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RESEARCH ARTICLE - COMPUTER ENGINEERING AND COMPUTER SCIENCE

Personalized Search by a Multi-type and Multi-level User Profile in Folksonomy

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Abstract
With the development of the web 2.0 communities, more and more collaborative tagging systems become popular in recent years. Based on previous relevant works on the collaborative tagging system, this paper proposes a concept of a multi-type and multi-level user profile for improving the efficiency of personalized search. User profile consists of different types of resource attributes, and every type reflects multi-level favorites and nuisances from user. A detailed design process of user profile is presented in this paper. We propose a personalized search method by using the multi-type and multi-level user profile. Experimental results on a large real dataset demonstrate that the multi-type and multi-level user profile outperforms the baseline methods.

Keywords User profile · Personalized search · Tagging · Rating · Genre

1 Introduction

Personalized search has been widely applied in various fields. Some research works such as [1,2] are conducted to model the user interest profile from the search behavior, such as user's search history and browse history. However, these search behaviors are greatly affected by interference.

In recent years, more and more social resource sites support tagging mechanism. For example, Last.fm allows users to annotate their favorite music. In Flicker, users can annotate and upload their favorite photographs and videos. Users' interest resources may be annotated in Del.icio.us. These collaborative tagging systems (also known as folksonomy) allow users to annotate resources freely according to their interests, the tagging information provide low interference source of information to construct user interest profile. In other words, collaborative tagging systems organize and share tags for all users, besides the tags are more accurate information for personalized search [3]. Some research works such as [4–8] construct user profile and resource profile for personalized search in folksonomy. Currently, some collaborative tagging systems allow users to rate resource, e.g., MovieLens. These systems provide more detailed information to express users' interests. Relevant researches works such as [3,4,7,9–12] show that integrating tags and ratings to construct user profile for personalized search more effectively. Furthermore, users rate some resources with high ratings or low ratings so as to indicate their favorites or nuisances on resource attributes.

However, two limitations exist in these personalized search methods, including the following:

– Some research works assume that all tags annotated by a user are the user's favorite tags, ignoring user's nuisances. A few tags are also used by a user to annotate annoying resources. For example, Lucy likes science movies but she does not like extraterrestrials, and Lucy may use the tag "extraterrestrials" to annotate some movies about extraterrestrials to reminder herself that these movies include extraterrestrials. In other words, the tags given by users include not only users' favorite tags but also annoying tags.

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- All current studies do not get the utmost out of resource attributes by ratings for personalized search, e.g., resource genre. In the movie system, films are segmented into genres, such as action, adventure, drama, horror, comedy, and so on. For example, Lucy likes to watch science fiction movies and usually rates them with high score. On the contrary, Lucy dislikes horror movies and rates them with low score. That is, genre is an important factor influencing personalized search results. It is used in recommender systems, but it is hardly used in personalized search.

In this paper, the information source of tags, ratings and resources' genres is used to construct a multi-type and multi-level user profile for improving personalized search. The contributions of this paper are as follows.

- We reveal and discuss the limitations of main current relevant works on personalized search in folksonomy.
- We propose a new concept of a multi-type and multi-level user profile, which consists of different types of resource attributes including tags and genres. At the same time, every type reflects multi-level of a user's favorites and nuisances.
- This research applies multi-type and multi-level user profile to enhance personalized search in folksonomy.
- For a preliminary evaluation, we compare the proposed method with the state-of-the-art methods in the experiments with real dataset from MovieLens. The experiment results show that our proposed method is more effective for personalized search in folksonomy.

The rest sections of this paper are organized as follows. Sect. 2 reviews related works on personalized search in folksonomy. A new concept of a multi-type and multi-level user profile is introduced in Sect. 3. Section 4 presents the construction of resource profile that consists of tags and genres. Section 5 proposes the personalized ranking method by using the user profile and resource profile; Sect. 6 conducts the experiment on a large public dataset and discusses the results. Finally, the research in this paper is summarized, and suggestions for future works are proposed in the conclusion section.

2 Related Works

In this section, we review the related works on folksonomy, genre and personalized search. Then we analyze the limitations of the work in terms of personalized search.

2.1 Folksonomy

Folksonomy is a new method of classifying information with the advent of Web 2.0, and it has been widely applied in various fields in recent years. Early in the development of folksonomy, Choy and Lui [13] proposed information retrieval upon folksonomy. After that, it is proved in [14] that search results found by both search engines and folksonomies are more relevant than those returned by single information retrieval system. Xu et al. [15] presented a framework of personalized search with folksonomy, which utilized not only keywords matching but also users' interests matching. Based on tags co-occurrence, a method of query words extension for search in folksonomy was introduced in [16]. Hsieh et al. [17] designed an application in patent analysis based on a desktop collaborative tagging system to recommend tags and search relevant information. To help users annotate the content of online resources, Font et al. [18] designed a general scheme for building a folksonomy-based tag recommendation system. A new fusion approach in which the semantics travels in both directions from folksonomies to ontologies and vice versa was proposed in [19]. Li and Zhang [20] analyzed users' tagging behaviors based on the characteristics of tags related to blog contents. These characteristics can be used to promote organization and propagation of academic knowledge in the academic tagging system. Pandya et al. [21] proposed implementation of folksonomy based on tag cloud model for information retrieval. Godoy and Corbellini [22] provided a comprehensive overview of the literature in the field of folksonomy-based recommender systems.

