A Combined Method for Mitigating Sparsity Problem in Tag Recommendation

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Abstract

Tag recommendation is a specific recommendation task for recommending metadata (tag) for a web resource (item) during user annotation process. In this context, sparsity problem refers to situation where tags need to be produced for items with few annotations or for user who tags few items. Most of the state of the art approaches in tag recommendation are rarely evaluated or perform poorly under this situation. This paper presents a combined method for mitigating sparsity problem in tag recommendation by mainly expanding and ranking candidate tags based on similar items' tags and existing tag ontology. We evaluated the approach on two public social bookmarking datasets. The experiment results show better accuracy for recommendation in sparsity situation over several state of the art methods.

1. Introduction

Tags are freely chosen words which act as annotation or metadata for describing web resources which can be used for personal organization, easy retrieval or finding related resources [1]. As tags are easy to use by ordinary users, the usage of tags are very popular in most of Web 2.0 platforms (Examples are social bookmarking sites e.g. *https://delicious.com* and *http://www.bibsonomy.org* or e-commerce sites e.g. *http://www.amazon.com* and many others).

However, with this free vocabulary there are also problems with ambiguity such as synonymy and *polysemy*, as well as personal tags which are sometimes only meaningful to individuals [2]. Besides these problems, there are also variations in morphology such as plurality and singularity, acronyms, abbreviations and typos.

To alleviate these problems, tag recommendation is a well known process for assisting users in the annotation or tagging process. Its objectives are to provide relevant tags and to help consolidate the annotation vocabulary in the systems [3]. In this regards, tag recommender can be seen as a specialized recommender system for suggesting tags for annotating web resources, as in contrast to the traditional recommender systems for recommending items. Specifically, tag recommender systems will recommend for a given user and a given item, a set of tags for annotating the item.

In item recommendation context, *sparsity* problem [4] refers to a situation whereby recommendations need to be produced for users who have rated very few items in a large item collection or items which have received very few ratings from a large user collection.

In relation to that, *sparsity* problem in tag recommendation context refers to users who tag a few or very few resources, and in some situation only one resource. It could also mean there are resources which received very few annotations and there are tags which are only used by very few users. It is observed that in these cases of *sparsity* and cold-start situations, most of the state of the art tag recommendation methods perform poorly [5].

In this paper we present a tag recommendation approach which can alleviate these problems by incorporating collaborative filtering (CF) method with expansion methods to find more candidate tags. For a given user and a given item, by using CF technique, a set of candidate tags can be produced based on user's similar preferences. Then, we propose methods to expand the candidate tags set by including similar items' tags and terms consolidated under concepts on an existing ontology. Further, we expand these candidate tags set by including more general and specific concepts of the ontology. This ontology could be any general ontology or domain ontology generated from *folksonomy* [6]. The ontology serves as semantic representation of concepts which can be recommended to users to annotate their items.

This paper is structured as follows. We present the related work in Section 2. In Section 3 we define several key concepts. Section 4 discusses basic user based CF as one of the baseline systems and proposed tag recommendation based on candidate tags set expansion. Section 5 discusses the experiment set up and evaluation method which consist of evaluation for dense, sparse and combined datasets. Section 6 discusses experiment results, and in Section 7 we conclude this paper and discuss some ideas for future work.

2. Related work

In this section we discuss related work in tag recommendation which include content, collaborative, and graph-based approaches. We introduce emerging works in ontology-based recommendation which motivate one of the main parts of our proposed approach which is ontology-based expansion method.

2.1. Tag recommender systems

Tag recommender systems are broadly divided into three classes: content-based, collaborative, and graph-based approaches [7]. A content-based tag recommender exploits textual content (resource information/ metadata) or multimedia content (resource audio/ visual feature) while a collaborative-based uses CF method to find similarities among resources, users and tags to generate recommendation. Graph-based method uses relationship structures and strengths among resources, users and tags in a form of graph representation to generate recommendation.

The state of the art works in content-based method are the approaches proposed by (1) Tatu et al. [8] which mapped textual contents in bookmarks, not just the tags, to concepts in WordNet; and (2) Lipczak et al. [9] which explored resource content as well as resource and user profiles. However, there is a drawback that these works relied on extended textual contents provided by the Bibsonomy site which are not always available in other collaborative tagging system.

The baseline tag recommender system in collaborative-based method is the user-based CF [10] because of its effectiveness, ease of implementation and general applicability to most collaborative tagging system. There is also a notable work by Sigurbjornsson and van Zwol [11] which is based on tag co-occurrences. Although this work has achieved good result in the past, it did not rely on actual meaning of tags which may miss the semantic relationships among tags.

The most notable works in graph-based approaches are the works by (1) Jaschke et al. [3] which utilized a graph-based tag ranking method named FolkRank [12] and (2) Symeonidis et al. [13] which proposed the Tensor Dimensionality Reduction method. Also, there are many recent works which are using hybrid approaches or incorporating machine learning techniques such as Pairwise Interaction Tensor Factorization (PITF) [14].

However, there was not much work done in using domain ontology for tag recommendation. Beside the work proposed in this paper, there is one work by Baruzzo et al. [15] which used existing domain ontology to recommend new tags by analyzing textual content of a resource needed to be tagged. However, they did not provide quantitative evaluation.

Above all, most of the state of the arts in tag recommendation, mostly in collaborative and graph-based method, is evaluated on the dense part of dataset and rarely on the sparse part of dataset. The work we present in this paper is a combined tag recommender which includes collaborative and graph-based method but not the content-based method. Although content-based method may achieve good solution for cold-start situation, it may not be applicable to all collaborative tagging system because it relies on extra information in resources which are not always available. It also may not be practical since for different content type it will need different version of the algorithm [5].

