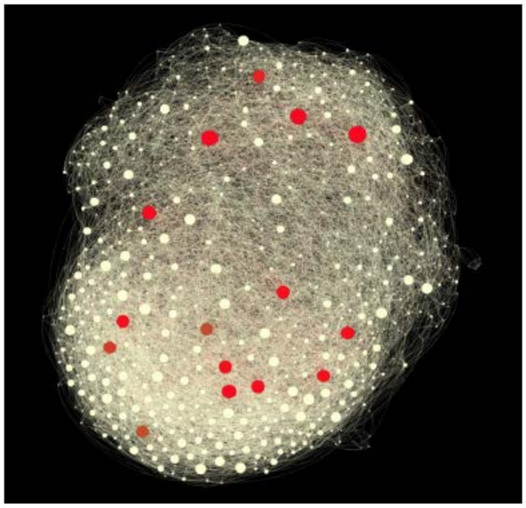

Fig. 3: Visualization lastfm dataset

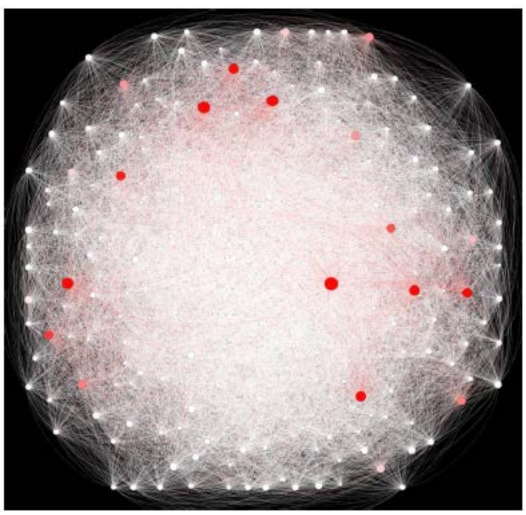

Fig. 4: Visualization ciao dataset

Lastfm-2k and ciaoDVD datasets is strong, hence are represent one community as shown in Fig. 3 and 4.

For evaluation and comparison purpose, firstly the user-oriented memory based social collaborative filtering has been used as a baseline for the proposed system. Hence, it is has been implemented on all data set (without separate cold start users) using all friends of each user as a nearest neighbours and then predict the ratings of users depend on friends preferences for each user.

Secondly, our proposed approach has been applied on the dataset. As mentioned previously, the dataset is divided into two groups. According to that two prediction methods have been applied; user-oriented memory based social collaborative filtering for the all

Table 3: Recall measures of 5- fold cross validation (Number of influential nodes M=10)

Variables	R@10 (%)	R@50 (%)	R@100 (%)
Fold 1			
Baseline	12.3	25.8	32.2
Proposed Approach	15.5	29.1	35.2
Fold 2			
Baseline	12.6	25.3	31.9
Proposed Approach	15.9	28.9	35.1
Fold 3			
Baseline	12.1	25.7	32.3
Proposed Approach	15.8	29.3	34.8
Fold 4			
Baseline	12.5	25.8	32.1
Proposed Approach	15.9	28.8	34.9
Fold 5			
Baseline	12.2	25.6	31.8
Proposed Approach	15.6	29.1	35.0

Table 4: Recall measures of 5- fold cross validation (Number of influential nodes M=15)

Variables	R@10 (%)	R@50 (%)	R@100 (%)
Fold 1			
Baseline	12.3	25.8	32.2
Proposed Approach	15.7	30.4	35.7
Fold 2			
Baseline	12.6	25.3	31.9
Proposed Approach	16.1	29.6	35.4
Fold 3			
Baseline	12.1	25.7	32.3
Proposed Approach	16.0	29.7	35.3
Fold 4			
Baseline	12.5	25.8	32.1
Proposed Approach	16.1	29.3	35.2
Fold 5			
Baseline	12.2	25.6	31.8
Proposed Approach	15.8	29.6	35.3

users except cold start users and the proposed approach for only cold start users. Important to say, the social collaborative filtering recommender system has no enough inferences for users that have few number of friends such as 1,2 or 3 friends, for that reason the selected value of threshold t is 3 as a threshold to assign cold start users.

Worthy mention that 20% of sequence of actions for each user in first group has been used for evaluation purposes. As for the cold start users (second group), all their preference have been removed for the same purpose above.

