Connecting Users and Items with Weighted Tags for Personalized Item Recommendations

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ABSTRACT

Social tags are an important information source in Web 2.0. They can be used to describe users' topic preferences as well as the content of items to make personalized recommendations. However, since tags are arbitrary words given by users, they contain a lot of noise such as tag synonyms, semantic ambiguities and personal tags. Such noise brings difficulties to improve the accuracy of item recommendations. To eliminate the noise of tags, in this paper we propose to use the multiple relationships among users, items and tags to find the semantic meaning of each tag for each user individually. With the proposed approach, the relevant tags of each item and the tag preferences of each user are determined. In addition, the user and item-based collaborative filtering combined with the content filtering approach are explored. The effectiveness of the proposed approaches is demonstrated in the experiments conducted on real world datasets collected from Amazon.com and citeULike website.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval-Information Filtering; H.5.3 [**Information Interfaces and Presentation**]: Group and Organization Interfaces-Collaborative computing

General Terms

Algorithms, Experimentation

Keywords

Recommender systems, Tags, Personalization, Web 2.0

1. INTRODUCTION

Recommender System is one kind of effective tool to deal with the information overload issue. Typically, users' explicit rating information is used to make recommendations. However, since explicit ratings are not always available in real life applications, how to make recommendations based on implicit rating information becomes very important [1]. In Web 2.0, the tag information is becoming another important implicit rating information source to profile users' interests as well as to describe the contents or classifications of items. Compared with explicit ratings or other implicit user information like click streams and web logs, tags are lightweight, human understandable, and have multiple functions such as organizing items, building networks, and expressing explicit topic interests and opinions. Different from other kinds of content information, tags are given by users directly and can be used to describe any types of items including videos, photos, web pages, audios, documents and others. Because of their simplicity and multiple functions, tags are popularly used in various kinds of application areas, for example, del.icio.us, amazon.com and last.fm.

However, since there is no restriction or boundary on selecting words for tagging items, the tags used by users are free-formed and contain semantic ambiguities which mean that the same tag name has different meanings for different users and tag synonyms which mean that different tags actually have the same meaning. Another concern related to tags is that nearly 60% of tags are personal tags that are only used by one user [7]. These disadvantages bring challenges to the use of tags for describing the topics of the items or profiling users' topic preferences. As a result, improper neighborhood forming or inaccurate content mapping problems may occur. Moreover, since the items follow the power law distribution [10], a large number of items are described by a very small number of tags. Resulting in very short content representations, it becomes difficult to do content mapping or filtering based on tags [22]. All these problems generate difficulties in improving the accuracy of item recommendations based on tags. Currently, the research of tag based recommender systems are mainly focus on tag recommendations [21] and not so much work has been done on item recommendations. The earlier work didn't consider the tag quality problem [6] [4]. Recently, the tag quality problem [19] or usefulness of tags [7] [15] has begun to arouse attentions. Mainly, the current approaches treated tags as textural information including some terms or keywords processing methods and latent semantic topic models. However, these approaches ignored the distinctive feature of tag information: tags are given by users directly and contain rich relationship information.

By nature tags are given by users to organize or describe their own items. Thus, a tag is a textural entity dependant with its user from the perspective of individual users. Therefore, the relationships among users, items and tags not only include a set of aggregated two dimensional relationships such as User-Tag, Tag-Item and User-Item, but also a set of three dimensional relationships such as User-Tag-Item that recording the personal tagging information of each individual user. Based on the latter ones, we can find the most related or similar items, users and tags for each user personally while based on the former ones, we can find the related or similar items, users and tags in a impersonalized way that based on users' common understanding of the textural meaning of tags. Since our purpose is to recommend the items that are uncollected or new to the target user, with these relationships, we could estimate each user's preferences or interests in other tags that are not used by himself/herself as well as the relevance of each item with those tags that have not been used to label that item. Then, we could estimate how much a user could be interested in an uncollected item that may have been given different tags by other users. Therefore, tags can be used as inter media to find each user's potentially interested items.

In this paper, we propose to make use of the multiple relationships among users, items and tags to find a set of related tags of each tag for each user individually as well as to find a set of related tags to expand the tag based content representation of each item with the purpose of finding each user's most likely interested items. This paper is organized as follows. Firstly, the related work is briefly reviewed in Section 2. Then, some important definitions are given in Section 3. The proposed approaches are discussed in Section 4, where the multiple relationships and the approaches of representing tags and items with a set of related tags along with their weights are presented. After that, the user profiling, the neighborhood forming and recommendation generation approaches are discussed. In Section 5 and 6, the design of the experiments, experimental results and discussions are presented. The conclusions and future work are discussed in Section 7.

2. RELATED WORK

Recommender systems have been an active research area for more than a decade. The recommendation approaches based on explicit ratings are the major focus. The recommender systems based on explicit ratings have been intensively explored while those based on implicit rating information have been attracted less attentions [1]. The tasks of recommender systems include rating prediction and top N recommendation. The former task that is to predict the rating value a user will give to a rated item while the latter one is to recommend a set of unrated/new items to the target user [1]. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are widely used to measure the accuracy of the rating prediction while precision and recall are commonly used for the top N recommendation. For explicit ratings, both tasks are applicable while for implicit ratings, the top N recommendation is more applicable [1]. Recommender systems can be broadly classified into three categories: content-based, collaborative filtering (CF), and hybrid approaches [1].

The content based approaches are mainly based on the content related information of items such as keywords, taxonomic/ontology topics or categories/genes. The term vector model, latent semantic topic model such as latent Dirichlet allocation (LDA) and PLSI are popularly used to process large textural corpus to recommend the most relevant items to users [1]. The collaborative filtering approach can be classified into memory based and model based approaches. The user and item based K nearest neighborhood (KNN) based approaches are two kinds of memory based CF approaches. More recently, the model based CF approaches such as matrix factorization techniques [27] get better performances for the rating prediction task based on large scaled explicit rating dataset such as Netflix dataset. But how to use matrix factorization approaches to recommend top N unrated items to the target user and how to apply them on implicit ratings still remain open research questions [27]. Therefore, for implicit ratings, the memory based CF approaches are still popularly used. The hybrid approaches that combining the CF and content based approaches have been applied in many applications [9] [20].

Recently, social tags are becoming an important research focus. Implying users' explicit topic interests, social tags can be used to improve searching [2], clustering [3], and recommendation [4]. The research of tag based recommender systems mainly focuses on how to recommend tags to users. The problem of tag recommendation can be described as given a target user and a set of items, how to recommend tags to a set of items for the user [21]. Some approaches such as using the co-occurrence of tags [3], association rules [10], folkrank [21], tensor [22] and link networks [17] have been proposed. Since recommending a tag to a user to

label an item is different with recommending an item to a user, the tag recommendation approaches usually cannot be used to recommend items directly [16].