2.2 Genre Preferences

The genre of resource is widely applied in recommender systems. A collaborative filtering recommendation algorithm based on item genre and rating similarity was proposed in [23]. Kim and Moon [24] designed and generated a movie genre similarity profile in a mobile experimental environment. Genre similarity was then used to recommend new genres to targeted customers. Ashkezari-T and Akbarzadeh-T [25] described a hybrid fuzzy-Bayesian network approach to genre-based recommender system. Bansal et al. [26] proposed a method to predict genre of movies based on users' posted movie tweets and recommend movies to users according to predicted genre. In [27] and [28], the genre of the movie was exploited to enhance the rating accuracy for movie recommendation. Zheng and Ip [29] designed a framework based on the trade-off between genre difference and similarity to generate customizable surprising recommendations. A clustering approach based on item genre for a recommender system was presented in [30]. In [31], a method of folksonomy-based fuzzy user profile was proposed for improved recommendations. Ma et al. [32] designed a novel latent genre-aware micro-video recommendation model on social media. A hybrid collaborative filtering method based on users and genres was proposed in [33].

2.3 Personalized Search in Folksonomy

At present, there are some studies on utilizing user profile and resource profile to improve personalized search in folksonomy. At early times, some research works such as [3,9–12] were conducted to construct user profile and resource profile by using term frequency (TF), term frequency–inverse document frequency (TF-IDF), Best Matching25 (BM25) and their hybrid paradigms, respectively. Later, the method of using a normalized term frequency (NTF) to model user profile and resource profile to improve previous works was presented in [33]. Biancalana and Micarelli [34] presented a novel approach to extend the family of well-known co-occurrence matrix technique models for personalized web search. A user preference model based on tag clustering was proposed in [35], which can analyze users' different interests and dynamically generate user profile against different personalized search queries. Du et al. [36] proposed a multi-level user profile by integrating tags and ratings for personalized search, which can express users' likes and dislikes. Kumar et al. [37] used singular value decomposition to build a clustered user interest profile. Kim et al. [38] built a latent tag preference model and a latent tag annotation model to find the most desirable content relevant to the user's needs for personalized search. Han et al. [39] collected user tags from folksonomy and mapped them onto existing domain ontology, and experiment integrating user interest profile to a personal search engine showed that the approach can accurately capture users' multiple interests at the semantic level. A topical query expansion model which can enhance the personalized search by utilizing individual user profile was designed in [40]. To be adaptive and aware of multiple interests of a user, Han et al. [41] proposed a folksonomy network structure used in creating user profiles to achieve the personalization of search results.

Some accomplishments are achieved by the existing research works with user profile and resource profile for personalized search in folksonomy, but unfortunately two limitations exist as follows.

Most research works suppose that all tags annotated by a user are the user's favorite tags, ignoring user's nuisances. However, some tags are also used by a user to annotate annoying resources. Lots of studies do not get the utmost out of resource attributes by ratings for personalized search, e.g., resource genre. To handle these two limitations, this paper proposes a multi-type and multi-level user profile to achieve personalized search. To the best of our knowledge, this is the first method of integrating multi-type and multi-level user profile for personalized search.

3 User Profile

There are many attributes of resources in commercial Web sites. In a music system, the musical styles including rock, jazz, blues and folk is an attribute; the pitch including treble, tenor, bass and double bass is another attribute. In a movie system, movie's attributes contain genre, director, starring and so on. For example, the genres of movies include action, comedy, horror.

In this section, we utilize tags and genres to construct a multi-type and multi-level user profile.

3.1 Multi-type and Multi-level User Profile

User profile consists of two parts, tag and genre. A user profile for a user i is denoted by MMU_i. We can construct a multi-type and multi-level user profile for user i as follows.

$$\mathrm{MMU}_i = (t_{i,1} : v_{i,1}, \ldots t_{i,k} : v_{i,k}, \ldots t_{i,n} : v_{i,n},\\ g_{i,1} : p_{i,1}, \ldots g_{i,k} : p_{i,k}, \ldots g_{i,m} : p_{i,m})$$

where $t_{i,k}$ is the kth tag that is annotated by user i, $v_{i,k}$ is the preference degree of tag $t_{i,k}$ and n is the total number of tags that user i has annotated, $g_{i,k}$ is the kth genre that is rated by user i, $p_{i,k}$ is the preference degree of genre $g_{i,k}$ and m is the total number of genres. The degree value of user's favorites and nuisances with genres and tags is from -1 to 1. So the levels of multi-level should be infinite, rather than specific.

Based on MMU_i, we expatiate procedure to construct tag and genre in MMU_i, respectively.

3.2 Tagging and Rating-Based User Profile

Some systems allow users to annotate and rate resources. Rating can better identify users' interest. If a user annotates a resource and rates with a high score, we consider that the user likes this resource and all the tags annotated by the user are assumed as the user's concerned tags. On the contrary, if a user annotates a resource and rates with a low score, we consider that the user dislikes this resource and all the tags annotated by the user are assumed as the user's unconcerned tags. Based on the above illustrations, we make the following assumptions.

Assumption 1 for a user i, a tag t annotated by i in a resource without score is assumed as i likes t.

