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Social tagging in recommender systems: a survey of the state-of-the-art and possible extensions

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Abstract Social tagging systems have grown in popularity over the Web in the last years on account of their simplicity to categorize and retrieve content using open-ended tags. The increasing number of users providing information about themselves through social tagging activities caused the emergence of tag-based profiling approaches, which assume that users expose their preferences for certain contents through tag assignments. Thus, the tagging information can be used to make recommendations. This paper presents an overview of the field of social tagging systems which can be used for extending the capabilities of recommender systems. Various limitations of the current generation of social tagging systems and possible extensions that can provide better recommendation capabilities are also considered.

Keywords Recommender systems · Social tagging · Folksonomy · Personalization

1 Introduction

The information in the Web is increasing far more quickly than people can cope with. Personalized recommendation (Resnick and Varian 1997) can help people to conquer the information overload problem, by recommending items according to users' interests.

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Recommender systems use the opinions of a community of users to help individuals in that community more effectively identify content of interest from a potentially overwhelming set of choices (Resnick et al. 1994).

One of the most successful technologies for recommender systems is collaborative filtering (Konstan et al. 2004). It is built on the assumption that people who like the items they have viewed before are likely to agree again on new items. Although the assumption that collaborative filtering relied on works well in narrow domains, it is likely to fail in more diverse or mixed settings. The reason is obvious: people have similar taste in one domain may behave quite different in others.

To improve recommendation quality, metadata such as content information of items has typically been used as additional knowledge. With the increasing popularity of the collaborative tagging systems, tags could be interesting and useful information to enhance algorithms for recommender systems.

Collaborative tagging systems allow users to upload their resources, and to label them with arbitrary words, so-called tags. The systems can be distinguished according to what kind of resources are supported. Flickr,[1] for instance, allows the sharing of photos, Delicious[2] the sharing of bookmarks, CiteULike[3] and Connotea[4] the sharing of bibliographic references, and 43Things[5] even the sharing of goals in private life. These systems are all very similar. Once a user is logged in, he can add a resource to the system, and assign arbitrary tags to it. The collection of all his assignments is his personomy, the collection of all personomies constitutes the folksonomy. The user can explore his personomy, as well as the personomies of the other users, in all dimensions: for a given user one can see all resources he had uploaded, together with the tags he had assigned to them (Hotho et al. 2006a,b,c).

Besides helping user to organize his or her personal collections, a tag also can be regarded as a user's personal opinion expression, while tagging can be considered as implicit rating or voting on the tagged information resources or items (Liang et al. 2008). Thus, the tagging information can be used to make recommendations.

In this paper, we describe social tagging systems which can be used for extending the capabilities of recommender systems. A comprehensive survey of the state-of-the-art in collaborative tagging systems and folksonomy is presented in Sect. 2. Section 3 presents a model for tagging activities. Tag-based recommender systems and different approaches to find best tag recommendations for items are described in Sect. 4. In Sect. 5 we identify various limitations of the current generation of folksonomy systems and discuss some initial approaches to extending their capabilities in Sect. 6. Finally, Sect. 7 concludes this paper.

2 The survey of collaborative tagging systems and folksonomy

Collaborative tagging is the practice of allowing users to freely attach keywords or tags to content (Golder and Huberman 2005). Collaborative tagging is most useful when there is nobody in the "librarian" role or there is simply too much content for a single authority to classify. People tag pictures, videos, and other resources with a couple of keywords to easily retrieve them in a later stage.

1 http://www.flickr.com, now part of Yahoo!

2 http://del.icio.us, now part of Yahoo!

3 http://www.citeulike.org.

4 http://www.connotea.org.

5 http://www.43things.com.

The following features of collaborative tagging are generally attributed to their success and popularity (Mathes 2004; Quintarelli 2005; Wu et al. 2006).

- *Low cognitive cost and entry barriers.* The simplicity of tagging allows any Web user to classify their favourite Web resources by using keywords that are not constrained by predefined vocabularies.
- *Immediate feedback and communication.* Tag suggestions in collaborative tagging systems provide mechanisms for users to communicate implicitly with each other through tag suggestions to describe resources on the Web.
- *Quick Adaptation to Changes in Vocabulary.* The freedom provided by tagging allows fast response to changes in the use of language and the emergency of new words. Terms like Web2.0, ontologies and social network can be used readily by the users without the need to modify any pre-defined schemes.
- *Individual needs and formation of organization.* Tagging systems provide a convenient means for Web users to organize their favorite Web resources. Besides, as the systems develop, users are able to discover other people who are also interested in similar items.

Since tags are created by individual users in a free form, one important problem facing tagging is to identify most appropriate tags, while eliminating noise and spam. For this purpose, Au Yeung et al. (2007) define a set of general criteria for a good tagging system.

- *High coverage of multiple facets.* A good tag combination should include multiple facets of the tagged objects. The larger the number of facets the more likely a user is able to recall the tagged content.
- *High popularity.* If a set of tags are used by a large number of people for a particular object, these tags are more likely to uniquely identify the tagged content and the more likely to be used by a new user for the given object.
- *Least-effort.* The number of tags for identifying an object should be minimized, and the number of objects identified by the tag combination should be small. As a result, a user can reach any tagged objects in a small number of steps via tag browsing.
- *Uniformity (normalization).* Since there is no universal ontology, different people can use different terms for the same concept. In general, we have observed two general types of divergence: those due to syntactic variance, e.g., color, colorize, colorise, colourise; and those due to synonym, e.g., student and pupil, which are different syntactic terms that refer to the same underlying concept. These kinds of divergence are a double-edged sword. On the one hand, they introduce noises to the system; on the other hand it can increase recall.
- *Exclusion of certain types of tags.* For example, personally used organizational tags are less likely to be shared by different users. Thus, they should be excluded from public usage. Rather than ignoring these tags, tagging system includes a feature that auto-completes tags as they are being typed by matching the prefixes of the tags entered by the user before. This not only improves the usability of the system but also enables the convergence of tags.

Another important aspect of tagging systems is how they operate. Marlow et al. (2006) describe some key dimensions of tagging systems' design that may have immediate effect on the content and usefulness of tags generated by the system. Some of these dimensions are listed below.