Currently, not so much work has been done on the item recommendations based on tags. Since tagging is a kind of implicit rating behavior [16] and the tags are pieces of textural information describing the content of items, mainly, the memory based CF and content based approaches are used. Diederich [4] proposed an exploratory user based CF approach based on tag based user profiles. The *tf-iuf* weighting approach that similar with *tf-idf* approach in text mining was used for each user's tags. The work of Tso-shuter [6] extended the binary user-item matrix to binary user-item-tag matrix and used the Jaccard similarity measure approach to find neighbors. It was claimed that because of the tag quality problem, tag information failed to be very useful to improve the accuracy of memory based CF approaches [6]

More recently, the noise of tags or the quality [19] and usefulness [7] of tags arouses attentions. Some content based approaches that deal with the noise of textural contents were proposed. In the work of Niwa [5] and Shepitsen [18], the clustering approaches were used to find the item and tag clusters based on the tag based *tf-idf* content representations. The mapping of tags between user's tags and the representative tags of item clusters were used to make content based web page recommendations. The Latent Semantic Analysis such as PLSI [11] and LDA [24] based approaches have been proposed to remove the noise of tags and build latent semantic topic models to recommend items to users. The work of Liang [12] proposed to use the standard item taxonomy given by experts to find the semantic meaning of each user's tag to eliminate the noise of tags. Besides these memory based CF approaches and content filtering models, in the work of Sen [16], a special tag rating function was used to infer users' tag preferences. Along with the inferred tag preferences, the click streams, tag search history of each user were used to get user's preferences for items. The various kinds of extra information and special function make Sen's work incomparable and give restrictions to the applications of the work. More recently, Zhang [25] proposed to integrate the user-tag-item tripartite graph to rank items for the purpose of recommending unrated items to users. The user-tag-item graph was divided into user-tag and tag-item while the three dimensional relationships reflecting the personal tagging relationships were ignored by Zhang's work. Zhen [26] proposed to integrate tag information and explicit ratings to improve the accuracy of rating predictions of a model based CF approach.

Since in typical tagging communities, no or rare explicit ratings are available, to be more general, in this paper, we focus on the typical tagging information and discuss how to use the distinctive feature of tag information to solve the tag quality problem and improve the top N recommendation accuracy of the popularly used memory based CF approach.

3. DEFINITIONS

To describe the proposed approach, we define some key concepts and entities used in this paper as below.

- **Users:** $U = \{u_1, u_2, \dots, u_{|U|}\}$ contains all users in an online community who have used tags to label and organize items.
- **Items (i.e., Products, Resources):** $P = \{p_1, p_2, \dots, p_{|P|}\}$ contains all items tagged by users in U. Items could be any type of resources or products in an online community such as

web pages, videos, music tracks, photos, academic papers, documents and books etc.

- **Tags:** $T = \{t_1, t_2, \ldots, t_{|T|}\}$ contains all tags used by users in U. A tag is a piece of textural information given by one or more users to label or collect items.
- **Tagging:** the basic tagging behaviour is defined as $e: U \times T \times P \to \{0,1\}$. If a user u_i collected one item p_k with a tag t_j, then $e(u_i, t_j, p_k) = 1$, otherwise, $e(u_i, t_j, p_k) = 0$.

In this paper, we focus on the top N item recommendation task. Let $u_i \in U$ be a target user, P_{u_i} be the item set that the user u_i already has, $p_k \in P - P_{u_i}$ be a candidate item, $A(u_i, p_k)$ be the prediction score of how much user u_i would be interested in the item p_k, the problem of item recommendation is defined as generating a set of rank-ordering items $p_l, \ldots, p_m \in P - P_{u_i}$ to the use u_i, which is shown as below:

$$rec(u_i) = \{p_l, \ldots, p_m\}, where\ A(u_i, p_l) \geq \ldots \geq A(u_i, p_m).$$

4. THE PROPOSED APPROACHES
4.1 The multiple relationships of tagging
As discussed in Introduction, there are multiple relationships among users, items and tags. Figure 1 (a) illustrates an example of tagging. For example, user u_4 has used the tag t_5 and tagged item p_5 and p_6. The users, items and tags are three different kinds of entities. With different combinations of these three kinds of entities, six kinds of direct relationships can be derived. These relationships include three kinds of aggregated two-dimensional relationships User-Item, User-Tag and Item-Tag relationships and three kinds of three-dimensional relationships (Item×Tag)-User, (Use×Tag)-Item, (User×Item)-Tag. Each relationship includes two mappings and each mapping reflects the relationship of one entity to the other one or two entities. These relationships include:

- **User-Item relationship:** records the implicit ratings of each user and the user group of each item. It includes User-Item mapping and Item-User mapping, which are defined as below:
  1) *User-Item mapping* $f_1: U \to 2^P, f_1(u_i) = \{p_k | \exists t_j \in T, \forall p_k \in P, e(u_i, t_j, p_k) = 1\}$. *It maps a user to his/her collected items. For simplicity, P_{u_i} is used to stand for $f_1(u_i)$.*
  2) *Item-User mapping* $g_1: P \to 2^U$, $g_1(p_k) = \{u_i | \exists t_j \in T, \forall u_i \in U, e(u_i, t_j, p_k) = 1\}$. *It maps an item to a set of users who have collected the item. U_{p_k} is used to stand for $g_1(p_k)$.*
- **User-Tag relationship:** records each user's own tags and the user group of each tag. It includes User-Tag mapping and Tag-User mapping. We define them as below:
  3) *User-Tag mapping* $h_1: U \to 2^T, h_1(u_i) = \{t_j | \exists p_k \in P, \forall t_j \in T, e(u_i, t_j, p_k) = 1\}$. *It maps a user to a set of tags that are used by the user. T_{u_i} is used to stand for $h_1(u_i)$.*
  4) *Tag-User mapping* $g_2: T \to 2^U, g_2(t_j) = \{u_i | \exists p_k \in P, \forall u_i \in U, e(u_i, t_j, p_k) = 1\}$. *It maps a tag to a set of users who have the tag. U_{t_j} is used to stand for $g_2(t_j)$.*
- **Item-Tag relationship:** records each item's tags and the aggregated items of each tag. Similarly, it includes the following two kinds of mappings:
  5) *Item-Tag mapping* $h_2: P \to 2^T, h_2(p_k) = \{t_j | \exists u_i \in U, \forall t_j \in T, e(u_i, t_j, p_k) = 1\}$. *It maps an item to a set of tags*

that are used by some users to label the item. T_{p_k} is used to stand for $h_2(u_i)$.

  6) *Tag-Item mapping* $f_2: T \to 2^P, f_2(t_j) = \{p_k | \exists u_i \in U, \forall p_k \in P, e(u_i, t_j, p_k) = 1\}$. *It maps a tag to a set of items that are collected by some users with the tag. P_{t_j} is used to stand for $f_2(t_j)$.*
- **User-Tag-Item relationship:** records each user's personal tagging relationships. It includes three kinds of relationships or three pairs of mappings, which are (Item×Tag)-User/User-(Item×Tag), (User×Tag)-Item/Item-(User×Tag), and (User×Item)-Tag/Tag-(User×Item) mappings. Since only the (User×Tag)-Item and Item-(User×Tag) mappings are used in this paper, we give their formal definitions as below:
  7) *(User×Tag)-Item mapping* $f_3: U \times T \to 2^P$, $f_3(u_i, t_j) = \{p_k | \forall p_k \in P, e(u_i, t_j, p_k) = 1\}$. *It maps a user-tag pair to a set of items that are collected under the tag by the user. P_{u_i, t_j} is used to stand for $f_3(u_i, t_j)$.*
  8) *Item-(User×Tag) mapping* $h_3: P \to 2^{U \times T}, h_3(p_k) = \{(u_i, t_j) | \forall u_i \in U, \forall t_j \in T, e(u_i, t_j, p_k) = 1\}$. *It maps an item to its user-tag pairs. $T_{p_k}^u$ is used to stand for $h_3(p_k)$.*

