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DIVERSITY ENHANCEMENT IN COMMUNITY RECOMMENDATION USING TENSOR DECOMPOSITION AND CO-CLUSTERING

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ABSTRACT

The major aim of Recommender System is to provide appropriate items for user, based on his preferences and intuitively be assessed with accuracy based metrics like precision and recall. Though, diversity of recommended lists is a new emerging debate in RS evaluation. This work tries to improve diversity of community recommendation, using membership as main and tag collection as complementary resource. With exploiting Tensor Decomposition and using Latent Semantic Analysis, communities can be represented in latent topics, based on different modes including member-users and tag-collections. As the main contribution, this work applies diversification on recommended list in different modes, based on intuitive idea that, communities can be differ from different points of view such as membership, or tag collections. Experimental results accomplished on a Flicker dataset show the meaningful improvement in aggregate diversity (for the system) with less accuracy-loss comparing to current methods; moreover it also shows improvements in intra-list diversity (for single user) which is neglected in previous works. As a result, clustering the communities with similar users, or tags, gives the opportunity to diversify the recommended lists to cover more diverse communities with different member users, or different tag content, and this multi-mode diversity lead to better list for user and better coverage for system.

Keywords: *Recommender System, Community Recommendation, Diversity, Coverage, Tensor Decomposition, Co-clustering*

1. INTRODUCTION

Social Recommendation is defined as a solution to filter items for user based on his preferences. The preferences of user are derived from his past ratings (or interaction) in content-based models, or join with similar users' preferences in collaborative filtering models to provide the top recommendations for him. From the modeling point of view, this implies to use the matrix structure to represent users, items, and the relevant value (of rating), as rows, columns, and value of cells of matrix, respectively.

With emergence of social media, people increasingly tend to generate and share content, establish relation with the others, and join the communities with desired topics or members. In social media, "tag" is a user-defined keyword attached to the item for organizing and future retrieve [1]. Tags also can express preferences of users so that a collection of user's tags might be evaluated as user's profile. Some social tagging systems let users attach their desired tags to items and share with the other users. *BibSonomy* for publications, *del.icio.us* for urls, and *Flickr* for photos, are examples of online social media supporting user tag annotation. the overall of users, contents, and tags create a collection so-called folksonomy [2].

With the overwhelming and fast increasing size of online social media, using Recommender Systems to provide personalized content, peer, or community recommendation looks inevitable. Unlike typical models of Recommender Systems, which are limited to two entities, say user and item, new approaches try to take into account auxiliary information about user (or item) to enrich their prediction and recommendation and overcome with sparsity problem from lack of proper user's data. As an example, there is remarkable attention in researches to introduce "context" as third element in Recommender System models [3][4]. In social

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media context, these "dimensions" include users, resources, tags, relations, and affiliations. This area provides prolific opportunity to exploit multiway structures to represent multidimensional data of social media.

2. RELATED WORKS

2.1 Social Recommendation

In collaborative filtering models, user receives recommendation which is based on collective preference of people who are similar to him [5]. In further meaning of this concept, trust-based recommendation is introduced with the intuition that, user mostly accepts the recommendation comes from trusted users such as friends [6]. In social media, the opportunity of using explicit user-generated annotations and relations, describing personal preferences of user, leverage the recommendation power to a new ground called Social Recommendation. Figure 1 shows a sample of social media activities including community membership and tagging for some users.

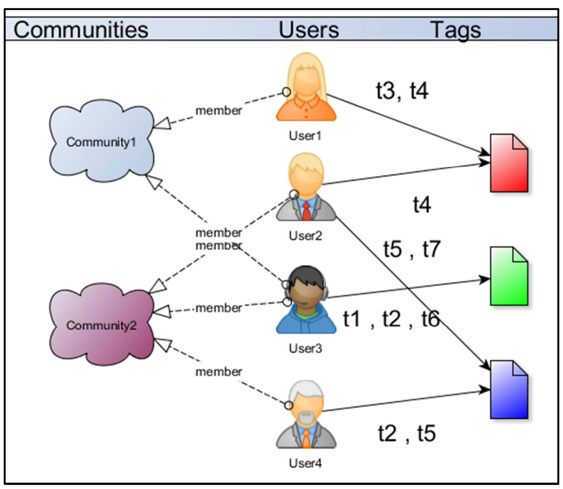

Figure 1. Example Of Users Who Attach Tags To Items, And Join Communities In Social Network