Assumption 2 for a user i, a tag t annotated by i in a resource with a high score (more than the average rating of i) is assumed as i likes t.

Assumption 3 for a user i, a tag t annotated by i in a resource with a low score (less than the average rating of i) is assumed as i dislikes t.

Assumption 4 for a user i, two tags t_1 and t_2 annotated by i in resources with t_1's score greater than t_2's score are assumed as i like t_1 more than t_2.

Based on Assumptions 1, 2, 3 and 4, for user i, we use ratings to construct a vector of tags that is a part of user profile, denoted by $\vec{U}_{i,t}$, as follows.

$$\vec{U}_{i,t} = (t_{i,1} : v_{i,1}, t_{i,2} : v_{i,2}, \ldots t_{i,k} : v_{i,k} \ldots t_{i,n} : v_{i,n})$$

where n is the total number of tags that user i has annotated, $t_{i,k}$ is the kth tag that is annotated by user i, $v_{i,k}$ is the preference weight of $t_{i,k}$.

And $v_{i,k} \in [-1, 1]$, the closer to 1 $v_{i,k}$ is, the more the user likes $t_{i,k}$. On the contrary, the closer to -1 $v_{i,k}$ is, the more the user dislikes $t_{i,k}$. According to assumptions and $\vec{U}_{i,t}$, $v_{i,k}$ should comply with the following axioms.

Axiom 1 For a user i and a tag $t_{i,k}$, if $t_{i,k} \in F_{i,h}, t_{i,k} \notin F_{i,l}, t_{i,k} \notin F_i$, and $\mathrm{AVG}_i(t_{i,k}) \geq \mathrm{MAX}_i$, then $v_{i,k} = 1$.

Axiom 2 For a user i and a tag $t_{i,k}$, if $t_{i,k} \in F_{i,l}, t_{i,k} \notin F_{i,h}, t_{i,k} \notin F_i$, and $\mathrm{AVG}_i(t_{i,k}) \leq \mathrm{MIN}_i$, then $v_{i,k} = -1$.

Axiom 3 For a user i and a tag $t_{i,k}$, if $t_{i,k} \in F_{i,h}, t_{i,k} \notin F_{i,l}, t_{i,k} \notin F_i$, and $\mathrm{AVG}_i(t_{i,k}) < \mathrm{MAX}_i$, then $v_{i,k} \in (0, 1)$.

Axiom 4 For a user i and a tag $t_{i,k}$, if $t_{i,k} \in F_{i,l}, t_{i,k} \notin F_{i,h}, t_{i,k} \notin F_i$, and $\mathrm{AVG}_i(t_{i,k}) > \mathrm{MIN}_i$, then $v_{i,k} \in (-1, 0)$.

Axiom 5 For a user i and a tag $t_{i,k}$, if $t_{i,k} \in F_{i,l}, t_{i,k} \in F_{i,h}, t_{i,k} \notin F_i$, and $\mathrm{AVG}_i(t_{i,k}) \leq \mathrm{AVG}_i$ $\big($or $\mathrm{AVG}_i(t_{i,k}) > \mathrm{AVG}_i\big)$, then $v_{i,k} \in (-1, 0]$ $\big($or $v_{i,k} \in (0, 1)\big)$.

Axiom 6 For a user i and a tag $t_{i,k}$, if $t_{i,k} \in F_i, t_{i,k} \notin F_{i,l}$, and $t_{i,k} \notin F_{i,h}$ then $v_{i,k} \in (0, 1)$.

Axiom 7 For a user i and two tags t_{i,k_1} and t_{i,k_2}, if t_{i,k_1} and $t_{i,k_2} \in F_{i,l}, t_{i,k_1}$ and $t_{i,k_2} \in F_{i,h}, t_{i,k_1}$ and $t_{i,k_2} \notin F_i$, and $\mathrm{AVG}_i(t_{i,k_1}) \geq \mathrm{AVG}_i(t_{i,k_2})$, then $v_{i,k_1} \geq v_{i,k_2}$.

Axiom 8 For a user i and two tags t_{i,k_1} and t_{i,k_2}, if t_{i,k_1} and $t_{i,k_2} \in F_{i,l}, t_{i,k_1}$ and $t_{i,k_2} \in F_{i,h}, t_{i,k_1}$ and $t_{i,k_2} \in F_i$, $f_i(t_{i,k_1}) = f_i(t_{i,k_2})$, and $\mathrm{AVG}_i(t_{i,k_1}) \geq \mathrm{AVG}_i(t_{i,k_2})$, then $v_{i,k_1} >= v_{i,k_2}$.

Axiom 9 For a user i and two tags t_{i,k_1} and t_{i,k_2}, if t_{i,k_1} and $t_{i,k_2} \in F_{i,l}$, $t_{i,k_1}$and $t_{i,k_2} \in F_{i,h}, t_{i,k_1}$ and $t_{i,k_2} \in F_i$, $f_i(t_{i,k_1}) \geq f_i(t_{i,k_2})$, and $\mathrm{AVG}_i(t_{i,k_1}) = \mathrm{AVG}_i(t_{i,k_2})$, then $v_{i,k_1} >= v_{i,k_2}$.

where $F_{i,l}$ is the set of the tags with low score reviews annotated by user i, $F_{i,h}$ is the set of the tags with high score reviews annotated by user i, F_i is the set of the tags without score reviews annotated by user i, $f_i(t_{i,k})$ is frequencies of the tag $t_{i,k}$ annotated by the user i, AVG_i, MAX_i, MIN_i are the average, max and min rating of i, respectively, $\mathrm{AVG}_i(t_{i,k})$ is the average rating of tag $t_{i,k}$ annotated by the user i.