These relationships can be used to find the related/similar items, tags and users. Since tags have direct connections with users and items and reflect users' preferences to tags as well as items' relevance to tags, tags can be used as inter media to find the most potentially interested items for users, if we could profile each user's tag preferences as well as items' relevance to tags accurately. Therefore, we use a set of tags along with their weights to represent each user's tag preferences or called user representation and each item's relevance to tags or called item representation, which are defined as below:

- **User representation:** represents each user $u_i \in U$'s preferences to each tag $t_y \in T$. Let w_y^u denote the weight of how much the user u_i is interested in the tag t_y, the relationship between a user and a set of tags can be defined as the mapping $RU: U \to 2^{T \times [0,1]}$.
  Such that $RU(u_i) = \{(t_y, w_y^u) | t_y \in T\}$. $RU(u_i)$ is called the representation of user u_i.
- **Item representation:** represents each item $p_k \in P$'s relevance to each tag $t_y \in T$. Let w_y^p denote the weight of how much the item p_k is relevant to the tag t_y, the relationship between an item and tags can be defined as the mapping $RP: P \to 2^{T \times [0,1]}$.
  Such that $RP(p_k) = \{(t_y, w_y^p) | t_y \in T\}$. $RP(p_k)$ is called the representation of item p_k.

An important task of generating user and item representations is to determine the weights to the tags. We propose new methods to generate the weighs which will be discussed in Section 4.2, 4.3 and 4.4. After representing each user and each item with the weighted tags, the similarity of user/item representations can be used to measure the similarity of two users/items or the content mapping between a user and an item to find nearest neighborhood and generate recommendations, which will be discussed in Section 4.5 and 4.6.
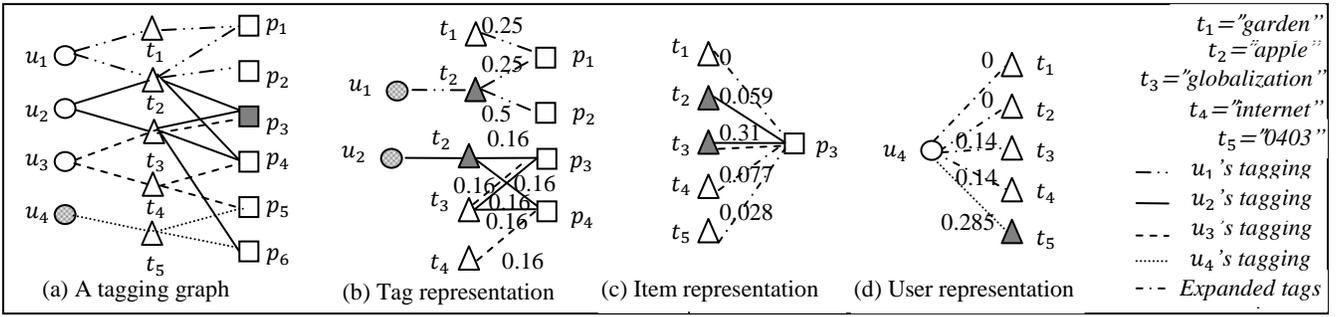
Figure 1. An example of tagging and representations

The standard user and item based Collaborative Filtering recommendation approaches are only based on the User-Item relationship while the other relationships related to tags such as User-Tag, Item-tag and User-Tag-Item are ignored. However, these ignored relationships are very helpful to eliminate the noise of tags to generate more accurate user and item representations and to find more similar users/items. We will discuss how to make use of the multiple relationships to eliminate the noise of tags and generate user and item representations in details in the following sub sections.

4.2 Tag representation

Usually the two dimensional User-Tag relationship and Item-Tag relationship are used to profile users' preferences and items' relevance to tags. These relationships only record the users' preferences and items' relevance to their own tags while other tags are considered not interested or non relevant (i.e., with the weight value of "0"). Therefore, those users have used personal tags and those items are being described with personal tags can't find any similar users or items. Moreover, the semantic ambiguity of tags and tag synonyms cause inaccurate neighborhood forming and item recommendations. For example, in Figure 1 (a), since t_5 "0403" is a personal tag, u_4 can't find any similar users based on the similarity of users' tag sets obtained by the User-Tag mapping h_1. In addition, u_1 and u_2 will be considered as similar users since they have the same tag t_2 "apple" even though for u_1 "apple" means a kind of fruit while for u_2, it means a brand of computer product.

Different from the two dimensional relationships, the three dimensional relationship records each individual user's personal tagging relationships. Based on the (User×tag)-item mapping $f_3(u_i, t_j)$, we can see that labeled with tag t_j, a set of items are collected and grouped together according to the user u_i's viewpoint. For this user, the collected items are similar or closely related with each other in some way, otherwise the user won't put them together and labeled with the same tag. Or in another word, if a set of items are being put together under the same tag by the same user, then, these items are similar and closely related with each other.

Since the relevant tags of each item are recorded in the Item-Tag mapping, we can combine the (User×tag)-Item mapping and the Item-Tag mapping together to find the closely related tags of each tag for each user individually. For example, shown in Figure 1 (b), based on (User×tag)-Item mapping f_3, we can get the collected items of tag t_2 for user u_1 and u_2 individually. $f_3(u_1, t_2) = \{p_1, p_2\}, f_3(u_2, t_2) = \{p_3, p_4\}$. Then, based on Item-Tag mapping h_2, we can get the relevant tags of each item. $h_2(p_1) = \{t_1, t_2\}, h_2(p_2) = \{t_2\}, h_2(p_3) = \{t_2, t_3\}, h_2(p_4) = \{t_2, t_3, t_4\}$. Thus, for u_1, the tag t_2 "apple" is related to the tags t_1 "garden".

But for user u_2, t_2 is related to the tags t_3 "globalization" and t_4 "internet". Therefore, the different meanings of the same tag for different users can be determined. Because the tags of each item can be interpreted as the topics of each item [10], the process of finding the related tags of each tag for each user can be interpreted as finding the personalized semantic meaning or related topics of each tag for each user, which is called tag representation. We give the definition of tag representation as below:

- **Tag representation:** represents each tag $t_x \in T$'s relevance to each tag $t_y \in T$ with respect to the user u_i. Let $r_{u_i,t_x}(t_y)$ denote how strong t_x is related to t_y with respect to user u_i, the relationship between a tag and other tags with respect to a user can be defined as the mapping $RT: U \times T \to 2^{T \times [0,1]}$. Such that $RT(u_i, t_x) = \{(t_y, r_{u_i,t_x}(t_y)) \mid t_y \in T\}$. $RT(u_i, t_x)$ is called the representation of tag t_x with respect to the user u_i.

Therefore, tag representation can help to remove the noise of tags through finding the personally most related tags of each tag for each user. Based on the tag representations, we can generate more accurate user and item representations, which will be discussed in Section 4.3 and 4.4 respectively.

Before we discuss how to calculate the weight $r_{u_i,t_x}(t_y)$, we firstly define the probability of t_x being used to tag item p_k, given the item p_k and the probability of t_x being used by user u_i, given the user u_i.