For Lastfm dataset, Table 3-5 show the results for 5-fold cross validation with the numbers of influential nodes M = 10 ,15 ,20 respectively . Table 6 shows the coverage ratio results for the cold start users before and after separate them. Table 7 shows the proposed method's Recall metric when we use only degree centrality measure to assess the influential nodes and it's differences from hybrid centrality (closeness and degree). For CiaoDVD dataset, Table 8-10 show the average of results for 5-fold cross validation with the numbers of influential nodes M = 10, 15, 20, respectively. Table 11

Table 5 : Recall measures of 5- fold cross validation (Number of influential nodes M=20)

Variables	R@10 (%)	R@50 (%)	R@100 (%)
Fold 1			
Baseline	12.3	25.8	32.2
Proposed Approach	15.9	30.2	36.3
Fold 2			
Baseline	12.6	25.3	31.9
Proposed Approach	16.3	30.0	36.2
Fold 3			
Baseline	12.1	25.7	32.3
Proposed Approach	16.2	30.3	35.9
Fold 4			
Baseline	12.5	25.8	32.1
Proposed Approach	16.3	30.0	35.9
Fold 5			
Baseline	12.2	25.6	31.8
Proposed Approach	16.0	30.1	36.2

Table 6: Coverage measure for Lastfm data set

Variables	Top 10 items (%)	Top 50 items (%)	Top 100 items (%)
Baseline	35.1	60.3	64.2
Proposed Approach M=10	95.1	95.4	95.6
Proposed Approach M=15	96.1	96.3	96.4
Proposed Approach M=20	96.7	96.9	97.2

shows the coverage measure for the new users in the CiaoDVD data set.

CONCLUSION

In this research we propose a method that utilize the influential nodes for the reduce the cold start problem that considered as one of the main problems in the recommender systems, the user-oriented memory based social CF used as baseline. Hybrid centrality measure (closeness and degree) has been used to assess the importance nodes in social friend network communities. We found that at least 27% of Lastfm users have very few friends (1,2 or 3 friends) and 27% of ciaoDVD trustors have very few trustees (1,2,3 or 4 trustees) that means, there are no sufficient social information about them, hence the social CF system has no enough inferences for the users. When we use the proposed method, the obtained results showed that the accuracy of system improved because the system can inference new item for those users who have a few friends (cold start users) by exploiting from the preferences of influential nodes .

As Shown in Table 6 and 11, the number of the beneficiaries' new users from the recommendations has been increased by using proposed method. For the lasfm and CiaoDVD datasets, the values of coverage ratio are >95 and 40%, respectively. In other words, those new users have been benefited from the system's recommendations even though one item has been recommended correctly as a minimum. As noted from tables, the coverage ratios have been improved than in past. The obtained results in Table 7 proof that the hybrid centrality measure gives best node's importance indicator than degree centrality alone.

Table 7: Average Recall metric for the proposed method using different centrality measures

M=10	R@10 (%)	R@50 (%)	R@100(%)
Degree centrality	14.2	27.6	33.6
Closeness and degree	15.8	29.1	35.0

Table 8: Average Recall measures of 5- fold cross validation (Number of influential

Variables	R@10 (%)	R@50 (%)	R@100 (%)
Baseline	15.2	20.5	21.1
Proposed Approach	16.9	23.4	24.2

Table 9: Average Recall measures of 5- fold cross validation (Number of influential nodes M=15)

Variables	R@10 (%)	R@50 (%)	R@100 (%)
Baseline	15.2	20.5	21.1
Proposed Approach	18.4	25.6	26.1

Table10: Average Recall measures of 5- fold cross validation (Number of influential nodes M=20)

Variables	R@10 (%)	R@50 (%)	R@100 (%)
Baseline	15.2	20.5	21.1
Proposed Approach	19.1	26.8	27.3

Table 11: Coverage measure for the ciao DVD dataset

Variables	Top 10 items (%)	Top 50 items (%)	Top 100 items (%)
Baseline	5	7	11
Proposed Approach M=10	29.1	29.4	29.6
Proposed Approach M=15	40.1	40.3	40.4
Proposed Approach M=20	42.1	42.6	42.9

The accuracy measure of recall as shown in tables for both data sets proves the superior of the proposed system over baseline. Generally, the results are improved when the number of influential nodes are increased which indicates the role of the influential nodes in this regard.

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