The average score of user i is the criteria for distinguishing the set of the tags with high score reviews and low score reviews. Axioms 1 and 2 declare the boundary case of $v_{i,k}$. If a tag t only belongs to $F_{i,h}$ and t's score is more than or equal to the max of the user's ratings, then $v_{i,k} = 1$. If a tag t only belongs to $F_{i,l}$ and t's score is less than or equal to the min of the user's ratings, then $v_{i,k} = -1$. Axioms 3, 4, 5 and 6 specify the range of $v_{i,k}$ in accordance with different situations. Axioms 7, 8 and 9 illustrate the essence of calculating for $v_{i,k}$.

The possible function to calculate the weight of tag satisfies Axioms 1–9 as follows.

$$v_{i,k} = \alpha * \frac{|T_{i,k}|}{|F_i|} + (1-\alpha) * \frac{\sum_{x=1, x\in H_{i,k}} \theta_{i,x}}{|F_{i,h}|} + \beta * \frac{\sum_{x=1, x\in L_{i,k}} \theta_{i,x}}{|F_{i,l}|} \ (\alpha, \beta \in [0, 1]) \quad (1)$$

where α and β are parameters to adjust the effects of different components in Eq. (1), The higher α is, the greater weight of F_i is. On the contrary, there is a greater weight of $F_{i,h}$. If β is a higher value, $F_{i,l}$ has more influence. $T_{i,k}$, $H_{i,k}$, $L_{i,k}$ indicates the set of $t_{i,k}$in F_i, $F_{i,h}$ and $F_{i,l}$, respectively. $\theta_{i,x}$ is the degree of preference or nuisance of $t_{i,k}$ used to annotate resources with every rating, where $\theta_{i,x} \in [-1, 1]$, $\theta_{i,x}$ is calculated as follows.

$$\theta_{i,x} = \begin{cases} 1 & (r_{i,k} \geq \max_i) \\ \frac{r_{i,k} - \mathrm{avg}_i}{\max_i - \mathrm{avg}_i} & (\max_i > r_{i,k} \geq \mathrm{avg}_i) \\ \frac{r_{i,k} - \mathrm{avg}_i}{\mathrm{avg}_i - \min_i} & (\mathrm{avg}_i > r_{i,k} > \min_i) \\ -1 & (r_{i,k} \leq \min_i) \end{cases} \quad (2)$$

where $r_{i,k}$ is the rating to resource with $t_{i,k}$, avg_i, $\max_i$, $\min_i$ are the average, max and min rating of i, respectively. If $r_{i,k} \geq \max_i$ or $\max_i > r_{i,k} \geq \mathrm{avg}_i$, then x $\in H_{i,k}, \theta_{i,x} \in [0, 1]$. It is indicated that i likes the resource and $t_{i,k}$. On the contrary, if $r_{i,k} \leq \min_i$ or $\mathrm{avg}_i > r_{i,k} > \min_i$, then x $\in L_{i,k}, \theta_{i,x} \in [-1, 0)$. It is indicated that i dislikes the resource and $t_{i,k}$.

3.3 Genre and Rating-Based User Profile

We use ratings to construct a vector of genres that is a part of user profile, denoted by $\vec{U}_{i,g}$, as follows.

$$\vec{U}_{i,g} = \big(g_{i,1} : p_{i,1}, g_{i,2} : p_{i,2}, \ldots g_{i,k} : p_{i,k} \ldots g_{i,m} : p_{i,m}\big)$$

where m is the total number of genres that user i rated, $g_{i,k}$is the kth genre that is rated by user i, and $p_{i,k}$ is the preference weight of $g_{i,k}$.

For $p_{i,k} \in [-1, 1]$, the closer to 1 $p_{i,k}$ is, the more the user likes $g_{i,k}$. On the contrary, the closer to -1 $p_{i,k}$ is, the more the user dislikes $g_{i,k}$.

We predicate whether a user likes a genre or not through the average of ratings. $p_{i,k}$ is the degree of presence of genre $g_{i,k}$ in user i profile and it is defined as follows.

$$p_{i,k} = \frac{\sum_{j=1}^{S} p_{i,k,j}}{S} \tag{3}$$

where S is the total number of rating for genre $g_{i,k}$, $p_{i,k,j}$ integrates the degree of preference or nuisance to the resource j on genre $g_{i,k}$, $p_{i,k,j}$ is calculated as follows.

$$p_{i,k,j} = \begin{cases} \frac{\theta_{i,x}+R_j(g_{i,k})}{2} & (r_{i,k} > \mathrm{avg}_i) \\ 0 & (r_{i,k} = \mathrm{avg}_i) \\ \frac{\theta_{i,x}-R_j(g_{i,k})}{2} & (r_{i,k} < \mathrm{avg}_i) \end{cases} \tag{4}$$

where $\theta_{i,x}$ is calculated by Eq. (2), $R_j\left(g_{i,k}\right)$ is the degree of the resource j to the genre $g_{i,k}$, $r_{i,k}$ denotes the rating given by user i for the genre $g_{i,k}$ of resource j.