2.1 Tagging rights

The permission a user has to tag resources can effect the properties of an emergent folksonomy. Systems can determine who may remove a tag. Also, systems can choose the resources which users tag or specify different levels of permissions to tag. The spectrum of tagging permissions ranges from:

a. Self-tagging—users can only tag their own contributions (e.g. Technorati[6]), through
b. Permission-based—users decide who can tag their resources (e.g. Flickr), to
c. Free-for-all—any user can tag any resource

2.2 Tagging support

One important aspect of a tagging system is the way in which users assign tags to items. They may assign arbitrary tags without prompting, they may add tags while considering those already added to a particular resource, or tags may be proposed. There are three distinct categories:

a. Blind tagging—user cannot see the other tags assigned to the resource they're tagging
b. Viewable tagging—users can see the other tags assigned to the resource they're tagging
c. Suggestive tagging—user sees suggested tags for the resource they're tagging

2.3 Aggregation

The aggregation of tags around a given resource is an important consideration. The system may allow for a multiplicity of tags for the same resource which may result in duplicate tags from different users. Alternatively, many systems ask the group to collectively tag an individual resource. It is able to distinguish two models of aggregation.

a. Bag-model—the same tag can be assigned to a resource multiple times, like in Delicious, allowing statistics to be generated and users to see if there is agreement among taggers about the content of the resource
b. Set-model—a tag can be applied only once to a resource, like in Flickr

2.4 Types of object

The implications for the nature of the resultant tags are numerous. The types of resource tagged allow us to distinguish different tagging systems. Popular systems include simple objects, like: webpages, bibliographic materials, images, videos, songs, etc. Tags for text objects and multimedia objects can be varied. In reality, any object that can be virtually represented can be tagged or used in a tagging system. For example, systems exist that let users tag physical locations or events (e.g., Upcoming[7]).

2.5 Sources of material

Some systems restrict the source through architecture (e.g., Flickr), while others restrict the source solely through social norms (e.g., CiteULike). Resources to be tagged can be supplied:

[6] http://www.technorati.com.

[7] http://www.upcoming.yahoo.com.

a. by the participants (YouTube[8], Flickr, Technorati, Upcoming)
b. by the system (ESP Game[9], Last.fm[10], Yahoo! Podcasts[11])
c. open to any web resource (Delicious, Yahoo! MyWeb2.0[12])

2.6 Resource connectivity

Resources in a tagging system, may be connected to each other independently of their tags. For example, Web pages may be connected via hyperlinks, or resources can be assigned to groups (e.g. photo albums in Flickr). Connectivity can be roughly categorized as: linked, grouped, or none.

2.7 Social connectivity

Users of the system may be connected. Many tagging systems include social networking facilities that allow users to connect themselves to each other based on their areas of interest, educational institutions, location and so forth. Like resource connectivity, the social connectivity could be defined as linked, grouped, or none.

The term **folksonomy** defines a user-generated and distributed classification system, emerging when large communities of users collectively tag resources (Wal 2005). Folksonomies became popular on the Web with social software applications such as social bookmarking, photo sharing and weblogs. A number of social tagging sites such as Delicious, Flickr, YouTube, CiteULike have become popular. Commonly cited advantages of folksonomies are their flexibility, rapid adaptability, free-for-all collaborative customisation and their serendipity (Mathes 2004). People can in general use any term as a tag without exactly understanding the meaning of the terms they choose. The power of folksonomies stands in the aggregation of tagged information that one is interested in. This improves social serendipity by enabling social connections and by providing social search and navigation (Quintarelli 2005). Folksonomy shows a lot of benefits (Peters and Stock 2007):

- represent an authentic use of language,
- allow multiple interpretations,
- are cheap methods of indexing,
- are the only way to index mass information on the Web,
- are sources for the development of ontologies, thesauri or classification systems,
- give the quality “control” to the masses,
- allow searching and—perhaps even better—browsing,
- recognize neologisms,
- can help to identify communities,
- are sources for collaborative recommender systems,
- make people sensitive to information indexing.

There are two types of folksonomies: broad and narrow folksonomies (Wal 2005). The **broad** folksonomy, like Delicious, has many people tagging the same object and every person can tag the object with their own tags in their own vocabulary. Thus, in theory there is a great

[8] http://www.youtube.com.

[9] http://www.espgame.org.

[10] http://www.last.fm.

[11] http://podcasts.yahoo.com.

[12] http://myweb.yahoo.com.

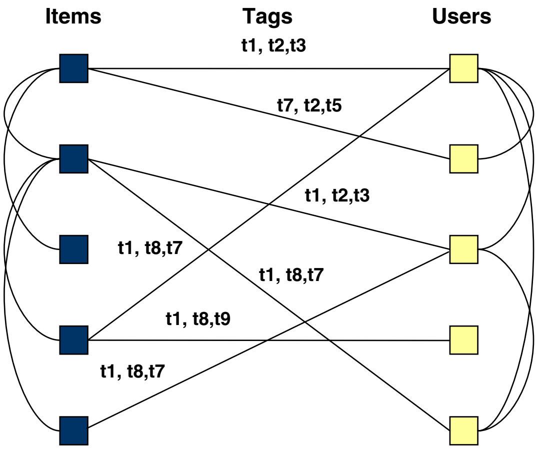


Fig. 1 Conceptual model of a collaborative tagging system (Marlow et al. 2006)

number of tags that all refer to the same object (item), because users might independently use very distinct tags for the same content. The **narrow** folksonomy, which a tool like Flickr represents, provides benefit in tagging objects that are not easily searchable or have no other means of using text to describe or find the object. The narrow folksonomy is done by one or a few people providing tags that the person uses to get back to that information. The tags, unlike in the broad folksonomy, are singular in nature. The same tag cannot be associated with a single object multiple times; in other words, the creator or publisher of an object is often the person who creates the first tags (unlike in broad folksonomies), and the option to tag may be even restricted to that person. After all, a much smaller number of tags for one and the same object can be identified in a narrow folksonomy.

3 A model for tagging activities

Social tagging systems allow their users to share their tags of particular resources. Each tag serves as a link to additional resources tagged in the same way by other users (Marlow et al. 2006). Certain resources may be linked to each other; at the same time, there may be relationships between users according to their own social interests, so the shared tags of a folksonomy come to interconnect the three groups of protagonists in social labeling systems: Users, Items, and Tags.

Many researchers (Mika 2005; Harry et al. 2006; Ciro et al. 2007) suggested a tripartite model that represents the Tagging Process:

$$Tagging : (U, T, I) \tag{1}$$

where U is the set of users who participate in a tagging activity, T is the set of available tags and I is the set of items being tagged. Figure 1 shows a conceptual model for social tagging system where users and items are connected through the tags they assign. In this model, users assign tags to a specific item; tags are represented as typed edges connecting users and items. Items may be connected to each other (e.g., as links between web pages) and users may be associated by a social network, or sets of affiliations (e.g., users that work for the same company).

Examination (Golder and Huberman 2005) of the collaborative tagging system, such as Delicious, has revealed a rich variety in the ways in which tags are used, regularities in user activity, tag frequencies, and bursts of popularity in bookmarking, as well as a remarkable stability in the relative proportions of tags within a given url.