Based on the social media resources, [7] propose a recommendation model using a social graph constructed among users, tags, and items. They implement their model on Last.FM, a music social network, and exploit the user generated tags to derive implicit feedbacks, for music track recommendation. Despite the intuitive shape of their ternary resources including users, tags, and tracks, they represent the graph in two-dimensional matrix by putting dyadic matrices next to each other. This trick is a typical solution to overcome the dimension problem in many works in literature, but preserving multi dimension structure prevent from loss of data. There are a remarkable and still growing literature on social recommendation on news recommendation [8], tag recommendation [9][10], friend recommendation [11] [12], and finally community recommendation [13][14].

2.2 Community Recommendation

Since social networks are based on sharing contents and establishing relations between users, they also support creating and joining groups and communities to form aggregation on similar users or topics. With the rapid increase of number of communities in social networks, similar to other kind of resources, finding appropriate community to join is becoming a problem for users. This problem is more challenging when user is not previously joined to any community (cold-start problem), or members of communities are not connected together via friendship ties.

Combinational Collaborative Filtering (CCF) is the name of a method is proposed by Chen and Chang in [15] to recommend the community to the user. It combines information from multiple sources and looks at the community from different views: bag of users to satisfy the personalization, and bag of words to overcome the sparsity problem. CCF is a good example of multidimensional extension of PLSA (Probabilistic Latent Semantic Analysis) for community recommendation on triple factors. However, the weakness of this model is on recommendation for users with no or low community memberships, as such when the user has not joined the communities CFF fails to recommend him even if he has contribution on lot of documents.
Chen et al. in [16] compare two algorithms from different scopes for community recommendation: Association Rule Mining (ARM), and Latent Dirichlet Allocation (LDA). With ARM, they consider users as transactions and their joined communities as items. Then by means of ARM, they try to find association rules between co-occurrence of item sets which are sets of communities. It will find the explicit relations between communities. Contrary to ARM, LDA discovers the implicit relation between communities by means of latent aspects, models the co-occurrence of user-community, then makes recommendation based on the learned model. They confirm the advantages of discovering latent aspects in communities' co-occurrence, with better performance report for LDA. However, remaining limited in two dimensions (community-user and

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community-items), this work is likely to lose useful data in third dimension (user-item).

In another study [17], authors have a comprehensive and systematic evaluation over different memory-based (user-based, item-based, and tag-based) and model-based (matrix factorization and tensor factorization) CF algorithms for community recommendation. The main contribution of [17] is applying non-negative CANDECOMP/ PARAFAC (NNCP) algorithm for tensor factorization on Flickr dataset. The idea of NNCP is based on estimation the main tensor with a group of non-negative rank-one tensors. In fact they applied this idea on Flickr in their previous work [18]. Their model includes latent topic discovery and recommendation based on discovered topics. They conclude that memory-based models are better for higher efficiency, and tag-aware models for higher quality with sparse data, and factorization models are good choices with dense data. This work, with good contribution in comparing different methods for community recommendation, approves and supports some part of our proposed model using Tensor Factorization.

2.3 Evaluation Metrics: Accuracy VS Diversity

Evaluating of Recommender Systems is always one of the most controversial issues in this area. There are several evaluation metrics and none of them outperforms the other metrics for different methods. Generally there are two type of task in recommender system to evaluate: rating prediction and item recommendation.

There are some popular metrics to measure the ratio of correct recommendations; Precision, Recall, and F1-measure. Accuracy measurement is the main goal of these metrics. However, these evaluation metrics operate on narrow of whole collection of data. In the other hand, they only evaluate the proportion of items which user has interacted with, and forsake the rest of items. The current evaluation metrics are unable to measure the coverage of recommended items. In addition to coverage, there are other concepts of Recommendation Quality which are in contrast with accuracy.