4.2.1 The calculation of probabilities $\mathcal{P}r(t_x \mid p_k)$ and $\mathcal{P}r(t_x \mid u_i)$

For an item p_k, we define the probability of p_k being tagged by users using any tags, denoted as $\mathcal{P}r(p_k)$, as the ratio between the number of users who tagged p_k and the total number of users, that is $\mathcal{P}r(p_k) = \frac{|U_{p_k}|}{|U|}$, where $|U_{p_k}|$ is the number of users that have the tagged item p_k, $U_{p_k} = g_1(p_k)$ and $|U|$ is the total number of users. The probability $\mathcal{P}r(p_k)$ is 0 if no user has tagged p_k and 1 if all users have tagged p_k. We can further define the probability of p_k being tagged by users using a specific tag t_x, which is the ratio between the number of users who tagged the item p_k using tag t_x and the total number of users defined as $\mathcal{P}r(p_k, t_x) = \frac{|U_{p_k,t_x}|}{|U|}$, where $|U_{p_k,t_x}|$ is the number of users tagged p_k with t_x. Based on these two probabilities, we can define an important conditional probability $(t_x \mid p_k)$, as shown below:

$$\mathcal{P}r(t_x \mid p_k) = \frac{\mathcal{P}r(p_k, t_x)}{\mathcal{P}r(p_k)} = \frac{|U_{p_k,t_x}|}{|U_{p_k}|} \qquad (1)$$

$\mathcal{P}r(t_x \mid p_k)$ is the probability of t_x being used to tag item p_k, given the item p_k. The probability $\mathcal{P}r(t_x \mid p_k)$ indicates how

popularly the tag t_x has been used by users to describe or classify a given item p_k. It reflects the "wisdom of crowds" in terms of the classification of the item p_k. Reflecting the common viewpoint of users, the higher the probability, the more likely the tag t_x represents the major topic for the item p_k, or in another word, the more likely the item p_k will be found in the tag t_x.

Similarly, we define the conditional probability $Pr(t_x \mid u_i)$. It represents the possibility of t_x being used by user u_i, given the user u_i. The higher the value, the more the user is interested in t_x.

$$Pr(t_x \mid u_i) = \frac{|P_{u_i,t_x}|}{|P_{u_i}|} \qquad (2)$$

Where $|P_{u_i,t_x}|$ is the number of items that being tagged with t_x by user u_i and $P_{u_i,t_x} = f_3(u_i, t_x)$. $|P_{u_i}|$ is the number of items that being tagged by user u_i and $P_{u_i}=f_1(u_i)$.

[Example 1] In Figure 1, the item p_3 has the tag t_2 and t_3. $Pr(t_2 \mid p_3) = 1/3$, $Pr(t_3 \mid p_3) = 2/3$. With a higher value, the tag t_3 "globalization" can be considered a major topic of the item p_3 while the tag t_2 "apple" representing a minor topic. User u_4 only has tag t_5, $Pr(t_5 \mid u_4) = 1$.

4.2.2 The relevance of two tags in terms of each individual user

As discussed in Section 4.2.1, the probability $Pr(t_x \mid p_k)$ measures the strength of how important the tag t_x is for representing the topics of the item p_k. Since $Pr(t_x \mid p_k)$ is calculated by considering all users who have used t_x to tag the item p_k, it represents the importance of t_x to p_k globally in terms of all users. For a given user u_i and a tag t_x, the strength of a tag t_y being related to the tag t_x for the user u_i can be estimated based on the probabilities of t_y being used to tag the items collected in the tag t_x of the user u_i (i.e., the probabilities $Pr(t_x \mid p_k)$ for all the items p_k in t_x of u_i), because those probabilities measure the possibilities that other users use t_y to tag the items in t_x of the user u_i. The items in t_x of u_i is the mapping $f_3(u_i, t_x)$, i.e., P_{u_i,t_x}. Let $P_{u_i,t_x} = \{p_{i1}, p_{i2}, \dots, p_{in}\}$, we could use any of $Pr(t_y \mid p_{i1})$, …, $Pr(t_y \mid p_{in})$ to estimate the relevance of t_y to t_x for user u_i. In this paper, we propose to use the expectation of $Pr(t_y \mid p_{i1})$, …, $Pr(t_y \mid p_{in})$ to estimate the relevance of t_y to t_x. Assuming that $Pr(t_y \mid p_{i1})$, …, $Pr(t_y \mid p_{in})$ are equally important to the user u_i to calculate the relevance of t_y to t_x, the expectation is actually the average value of $Pr(t_y \mid p_{i1})$, …, $Pr(t_y \mid p_{in})$. Let $r_{u_i,t_x}(t_y)$ denote the relevance of a tag t_y to a tag t_x for user u_i, the relevance can be calculated as below:

$$r_{u_i,t_x}(t_y) = \sum_{p_k \in P_{u_i,t_x}} \frac{Pr(t_y \mid p_k)}{|P_{u_i,t_x}|} \qquad (3)$$

$r_{u_i,t_x}(t_y)$ represents the weight of how strong that t_y is related to t_x with respect to user u_i, $\sum_{t_y \in T} r_{u_i,t_x}(t_y)$ =1. Since different items may be collected with the tag t_y for user u_i, the relevance measure weigh $r_{u_i,t_x}(t_y)$ usually is not symmetric (i.e., $r_{u_i,t_x}(t_y) \neq r_{u_i,t_y}(t_x)$).

Therefore, let t_x be a tag used by user u_i, the representation of tag t_x consists of a set of related tags that reflects the related topics of tag t_x and their corresponding weights. Since the differences of individual vocabularies are considered and the meanings or related topics of each tag are obtained, we can effectively solve the problems of tag synonyms, tag semantic ambiguity, and spelling variations.

[Example 2] We can get the relevance weights $r_{u_i,t_x}(t_y)$ of each two tags in terms of each individual user with Equation 3, shown in Figure 1 (b). For example, $r_{u_2,t_2}(t_3) = \frac{1}{2} \cdot \frac{1}{3} + \frac{1}{2} \cdot \frac{2}{3} = 0.5$. The representation of t_2 for user u_1 is $RT(u_1, t_2)= \{(t_1, 0.25), (t_2, 0.75), (t_3, 0.0), (t_4, 0.0), (t_5, 0.0)\}$, while the representation of t_2 for user u_2 is $RT(u_2, t_2)= \{(t_1, 0.0), (t_2, 0.16), (t_3, 0.5), (t_4, 0.34), (t_5, 0.0)\}$. Since different representations of tag t_2 are generated for different users, the semantic ambiguity can be eliminated. Similarly, we can get the representation of tag t_5 for user u_4. $RT(u_4, t_5) = \{(t_1, 0.0), (t_2, 0.0), (t_3, 0.25), (t_4, 0.25), (t_5, 0.5)\}$. We can see the personal tag "0403" mainly means "globalization" and "internet" for user u_4. Similarly, it's easy to find the tag synonyms through comparing their tag representations.