2.2. Ontology from *folksonomy*

Ontology is formal description and explicit specification of a shared conceptualization [16]. Depending on the types of stored knowledge, ontology can be categorized in two types: general ontology and domain ontology [17]. *Folksonomy* which is emerging from collaborative tagging has been acknowledged as potential source for constructing ontology. As it captures vocabulary of users which may be aggregated to produce emergent semantics, people may develop lightweight ontologies [18].

Work by Garcia-Silva et al. [19] compares approaches for associating tags with semantics in order to make explicit the meaning of those tags. They have identified three groups of approaches which are based on 1) clustering techniques i.e. to cluster tags according to some relations among them (statistical techniques); 2) ontologies i.e. aiming at associating semantic entities e.g. WordNet, Wikipedia, to tags as a way to formally define their meaning; 3) hybrid approach i.e. mixing clustering techniques and ontologies.

The approach proposed by Djuana et al. [6] represents the state of the art work for the second approach (general ontology based method). It constructs tag ontology from folksonomy based on an existing general ontology WordNet [20]. Other ontologies, such as YAGO [21] also can be used with this method.

For the work presented in this paper we utilized the ontology generated by Djuana et al. [6] mainly because its capability of semantic vocabulary expansion given it is based on WordNet synonym sets. It is also possible to apply the same technique to expanded WordNet general ontology using Wikipedia such as YAGO to achieve wider vocabulary coverage.

3. Definitions

3.1. Collaborative tagging system

A collaborative tagging system contains three entities: users, tags, and items, which are described below:

- Users $U = \{u_1, u_2, .. u_{|U|}\}$ contains all users in an online community who have used tags to annotate their items;
- Tags $T = \{t_1, t_2, .. t_{|T|}\}$ contains all tags used by users in U. Tags are typically arbitrary strings which could be a single word or short phrase. In this respect, a tag is defined as a sequence of terms. For $\in T$, $t =< term_1, term_2, \ldots\ldots, term_m >$. A function $tagset(t) = \{term_1, term_2, .. term_m\}$ is defined to return the terms in a tag;
- Items $I = \{i_1, i_2, .. i_{|I|}\}$ contains all domain-relevant items or resources. What is considered by an item depends on the type of collaborative tagging system, for instance, in the Delicious and Bibsonomy sites the items are mainly bookmarks.

Based on these three entities, a collaborative tagging system is formulated as *Folksonomy* which consists of 4-tuple: $F = (U, T, I, Y)$ where U, T, I are finite sets, whose elements are the users, tags and items, respectively. Y is a ternary relation between those elements, i.e., $Y \subseteq U \times T \times I$, whose elements are called tag assignments or taggings. An element $(u, t, i) \in Y$ represents that user u annotated item i using tag t. A function $Ft(u, i)$ is defined to return a set of tags that a user u has assigned to an item i whereby $Ft(u, i) = \{t \in T | (u, t, i) \in Y\}$ for all $u \in U$ and $i \in I$.

3.2. Tag recommendation

A tag recommender is a specific kind of recommender systems in which the goal is to recommend a set of tags to use for a particular item. Based on previous formulation of *Folksonomy,* the task of a tag recommender system is to recommend, for a given user $u \in U$ and a given item $i \in I$ which has not been tagged by the user or with $Ft(u, i) = \emptyset$, a set $\tilde{T}(u, i) \subseteq T$ of tags. In many cases $\tilde{T}(u, i)$ is computed by first generating a ranking on the set of tags according to some criterion, for instance by a collaborative filtering, content based, or other recommendation algorithms, from which then the top n tags are selected.

3.3. Ontology and tag-to-concept mapping

An ontology can be defined as a 2-tuple $\boldsymbol{ONTO} = (\boldsymbol{C}, \boldsymbol{R})$ where $C = \{c_1, c_2, .., c_{|C|}\}$ is a set of concepts and $R = \{r_1, r_2, .., r_{|R|}\}$ is a set of relations representing the relationships between concepts. Associated with each concept c in C, there is a set of synonymic terms, denoted as $synset(c)$, representing the meaning of the concept c.

The ontology used in this paper is constructed from a tagging system i.e., *folksonomy* based on WordNet by using the methods proposed in Djuana et al. [6]. Since the ontology is constructed from a tagging system which contains a set of tags T, for each tag t in T, the ontology construction method maps the tag to a concept of the ontology, denoted as $M(t)$. $M(t) \in C$ is a concept of the ontology which is a mapping of t. Readers who are interested in the details of the ontology construction are referred to Djuana et al. [6].

4. The Proposed Approach

In this paper, we propose a recommendation approach which consists of three parts. The first part is the user-based CF tag recommendation approach [3] [10]. Using this technique we can find candidate tags set from *neighbors* (similar users) based on chosen users' profiles. This user-based CF also serves as a baseline tag recommender for evaluation purpose.

The second part includes three proposed methods which aim to expand the candidate tags set. The first expansion method is to expand the candidate tags set by looking at the items which are similar to the target item. Using this technique we expand the candidate tags set generated from the user-based CF with more tags from those similar items. This technique may help to solve the problem of sparse users by finding more tags based on similar items.

However, because this method can only find previously used tags as candidate tags and may not be able to find tags which are semantically related but have not been used by the target user's *neighbors*, this method may not be able to solve the problem of sparse tags, i.e., tags that are used by only a few users. Therefore, we propose the second and third expansion method which is based on the ontology which expands the candidate tags set by utilizing the concepts and concepts relationships of the ontology. We attempt to improve the coverage and accuracy by making use of synonym terms and semantic relationships among related concepts in the ontology.