Quality, as a concept of measuring, has been discussed and different definitions have released. In Recommendation context, diversity, coverage and novelty are mostly discussed as quality measures. While diversity is defined as the extent of dissimilarity of pair of recommended items, novelty is introduced as the unexpectedness of recommended items for user, and how much it is relevant to the user preferences [19]. It worth to mention that, every novel item recommendation leads to better diversity, but every diverse recommendation is not novel (useful and interesting for user) necessarily.

3. MULTI-DIVERS RECOMMENDATION

3.1 Problem Definition and Preliminaries

Let there be a set of users $U=\{u_1,u_2,\ldots,u_I\}$, a set of tags $T=\{t_1,t_2,\ldots,t_J\}$, and a set of communities $C=\{c_1,c_2,\ldots,c_N\}$. The ternary relation $X \subseteq U \times T \times C$, represents the frequency of assignment of a tag by a user in a specific community. For community recommendation, we are interested in recommending for a given item u, a list of desired communities. We construct tensor $\boldsymbol{X} \in R^{I\times J\times N}$ based on ternary relation of communities, users, and tags.

Tensor Decomposition: Canonical Decomposition (CANDECOMP) also known as Parallel Factor Analysis (PARAFAC), is one of the most popular tensor factorization techniques based on Tucker Decomposition [20]. Figure 2 shows expresses decomposition based on CANDECOMP method.

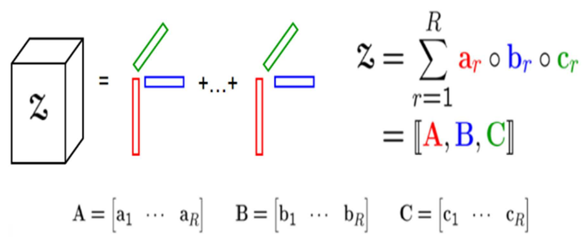

Figure 2. CANDECOMP/PARAFAC (CP)

Decomposes A Tensor As The Sum Of Rank-1 Factors

We apply CANDECOMP/PARAFAC (CP) technique on $\boldsymbol{X}$ to capture the latent semantics in tensor data. The main idea of CP decomposition is fitting X with a set of rank-one components based on:

$$\boldsymbol{X} \cong \sum_{r=1}^{R} \lambda_r \; \mathbf{a}_r \odot \mathbf{b}_r \odot \mathbf{c}_r \qquad (1)$$

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where symbol ⨀ shows the outer product of matrixes, r is the decomposed rank of tensor, λ_r is the importance weight of r-th component, $a_r \in R^I$, $b_r \in R^J$, and $c_r \in R^N$. With these rank-one components of decomposition we derive three matrices **A**(I×R) ,**B**(J×R), and **C**(N×R), for users, tags, and communities respectively [21], [22]. The main benefit of CP decomposition is projection of tags, users, and communities to similar size r, and deriving rich relations among them into r components.

Co-Clustering: In unsupervised learning, clustering play an important role, as such partitioning the columns of a data, to earn closer item set, and comparatively far from other sets. Most clustering algorithms focus on one-dimensional data, for example partitioning documents based on their words distribution. However, with two or more dimensions, co-clustering is defined to cluster item set in two or more dimension simultaneously. The idea of co-clustering is to maximize the reciprocal dependent information to all present variables [23]. Using clustering and co-clustering in RS is reported for tackling the sparsity [24], and improving diversity [25].

3.2 Multiverse Community Recommendation

We initially construct three-way tensor (X) including user, user's respective tag list (be treated as user preference), and user's community membership data. The proposed multiverse community recommendation includes tensor decomposition, and co-clustering.