If $r_{i,k} > \mathrm{avg}_i$, then $\theta_{i,x} > 0$, $p_{i,k,j}$ is the average of $\theta_{i,x}$ and $R_j\left(g_{i,k}\right)$. On the contrary, if $r_{i,k} < \mathrm{avg}_i$, then $\theta_{i,x} < 0$, $p_{i,k,j}$ is the average of $\theta_{i,x}$ and the opposite of $R_j\left(g_{i,k}\right)$. If $r_{i,k} = \mathrm{avg}_i$, then $\theta_{i,x} = 0$, $p_{i,k,j} = 0$.

In general, the genre denoted "1" or "0" in resource is represented by the crisp set, e.g., if a movie m has two genres including action and comedy, then it can be represented as $(\text{action} : 1, \text{comedy} : 1)$. However, not all resources are suitable for the crisp set, e.g., the degree of genres of movie resource is different [31], action is the major genre of a movie m and the degree of m to the genre action is 80%, comedy is the minor genre of m and the degree of m to the genre comedy is 50%; it can be represented as $(\text{action} : 0.8, \text{comedy} : 0.5)$.

In this paper, we adopt the Gaussian-like fuzzy set membership function that is proposed by the literature [42] to calculate $R_j\left(g_{i,k}\right)$. $R_j\left(g_{i,k}\right)$ is described as follows.

$$R_j\left(g_{i,k}\right) = \frac{r_g}{2^{\sqrt{\gamma * |L_j| * (r_g - 1)}}} \tag{5}$$

where r_g is the rank position of $g_{i,k}$ in resource j, L_j is the total number of genres in resource j, $\gamma > 1$ is a parameter used to control the difference in importance among genres having consecutive ranks in resource j.

In IMDB (www.imdb.com), the genres of movie are presented in the order of their importance by movie producer. For example, action is a major genre of the movie "Resident Evil: The Final Chapter", horror is the first minor, and the second minor is sci-fi. We assume that $\gamma = 1.2$, and the movie "Resident Evil: The Final Chapter" is presented in term of genres, for $L_j = 3$, the degree of action, horror and sci-fi in the movie are 1, 0.537 and 0.467, respectively.

4 Resource Profile

Similar to the definition of user profile, a resource profile is consisted of tags and genres. It is described as follows.

$$\mathrm{MMR}_j = (t_{j,1} : w_{j,1}, \ldots t_{j,k} : w_{j,k}, \ldots t_{j,n} : w_{j,n}, \\ g_{j,1} : q_{j,1}, \ldots g_{j,k} : q_{j,k}, \ldots g_{j,m} : q_{j,m})$$

where $t_{j,k}$ is the kth tag which is used to represent resource j, $w_{j,k}$ is the weight of resource on tag $t_{j,k}$, n is the total number of tags which are used to represent resource j, $g_{j,k}$ is the kth genre, $q_{j,k}$ is the degree of resource j to genre $g_{j,k}$ and calculated by Eq. (5), that means $q_{j,k} = R_j\left(g_{i,k}\right)$, and m is the total number of genres.

For $w_{j,k} \in [0, 1]$, the more close to 1 $w_{j,k}$ is, the more representative for resource j the tag is, which can be obtained according to the literature [10] as follows.

$$w_{j,k} = \frac{N_{j,k}}{N} \tag{6}$$

where N is the total number of users using tags to annotate resource j, $N_{j,k}$ is the number of users who use tag $t_{j,k}$ to annotate resource j, and $w_{j,k}$ is the actually normalized term frequency of tag $t_{j,k}$ which is used to annotated resource j.

5 Personalized Search

In a personalized search system, users need different information which consists of queries and interests from users. We measure the relevance between query and resource, and then the degree of resource matching with users' interest is measured in our search framework. Based on the two relevance parts, we obtain the final rankings as the results.

5.1 Query Relevance Measurement

A query is a vector that consists of a series of terms by user i denoted by $\vec{q}_i$ as follows.

$$\vec{q}_i = \left(q_t^1 : w_t^1, q_t^2 : w_t^2, \ldots, q_t^m : w_t^m\right)$$

where m is the total number of terms in query, q_t^i is a term and w_t^i is the weight of the term, w_t^i is calculated as follows.

$$w_t^i = \frac{|q_t^i|}{|\vec{q}_i|_i} \tag{7}$$

where $q_t^i|$ is the number of term q_t^i, $|\vec{q}_i|_i$ is the total number of terms in $\vec{q}_i$, for example, a user issues a query and inputs

Table 1 The details of the MovieLens-20M dataset

Attribute	Value
Users#	138,493
Movies#	27,278
Tags#	465,564
Ratings#	21,048,839
Avg.tags/user#	3.36
Avg.tags/movie#	17.06
Avg.ratings/user#	144.41
Avg.ratings/movie#	733.2

terms "action" and "comedy", and the vector of query is described as follows.

$$\vec{q}_i = (\text{action} : 0.5, \text{comedy} : 0.5)$$

In this paper, we adopt the cosine similarity measurement to calculate relevance function, e.g., the query relevance function $\gamma(\vec{q}_i, \vec{R}_{j,t})$ can be obtained by Eq. (8).

$$\gamma\left(\vec{q}_i, \vec{R}_{j,t}\right) = \frac{\vec{q}_i \ \vec{R}_{j,t}}{|\vec{q}_i| \times \left|\vec{R}_{j,t}\right|} \tag{8}$$

where $\vec{q}_i$ is a query issued by user i, $\vec{R}_{j,t}$ is a vector with the same size and terms of $\vec{q}_i$, so it consists of tags that are extracted from resource profile according to the terms of $\vec{q}_i$.