The second expansion method is to expand the candidate tags set by using the synonym set (*synset)* information captured in the tag ontology. The third expansion method is to expand the candidate tags set by using the parent and children concepts in the ontology.

Lastly, the third part is to produce final recommended tags by ranking the candidate tags. In the following subsections, these three parts will be discussed respectively.

4.1. User-based CF method

In the traditional user-based CF recommender systems for recommending items, user profiles are represented as an user-item matrix $X = U \times I$. For each row vector: $\vec{x}_u = [x_{u,1}, .. x_{u,|I|}]$, for $u = 1,.., |U|$, $x_{u,i}$ indicates that user u rated item i by a rating value. Each row vector $\vec{x}_u$ corresponds thus to a user profile representing the user's preferences to the items.

However, because of the ternary relational nature of user tagging system, the traditional user-item matrix X cannot be applied directly to tag recommenders, unless the ternary relation Y is reduced to a lower dimensional space [11].

In order to apply the user-based CF to tag recommendation, the ternary relation Y can be used to generate a binary user-item (tag) matrix $X = U \times I$ where $x_{u,i} \in \{0,1\}$ indicating that there are tags used by user u to tag item i if $x_{u,i} = 1$, otherwise there are no tags used by user u to tag this item i.

Based on the profile matrix X, the neighborhood of the most similar k users to the user u can be computed as follows:

$$N_u^k = argmax_{v \in U}^k \, sim(\vec{x}_u, \vec{x}_v)$$

where $sim(\vec{x}_u, \vec{x}_v)$ is the similarity between user u and another user v. It can be calculated using a similarity calculation method such as the cosine similarity, i.e.

$$sim(\vec{x}_u, \vec{x}_v) = \frac{\vec{x}_u . \vec{x}_v}{|\vec{x}_u||\vec{x}_v|}$$

In the experiment, we implemented the user-item (tag) projection as the user profile matrix for calculating user neighborhood. The user-item (tag) matrix is a binary matrix. The Jaccard's coefficient is usually used to measure the similarity of two binary vectors. We use the following Jaccard's coefficient to calculate the similarity of two users u_i and u_j:

$$SimU_{ij} = \frac{p}{p + q + r}$$

where p is the number of items that are tagged by both users, q is the number of items that are tagged by u_i but not by u_j, r is the number of items that are not tagged by u_j but tagged by u_j.

In this user-based CF method, in order to recommend tags to a target user for tagging a particular item, it first generates a set of candidate tags which have been used by other users (usually *neighbor* users) to tag the item that the target user is tagging. It then ranks the candidate tags based on the similarity between the target user and neighbor users to decide the top n tags as the final recommendations.

Let $CT(u, i)$ be a set of tags which have been used by u's neighbors to tag item i. $CT(u, i)$ is the candidate tags set to be selected for generating recommendations for u to tag i. For a candidate tag t in $CT(u, i)$, its ranking can be calculated by the following equation:

$$w(u, t, i) = \sum_{v \in N_u^k} sim(\vec{x}_u, \vec{x}_v) * \delta(v, t, i), \qquad (1)$$

$$\delta(v, t, i) = \begin{cases} 1 & (v, t, i) \in Y \\ 0 & otherwise \end{cases}$$

where $\delta(v, t, i) = 1$ indicates if the user v has used this tag t to tag the item i, N_u^k is the neighborhood of user u. The top n tags can be determined based on the ranking:

$$T(u, i) = argmax_{t \in T}^n w(u, t, i) \qquad (2)$$

4.2. Candidate tags set expansion

4.2.1. Synonym based tags set expansion

For a user u and a target item i, let $CT(u, i)$ be the set of candidate tags generated based on neighbor users' preferences. For each candidate tag t in $CT(u, i)$, t can be mapped to concepts $M(t)$ in the tag ontology.

For the mapped concepts, from the synset terms of these concepts, an expanded set of candidate tags can be generated:

$$Exp\_CT_{\mathrm{Syn}}(u, i) = \bigcup_{t \in CT(u,i)} synset(\mathrm{M}(t)) \qquad (3)$$

4.2.2. Similar item based tags set expansion

In the traditional CF based recommender systems for recommending items, an item-based method which explores item to item similarity has been proposed for alleviating the *sparsity* problem in the user-based CF recommender systems [27]. This method works by finding similar items to the ones used by users in previous interaction. These similar items are then exploited to help generate item recommendation. As item to item relationships seem to be more static as compared to relationships between users to users, the computation is scalable. However, this method requires additional information about items which needs to be used for calculating similarities.

In the tag recommendation scenario, as items are annotated by users with tags, the similarity between items can be estimated by looking at the items' tags.

The simplest and straightforward method would be to generate an item-tag matrix $Z = I \times T$ from the ternary relation Y and use Z as item profiles. Each row vector $\vec{z}_i$ corresponds to an item profile representing the tags attached to the item. For each row vector $\vec{z}_i = [z_{i,1}, .. z_{i,|T|}]$, where $i = 1, .., |I|$, and $z_{i,t} \in \{0,1\}$. $z_{i,t} = 1$ is indicating that tag t has been used on item i, otherwise this tag t was not used on this item i. Similar to the user neighborhood similarity calculation, in the experiment we also use Jaccard's coefficient to calculate the similarity of two items i_k. and i_l in the similar manner as similarity calculation of two users u_i and u_j as defined previously.

For a user u and a target item i_a, in order to improve the tag recommendation for tagging the target item, we propose to expand the candidate tags set with the tags of items which are similar to the target item i_a. Using similarity values between items, we can find a set of items SI_a which are similar to item i_a.