- Decompose tensor (***X***) with selected decomposition method, PARAFAC, to derive latent components of users, communities, and tags and also to leverage curse of dimensionality [26].
- Estimate $\tilde{\boldsymbol{X}}$ a low-rank estimation of original tensor, and predict the unrated values for potential user community membership. First top N items of the sorted user-community list provides top-N recommendation list.
- Apply co-clustering technique on User-Community and Tag-Community matrices to infer latent groups of communities with similar topic in two ways:
  - User-based: Cluster of communities which their member users are similar.
  - Tag-based: Cluster of communities which their annotated tags are similar.

This step provides two sets of information about user-based community clusters (U1), and tag-based community clusters (T1). Cluster membership for Communities is later used in re-ranking top-N recommendation which provides higher diversity.

Applying Naïve Recommendation Techniques on $\tilde{\boldsymbol{X}}$ provide us an intrinsically Accurate recommendation list for current user. It means the list tends to be more similar to previous ratings of user and this property leads to higher value of accuracy in commonly used metrics such as Precision, Recall, and F-measure.

Community Co-clustering

The standard clustering approaches, such as k-means, cluster the columns of input matrix (say term-document matrix in IR, or tag-user matrix in RS), into groups which minimizes the intra-distance between cluster members. Co-clustering partitions rows and columns of matrix simultaneously and produces coherent groups of items with similarity in both dimensions. Similar users tend to join to similar communities, and similar communities are likely to have similar members. In the same manner, similar tags are likely to appear in similar communities, and similar communities are likely to contain similar tags. Based on these intuitive iterative ideas, we propose a new framework of co-clustering in multi-dimensional space. User-based (or tag-based) community co-clustering organizes simultaneously subset of communities and subset of users (or tags) in order to improve the clustering quality of both of them.

We apply co-clustering techniques on decomposed components of $\tilde{X}$ to infer latent groups of communities with similar Latent Aspects in two ways: User-based and Tag-based. This step provides us two sets of information about user-based community clusters (G_{c_u}), and tag-based community clusters (G_{c_t}).

Suppose $C \subset R^k$ collection of communities with k-dimensional features. $c = (d_1, \dots, d_k)$ and $d_i = (f_1, \dots f_l)$ shows community c in dimension i contains l feature in aspect space. Accordingly, di-based co-clustering is accomplished on i-th component of PARAFAC decomposition, based on similarity in features fj of di . This clustering find G<<K cluster means $\{\mu_{g_{di}} \in R^N\}_{g=1}^{G}$ and assign each c to the best matching cluster. For our context, community recommendation based on ternary <c,u,t>, user-based clustering is defined as:

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$$G_{c_u} = \{\{g_{c_u}\} \mid c \in C, \exists < c,u,t >,$$
$$dist(c(f_1, \ldots . f_l), \mu_{g_c}) <$$
$$\mathcal{E}_{g_c} \;\&\; dist(u(f_1, \ldots . f_l), \mu_{g_c}) < \mathcal{E}_{g_u}\} \qquad (2)$$

Therefore, g_{c_u} is co-clustering of communities based on user-similarity, dist is distance function between sets of features in aspect space, and $\mathcal{E}$ is range of clusters. In a similar manner, for community recommendation based on ternary <c,u,t>, tag-based clustering is defined as:

$$G_{c_t} = \{\{g_{c_t}\} \mid c \in C, \exists < c,u,t >,$$
$$dist(c(f_1, \ldots . f_l), \mu_{g_c}) <$$
$$\mathcal{E}_{g_c} \;\&\; dist(t(f_1, \ldots . f_l), \mu_{g_c}) < \mathcal{E}_{g_t}\} \qquad (3)$$

3.2.2 Topic Diversification

Recommender systems refer to diversity as "how accumulate dissimilarity are between pairs of items in a recommendation list for specific user (intra-list diversity) or whole recommendations of system (aggregate diversity)". Whereas novelty of an item is defined as "how different it is with previously seen/known items". In fact novelty refers to and exploits the Long-Tail effect to find items which are less popular (in the Long-Tail). Fig. 3 depicts a condition of the Long-Tail which few items have massive popularity and most of items have few popularity.