- Tags may be used to identify the topic of a resource using nouns and proper nouns (i.e. photo, album, photographer).
- To classify the type of resource (i.e. book, blog, article, review, event).
- To denote the qualities and characteristics of the item (i.e. funny, useful, cool).
- A subset of tags, such as myfavourites, mymusic and myphotos reflect a notion of self reference.
- Some tags are used by individuals for task organisation (e.g. to read, job search, and to print).

Time is an important factor in considering collaborative tagging systems, in fact definitions and relationships among tags could vary over time. For certain users, the number of tags can become stable over time, while for others, it keeps growing. There are three hypotheses about tags behavior over time (Harry et al. 2006):

a. *Tags convergence*: the tags assigned to a certain Web resource tend to stabilize and to become the majority.
b. *Tags divergence*: tag-sets that don't converge to a smaller group of more stable tags, and where the tag distribution continually changes.
c. *Tags periodicity*: after one group of users tag some local optimal tag-set, another group uses a divergent set but, after a period of time the new group's set becomes the new local optimal tag-set. This process may repeat and so lead to convergence after a period of instability, or it may act like a chaotic attractor.

4 Tag-based recommender systems

Recommender systems in general recommend interesting or personalized information objects to users based on explicit or implicit ratings. Usually, recommender systems predict ratings of objects or suggest a list of new objects that the user hopefully will like the most. The approaches of profiling users with user-item rating matrix and keywords vectors are widely used in recommender systems. However, these approaches are used for describing two-dimensional relationships between users and items. In tag recommender systems the recommendations are, for a given user $u \in U$ and a given resource$r \in R$, a set $\hat{T}(u, r) \subseteq T$of tags. In many cases, $\hat{T}(u, r)$is computed by first generating a ranking on the set of tags according to some quality or relevance criterion, from which then the top n elements are selected (Jäschke et al. 2007).

Personalized recommendation is used to conquer the information overload problem, and collaborative filtering recommendation is one of the most successful recommendation techniques to date. However, collaborative filtering recommendation becomes less effective when users have multiple interests, because users have similar taste in one aspect may behave quite different in other aspects. Information got from social tagging websites not only tells what a user likes, but also why he or she likes it.

In the remainder of this section, we first describe the proposed extension with integrating tags information to improve recommendation quality. We then present well-known recommendation algorithms for developing Tag-Based Recommender Systems. Probabilistic latent

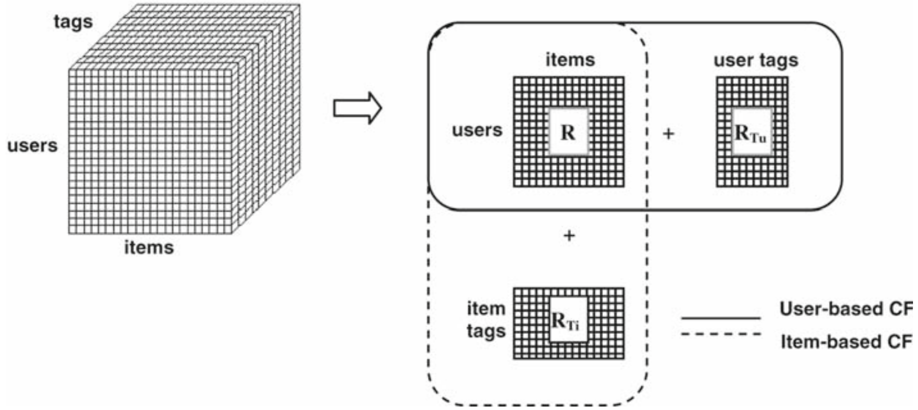


Fig. 2 Extend user–item matrix by including user tags as items and item tags as users (Tso-Sutter et al. 2008)

semantic analysis (PLSA), as a novel statistical technique for the analysis of two-mode and co-occurrence data, is described in Sect. 4.2. A new kind of resource sharing system, called GroupMe!, is presented in Sect. 4.3. The FolkRank algorithm developed as a folksonomy search engine by using the graph model is reported in Sect. 4.4. Section 4.5 reviews methods for tag-based profile construction with a vector of weighted tags. In later Sect. 4.6, we compare the method for tag-based profile construction with a single vector of weighted tags, called the naive approach, with two different approaches, one based on co-occurrence and another based on adaptation. A clustering algorithm, named WebDCC (Web Document Conceptual Clustering) is shown in Sect. 4.7. In Sect. 4.8, we give a comprehensive survey of state-of-the-art algorithms to improve music recommendation in online music recommender system, as one prominent example of companies wich offers personalized services toward users.

4.1 Extension with tags

The current recommender systems are commonly using collaborative filtering techniques, which traditionally exploit only pairs of two-dimensional data. As collaborative tagging is getting more widely used, social tags as a powerful mechanism that reveal three-dimensional correlations between users–tags–items, could also be employed as background knowledge in Recommender System.

The first adaptation lies in reducing the three-dimensional folksonomy to three two-dimensional contexts: $<user, tag>$ and $<item, tag>$ and $<user, item>$. This can be done by augmenting the standard user-item matrix horizontally and vertically with user and item tags correspondingly (Tso-Sutter et al. 2008). User tags, are tags that user *u*, uses to tag items and are viewed as items in the user-item matrix. Item tags, are tags that describe an item *i*, by users and play the role of users in the user-item matrix (See Fig. 2). Furthermore, instead of viewing each single tag as user or item, clustering methods can be applied to the tags such that similar tags are grouped together.

Supporting users during the tagging process is an important step towards easy-to-use applications. Consequently, different approaches have been studied in the past to find best tag recommendations for resources.

4.2 PLSA

Probabilistic latent semantic analysis (PLSA) is a novel statistical technique for the analysis of two-mode and co-occurrence data, which has applications in information retrieval and filtering, natural language processing, machine learning from text, and in related areas. PLSA has been shown to improve the quality of collaborative filtering based recommenders (Hofmann 1999) by assuming an underlying lower dimensional latent topic model. Compared to standard Latent Semantic Analysis which stems from linear algebra and performs a Singular Value Decomposition of co-occurrence tables, the proposed method is based on a mixture decomposition derived from a latent class model. This results in a more principled approach which has a solid foundation in statistics.

Cohn and Hofmann (2000) consider the problem of document clustering and extend the PLSA algorithm to combine content-based and hyperlink-based similarities into a unified model. Wetzker et al. (2009) extended this aproach in such that the topic model is estimated from the item-user as well as the item-tag observations in parallel. The inclusion of tags reduces known collaborative filtering problems related to overfitting and allows for higher quality recommendations. Experimental results on a large snapshot of the Delicious bookmarking service showed the scalability of their approach and an improved recommendation quality compared to two-mode collaborative or annotation based methods. Model fusion using PLSA was also successfully applied to the discovery of navigational patterns on the Web (Jin et al. 2004), in music recommendation combining multiple similarity measures (Arenas-García et al. 2007) and for the cross-domain knowledge transfer (Gui-Rong et al. 2008).