4.3 The Representation of Items

The $r_{u_i,t_x}(t_y)$ proposed in Section 4.2.2 estimates the relevance of a tag t_y to a tag t_x with respect to a user u_i. Since the items collected in t_x must have something in common (otherwise the user won't put them together in one tag), the related tag t_y should reflect some topics of the items in t_x. Therefore, if an item p_k is collected by user u_i under a tag t_x, we could use the relevance $r_{u_i,t_x}(t_y)$ of t_y to t_x to estimate the relevance of t_y to the item p_k. For a given item p_k, the total number of times that the item p_k has been tagged by users is the total number of user-tag pairs (u_i, t_x) of item p_k: $M = |T_{p_k}^u|$, where $T_{p_k}^u = h_3(p_k)$. That means, we have M number of $r_{u_i,t_x}(t_y)$ values of the possible user-tag pairs (u_i, t_x) to estimate the relevance of t_y to the item p_k. Similar to the estimation of $r_{u_i,t_x}(t_y)$, we assume that all the $r_{u_i,t_x}(t_y)$ values are equally important to estimate the relevance of t_y to p_k. The estimation of the relevance of t_y to p_k, denoted as $wp(t_y)$, is shown as below:

$$wp(t_y) = \sum_{u_i \in U_{p_k}, t_x \in T_{p_k}} \frac{1}{M} \cdot r_{u_i,t_x}(t_y) \qquad (4)$$

where $M \geq 1$, $\sum_{t_y \in T} wp(t_y)$ =1. Thus, each item is represented by a set of related tags and their weights. The higher the weight of a tag is, the more important topic this tag is for the item, or in another word, the more likely this item will be labeled with this tag.

However, if a tag is popularly used to describe items, it is not a distinctive tag to represent this item. Similar to the *idf* weighting approach in text mining, we also should take the popularity of a tag for all items into consideration to measure the importance of a tag to a specific item. Let t_y be a tag, $|P|$ be the total number of items, $iif(t_y)$ is defined as the inverse item frequency of tag t_y. Usually, $iif(t_y) = |P|/log(|P_{t_y}|)$, where $|P_{t_y}|$ is the number of items that have been described by t_y and the value of $|P_{t_y}|$ is calculated after the tag expansion for the whole item set P. To get a value between 0 and 1 to facilitate comparison, we set $iif(t_y) = 1/log(e + |P_{t_y}|)$, where e is an irrational constant approximately equal to 2.72 and $0 < iif(t_y) \leq 1$. By taking the inverse item frequency into consideration, the weight of a tag for the relevant topic/tag representation of an item can be calculated with the following equation.

$$w_y^p = wp(t_y) \cdot iif(t_y) \qquad (5)$$

Thus, we profile each item p_i with a tag vector. The values in the vector reflect how much p_k is relevant with the tags and can be calculated based on Equation 5.

[Example 3] we can get the weight of each tag for item p_3 with Equation 5, shown in Figure 1 (c). For example, $wp(t_5) = \frac{1}{3} \cdot \frac{1}{3} \cdot \frac{1}{2} = 0.055$. After the representation of each item, not only p_5 and p_6 are relevant to t_5, but also p_3 and p_4 are relevant to t_5. Therefore, $|P_{t_5}| = 4$ and $iif(t_5) = \frac{1}{log(e+4)} = 0.52$. The item representation of p_3 is $RP(p_3) = \{(t_1, 0.0), (t_2, 0.059), (t_3, 0.31), (t_4, 0.077), (t_5, 0.028)\}$. We can see that t_3 "globalization" is still a major topic/tag of p_3 while p_3 is slightly relevant with t_5.

4.4 User profiling

User profile is used to describe user's interests and preferences information. Typically, an item explicit or implicit rating vector is used in collaborative filtering based recommender systems to profile a user's preferences or interests to the items, it is also called users' item preferences [12]. For content based approaches, a set of topics extracted from the content or taxonomic information of items are used to profile users' topic preferences [1]. To get better recommendations, both users' topic preferences and item preferences are profiled and hybrid recommendation approaches are used to recommend users those items that are not only rated by similar users but also have similar topics with users' topic preferences [9].

In this paper, we profile each user u_i with his/her item preferences and tag preferences as well, which is denoted by $u_i = \{u_i^P, u_i^T\}$. u_i^P is a |P|-sized binary item vector representing u_i's item preferences. Based on User-Item mapping f_2, if u_i has tagged or collected the item p_k, then the value of this item in vector u_i^P is 1, otherwise is 0. u_i^T is the tag preferences of u_i and is represented by a |T|-sized tag vector with values reflecting how much u_i is interested in the tags. How to calculate the value or weight of each tag is the major focus of this sub section.

Based on the User-Tag mapping f_1, we can get the weight of each tag t_x used by the user u_i with Equation 2. With the tag representation Equation 3, we can get the relevance weight of $t_y \in T$ to t_x for user u_i. To calculate how much u_i will be interested in t_y, we firstly calculate how much the user is interested in the tag t_x, then, based on the relevance weight $r_{u_i,t_x}(t_y)$, we can get u_i's preferences to t_y. Thus, for each tag $t_y \in T$, we use the product of these two weights to measure how much the user u_i will be interest in the tag t_y, which is defined as below:

$$wu(t_y) = \sum_{t_x \in T} \mathcal{P}r(t_x \mid u_i) \cdot r_{u_i,t_x}(t_y) \qquad (6)$$

Therefore, the tag preferences of each user are represented by a set of tags with their weights. Similar with the item representation, we also take the occurrence of a tag (i.e., tag popularity) for all users into consideration to measure the general importance of a tag in the identification of the tag preference of a user. Let t_y be a tag, $iuf(t_y)$ is defined as the inverse user frequency of tag t_y. Similar with $iif(t_y)$, we set $iuf(t_y) = 1/log(e + |U_{t_y}|)$, $0 < iuf(t_y) \leq 1$. By taking the inverse item frequency into consideration, the weight of a tag for the tag preference representation of a user can be calculated with the equation below.

$$w_y^u = wu(t_y) \cdot iuf(t_y) \qquad (7)$$

Based on Equation 7, we can calculate the values of the tag preference vector u_i^T for each user u_i.

[Example 4] We can get the weight of each tag for user u_4 with Equation 7, shown in Figure 1 (d). For example, $wu(t_5) = 0.5$. After the representation of each user, not only u_4 has preference on t_5, but also u_2 and u_3 have preferences on t_5. Therefore, $|U_{t_5}| = 3$, $iuf(t_5) = \frac{1}{log(e+3)} = 0.57$. The user representation of u_4 is $RU(u_4) = \{(t_1, 0.0), (t_2, 0.0), (t_3, 0.14), (t_4, 0.14), (t_5, 0.285)\}$. We can see that after the representation, u_4 not only has preference to t_5, but also has preferences to t_3 and t_4.

Therefore, with the user and item representations, each user and item are represented with a set of tags along with their weights. Based on these representations, the collaborative filtering and content mapping approaches can be used to form neighborhood and recommend items.