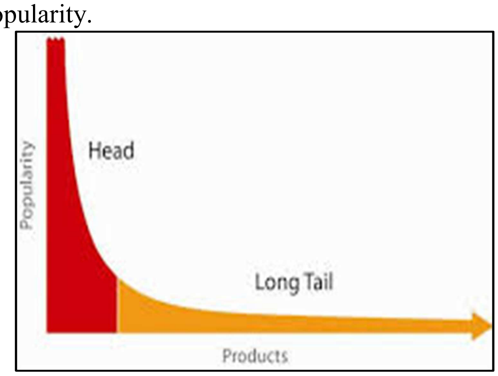

Figure 3. The Long-Tail effect

In current context, big clusters (which have significant communities) in terms of popularity, have popular communities (head of diagram) which are usually famous and well-known groups. Therefore they have less importance in terms of novelty to recommend.

Most of previous works which propose items on long-tail for diversity, neglect considering the similarity of candidates from lower-popular items and merely choose an item with lower popularity score. Fig. 4 depicts the situation which re-ranking of items from same cluster (similar), don't improve diversity. We address this shortcoming with taking the cluster membership of items in to account.

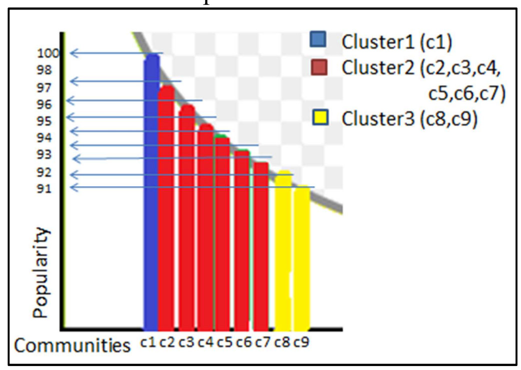

Figure 4. Clusters of Items in the Long-Tail: Re-ranking between Items of Same Clusters (e.g. c2…c7) doesn't Improve Diversity as Well.

Applying Naïve Recommendation Techniques on $\tilde{X}$ provide us an intrinsically accurate recommendation list. It means the list tends to be more similar to previous ratings of users and this property leads to higher value of accuracy with commonly used metrics such as Precision, Recall, and F-measure.
There exist a tradeoff relation between accuracy and diversity. [27] Suggest tunable diversification techniques which user can control the acceptable accuracy-loss for diversity maximization. To provide diverse list for user, and improve coverage for overall system, we develop the proposed diversification method.

Re-ranking top-N recommendation list, in such a way that maximizes the including clusters and don't exceed the accuracy-loss threshold. There are evidences that current recommender models place randomly one of items before the others when there exist different items with the same ranking value [28]. In this case, even re-ranking the list to involve more clusters, doesn't lead to accuracy-loss.

3.2.3 Re-Rank Strategy

Item popularity-based re-ranking is a ranking approach that tries to give priority to items with lower-popularity. This method which is proposed and analysed critically by Adomavicius & Kwon in

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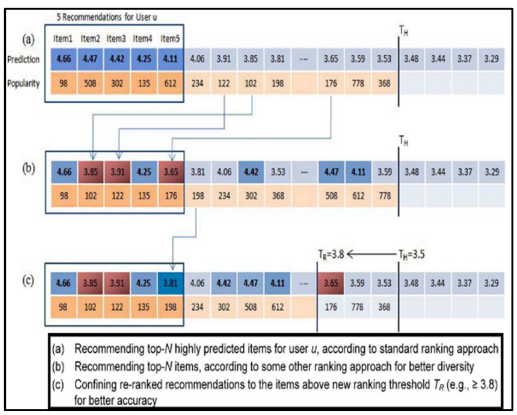
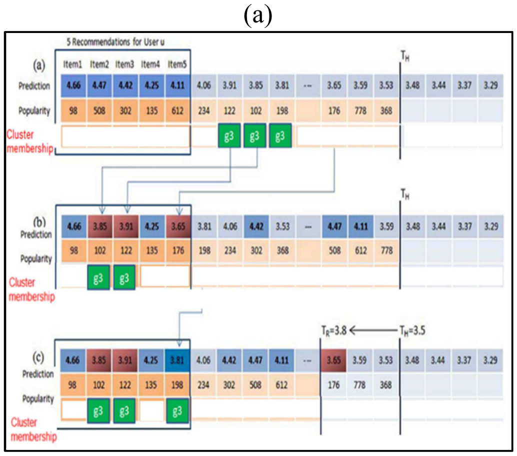
[27] is a solution for diversity improvement. This solution, is using ranking and popularity of items and tries to promote the rank of less popular items in ranking list.