According to Hotho et al. (2006a,b,c), a folksonomy can be described as a tripartite graph whose vertex set is partitioned into three disjoint sets of users $U = \{u_1, \ldots, u_l\}$, tags $T = \{t_1, \ldots, t_n\}$ and items $I = \{i_1, \ldots, i_m\}$ his model can be simplified to two bipartite models where the collaborative filtering model IU is built from the item user co-occurrence counts $f(i, u)$ and the annotation-based model IT derives from the co-occurrence counts between items and tags $f(i, t)$. In the case of social book marking IU becomes a binary matrix $(f(i, u) \in \{0, 1\})$, as users can bookmark a given web resource only once.

The aspect model of PLSA associates the co-occurrence of observations with a hidden topic variable $\{Z = z_1, \ldots, z_k\}$. In the context of collaborative filtering an observation corresponds to the bookmarking of an item by a user and all observations are given by the co-occurrence matrix IU (Wetzker et al. 2009). Users and items are assumed independent given the topic variable Z. The probability that an item was bookmarked by a given user can be computed by summing over all latent variables Z:

$$P(i_m|u_l) = \sum_k P(i_m|z_k)P(z_k|u_l), \tag{2}$$

Analog to (2), the conditional probability between tags and items can be written as:

$$P(i_m|t_n) = \sum_k P(i_m|z_k)P(z_k|t_n), \tag{3}$$

Following the Cohn's and Hofmann's procedure (2000), we can now combine both models based on the common factor $P(i_m|z_k)$ by maximizing the log-likelihood function:

$$L = \sum_m \left[\alpha \sum_l f(i_m, u_l) \log P(i_m|u_l) + (1-\alpha) \sum_n f(i_m, t_n) \log P(i_m|t_n) \right], \tag{4}$$

where is a predefined weight for the influence of each twomode model. Using the Expectation-Maximization (EM) algorithm (Cohn and Hofmann 2000) it can be performed maximum likelihood parameter estimation for the aspect model. The standard procedure for maximum likelihood estimation in latent variable models is the EM algorithm (Arenas-García et al. 2007). EM alternates two coupled steps: (i) an expectation (E) step where posterior probabilities are computed for the latent variables, (ii) an maximization (M) step, where parameters are updated. Standard calculations yield the E-step equation:

$$P(z_k|u_l, i_m) = \frac{P(i_m|z_k)P(z_k|u_l)}{P(i_m|u_l)}$$
$$P(z_k|t_n, i_m) = \frac{P(i_m|z_k)P(z_k|t_n)}{P(i_m|t_n)} \tag{5}$$

and then re-estimate parameters in the M-step as follows:

$$P(z_k|u_l) \propto \sum_m f(u_l, i_m)P(z_k|u_l, i_m) \tag{6}$$

$$P(z_k|t_n) \propto \sum_m f(t_n, i_m)P(z_k|t_n, i_m) \tag{7}$$

$$p(i_m|z_k) \propto \alpha \sum_l f(u_l, i_m)P(z_k|u_l, i_m) + (1-\alpha) \sum_n f(t_n, i_m)P(z_k|t_n, i_m) \tag{8}$$

Based on the iterative computation of the above E and M steps, the EM algorithm monotonically increases the likelihood of the combined model on the observed data. Using the parameter, this model can be easily reduced to a collaborative filtering or annotation-based model by setting to 1.0 or 0.0, respectively.

It is possible to recommend items to a user u_l weighted by the probability $P(i_m|u_l)$ from Eq. (1). For items already bookmarked by the user in the training data this weight set to 0, thus they are appended to the end of the recommended item list.

A hybrid approach to the task of item recommendation in folksonomies that includes user generated annotations produces better results than a standard collaborative filtering or annotation-based method.

4.3 The GroupMe! system

GroupMe! is a new kind of resource sharing system (Abel et al. 2007). It extends the idea of social bookmarking systems, with the ability to create groups of multimedia Web resources. GroupMe! has an easy-to-use interface which enables the creation of groups via drag & drop operations.

An important feature of the GroupMe! system is its visualization of groups (Abel et al. 2007). Resources are visualized according to their media type, e.g. pictures are displayed as thumbnails, videos and audio recordings can be played directly within the group, and RSS (Rich Site Summary) feeds are previewed by displaying recent headlines. GroupMe! groups are interpreted as regular Web resources and can also be arranged within groups. This enables users to build hierarchies of Web resources. GroupMe! groups are dynamic collections, which may change over time. Other users who are interested in the content of a group can subscribe to the group and will be notified whenever the group is modified, e.g. a new resource is added or removed, new tags have been assigned, etc. Users can also utilize their favored news reader to be up-to-date about changes within the group as each GroupMe! group provides an RSS feed. An important feature of GroupMe! is that content of groups is accessible for machines like SemanticWeb agents as well (Abel et al. 2007). GroupMe! is there with an RDF (Resource Description Framework) generator as it extracts RDF data about resources, and captures each user interaction as RDF. Other applications benefit from the feature of grouping and enriching resources with machine understandable semantics as RDF generated in GroupMe! is made available according to the principles of Linked Data. Hotho et al. (2006a,b,c) are defined a folksonomy as follows.

Definition 1 A folksonomy is a quadruple $F := (U; T; R; Y)$, where U, T, R are finite sets of instances of users, tags, and resources and Y defines a relation, the tag assignment, between these sets, that is, $Y \subseteq U \times T \times R$. GroupMe! extends this folksonomy definition by the concept of groups.

Definition 2 A group is a finite set of resources. A group is a resource as well. Groups can be tagged or arranged in groups, which affects hierarchies among resources. In general, tagging of resources within the GroupMe! system is done in context of a group. Hence a GroupMe! folksonomy is formally characterized via Definition 3 (Abel et al. 2007).

Definition 3 A GroupMe! folksonomy is a 5-tuple $F := (U; T; \breve{R}; G; \breve{Y})$, where:

- U, T, R, G are finite sets that contain instances of users, tags, resources, and groups
- $\breve{R} = R \cup G$ is the union of the set of resources and the set of groups
- $\breve{Y}$ defines a GroupMe! tag assignment: $\breve{Y} \subseteq U \times T \times \breve{R} \times (G \cup \{\varepsilon\})$ where ε is a reserved symbol for the empty group context, i.e. a group that is not contained in another group when it is tagged by a user.