4.5 Neighborhood Forming

Neighborhood formation is to generate a set of like-minded peers for a target user $u_i \in U$ or a set of similar peer items for an item $p_i \in P$. The "K-Nearest-Neighbours" technique is used to select the top K neighbours with shortest distances to u_i or p_i through computing the distances between u_i and all other users or the distances between p_i and all other items. The more accurate a user profile or item representation is, the more similar neighbour users or items will be found. The distance or similarity measure can be calculated through various kinds of proximity computing approaches such as cosine similarity and Pearson correlation. Cosine similarity is popularly used to calculate the similarity of two vectors. Since a vector of tags with their correspondent weights is used to represent each item and the topic preferences of each user, the topic similarity of each item pair and user pair, and the topic similarity between an item and a user can be measured through calculating the similarity of their weighted tag vectors. For any two weighted tag vectors v_i and v_j, the cosine similarity is defined as:

$$cosine(v_i, v_j) = \frac{\sum_{y=1}^{|T|} v_{i,y} \cdot v_{j,y}}{\sqrt{(\sum_{y=1}^{|T|} v_{i,y}^2) \cdot (\sum_{y=1}^{|T|} v_{j,y}^2)}} \qquad (8)$$

Since each user is profiled with item preference and topic preference, the similarity of two users u_i and u_j includes two parts: the similarity of topic preferences is denoted as $sim_u^T(u_i, u_j)$ and the similarity of item preference is denoted as $sim_u^P(u_i, u_j)$. Cosine similarity is used to measure the similarity of topic preferences between two users. To measure the similarity of item preferences with implicit binary ratings, a simple approach is to count the overlap of commonly rated items between two users [14]. Since the approach of weighting each commonly rated item with inversed user frequency or iuf [14] takes the user frequency of item into account, it performs better for binary ratings in many cases [14]. We use this iuf approach to calculate the similarity of item preferences of two users, which is defined as below.

$$sim_u^P(u_i, u_j) = \frac{\sum_{p_k \in P_{u_i} \cap P_{u_j}} iuf(p_k)}{\sqrt{|P_{u_i}| \cdot |P_{u_j}|}} \qquad (9)$$

Thus, the similarity of two users is defined as below:

$$sim_u(u_i, u_j) = (1 - \eta) \cdot sim_u^T(u_i, u_j) + \eta \cdot sim_u^P(u_i, u_j) =$$
$$(1 - \eta) \cdot cosine(u_i^T, u_j^T) + \eta \cdot \frac{\sum_{p_k \in P_{u_i} \cap P_{u_j}} iuf(p_k)}{\sqrt{|P_{u_i}| \cdot |P_{u_i}|}} \qquad (10)$$

Where $0 \leq \eta \leq 1$. Similar with the similarity measure of the users' topic preferences, cosine similarity is used to measure the similarity of two items p_i and p_j based on their representations that represented by weighted tags vectors. The similarity of two items is defined as $sim_p(p_i, p_j) = cosine(p_i, p_j)$. Using the similarity measure approach, we can generate the neighborhood of the target user u_i, which includes K nearest neighbor users who have similar user profile with u_i. The neighborhood of u_i, is denoted as $\check{N}(u_i) = \{u_j | u_j \epsilon\ maxK\{sim_u(u_i, u_j)\}, u_j \in U$, where $maxK\ \{\}$ is to get the top K values. Similarly, we can generate the top K nearest neighbor items of each item p_i, which is denoted as $\check{N}(p_i) = \{p_j | p_j \epsilon\ maxK\{sim_p(p_i, p_j)\}, p_j \in P$.

4.6 Recommendation Generation

Typically, from the generated neighborhood, a set of items that are most frequently rated or tagged by the neighbor users of the target user or most similar to the target user's rated items will be recommended to the target user. Since the topics of items and the topic preferences of users can be represented by weighted tags, the topic similarity between the target user and the candidate item can be used to improve the accuracy of recommendations through selecting those items that are not only rated by the most similar users, but also have similar topics with the target user. With the topic match measure, it makes the collaborative filtering approach actually takes the benefits of content based recommendation approaches [20]. We discuss both user and item based CF approaches that combine the topic match measure respectively.

4.6.1 User based approach

For each target user u_i, a set of candidate items will be generated from the items tagged by u_i's neighbourhood formed based on the similarity of user profiles, which is denoted as $\check{C}_u(u_i)$, $\check{C}_u(u_i) = \{p_k | p_k \epsilon P_{u_j}, u_j \epsilon \check{N}(u_i), p_k \notin P_{u_i}\}$. For each candidate item $p_k \epsilon \check{C}_u(u_i)$, $\check{N}(u_i) \cap U_{p_k}$ is the sub set of users in $\check{N}(u_i)$ who have tagged the item p_k, the prediction score of how much u_i may be interested in p_k is calculated in terms of the aspects of how similar those users who have the item p_k and how similar the item's topics with u_i's topic preferences. We use the simple linear combination to hybrid the two parts. With Equation 10, the similarity of two users can be measured. Similarly, the cosine similarity is used to calculate the topic match between the target user u_i and the candidate item p_k denoted as $sim_{u,p}(u_i, p_k)$. Thus, the prediction score for each candidate item $p_k \epsilon \check{C}_u(u_i)$ denoted as $A_u(u_i, p_k)$ can be calculated as below:

$A_u(u_i, p_k) = \sum_{u_j \epsilon \check{N}(u_i) \cap U_{p_k}} (\alpha \cdot sim_u(u_i, u_j) + (1 - \alpha) \cdot$
$simu, pui\ ,pk) = uj\epsilon \check{N}ui\cap Upk(\alpha \cdot simuui\ ,uj + 1 - \alpha \cdot cosineuiT, pk$
$)$(11)
Where $0 \leq \alpha \leq 1$. The top N items with high prediction scores will be recommended to the target user u_i.

4.6.2 Item based approach

For item based approach, the candidate item set can be the whole item set except those items that are already rated or tagged by the target user. To avoid unnecessary computation of item pairs, the top K most similar items of each rated or tagged item of the target user u_i can be aggregated together as the candidate item set, which is denoted as $\check{C}_t(u_i)$, $\check{C}_t(u_i) = \cup_{p_y \epsilon P_{u_i}} \check{N}(p_y) - P_{u_i}$. For each candidate item $p_k \epsilon \check{C}_t(u_i)$, usually, the prediction score can be calculated through the calculation of the sum or average similarity of the candidate item with all rated or tagged items of the target user u_i. Since the user's topic preferences are obtained

based on the related tags of all the items that the user has, the similarity of the candidate item with the user's topic preferences actually measures the average or total similarity of the candidate item with all tagged items of the target user. Thus, if a candidate item has the most similarity score with one of the user's tagged item, and it has the most similar topics with the user's topic preferences, then this item will have higher prediction score than other items. Thus, we propose to calculate the prediction score of a candidate item based on the maximum score of the linear combination of the similarity with each tagged/rated item and the similarity with the target user's topic preferences, which is shown as below.

$A_p(u_i, p_k) = max_{p_y \epsilon P_{u_i}} \{\beta \cdot sim_p(p_y, p_k) + (1 - \beta) \cdot$
$simu,\quad pui\quad ,pk\} = max\quad\quad py\epsilon Pui\{\beta \cdot cosinepy$
$,pk + 1 - \beta \cdot cosineuiT, pk\}$ \hspace{2em} (12)

5. EXPERIMENT DESIGN
5.1 Data preparation
We conducted the experiments with two real world datasets Amazon.com dataset and CiteULike.com datasets.

1) Dataset D1: Amazon.com dataset. This dataset was crawled from amazon.com on April, 2008. The items of the dataset are books. To avoid too sparse, we only select those users that have at least 5 items and those items that have been used by at least 3 users. The final dataset consists of 4112 users, 34201 tags, 30467 items. To facilitate comparison, we also extracted the taxonomic descriptors [12] of each item from amazon.com. The taxonomy formed by the descriptors is tree-structured and contains 9919 unique topics.