$$\mathrm{ItemPop}(i) = |U(i)|, U(i) = \{u \in U \mid \exists R(u,i)\} \quad (4)$$

Based on above ranking approach, authors present a scenario to re-rank recommendation list for better diversity. Fig. 5(a) shows the scenario for re-ranking top-5 recommendation with items which have prediction value upper than threshold (TH) and smaller popularity. In fig. 5(b) we show if the selected items for re-ranking are from one cluster (are similar to each other) this scenario fails and doesn't satisfy diversification.



(a)



(b)

Figure 5. Re-rank for diversification [27]

Most of previous works which propose items on the Long-Tail for diversity, neglect considering the similarity of candidates from lower-popular items and merely choose an item with lower popularity score. If the selected items for re-ranking are from one cluster (similar to each other), this scenario fails and doesn't satisfy diversification.

This works is addressing this shortcoming with taking the cluster membership of items in to account. Based on above ranking approach, this work presents a method to re-rank recommendation list for better diversity. For better diversification, we propose using complementary information filed, called cluster membership. Selection of candidate items for diversification from different clusters, helps improving diversity.

4. EXPERIMENTS

Dataset: To evaluate the proposed method, we use a dataset from Flickr photo sharing social network. Flickr dataset is a good instance of social media which use social tagging for its items, and also manage big amount of user-generated communities. the below Table 1 shows the statistics of used dataset [29].

Table 1: Statistics of Flickr Dataset

Number of Items			Non-Zero Items		
U	T	C	U×T	U×C	C×T
500	300	200	10567	12297	31187
U:User, T:Tag, C:Community					

It is common to deal with very sparse dataset in recommender systems (e.g. 99% sparsity). However decreasing sparsity helps for better accuracy. Therefore below methods is applied on dataset for lower sparsity:

- Since considering tag list of users as their preferences, users without contribution (those who doesn't generate any tag) is removed from dataset.
- Similarly, communities without any tag in profile (tags derived from member users), is removed from dataset.
- TF-IDF weighting scheme is applied on tensor data (X).

Applied diversification can be measured with dimension-based metrics which shows how much the items of recommended list are dissimilar to each other. For coverage measurement also, the aggregate number of used tags or users in overall recommendations can be considered as coverage metrics.

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Evaluation 1 - User-based Aggregate Diversity (usrAggDiv): Captures the overall coverage of users in community recommendation. On the other hands, it shows percentage of all member users in communities that recommender system is able to cover in recommendation (User Coverage).

$$UsrAggDiv@topN = \frac{\sum_{c \in L,\ C(c,u)=1} |u|}{|U|} \quad (5)$$

Figure 6. shows the results for user aggregate diversity (coverage) for recommendation list from length=1..50. As it is clear from the figure, the proposed diversification method outperforms the standard CP method and Popularity-based method. It means the proposed method covers more member users in recommendation lists.

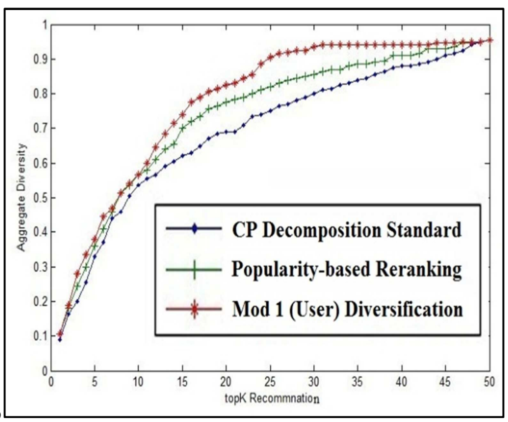

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Figure 6. User-based Aggregate Diversity @top-N