Let T_k be a set of tags which are used by users to tag item i_k, then $T_{SI_a} = \bigcup_{i_k \in SI_a} T_k$ is a set of tags that are used to tag the items in SI_a. The tags in T_{SI_a} are the potential tags to be used to expand the candidate tags set. In order to determine which tags in T_{SI_a} should be used as the candidates, we propose the following ranking method to rank the tags in T_{SI_a}. For a tag $t \in T_{SI_a}$, let I_t be a set of items which have been tagged by tag t, the following equation is used to calculate a ranking score $\mathrm{r}(t)$ for tag t

$$\mathrm{r}(t) = \frac{1}{|I_t \cap SI_a|} \sum_{i_k \in I_t \cap SI_a} SimI_{ak} \qquad (4)$$

The top tags in T_{SI_a} which have higher ranking scores are chosen to expand the candidate tags. For a user u and a target item i, the set of expanded candidate tags based on the similar items in SI_a is defined below:

$$Exp\_CT_{SI}(u,i) = \{\mathrm{t} \mid \mathrm{r(t)} > \sigma\} \qquad (5)$$

where σ is a threshold.

4.2.3. Ontology-based tags set expansion

It is a well known insight to explore the possibility of using a more general or more specific term in recommending a new tag to users. It is related to a feature known as the basic level variations or generality in collaborative tagging [2], in which certain users tend to use a more general vocabulary while other users tend to use a more specific vocabulary.

A concept's parent and children concepts in an ontology are considered as more general and more specific concepts, respectively. For the ontology- based expansion method, we propose to utilize both the synonym set (*synset)* information, and the parent (more general) and the children (more specific) concepts to expand the candidate tags set.

Let c be a concept, $parent(c)$ be the parent concept of c, and $children(c)$ be the set of children concepts of c. For a user u and a target item i, for each candidate tag t in $CT(u,i)$ which is the set of candidate tags generated based on neighbor users' preferences, t can be mapped to concept $M(t)$ in the tag ontology, and $PC(t)$, as defined below, contains the parent and children concepts of concept $M(t)$.

$$PC(t) = \{parent(M(t))\} \cup children(M(t))$$

From the parent and children concepts, based on the synonym set *(synset)*, another set of expanded candidate tags can be generated:

$$Exp\_CT_{PC}(u,i) = \bigcup_{t \in CT(u,i)} \bigcup_{c \in PC(t)} synset(c) \qquad (6)$$

4.3. Recommendation ranking

For a user u and a target item i, by using the methods discussed in previous sections, an expanded set of candidate tags, denoted as $All\_CT(u,i)$, is generated which contains the basic set of candidate tags $CT(u,i)$ and the three expanded candidate tag sets defined in equations (3), (5), and (6):

$$All\_CT(u,i) = CT(u,i) \bigcup Exp\_CT_{Syn}(u,i) \bigcup Exp\_CT_{SI}(u,i) \bigcup Exp\_CT_{PC}(u,i)$$

In this section, we will discuss how to rank the candidate tags in $All\_CT(u,i)$ to determine the top N tags to recommend. Different ranking methods are defined to calculate the ranking of candidate tags in different candidate subsets. It needs to be noticed that the four candidate subsets, $CT(u,i)$ and the three expanded candidate tag sets, are not necessarily exclusive, which means, a candidate tag may occur in more than one candidate subset. If a tag occurs in multiple candidate subsets, its ranking will be calculated using a ranking method of a candidate subset which has the highest preference among the candidate subsets that contain the tag. The basic candidate set $CT(u,i)$ has the highest preference, then followed by $Exp\_CT_{Syn}(u,i)$, $Exp\_CT_{PC}(u,i)$, and then by $Exp\_CT_{SI}(u,i)$ which has the lowest preference. The ranking methods for different candidate subsets are given below.

(1). *Tag Ranking at Basic Level*
For each of the candidate tag t, $t \in CT(u,i)$, no matter whether it occurs in other candidate sets or not, its ranking is calculated by using Equation (1).

(2). *Tag Ranking for tags at* Synonym Level
For each candidate tag t, $t \notin CT(u,i)$ and $t \in Exp\_CT_{Syn}(u,i)$, no matter thether it occurs in the other two candidate sets or not, its ranking is calculated by using the following equation:

$$w(u,t,i) = \sum_{v \in N_u^k} sim(\vec{x}_u, \vec{x}_v) * \delta(v,t,i) * \mathcal{P}(t)$$

where $\mathcal{P}(t)$ is the popularity of tag t, which is calculated as: $\mathcal{P}(t) = |\, UI_t| / max_{t_i \in T}|\, UI_{t_i}|$. $\mathcal{P}(t)$ is the ratio between $|UI_t|$ and the maximum number of times that a tag has been used to tag items in this tagging community. UI_t contains (user, item) pairs representing the tag assignments using tag t. $|UI_t|$ is the number of times that t has been used to tag items. The higher the $|UI_t|$, the more popular the tag t is.

(3). *Tag Ranking for tags at Parent-Children Level*
For each t of candidate tags which are not original candidate tags in $CT(u,i)$ or the expanded basic tags in $t \in Exp\_CT_{Syn}(u,i)$, t can be a parent or a child of a original candidate tag, i.e., belongs to $Exp\_CT_{PC}(u,i)$.

For each candidate tag t, $t \notin (CT(u,i) \cup Exp\_CT_{Syn}(u,i))$, and $t \in Exp\_CT_{PC}(u,i)$, no matter whether it occurs in $Exp\_CT_{SI}(u,i)$ or not, its ranking is calculated by using the following equation:

$$w_\gamma(u,t,i) = \sum_{v \in N_u^k} sim(\vec{x}_u, \vec{x}_v) * \delta(v,t,i) * \mathcal{P}(t) * \mathcal{S}(t, t_o)$$

where $\mathcal{S}(t,\ t_o)$ is the normalized similarity value between the tag t and its original candidate tag. In this approach we use Jiang-Conrath similarity measures [25]. We use the implementation provided in the WordNet Similarity package [26]. The more they are similar in semantic or closer in semantic distance, the higher the similarity value will be.