For $\gamma(\vec{q}_i, \vec{R}_{j,t}) \to [1, 0]$, the higher value of $\gamma(\vec{q}_i, \vec{R}_{j,t})$ illustrates the more relevance between the resource and the query.

5.2 User Interest Relevance Measurement

The user interest relevance consists of tag interest relevance function $\delta(\vec{U}_{i,t}, \vec{R}_{j,t})$ and genre interest relevance function $\zeta(\vec{U}_{i,g}, \vec{R}_{j,g})$, which are defined as follows.

$$\delta\left(\vec{U}_{i,t}, \ \vec{R}_{j,t}\right) = \frac{\vec{U}_{i,t} \cdot \vec{R}_{j,t}}{\left|\vec{U}_{i,t}\right| \times \left|\vec{R}_{j,t}\right|} \tag{9}$$

$$\zeta\left(\vec{U}_{i,g}, \ \vec{R}_{j,g}\right) = \frac{\vec{U}_{i,g} \cdot \vec{R}_{j,g}}{\left|\vec{U}_{i,g}\right| \times \left|\vec{R}_{j,g}\right|} \tag{10}$$

where $\vec{R}_{j,g}$ is a vector that consists of genres from resource profile. For $\delta(\vec{U}_{i,t}, \vec{R}_{j,t}) \to [-1, 1]$, the higher value illustrates that the resource is more relevant to the user in tags. In a similar way, for $\zeta(\vec{R}_{i,g}, \vec{R}_{j,g}) \to [-1, 1]$, the higher value illustrates that the resource is more relevant to the user in genres.

5.3 Personalized Ranking

The final personalized search result is resources that are satisfied with both the query requirement and the user's personal interest. We aggregate γ, δ, ζ into a final score so as to rank resources. The aggregation function is shown as follows.

$$\begin{aligned} F\text{Score} = {} & k_1 \cdot \gamma\left(\vec{q}_i\right), \vec{R}_{j,t} + k_2 \cdot \delta\left(\vec{U}_{i,t}\right), \vec{R}_{j,t} \\ & + k_3 \cdot \zeta\left(\vec{U}_{i,g}\right), \vec{R}_{j,g} \end{aligned} \tag{11}$$

where $k_1, k_2, k_3 \in [0, 1]$ are parameters and $k_1+k_2+k_3 = 1$.

In the personalized ranking process, to obtain resources by a personalized search system should match keywords of a query firstly. The more keywords the resource has, the higher position the resource has. Only if resources have the same number of keywords of a query, they are ranked according to the aggregation function. In addition, the query relevance function is more important than user interest relevance function, so it has a higher weight, where we set $k_1 > 0.5$.

6 Evaluations

In this section, we conduct experiments to verify the effectiveness of the proposed approach in a large real dataset. We describe dataset and metrics used. Performance improvement of our approach is compared with several personalized search methods in folksonomy.

6.1 Dataset

To demonstrate the efficiency of our proposed approaches, we use a benchmark dataset: the MovieLens-20M datasets collected by the GroupLens Web site (http://grouplens.org/datasets/). The MovieLens-20M dataset has 21,048,839 ratings and 465,564 tags, annotated by 138,493 users on 27,278 movies. Table 1 shows the more details of the dataset.

In the dataset, movies are described with: id, title, IMDB URL, genres and so on. In this dataset, genre is represented with binary values, but the true content of movies cannot be reflected in the genre space. We use the incorporating information of movies genres retrieved from the IMDB Web site (http://www.imdb.com/), which is a large Web site including the comprehensive information about movies.

To evaluate and test the efficiency of our proposed method, we randomly divide the MovieLens dataset into training and test sets, respectively. For the dataset, 80% of the dataset are retained in the training set, while the rest of the dataset are retained in the test set so as to test the efficiency of our personalized search methods.