Evaluation 2 - Tag-based Aggregate Diversity (tagAggDiv): Captures the overall coverage of tags in community recommendation. On the other hands, it shows percentage of all tags used in communities that recommender system is able to cover in recommendations (Tag Coverage).

$$TagAggDiv@topN = \frac{\sum_{c \in L,\ C(c,t)\neq 0} |t|}{|T|} \quad (6)$$

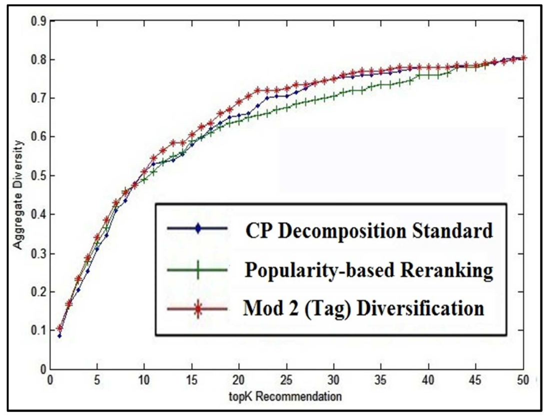

Figure 7. Tag-based Aggregate Diversity @top-N

Figure 7. shows the results for tag coverage. Tag coverage represents the covered topics in the recommendation list. As an improvement resulted from the proposed diversification method, Aggregate diversity (coverage) of tags is higher than the other solutions.

Evaluation 3 - Intra-List Diversity (ILD): ILD measures the dissimilarity of each pair of items in a list of specific user. Improvement in intra-list diversity helps user to receive diverse and heterogeneous list of recommendations. ILD is defined as

$$ILD(L) = 1 - \frac{2}{n|L|(|L|-1)} \sum_{i=1}^{n} \sum_{j,k \in L_i} 1 - s(j,k) \quad (7)$$

where L is the recommendation list, n the number of users, and s similarity function.

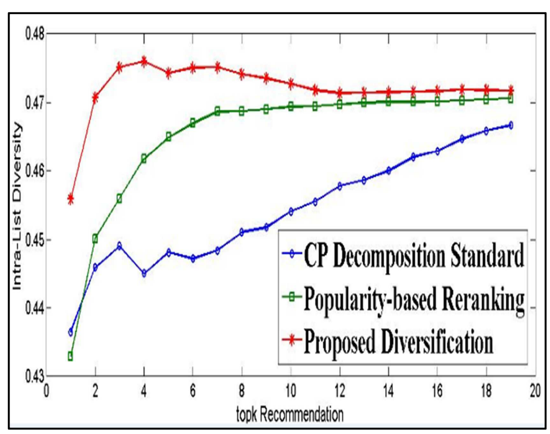

Figure 8. Intra-List Diversity @top-N

Figure 8. shows the results for ILD in recommendation list from length=1 to 20. As it is clear, dissimilarity between pair of recommended

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communities is increased with diversification method. However the proposed diversification method shows much higher values especially in lower length of recommendations. This method shows the highest value of intra list diversity for top-4 list with ILD=0.476. This result proves the effectiveness of the proposed method in terms of increasing dissimilarity among recommended items.

5. CONCLUSION

As a newly growing method, we proposed tensor decomposition for generating low-dimension data for community recommendation. Diversity and coverage of recommendations as the valuable quality metrics beside accuracy are introduced, and co-clustering is proposed to use for diversify the recommended item list. The results of aggregate user coverage and tag coverage shows significant improvement of the proposed method compared to HOSVD and Popularity-based re-ranking method.

For the future work, we are planning to expand and improve the proposed solution and gain experimental result with other datasets. For tensor decomposition, there are a lot of methods derived from original CP decomposition which the evaluation and selection of the best is a critical step. Also, the co-clustering on different mode of data reveals valuable information to use for diversification. Our future works will report about this solution with more technical details.

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