4.4 FolkRank algorithm

The original formulation of algorithm PageRank (Brin and Page 1998) reflects the idea that a page is important if there many pages linking to it, and if those pages are important themselves. The distribution of weights can thus be described as the fixed point of a weight passing scheme on the web graph. This idea was extended in a similar fashion to bipartite subgraphs of the web in HITS (Kleinberg 1999) and to n-ary directed graphs (Xi et al. 2004). The basic notion is that a resource which is tagged with important tags by important users becomes important itself. The same holds, symmetrically, for tags and users.

Inspired from the PageRank algorithm which exploits the network structures of Web pages, the FolkRank algorithm has been developed as a folksonomy search engine by using the graph model (Hotho et al. 2006a,b,c). The FolkRank algorithm adopted the same weight spreading approaches as in the PageRank. The main difference, however, lies in the graph. In the FolkRank, the graph of tags has no direction, while the PageRank uses directed graphs.

The FolkRank algorithm transforms the hypergraph formed by the traditional tag assignments (see Definition 1) into an undirected, weighted tripartite graph $G_F = (V_F, E_F)$, which serves as input for an adaption of PageRank (Page et al. 1998). At this, the set of nodes is $V_F = U \cup T \cup R$ and the set of edges is given via $E_F = \{\{u, t\}, \{t, r\}, \{u, r\} \,|(u, t, r) \in Y\}$. The weight $\omega$of each edge is determined according to its frequency within the set of tag assignments, i.e. $\omega(u, t) = |\{r \in R : (u, t, r) \in Y\}|$ is the number of resources the user u tagged with keyword t.

Accordingly, $\omega(t, r)$counts the number of users who annotated resource r with tag t, and $\omega(u, r)$determines the number of tags a user u assigned to a resource r. With G_F represented by the real matrix A, which is obtained from the adjacency matrix by normalizing each row to have a sum equal to 1, and starting with any vector $\vec{\omega}$ of non-negative reals, adapted PageRank iterates as $\vec{\omega} \leftarrow dA\vec{\omega} + (1-d)\,\vec{p}$.

Adapted PageRank utilizes vector $\vec{p}$, used to express user preferences by giving a higher weight to the components which represent the user's preferred web pages, fulfilling the condition$||\vec{\omega}||_1 = ||\vec{p}||_1$. Its influence can be adjusted by $d \in [0; 1]$. Based on this, FolkRank is defined as follows (Hotho et al. 2006a,b,c).

Definition 4 The FolkRank algorithm computes a topic specific ranking in folksonomies: If $\vec{p}$specifies the preference in a topic (e.g. preference for a given tag), $\vec{\omega}_0$ is the result of applying the adapted PageRank with $d = 1$ and $\vec{\omega}_1$ is the result of applying the adapted PageRank with some $d < 1$, then $\vec{\omega} = \vec{\omega}_1 - \vec{\omega}_0$ is the final weight vector. $\vec{\omega}\,[x]$ denotes the FolkRank of $x \in V$.

FolkRank yields a set of related users and resources for a given tag. Following these observations, FolkRank can be used to generate recommendations within a folksonomy system. These recommendations can be presented to the user at different points in the usage of a folksonomy system (Hotho et al. 2006a,b,c):

- Documents that are of potential interest to a user can be suggested to him. This kind of recommendation increases the chance that a user finds useful resources that he did not even know existed by "serendipitous" browsing.
- When using a certain tag, other related tags can be suggested. This can be used, for instance, to speed up the consolidation of different terminologies and thus facilitate the emergence of a common vocabulary.
- While folksonomy tools already use simple techniques for tag recommendations, FolkRank additionally considers the tagging behavior of other users.
- Other users that work on related topics can be made explicit, improving thus the knowledge transfer within organizations and fostering the formation of communities.

4.5 Recommendation based on tensor factorization

Recommendation algorithms based on tensor factorization generate their recommendations using ranking score which is computed according to spectral attributes extracted from the underlying folksonomy data structure. By representing **Y** as a tensor, one is able to exploit the underlying latent semantic structure in **A** formed by multi-way correlations between users, tags, and resources. There are different ways to represent **Y** as **A**. Symeonidis et al. (2008), for example, proposed to interpret **Y** as a sparse tensor (Fig. 3 left) in which 1 indicates positive feedback and the remaining data as 0:

$$a_{u,t,r} = \begin{cases} 1, & (u,t,r) \in Y \\ 0, & else \end{cases} \tag{9}$$

Rendle et al. (2009) on the other hand, distinguish between positive and negative examples and missing values in order to learn personalized ranking of tags. The idea is that positive and negative examples are only generated from observed tag assignments. Observed tag assignments are interpreted as positive feedback, whereas the non observed tag assignments of an already tagged resource are negative evidences. All other entries, i.e., all tags for a resource that a user has not tagged yet, are assumed to be missing values (Fig. 3 right).

The factorization of **A** is expressed in Eq. 10. $U \in U^{K_u \times K_u}$, $T \in R^{K_T \times K_T}$, $R \in R^{K_R \times K_R}$ are orthonormal matrices corresponding to the dominant singular vectors per mode.

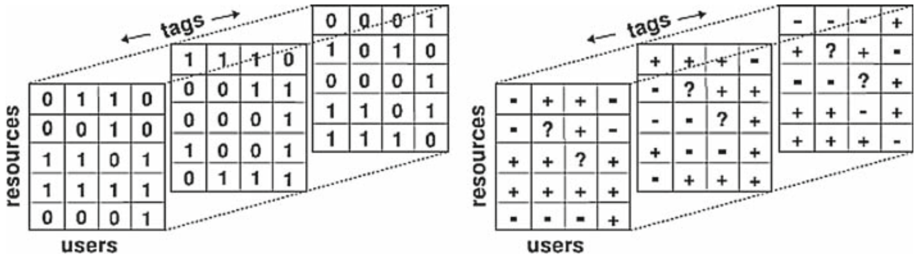
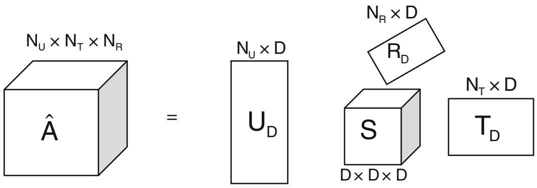


Fig. 3 Tensor representation *left* (Symeonidis et al. 2008), *right* (Rendle et al. 2009)

Fig. 4 Tensor factorization



S is the core tensor that contains the singular values, thus it has the same size as **A** and the property of all orthogonality. The symbol $\times_i$ denotes the i-mode multiplication between a tensor and a matrix.