(4). *Tag Ranking for tags based on Similar Items*
For each t of the candidate tags which is only in $Exp\_CT_{SI}(u,i)$, t must be a tag that belongs to tags of similar items, its ranking is calculated by using the following equation:

$$w_\gamma(u,t,i) = \sum_{v \in N_u^k} sim(\vec{x}_u, \vec{x}_v) * \delta(v,t,i) * \mathcal{P}(t) * \mathrm{r}(t)$$

5. Evaluation and experiments setup

We have conducted experiments mainly using two public social bookmarking datasets and the detail of each dataset is as follows:

(1). Bibsonomy dataset for ECML PKDD Discovery Challenge 2009 which is summarized in Jaschke et al. [22]. The dataset contains public bookmarks and publication posts of Bibsonomy which are used in the competition.

(2). Delicious dataset as discussed in Wetzker et al. [23]. The dataset contains all public bookmarks of users posted on Delicious.com between September 2003 and December 2007. In this paper we only use a portion of the dataset from September 2003 and July 2005.

For the purpose of evaluating the performance of the proposed approach we simulate three situations in tag recommendation context which involve datasets filtering. For each dataset we apply post core calculation [24] to create three datasets which simulate tag recommendation using dense dataset, sparse dataset and combined dataset. The details are discussed below:

(1). *Bibsonomy dataset*
The dataset originated from Bibsonomy contains two versions of training data: 1) snapshot of almost all dumps of Bibsonomy and 2) dense part of the snapshot. The dense part contains training data which has been filtered to include only users, resources or tags that appear in at least two posts (p-core at level 2). Table 1 summarizes the statistics of the datasets.

For the dense dataset we use the dense part of snapshot data in Table 1. In this simulation, all users, items and tags in testing dataset are all contained in the training data. For the combined dataset we use the combined snapshot in Table 1 which contains dense and sparse users. In this simulation some of the users, items or tags in testing data were not all contained in the dense part of training data which simulate combination of users and may contain sparse users and *cold-start* users or items.

Particularly for sparse dataset, we perform filtering to include only sparse users which are in the combined snapshot but not in dense part of snapshot and appear in at most only 2 posts as shown in Table 1.

Table 1: Bibsonomy data statistics.

Statistics (Sept 2003–July 2005)	Combined snapshot	Dense p-core 2	Sparse 1-2 posts
#items	378,378	22,389	19,682
#users	3,617	1,185	1,122
#tags	93,756	13,252	6,517

(2). Delicious dataset

The dataset originated from Delicious has initial statistics as shown in Table 2. This entire snapshot is used as combined dataset. For creating dense dataset, a filtering at post core level 10 is performed. For creating sparse dataset a similar filtering to Bibsonomy filtering is performed by taking only users that are not in dense dataset but in combined datasets and appear in at most only 2 posts. All these statistics are shown in Table 2.

Table 2: Delicious data statistics.

Statistics (Sept 2003–July 2005)	Combined snapshot	Dense p-core 10	Sparse 1-2 posts
#items	3,158,435	78.874	863
#users	75,245	37,399	1,289
#tags	456,697	22,170	215

For each of the datasets, a 5-fold splits are performed with 20% of users are taken for target users and 80% of users as training users. Top N tags are recommended to each target user for one random item of the target user's items in testing set. The recommended tags are compared to the target user's actual tags of these items in the testing dataset. If a recommended tag matches with an actual tag, we calculate this as a hit. The standard precision and recall are used to evaluate the accuracy of tag recommendations.

We have conducted following runs to compare performance between baseline recommender and the proposed methods.

- *User-CF*: this is the user-based CF tag recommender system as baseline.
- *Exp-User-Syn:* this method expands the candidate tags set according to synonym based tags set expansion as in Equation (3).
- *Exp-User-Syn-PC:* this method expands the candidate tags set according to synonym based and ontology-based tags set expansion as in Equations (3) and (6).
- *Exp-Item:* this method expands the candidate tags set according to similar item based tag set expansion as in Equation (5).
- *Exp-Item-Syn:* this method expands the candidate tags set according to synonym based and similar item based tag set expansion as in Equations (3) and (5).
- *Exp-Item-Syn-PC:* this method expands the candidate set according to synonym based, similar item based and ontology-based tags set expansion as in Equations (3), (5) and (6).
- *Folkrank-TR*: this is a state of the art graph-based tag recommender as described in Jaschke et al. [3].
- *PITF-TR*: this is another state of the art tensor-based tag recommender as described in Rendle and Schmidt-Thieme [15].

6. Experiment results and discussion

The recommendation results' precision and recall for each of tag recommendation scenarios are discussed as follows:

(1). Tag recommendation for dense dataset

Tag recommendation results precision and recall for Bibsonomy dense dataset are depicted in Table 3 and 4 respectively while for Delicious dense dataset are depicted in Table 5 and 6 respectively.

(2). Tag recommendation for combined dataset

Tag recommendation results precision and recall for Bibsonomy combined dataset are depicted in Table 7 and 8 respectively while for Delicious dense dataset are depicted in Table 9 and 10 respectively.

(3). Tag recommendation for sparse dataset

Tag recommendation results precision and recall for Bibsonomy sparse dataset are depicted in Table 11 and 12 respectively while for Delicious dense dataset are depicted in Table 13 and 14 respectively.