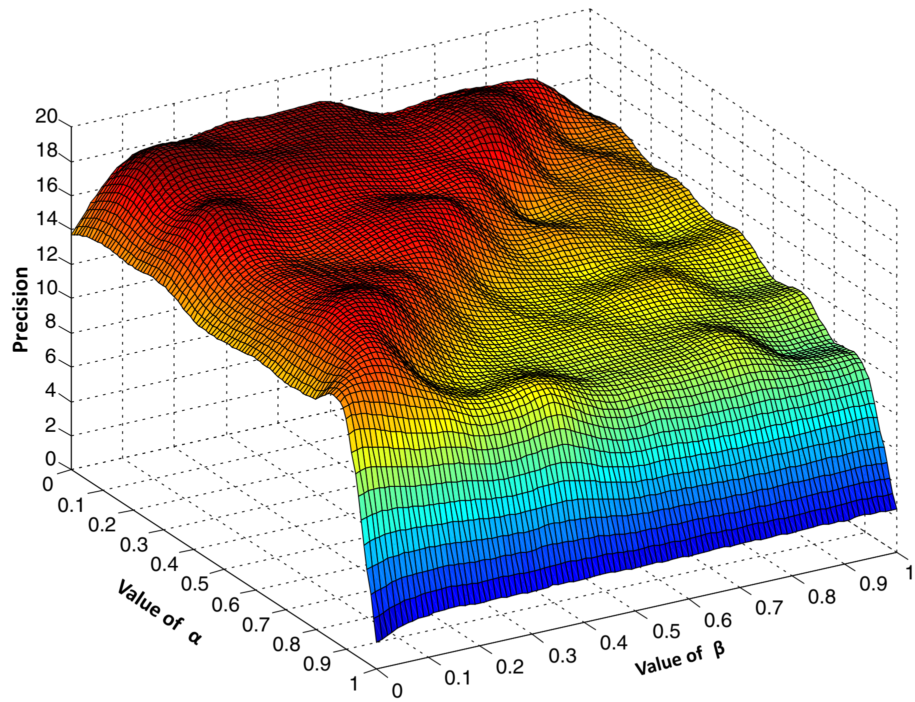

Fig. 1 Comparison of different α and β value on MRR using training set

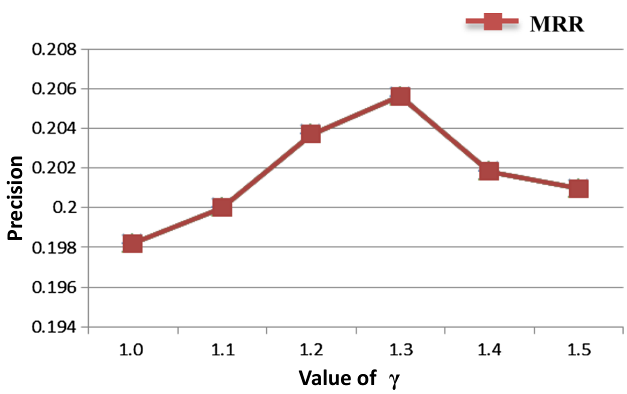

Fig. 2 Comparison of different γ value on MRR using training set

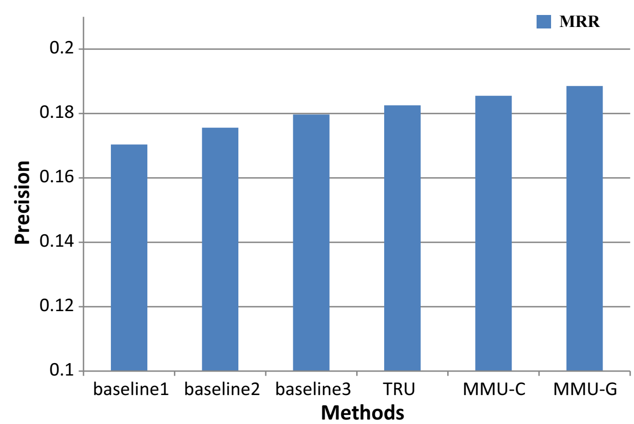

Fig. 3 Comparison of our and baseline methods on MRR using test set

Table 2 Experimental results with different weight settings

	k_1	k_2	k_3	MRR
Setting1	0.5	0.1	0.4	0.186
Setting2	0.5	0.2	0.3	0.203
Setting3	0.5	0.3	0.2	0.173
Setting4	0.5	0.4	0.1	0.135
Setting5	0.6	0.1	0.3	0.189
Setting6	0.6	0.2	0.2	0.209
Setting7	0.6	0.3	0.1	0.196
Setting8	0.7	0.1	0.2	0.205
Setting9	0.7	0.2	0.1	0.210
Setting10	0.8	0.1	0.1	0.201

6.2 Evaluation Metrics

Two metrics are used to evaluate the efficiency of the proposed method.

The first one is MRR (Mean reciprocal rank) that measure ranked query results. The reciprocal rank of a query result is computed while the first correct relevant resource is retrieved. The MRR is the average of the reciprocal ranks of results for a set of queries, as defined by Eq. (12):