$$\mathrm{A} := \mathbf{S} \times_1 U \times_2 T \times_3 R \tag{10}$$

After decomposing **A**, the matrices *U, T, R*, and the core tensor **S** are truncated by maintaining only the highest *D* singular values and the corresponding singular vectors per mode (henceforth, *D* denotes the fraction, e.g., 0.7, of the maintained values divided by the original number of values). This produces the truncated matrices $U_D \in R^{K_U \times D}$, $T_D \in R^{T_U \times D}$, $R_D \in R^{K_R \times D}$, and the truncated core tensor $S_D \in R^{D \times D \times D}$. Using truncation we can approximate with the reconstructed tensor $\hat{A} \in R^{K_U \times K_R \times K_T}$ as expressed in Eq. 11 and illustrated in Fig. 4.

$$A := \mathbf{S}_D \times_1 U_D \times_2 T_D \times_3 R_D \tag{11}$$

Once $\hat{A}$ is computed, the list with the *N* highest scoring tags for a given user *u* and a given resource *r* can be calculated by:

$$Top(u, r, N) := \underset{t \in T}{\overset{N}{\arg\max}}\, \hat{a}_{u,t,r} \tag{12}$$

Recommending *N* resources to a given user *u* for a particular tag *t* can be done in a similar manner. Moreover, other users can be recommended to a particular user *u* given a specific tag *t*, according to the total score that results by aggregating all resources that are tagged with *t* by *u*. Thus, according to the data representation, tensor modeling permits multi-mode recommendations in an easy way.

4.6 Methods for tag-based profile construction with a vector of weighted tags

Most methods for building tag-based profiles extract tags users associate to resources in folksonomies considering more frequently chosen tags as more important for describing user interests. Noll and Meinel (2007) are obtained a vector of weighted tags using tag frequency of occurrence in the resources a user tagged and it is applied to rank Web search results according to their similarity with this tag vector. TBProfile (Diederich and Iofciu 2006) also uses weighted vector of tags to represent user interests. The basic idea is to let people create their profiles by specifying the most relevant objects in the folksonomy. Afterwards, this *intermediate profile* comprising the objects is translated into the tag domain, assuming that the manually specified tags describe the objects with a high accuracy. Each user has the possibility to individually modify his profile by adding new objects or removing objects the user is no longer interested in. Also, it should be possible to mark certain topics as 'not interesting': "*If an object has been tagged by several persons, not all the tags of an object may describe the interests of one particular person*". This system locales like-minded users by comparing their corresponding vectors using the standard cosine similarity measure. In a similar way, Stoyanovich et al. (2008) used tags weighted according to the fraction they covered of the user tagging actions in to generate hot-lists of recommendations by combining tags and items overlapping for constructing per-tag common interest networks.

Using a single vector of weighted tags to represent the user interests has some drawbacks. First, more frequent tags tend to be too general for describing interests so that profiles tend to lose specificity. More importantly, users usually have diverse interests spanning across different domains that can not be embraced by a unique vector or tag-cloud. To overcome this problem Yeung et al. (2008) proposed an algorithm which performs graph-based clustering over the network of user tagged documents to identify interest topics and extract tag vectors for them. Multiple tag-clouds were also considered, which enrich descriptions of movie titles with user interests and opinions taken from a folksonomy for predicting the rating of an unseen movie (Szomszor et al. 2007). For each rating belonging to a predefined scale, a tag-cloud is assigned to the rating with the keywords belonging to all movies that the user has associated with that rating so that predictions for unrated movies are made based on their similarity to rating tag-clouds.

4.7 Naive, co-occurrence and adaptation approaches

Michlmayr et al. (2007) compared the method for tag-based profile construction with a single vector of weighted tags, which the authors called the *naive approach*, with two different approaches, one based on *co-occurrence* and another based on *adaptation*. In the co-occurrence approach, tags frequently used in combination for annotating objects are assumed to have certain semantic relation. Thus, profiles are represented by graphs in which nodes correspond to tags and edges denote relationships among them. The adaptive approach, implemented in Add-A-Tag (Michlmayr et al. 2007) algorithm, extends this model to include temporal information by updating the weights of edges in the graph using an evaporation technique known from ant algorithms for discrete optimization. Tag-based profiles built using both co-occurrence and adaptive approaches had better acceptance from users than those built with the naive approach.

4.7.1 Naive approach

Consider a user's bookmark collection. Each bookmark in the collection is composed of a title, a description, a URL, a date, and a set of tags.

To construct a user profile out of these data, the task is to aggregate it in such a way that the interests of the user are reflected according to their intensity. The more often a certain tag is used, the higher the interest of the user in the corresponding topic (Szomszor et al. 2007). Therefore, the simplest method for creating aggregated data for a user's bookmark collection is to count the occurrence of tags. This is the approach taken for creating tag-clouds. The result of this computation is a list of tags which is ranked according to tag popularity. The user profile can then be created by selecting the top k most popular tags from the ranked list. The benefit of this method is that it is very simple, and hence fast. However, it has some drawbacks. One major problem is that those tags which are most often used tend to be not very specific (e.g., the tag web is a very general one). Moreover, the resulting profile consists of unlinked tags. Although the tagging data includes information about the relationships between those tags, these relationships are not included in the user profile. The co-occurrence approach tackles both these drawbacks.

4.7.2 Co-occurrence approach

If two tags are used in combination (co-occur) by a certain user for annotating a certain bookmark, there is some kind of semantic relationship between them (Michlmayr and Cayzer 2007). Similarity between two tags can be measured by different forms. The easiest method is counting the number of co-occurrences, that is, the number of times when two tags are assigned to the same resource. Such as Szomszor et al. (2007) show, the non-trivial nature of co-occurrence relationships between tags might be considered as a kind of semantic relationship between tags, measured by means of relative co-occurrence between tags, known as Jaccard coefficient. Let A and B be the sets of resources described by two tags, relative co-occurrence is defined as:

$$RC(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{13}$$

That is, relative co-occurrence is equal to the division between the number of resources in which tags co-occur, and the number of resources in which appear any one of two tags. The more often two tags are used in combination, the more intense this relationship is. This is represented by a graph with labeled nodes and undirected weighted edges in which nodes correspond to tags and edges correspond to the relationship between tags (Michlmayr and Cayzer 2007). Each time a new tag is used, a new node for this tag is added to the graph. Each time a new combination of tags is used, a new edge with weight 1 between the corresponding nodes is created in the graph. If two tags co-occur again, the weight for the corresponding edge is increased by 1. The graph is created by parsing the tags for all items in the bookmark collection. In the second step, a user profile is derived from the resulting graph by selecting the top k edges with the highest weights and their incident nodes. One drawback of the co-occurrence approach is that it does not include bookmarks that are annotated with a single tag. In order to overcome this issue, it would be necessary to combine it with the naive approach. Another drawback of this approach is that the age of bookmarks and their temporal ordering is not considered. This issue is addressed by the adaptive approach.