Table 3: Precision for Dense Bibsonomy Dataset

N	5	10	15	20
User-CF:	0.183	0.103	0.070	0.052
Exp-User-CF-Syn	0.201	0.112	0.077	0.058
Exp-User-CF-PC	0.214	0.126	0.091	0.072
Exp-Item	0.215	0.136	0.098	0.076
Exp-Item-Syn	0.218	0.142	0.104	0.081
Exp-Item-PC	0.222	0.147	0.104	0.081
PITF-TR	0.218	0.128	0.102	0.081
Folkrank-TR	0.241	0.150	0.108	0.084

Table 4: Recall for Dense Bibsonomy Dataset

N	5	10	15	20
User-CF:	0.435	0.474	0.479	0.479
Exp-User-CF-Syn	0.481	0.513	0.531	0.561
Exp-User-CF-PC	0.505	0.555	0.562	0.564
Exp-Item	0.472	0.494	0.500	0.511
Exp-Item-Syn	0.482	0.509	0.514	0.518
Exp-Item-PC	0.523	0.578	0.588	0.593
PITF-TR	0.503	0.529	0.544	0.560
Folkrank-TR	0.576	0.685	0.726	0.750

Table 5: Precision for Dense Delicious Dataset

N	5	10	15	20
User-CF:	0.169	0.081	0.072	0.054
Exp-User-CF-Syn	0.183	0.104	0.072	0.056
Exp-User-CF-PC	0.191	0.109	0.075	0.058
Exp-Item	0.199	0.115	0.081	0.062
Exp-Item-Syn	0.206	0.118	0.084	0.065
Exp-Item-PC	0.211	0.120	0.086	0.067
PITF-TR	0.205	0.116	0.083	0.066
Folkrank-TR	0.241	0.140	0.098	0.075

Table 6: Recall for Dense Delicious Dataset

N	5	10	15	20
User-CF:	0.609	0.655	0.655	0.656
Exp-User-CF-Syn	0.641	0.697	0.703	0.711
Exp-User-CF-PC	0.649	0.707	0.708	0.714
Exp-Item	0.655	0.720	0.732	0.741
Exp-Item-Syn	0.686	0.702	0.773	0.801
Exp-Item-PC	0.705	0.758	0.798	0.842
PITF-TR	0.711	0.795	0.832	0.853
Folkrank-TR	0.723	0.825	0.856	0.871

Table 7: Precision for Combined Bibsonomy Dataset

N	5	10	15	20
User-CF:	0.074	0.059	0.053	0.051
Exp-User-CF-Syn	0.101	0.092	0.062	0.052
Exp-User-CF-PC	0.122	0.095	0.066	0.053
Exp-Item	0.163	0.105	0.071	0.054
Exp-Item-Syn	0.193	0.125	0.074	0.056
Exp-Item-PC	0.208	0.126	0.077	0.058
PITF-TR	0.183	0.125	0.081	0.065
Folkrank-TR	0.205	0.121	0.066	0.051

Table 8: Recall for Combined Bibsonomy Dataset

N	5	10	15	20
User-CF:	0.236	0.353	0.422	0.425
Exp-User-Syn	0.323	0.437	0.452	0.458
Exp-User-Syn-PC	0.365	0.448	0.461	0.470
Exp-Item	0.407	0.461	0.490	0.500
Exp-Item-Syn	0.459	0.502	0.531	0.542
Exp-Item-Syn-PC	0.516	0.576	0.587	0.589
PITF-TR	0.436	0.577	0.577	0.580
Folkrank-TR	0.491	0.561	0.574	0.585

Table 9: Precision for Combined Delicious Dataset

N	5	10	15	20
User-CF:	0.112	0.063	0.042	0.031
Exp-User-Syn	0.125	0.072	0.048	0.037
Exp-User-Syn-PC	0.129	0.075	0.051	0.039
Exp-Item	0.147	0.086	0.059	0.044
Exp-Item-Syn	0.151	0.088	0.062	0.046
Exp-Item-Syn-PC	0.156	0.092	0.063	0.047
PITF-TR	0.149	0.088	0.058	0.045
Folkrank-TR	0.154	0.089	0.055	0.044

Table 10: Recall for Combined Delicious Dataset

N	5	10	15	20
User-CF:	0.532	0.581	0.602	0.604
Exp-User-Syn	0.569	0.593	0.611	0.615
Exp-User-Syn-PC	0.581	0.608	0.619	0.623
Exp-Item	0.596	0.632	0.645	0.651
Exp-Item-Syn	0.609	0.646	0.654	0.665
Exp-Item-Syn-PC	0.617	0.658	0.682	0.711
PITF-TR	0.615	0.648	0.676	0.708
Folkrank-TR	0.636	0.657	0.682	0.703

Table 11: Precision for Sparse Bibsonomy Dataset

N	5	10	15	20
User-CF:	0.054	0.049	0.043	0.041
Exp-User-Syn	0.087	0.076	0.056	0.043
Exp-User-Syn-PC	0.089	0.078	0.058	0.045
Exp-Item	0.103	0.085	0.059	0.045
Exp-Item-Syn	0.116	0.091	0.062	0.048
Exp-Item-Syn-PC	0.129	0.096	0.067	0.051
PITF-TR	0.121	0.089	0.058	0.044
Folkrank-TR	0.115	0.085	0.056	0.043

Table 12: Recall for Sparse Bibsonomy Dataset

N	5	10	15	20
User-CF:	0.169	0.238	0.302	0.340
Exp-User-Syn	0.235	0.276	0.364	0.412
Exp-User-Syn-PC	0.274	0.293	0.395	0.435
Exp-Item	0.345	0.390	0.415	0.442
Exp-Item-Syn	0.385	0.402	0.425	0.465
Exp-Item-Syn-PC	0.397	0.427	0.440	0.476
PITF-TR	0.371	0.402	0.430	0.468
Folkrank-TR	0.341	0.375	0.411	0.423