2) Dataset D2: CiteULike dataset. The "Who-posted-what" dataset (http://static.citeulike.org/data/current.bz2) that contains the basic tagging information is used. The items of this dataset are research papers. The original dataset contains 50926 users, 346084 tags and 1681089 items. We select those users that have at least 5 items and those items that have been used by at least 2 users. The final dataset comprises 7103 users, 78414 tags, 117279 items.

5.2 Experiments setup
To evaluate the proposed approaches, each dataset was 5 folded and split into 5 datasets. For each split dataset, 80% of users were used as the training users while 20% of users were randomly selected as the test users. For each test user, randomly, 20% of the items of this user were hidden as the test/answer set while 80% of each user's items are used as his/her training set. The training set of each user contains user's items and corresponding tags information as well. For each test user, the recommender system will generate a list of ordered items that the test user didn't collect. The top N items with high prediction scores will be recommended to the user. If an item in the recommendation list was in the test user's hidden item list, then the item was counted as a hit. The average precision and recall of the whole test users of one split dataset were recorded as one run of the results. The average precision and recall values of the 5 split datasets were used to measure the accuracy performance of the recommendations.

6. RESULTS AND DISCUSSIONS
In this section, we firstly discuss the influence of personal tags to the accuracy of recommendations. Then, two sets of comparisons

that compare the proposed approaches with other related state-of-art work will be discussed in details.

The parameters for the proposed approaches include η, α and β. In the experiments, we tested the value of the parameters from 0.0 to 1.0 incrementally. Due to the space limit, the discussion of the setting process is omitted. The results indicated that with the η value ranging from 0.8 to 1.0 and the α value ranging from 0.4 to 0.5, the proposed user based approach achieved the best performances on the two datasets. With the β value ranging from 0.4 to 0.5, the proposed item based approach achieved the best results. The value ranges of the best setting suggest that item preferences performed more important role than tag preferences in neighborhood formation while both the collaborative filtering and the content mapping approaches played equal important roles for the recommendation generations for the two datasets. The following discussions are given on the basis of the best setting of the parameters.

6.1 The influence of personal tags

The distributions of tags and items follow the power law distributions [3]. Let θ denote the popularity of a tag (or the number of users of the tag), the number of tags used by at least θ users of both datasets are plotted in Figure 2 where θ was set from 1 to 10 incrementally. The chart shows that the distribution of tags follows the power law distribution. In dataset D1, 67% of tags (i.e., 22903) were personal tags used by only one user while only 4.8% of tags (i.e., 1648) were used by at least 10 users. In dataset D2, there were nearly 70% of tags (i.e., 55184) are personal tags while only 5.2% of tags (i.e., 4131) were used by at least 10 users in dataset D2. The distribution suggested that the majority of the tags existing in the tagging communities were personal tags.
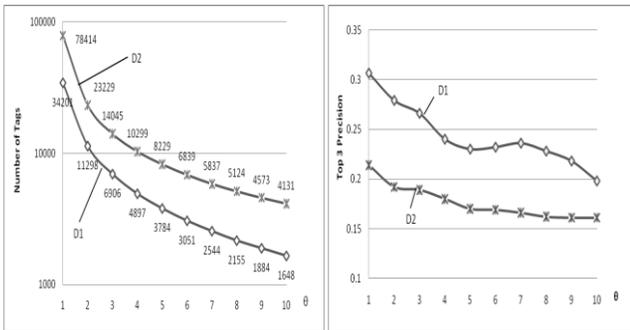
Figure 2. The distributions of tags

Figure 3. Top 3 Precision results with different θ values

In many approaches [4] [5] [6], the personal tags or tags with low popularity were removed in pre-processing. They were usually meaningless to other users and useless in finding neighbors (e.g., t_5 "0403" in Figure 1). With the proposed approaches, the personal tags are related to a set of other tags, and have influences to the improvement of the accuracy of recommendations. To evaluate the influence of the personal tags in the proposed approaches, we select a set of tags whose popularity are larger than or equal to θ, and only keep those selected tags in the user and item representations. The top 3 precision values of the proposed user based approach with different θ values are shown in Figure 3. The chart suggested that the personal tags can improve the precision results from 0.28 to 0.31 with θ changed from 2 to 1 for dataset D1. Similarly, the personal tags can improve the precision results from 0.19 to 0.21 with θ changed from 2 to 1 for dataset D2. Moreover, The graph indicated that

although keeping more tags not necessarily promoted the precision values, the precision values decreased dramatically when large number (i.e., 90%) of tags with lower θ values (i.e., $\theta \leq 5$) was removed.

6.2 The comparisons with other tag noise removing approaches

The objective of this experiment was to evaluate the effectiveness of the proposed approaches in terms of removing the noise of tags. We compared the precision and recall values produced with the following methods:

- **WTR-User** and **WTR-Item**: These are the proposed user and item based approaches.
- **Tag-TPR**. This approach used the item taxonomic topics to represent the semantic meaning or related topics of a tag [12]. With this approach, the entire tag vocabulary was converted to a set of standard taxonomic topics given by experts.
- **ARTE**: Association rule approach is popularly used to expand the tags of users/items with a set of associated tags to recommend tags [3] [10]. Inspired by the work of [23], we used association rules to expand the tags for the purpose of item recommendations. The same with *Heymann's* approach [10], each item's tag set was used as one transaction record in the whole transaction set. Based on the transaction set, a set of association rules with given confidence and support values were generated.
- **LDA**: This is the Latent Dirichlet allocation (LDA) approach proposed in [24] for item recommendations. The LDA model was used to find the hidden semantic topics of tags to remove the noise of tags.
- **Clustering**. This approach was used in the work of [5] and [18]. Items were clustered based on the their *tf-iuf* tag profiles. Treating user's tags as queries, the most relevant items were recommended.

The top 10 precision and recall results of these approaches of dataset D1 are shown in Figure 4.
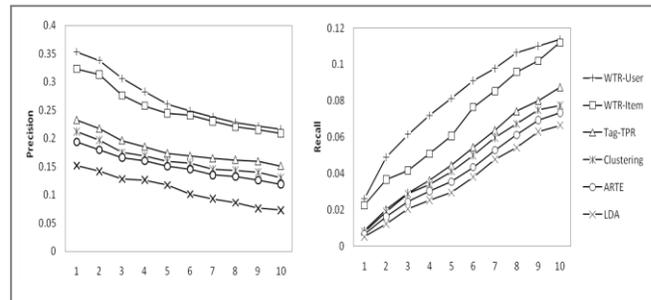
Figure 4. Top 10 Precision and recall results of dataset D1

Discussions:

As shown in Figure 4, that *WTR-User* (the proposed user based approach) performed slightly better than *WTR-Item* (the proposed item based approach). They performed better than the other approaches. The results demonstrated that the proposed tag representation approach is effective.

The proposed approach outperformed the *Tag-TPR* approach. Although tags were not as standard as the taxonomic topics, tags contained rich relationship information. Such information was helpful in finding the similar users and items to make recommendations. The *LDA* approach had the worst performance.

It only processed tags as common textural information. The short and sparse tag based content representations weakened the performance of *LDA*. As a result, the *LDA* approach was beaten by *CF-Item* (the standard item based CF approach) in Figure 5.