4.7.3 Adaptive approach

The age information of the tagging data is important. It makes a difference if a user has used a certain tag and, therefore, specified a certain interest, one day or one year ago. To include the age of the bookmarks in the user profile the co-occurrence approach can be extended with the evaporation technique known from ant algorithms (Dorigo and Caro 1999). Evaporation is a simple method to add time-based information to the weights of edges in a graph: Each time the profile graph is updated with tags from a newly added bookmark, it is necessary to start parsing from the oldest item and to process the items in the same temporal order as they were added to the bookmark collection.

4.8 WebDCC

User profiling is built upon a clustering algorithm, named *WebDCC* (Web Document Conceptual Clustering), with structures and procedures specifically designed for user profiling (Godoy and Amandi 2006). *WebDCC* carries out incremental, unsupervised concept learning over the collected experiences. First introduced by Michalski and Stepp (1983), conceptual clustering is defined as the task of, given a sequential presentation of experiences and their associated descriptions, finding clusters that group these experiences into concepts or categories, a summary description of each concept and a hierarchical organization of them (Thompson and Langley 1991). Experiences are analyzed to learn a conceptual description of user interests and organized within user profiles to be applied in recommendation. Identification of categories or topics a user is interested in is based on clustering of similar past experiences. Thus, user profiles are built starting from scratch and constantly refined as new experiences representing user interests become available. Hierarchies of concepts produced by this algorithm are classification trees in which internal nodes represent concepts and leaf nodes represent clusters of experiences. The root of the hierarchy corresponds to the most general concept, which comprises all the experiences the algorithm has seen, whereas inner concepts become increasingly specific as they are placed lower in the hierarchy, covering only subsets of experiences by themselves. Finally, terminal concepts are those with no child concepts but clusters. More formally, a hierarchy consists of a number of concepts, denoted by $C = \{c_1, c_2, \ldots, c_n\}$, which are gradually discovered by the algorithm as new experiences become available. In order to automatically assign experiences to concepts, the algorithm associates each of them with a description given by a set of terms, $C_i = \langle\langle t_1, w_1\rangle, \ldots, \langle t_m, w_m\rangle\rangle$, weighted according to their importance in the concept summarization (Godoy and Amandi 2008). This description constitutes a linear classifier for the category and emerges from observing the common features of experiences in the category and those a novel experience should have in order to belong to it. In order to build hybrid profiles, categories representing user interests in content-based profiles are populated with the tags users frequently associate to resources in that categories. To accomplish this goal, tagged resources have to be first categorized according to the current representation of user interests given by the interest hierarchy.

Initially, a resource belonging to the root category is categorized by classifiers at the first level of the tree. Then, classifiers at the second level take the resource that has been classified in one of the previous level categories and classify it into categories at the second one. This procedure continues until the resource has reached some leaf node in the hierarchy or it cannot be further classified down. Each node in the hierarchy acts as a linear classifier which is compared with the resource to be classified.

4.9 Music recommendation system

Online music recommender system is one prominent example of companies wich offers personalized services toward users. The main goal of a music recommendation system is to propose, to the end-user, interesting and unknown music artists and their available tracks, based on his musical taste. But musical taste and music preferences are affected by several factors, even demographic and personality traits. Then, the combination of music preferences and personal aspects such as: age, gender, origin, occupation, musical education, etc. could improve music recommendations (Uitdenbogerd and van Schnydel 2002).

Most available music recommender systems are based on collaborative filtering methods; i.e., they recommend music to a user by considering some other users' ratings for the same music pieces. This technique is quite widely utilized, including music shopping services like Amazon[13] or iTunes,[14] and has proven to be effective. However, this recommendation method suffers from the cold start problem.

Celma et al. (2005) give an overview of the Foafing the Music system, which uses the Friend-of-a-Friend (FOAF) and RSS vocabularies for recommending music to a user, depending on his musical tastes. Music information, such as new album releases, related news artists, or available audio pieces, is gathered from RSS feeds from the Web, whereas FOAF documents are used to represent information about people, their interests, relationships between them and social connections. The FOAF vocabulary contains terms for describing personal information (name, nick, mailbox, interest, images, etc.), membership in groups - member, group, organization, etc. FOAF is based on the RDF/XML vocabulary. The system reads an input FOAF profile, that is, an RDF/XML file, and extracts user's interests. Then, it queries a music repository in order to detect whether the interest is a music artist, and selects similar artists to the ones found. To get artists' similarities, a focused web crawled has been implemented to look for relationships between artists (such as: related to, influenced by, followers of, etc.). Moreover, a music similarity distance is used to recommend tracks that are similar to tracks composed or played by artists found in the FOAF profile.

Another hybrid music recommendation method is presented by Yoshii et al. (2006), which simultaneously considers user ratings and content similarity and is based on a three-way aspect model, proposed by Popescul et al. (2001). This model can directly represent substantial user preferences as a set of latent variables introduced in a Bayesian network. Probabilistic relations over users, ratings, and contents are statistically estimated.

An approach for producing music recommendations is applied to an interactive music system that generates playlists fitting the preferences indicated by the user (Pauws et al. 2006). For automatically generating music playlists, this approach uses a local search procedure in the solution space, based on simulated annealing: the algorithm iteratively searches the solution space moving from one solution to a neighboring solution, compares their quality and stops when an optimal solution is found.

A totally different recommendation technique is described by Stoyanovich et al. (2008). The authors of paper develop a unified framework, represented by a 3-order tensor, to model altogether users, tags, and items. Then, they recommend musical items according to users multimodal perception of music, by performing latent semantic analysis and dimensionality reduction using the higher order singular value decomposition technique.

Firan et al. (2007) investigated tag-based user profiles in contrast to conventional profiles based on song and track usage in the music search portal Last.fm. The tagging frequency on a track owned by a user is used in this work to determine relevant tags and their associated scores, then a search-based method employs tags to find similar users and recommend interesting songs. Compared with conventional track-based recommender approaches, tag-based profiles significantly improve the quality of recommendations.

5 The limitations of current folksonomy systems

In recent years, tagging systems have become increasingly popular. These systems enable users to add keywords to Internet resources without relying on a controlled vocabulary. Social tagging systems may afford multiple added benefits. For instance, a shared pool of

13 http://www.amazon.com/.

14 http://itunes.apple.com/.

tagged resources enhances the metadata for all users, potentially distributing the workload for metadata creation amongst many contributors.