Table 13: Precision for Sparse Delicious Dataset

N	5	10	15	20
User-CF:	0.106	0.058	0.039	0.029
Exp-User-Syn	0.122	0.069	0.046	0.035
Exp-User-Syn-PC	0.129	0.074	0.049	0.038
Exp-Item	0.151	0.089	0.059	0.045
Exp-Item-Syn	0.164	0.095	0.064	0.048
Exp-Item-Syn-PC	0.168	0.099	0.067	0.051
PITF-TR	0.159	0.090	0.061	0.045
Folkrank-TR	0.150	0.085	0.053	0.042

Table 14: Recall for Sparse Delicious Dataset

N	5	10	15	20
User-CF:	0.351	0.362	0.374	0.379
Exp-User-Syn	0.366	0.377	0.386	0.395
Exp-User-Syn-PC	0.375	0.381	0.393	0.408
Exp-Item	0.382	0.401	0.414	0.420
Exp-Item-Syn	0.390	0.413	0.423	0.431
Exp-Item-Syn-PC	0.401	0.422	0.432	0.445
PITF-TR	0.392	0.409	0.421	0.429
Folkrank-TR	0.375	0.396	0.411	0.423

For the recommendation using dense datasets we are mainly observing how significantly the candidate tags set expansion based on similar items' tags, parent-children's tags, and the combined method may improve over the baseline recommender.

For the recommendation using sparse datasets, we are mainly observing whether or not the proposed candidate tag expansion methods can improve over the state of the art recommendation methods in sparse situation while they are normally perform well under dense situation but are not known under sparse situation.

From Table 3 and Table 4 for tag recommendation on dense Bibsonomy dataset, all the proposed methods outperform the baseline method. The method *Exp-Item-Syn-PC* based on the similar items' tags, synset and parent-children concepts has achieved the best performance among the proposed methods. For the dense dataset, the state of the art method *Folkrank-TR* has achieved the best results.

Also from the same Tables (3 and 4) it is shown that the combination of both expansion methods has improved the results better than the *PITF-TR* (tensor-based) results but slightly lower than the *Folkrank-TR* (graph-based) results. This result shows the potential of the combined method to be comparable to state of the art methods in graph-based and tensor-based tag recommendation.

Looking at Table 5 and Table 6 for tag recommendation on combined (dense and sparse) Bibsonomy dataset, it is showing the same trends that the improvement from the tag expansion based on similar items' tags is higher than only based on the synonym or parent-children information in this situation. Also, the improvement is slightly higher than the improvement for dense dataset. It is showing the potential of using the combined methods for mitigating *sparsity* problem as the combined dataset contains sparse users beside dense users.

Table 5 and Table 6 also show that the combined method *Exp-Item-Syn-PC* has improved the results over the two state of the art methods. Table 7 and Table 8 confirm the effectiveness further that the combined method *Exp-Item-Syn-PC* has achieved for mitigating *sparsity* problem in tag recommendation on sparse Bibsonomy dataset.

Similar trends are also shown for tag recommendation on Delicious dataset as shown on Table 9 and Table 10 for dense dataset, that the improvement from the similar items tag based expansion is slightly higher than the expansion based on synonym or parent-children in this situation. Also it is shown that the combined method *Exp-Item-Syn-PC* has improved the results better than *PITF-TR*'s results but slightly lower than *Folkrank-TR*'s results.

The results on Table 11 and Table 12 for the combined dataset and the results on Table 13 and Table 14 for the sparse dataset show that the combined method *Exp-Item-Syn-PC* has improved the results over both the two state of the art methods. It is once again confirming the effectiveness of the combined method for mitigating *sparsity* problem in tag recommendation.

From all these results we can draw several conclusions that: (1) the similar items tags expansion method can improve user-based CF method quite significantly in most tag recommendation situations (dense and combined), and especially in sparse situation; (2) the ontology-based expansion method can improve user-based CF method and the similar items tag expansion method in most tag recommendation situations including in sparse situation; (3) the combined method *Exp-Item-Syn-PC* outperforms both the two state of the art methods in sparse situation.

7. Conclusion

We have presented a combined method for tag recommendation which has improved over user-based collaborative filtering in most situations, i.e. dense, combined (dense and sparse) and sparse datasets. The combined method includes similar items tag expansion method and ontology-based expansion methods i.e. basic level concepts and parent-children concepts expansion. The evaluation shows that this combined method is comparable to the state of the art methods (tensor-based and graph-based methods) in dense situation and more effective in sparse situation. For future work, it is desirable to compare the effectiveness of this method with other method for mitigating *sparsity* problem and also to evaluate this method for cold-start problems.

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8. References

[1] C. Marlow, M. Naaman, D. Boyd, and M. Davis, "HT06, Tagging Paper, Taxonomy, Flickr, Academic Article, To Read", In *Proc. 17th ACM Hypertext and Hypermedia*, ACM Press, Denmark, 2006, pp. 31-40.

[2] S. Golder, and B. Huberman, "Usage Patterns of Collaborative Tagging Systems", *J. of Inform. Sci.*, Publisher, 2006, Vol. 32(2), pp. 198–208.

[3] R. Jäschke, L.B. Marinho, A. Hotho, L. Schmidt-Thieme, and G. Stumme, “Tag Recommendations in Social Bookmarking Systems”, *AI Communications*, IOS Press, 2008, Vol. 21, pp. 231-247.

[4] G. Adomavicius, and A. Adomavicius, “Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions”, *IEEE Trans. Knowl. Data Eng.*, IEEE, 2005, Vol. 17 (6) pp. 734-749.