The experimental results of the Association rules based tag expansion approach *ARTE* were unsatisfactory. Since the antecedents and the consequences of each association rule should occur frequently in the transaction dataset, the personal tags that need to expand cannot find associated tags while only the frequent or popular tags were expanded with a set of associated poplar tags. This kind of tag expansion can promote the accuracy of tag recommendations because the popular tags have more chances to be used by users. But for item recommendations, usually the popular tags are not so useful to identify the tag preferences or the relevant topics/tags of items. As a result, the *ARTE* did not achieve a satisfactory level of performance. Also, the association rule based tag expansion is not a personalized approach. The occurrences of tags are calculated based on the tag names. The same set of associated tags was expanded for different users if they used the same tag names. Consequently, much noise of tags could not be detected or removed.

The *Clustering* approach was mainly a content filtering approach. It did not use the collaborative filtering. The tags of items were expanded based on the clustering approach. However, only the frequent tags in a cluster were selected to expand the user's topics. Such frequent tags were not able to identify the most similar items or users in many occasions. As a result, the *Clustering* approach was outperformed by the proposed approaches.

6.3 The comparisons with baseline models

The objective of this experiment was to evaluate the overall effectiveness of the proposed recommendation approaches by comparing with the state-of-art item recommendation approaches that based on the implicit ratings and tag information. Since this paper focus on the item recommendation based on tag information only, those kinds of work that recommend tags or use explicit ratings or other kinds of implicit information to make recommendations such as [21] and [26] are not included.

- **Graph Rank**. This approach was the most recently published work discussing the item recommendation using tagging information [25]. An integrated diffusion-based algorithm making use of both the user-item graph and the item-tag graph was proposed to make personalized item ranks for each user.
- **Tag tf-iuf**. This approach was proposed by Diederich [4]. The *tf-idf* tag profiles are used to represent users' topic preferences. This approach did not consider the noise of tags nor combine content filtering method.
- **TPR**. This well-known Ziegler's approach acquired a user's topic preferences based on the item taxonomic topics given by experts [13]. It used implicit ratings but not tag information nor item preferences. Thus, *TPR* was implemented combining the item preferences and item taxonomic topic preferences on the top of Ziegler's approach for a fair comparison with ours.
- **Tso-Sutter's approach**. This approach was proposed by Tso-Sutter that uses binary user-item-tag matrixes to make recommendations [6], which is an extended collaborative filtering approach.
- **CF-Item**. This was the standard item based collaborative filtering (CF) approach that based on the User-Item relationship or the binary user-item matrix. The similarity of two items was calculated based on the overlap of their user sets (i.e., the Item-User mapping). In our experiments, an

advanced version of CF that takes the *inverse item frequency (iif)* value of each user into consideration to measure the similarity of two items was implemented as suggested by [14].

The top 10 precision and recall results of these approaches of dataset D1 are shown in Figure 5.
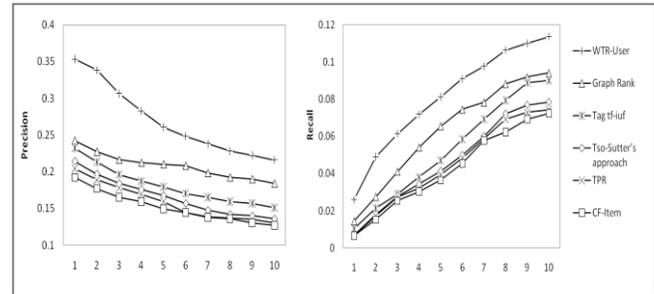
Figure 5. Top 10 Precision and recall results of dataset D1

The top 10 precision and recall evaluation results of dataset D2 for *WTR-User*, *Graph Rank*, *Clustering* and *CF-Item* are shown in Figure 6.
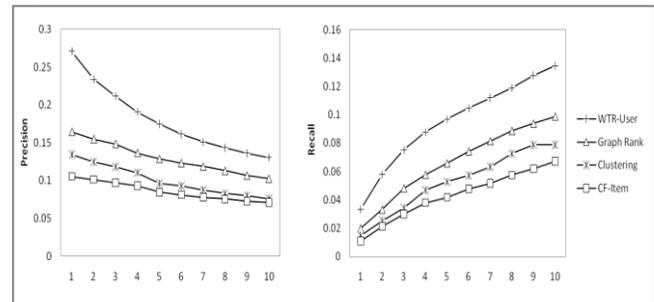
Figure 6. Top 10 Precision and Recall results of dataset D2

Discussions:

From the experimental results of Figure 4-6, the proposed user and item based weighted tag recommendation approaches outperformed the baseline models for both datasets. The overall precision and recall values are relative low mainly because the datasets are not dense datasets.

As shown in Figure 5, *Tso-Sutter's* approach only performed slightly better than the *CF-Item*. *Tso-Sutter's* approach did not use content filtering or any weighting approaches. The *Tag tf-iuf* approach simply removed the tags that used by less than certain users (i.e., $\theta \leq 5$) in the experiments and did not combine with the content filtering approach. It did not significantly improve the accuracy of recommendations. As shown in Figure 5 and 6, the *Graph Rank* approach performed better than the *CF-Item* as they claimed. It performed worse than the proposed approaches. Although *Graph Rank* approach was based on the relationships of users, items and tags, it simply divided the three dimensional tagging graph into user-tag and tag-item bipartite graphs. The three dimensional relationships reflecting the personal tagging relationships of each individual user were thus ignored.

The proposed approaches had the best performance. It relied on both two-dimensional and three-dimensional relationships among tags, users and items to find the personalized semantic meaning of each tags for a user. The proposed approach also eliminated the noisy tags, profiled a user's tag preferences, and extracted items' relevant topics/tags accurately. In addition, though no content

information of items is used, the proposed approaches actually benefit from combining the memory based collaborative filtering approaches with the content filtering approach that based on the content information given by users or called tags.

Since the content information are generated by the collaborative tagging of users, although the proposed approaches combined the collaborative filtering and content based approach, they still have the similar drawbacks as other collaborative filtering approaches such as cold start [1] when a user has tagged very few items or an item only tagged by a very few users.

7. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed to make use of the rich relationship information of tags to select a set of related tags to represent the related topics/tags of a tag for each user individually to remove the noise of tags. Based on the tag representations, we proposed approaches to find a set of most related tags with their weights to represent the relevant topics/tags of each item and the tag preferences of each user. Furthermore, based on the item or user profiles represented by the weighted tags, the item and user based collaborative filtering combining with the content filtering approaches are presented. The experimental results show that the proposed approaches are effective. The comparison with the item taxonomic topic based approaches suggests that after making use of the distinctive feature of tags, the tag information can be used as quality item content information to boost the accuracy of item recommendations.

Since the social tags can be used to describe any types of items or resources, this research can be used to recommend various types of items to users, especially for those items that the content information is difficult to process or the taxonomic topic information is not available. Moreover, because tags are less intrusive, lightweight, multi functional, and human understandable, we believe that tags will play more and more important role for item recommender systems. This research gives contribution to improving the accuracy of the popularly used memory based collaborative filtering approach for the top N item recommendation task through incorporating this new type of user information in web 2.0. The future work will explore how to integrate tags with other types of user information such as reviews, blogs, and explicit ratings to improve the accuracy of item recommendations.

8. ACKNOWLEDGMENTS

9. REFERENCES

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