$$\mathrm{MRR} = \frac{1}{Q}\sum_{i-1}^{Q}\frac{1}{\mathrm{Rank}_i} \tag{12}$$

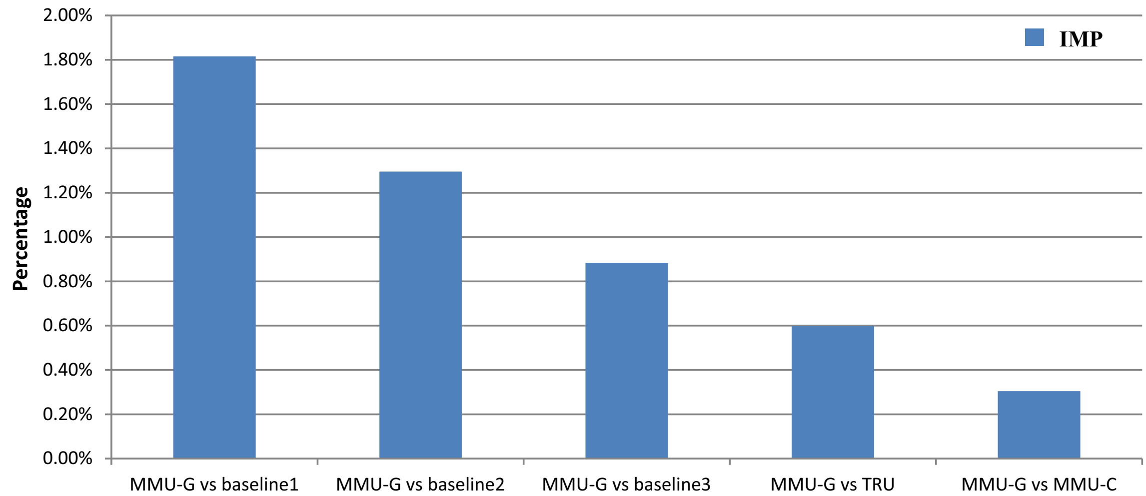

Fig. 4 Comparison of our and baseline methods on IMP using test set

Note that Q is the times of queries, Rank_i is the rank position of the first correct relevant resource for the ith query. MRR emphasizes the significance of the first correct relevant resource at the top of the result list. Users get the relevant resource faster when MRR is higher.

Imp is the second metric. This is a widely adopted metric to measure how our personalization search method is better than baseline methods, as defined by Eq. (13):

$$\text{Imp}\,(q_i) = \frac{1}{r_p} - \frac{1}{r_b} \tag{13}$$

A user issues a query (q_i). r_p is the ranking of the relevant resource in the result list by our personalization search method, while r_b is the same by a baseline method. Thus the average of imp shows the overall improvement in the test data, as defined by Eq. (14):

$$\text{Imp} = \frac{\sum_{i=1}^{Q} \text{Imp}\,(q_i)}{Q} \tag{14}$$

where Q is the times of queries. The higher value the Imp is, the greater improvement of the ranking result by the proposed approach there appears.

6.3 Baseline Methods

To assess the efficiency of our proposed approach, three state-of-the-art personalized search methods have been compared with our method. A normalized term frequency (NTF) to model user profile and resource profile is proposed in [12], denoted by baseline1. Yang et al. [43] explores ratings on reviews for personalized search and proposes a review-based user profile method, denoted by baseline2. Du et al. [36] proposes a multi-level user profile by integrating tags and ratings for personalized search, denoted by baseline3. A tagging and rating-based user profile is proposed by us with Eq. (1), denoted by TRU. Make the genre model in multi-type and multi-level user profile by using crisp set, denoted by MMU-C.

6.4 Experimental Results

The proposed method means that the genre is modeled in multi-type and multi-level user profile by Gaussian-like fuzzy set membership function, denoted by MMU-G. We conduct a comparison between different parameters with the MMU-G by using training dataset.

In Eq. (1), we set the value of α and β from 0 to 1.0. In Fig. 1, we can find Eq. (1) performs stably when $\alpha \in [0.1, 0.2]$ and $\beta \in [0.1, 0.5]$. Equation (1) obtains the highest MRR value when $\alpha = 0.1$ and $\beta = 0.2$. In other words, the set of tag's high score reviews are more important than sets of low score reviews and tag's reviews.

To determine the optimal parameter for the Gaussian-like fuzzy set membership function, the range of the parameter γ is from 1.0 to 1.5 according to experience. In Fig. 2, the MRR values of different parameters make a little differences. Equation (5) obtains the highest MRR value when $\gamma = 1.3$.

We also conduct experiments and gain the efficiency of different weight settings. Table 2 shows different weight settings for personalized search. The setting9 ($k_1 = 0.7, k_2 = 0.2, k_3 = 0.1$) performs the best. It proves that query relevance function is more important than user interest relevance function and sets a higher weight.

We then conduct a series of experiments on test dataset. All methods on MRR metric are shown in Fig. 3. According to Fig. 3, our method has the highest MRR value at 0.188, while the other methods are at 0.17, 0.175, 0.179, 0.182 and

0.185, respectively. MMU-G outperforms the baseline methods. Figure 4 shows the comparison of the MMU-G and the baseline methods on imp metric. MMU-G outperforms the method of baseline1 by 1.82%, the method of baseline2 by 1.3%, the method of baseline3 by 0.88%, the method of TRU by 0.6% and the method of MMU-C by 0.3% on imp. The MRR value of our method on the test dataset is slightly lower than on the training dataset, and we consider that the training dataset has more information than test dataset so as to construct more accurate user profile.

7 Conclusions

In this paper, we reveal and discuss the limitations of main current relevant works on personalized search in folksonomy. We further present a concept of a multi-type and multi-level user profile to improve the efficiency of personalized search. In addition, we compare our method with baselines in the experiment. The results show that our method is more effective than baseline methods for personalized search in folksonomy.

In the future, we plan to extend the MMU_i in the following directions. First, fuzzy approach is considered to represent genres, e.g., the OWA operator. Second, we plan to take more resource attributes into consideration in order to model user profile, e.g., actors and directors for movies. Third, inclusion of additional sentiment is expected to improve the MMU_i in folksonomy. Fourth, the topic model is extended to boost the efficiency of personalized search. Fifth, there is a need of parallel technology that can reduce the running time to model user profile.

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