[5] C. Preisach, L.B. Marinho, and L. Schmidt-Thieme, “Semi-supervised Tag Recommendation - Using Untagged Resources to Mitigate Cold-Start Problems”, In *Proc. PAKDD 2010 Part I LNAI 6118*, Springer, India, 2010, pp. 348–357.

[6] E. Djuana, Y. Xu, and Y. Li, “Constructing Tag Ontology from Folksonomy based on WordNet”, In *Proc. IADIS Int. Conf. on Internet Technologies and Society.*, IADIS, China, 2011, pp. 85-92.

[7] C. Musto, F. Narducci, P. Lops, and M. de Gemnis, “Combining Collaborative and Content-Based Techniques for Tag Recommendation”, In *Proc. 11th Int. Conf. on E-Commerce and Web Technologies (EC-Web 2010)*, Springer, Spain, 2010, pp. 13-23.

[8] M. Tatu, M. Srikanth, and T. D’Silva, “Tag Recommendations using Bookmark Content”, In *Proc. ECML PKDD 2008 Discovery Challenge Workshop,* Belgium, 2008, pp. 96-107.

[9] M. Lipczak, Y. Hu, Y. Kollet, and E. Milios, “Tag Sources for Recommendation in Collaborative Tagging Systems”, In *Proc. ECML PKDD 2009 Discovery Challenge Workshop*, Slovenia, 2009, pp. 157-172.

[10] L.B. Marinho and L. Schmidt-Thieme,“Collaborative Tag Recommendations”, In *Proc. 31st Annu. Conf. of the Gesellschaft fr Klassifikation (GFKL)*, Springer, Germany, 2007, pp. 533-540

[11] B. Sigurbjörnsson and R. van Zwol, “Flickr Tag Tecommendation based on Collective Knowledge”, In *Proc. 17th Int. Conf. on World Wide Web*, ACM, China, 2008, pp. 327-336.

[12] A. Hotho, R. Jäschke, C. Schmitz, and G. Stumme, “Information Retrieval in Folksonomies: Search and Ranking”, In *Proc. 3rd European Conf. on the Semantic Web: Research and Applications*, Springer, Montenegro, 2006, pp. 411-426.

[13] P. Symeonidis, A. Nanopoulos, and Y. Manolopoulos, “Tag Recommendations based on Tensor Dimensionality Reduction”, In Proc. 2nd ACM Conference on Recommender Systems, ACM, Switzerland, 2008, pp. 43-50.

[14] S. Rendle, and L. Schmidt-Thieme, “Pairwise Interaction Tensor Factorization for Personalized Tag Recommendation”, In Proc. 3rd ACM Int. Conf. on Web Search and Data Mining, ACM, USA, 2010, pp. 81-90.

[15] A. Baruzzo, A. Dattolo, N. Pudota, and C. Tasso, “Recommending New Tags using Domain-Ontologies”, In *Proc. IEEE/WIC/ACM Web Intelligence and Intelligent Agent Technology-Workshops*, IEEE, Italy, 2009, pp. 409-412.

[16] T.R. Gruber, “A Translation Approach to Portable Ontology Specifications”, *Knowledge Acquisition*, Academic Press Ltd, UK, 1993, Vol. 5 (2), pp. 199-220

[17] R. Navigli, P. Velardi, and A. Gangemi, “Ontology Learning and Its Application to Automated Terminology Translation”, *IEEE Intelligent Systems*, IEEE, 2003, Vol. 18, p. 22-31.

[18] P. Mika, “Ontologies are Us: A Unified Model of Social Networks and Semantics”, *Web Semantics*, Elsevier, 2007, Vol. 5(1), pp. 5-15.

[19] A. García-Silva, O. Corcho, H. Alani and A. Gómez-Pérez, “Review of the State of the Art: Discovering and Associating Semantics to Tags in Folksonomies”, *The Knowledge Engineering Review*, Cambridge University Press, 2012, Vol. 27 (1) pp. 57-85.

[20] Fellbaum, C. (ed.), “WordNet: An Electronic Lexical Database”, MIT Press, Cambridge, MA, 1998.

[21] F. M. Suchanek, G. Kasneci, and G. Weikum, “YAGO - A Core of Semantic Knowledge”, In *Proc. 16th Int. Conf. on World Wide Web*, ACM, Canada, 2007, pp. 697-706.

[22] R. Jäschke, A. Hotho, F. Mitzlaff, and G. Stumme,, “Challenges in Tag Recommendations for Collaborative Tagging Systems”, *Recommender Systems for the Social Web*, ISRL, 2012, pp. 65-87.

[23] R. Wetzker, C. Zimmermann, and C. Bauckhage, “Analyzing Social Bookmarking Systems: A Del.icio.us Cookbook”, In *Proc. European Conf. on Artificial Intelligence (ECAI)*, 2008, pp. 26-30.

[24] V. Batagelj, and M. Zaversnik, “Generalized cores”, *Arxiv preprint cs/0202039*, 2002

[25] J.J. Jiang and D. W. Conrath, “Semantic Similarity based on Corpus Statistics and Lexical Taxonomy”. In *Proc. Int. Conf. Research on Computational Linguistics (ROCLING X’1997)*, 1997.

[26] T. Pedersen, S. Patwardhan, and J. Michelizzi, Wordnet: : Similarity - Measuring the Relatedness of Concepts. In *Proc. 19th Nat. Conf. on Artificial Intell. (AAAI 2004)*, AAAI, 2004, pp. 1024–1025.

[27] B. Sarwar, G. Karypis, J. Konstan and J. Riedl, “Item-based Collaborative Filtering Recommendation Algorithms”, In *Proc. 10th Int. Conf. on World Wide Web*, ACM, Hongkong, 2001, pp. 285-295.