Tagging systems have the potential to improve search, recommendation, spam detection, reputation systems, and personal organization while introducing new modalities of social communication and opportunities for data mining. This potential is largely due to the social structure that underlies many of the current systems. Despite the rapid expansion of applications that support tagging of resources, the simplicity and ease of use of tagging however, lead to problems with current folksonomy systems, which hinder the growth or affect the usefulness of the systems. The problems can be classified in some categories (Mathes 2004; Shepitsen et al. 2008; Pluzhenskaia 2006; Gordon-Murnane 2006).

1. Tags have little semantics and many variations. Thus, even if a tagging activity can be considered as the user's cognitive process, the resulting set of tags does not always correctly and consistently represent the user's mental model.
2. Most tagging systems have their own specific ways of functioning with and interpreting the meaning of tags. Thus if we want to aggregate tagging data from different applications or services, it's very difficult to find out the meanings and correlations between sets of tags.
3. As an uncontrolled vocabulary that is shared across an entire system, the terms in a folksonomy have inherent ambiguity, as different users apply terms to documents in different ways.
4. Redundancy and ambiguousy in the tag database both hinder the precision and recall of tagging systems. Tag redundancy, in which several tags have the same meaning, can obfuscate the similarity among resources. Redundant tags can hinder algorithms that depend on identifying similarities between resources. On the other hand, tag ambiguity, in which a single tag has many meanings, can falsely give the impression that resources are similar when they are in fact unrelated.
5. Some systems allow users to input tags separated by spaces. Problems arise when users would like to use phrases with multiple words to describe the Web resources.
6. The use of different word forms such as plurals and parts of speech also exacerbate the problem.
7. Some tags do not describe the document, but give a judgment ("clever"). User-specific tags describe or evaluate a document only from the user's very own perspective, so that some tags "are virtually meaningless to anybody except their creators" (Pluzhenskaia 2006).
8. Many users in non-English-speaking countries tag documents using their own language (e.g: for Austrian capital there are following tags: "Viena", "Wien", "Becs"). This merging of languages leads to the problems of trans-language synonymy (i.e., translation) and homonymy (for example: in English a "gift" is a present, the meaning of the German word "Gift" is "poison"—which is certainly not a good gift; Gordon-Murnane 2006).

There are some different approaches aiming to solve the mentioned problems. First one can focus on the actors and try to educate users to improve "tag literacy" (Guy and Tonkin 2006). An important condition for this way of resolving problems is to establish user researches about folksonomies (Bar-Ilan et al. 2006; Winget 2006; Lin et al. 2006), concerning the "deep nature" of tags (Veres 2006a,b), discussing aspects of the folksonomy interoperability (Veres 2006a,b) and the "semiotic dynamics" of folksonomies in terms of tag co-occurrences (Cattuto et al. 2007).

For training the user's selection of "good" tags it may be useful that the system would suggest some tags (MacLaurin 2007). Tag-suggestions can operate on a syntactical level (e.g., a user attaches "graph" and the system suggests "graphics") or even on a relational level (e.g., a user attaches "graphics" and the system suggests "image", because both words do often co-occur in documents' tag clouds (Xu et al. 2006).

The second approach considers tags as elements of natural language and treats them by means of automatic methods of natural language processing (NLP; Stock 2007). It is known, that approximately 90% of all tags are nouns (Guy and Tonkin 2006). But it is an open question, whether images and videos will be additionally tagged by verbs in future.

Third, data mining techniques such as clustering provide a means to overcome redundancy and ambiguity thereby facilitating recommendation (Gemmell et al. 2008a,b). Data clustering is a common technique for statistical data analysis. Clustering provides partitioning of a dataset into subsets of similar objects or data clusters. Before actually using a clustering technique the first task one has to do is to transform the problem at hand into a numeric representation that can be used by clustering algorithms. The goal is first to provide a similiarity measure among tags and then to run clustering techniques on the tag space represented like this.

By clustering, redundant tags can be aggregated; the combined trend of a cluster can be more easily detected than the effect of a single tag. The effect of ambiguity can also be diminished, since a cluster imbues a tag with the meaning shared by the associated tags. Using the clusters as the nexus between users and resources, the relevance of a resource to a user can then be inferred and used for recommendation.

6 Areas for further research

As described in Sect. 4, there has been much research done on tag-based recommendation technologies, over the past several years that have used a broad range of statistical, machine learning, information retrieval, and other techniques that have significantly advanced the state-of-the-art in comparison to early recommender systems that utilized collaborative and content-based heuristics.

There are also clearly great benefits in user tagging and folksonomies, especially in the richness, currency, relevance and diversity of the terms used, and the collections of resources created. The success of tagging services like Flickr, Delicious and Technorati has shown that tagging is a great collaboration tool. Tagging seems to be the natural way for people to classify objects as well as an attractive way to discover new material. Tagging services provides users with a repository of tagged resources that can be searched and explored in different ways. More and more people use at least one tagging service and enjoy them as discovery tools.

The rapid development of collaborative tagging system and related emerging technology suggests new ideas for personalized recommendation and determine a great number of challenges for future work. Interesting additional features (Firan et al. 2007; Xu et al. 2006), which are worth for further research, are listed below.

- Incorporate relevance feedback into search-based recommendations, such that the user is able to select negative tags or items he does not like.
- Improve tag browsing experience by applying the same principles in constructing tag-cloud, e.g., by presenting tags with good facet mix while considering popularity and user interests.
- Examining the quantitative aspects of folksonomies and use of the terms wich describe items.

- Examining the distribution of tag use. That is, the most used tags are more likely for other users since they are more likely to be seen. There will be a few tags that are used by a substantial number of users. An order of magnitude more tags that are used by fewer users, and another order of magnitude more used by only a handful of users. Examining this sort of distribution of tag use could give a better indication of whether a folksonomy converges on terms, or the distribution of terms flattens, perhaps indicating less agreement.
- Examining user behavior through ethnographic observation or interview to understand his motivations and cognitive processes in tagging items. Although it seems that some users are intending to facilitate communication through tag use, especially in the unintended uses, interviews could make this point explicit. Interviews could also elucidate the conscious intentions of users in "normal" use of the system, which is much harder to observe simply from the documents and tags themselves.
- Analysis of the frequency which users modify or change their tags, or future tagging behavior based on the implicit feedback from the system in the form of what other documents are tagged with a term.
- The use of a folksonomy to supplement existing classification schemes and provide additional access to materials by encouraging and leveraging explicit user metadata. The organizational schemes developed by the users have the possibility to be of great interest to other users and improve the recommendation systems.
- Improve tag uniformity by normalizing semantically similar tags that are not similar in letters.

These extensions leave ample opportunity for future work in this area. They can improve tag-based recommendation capabilities and make collaborative tagging systems applicable to en even broader range of applications.

7 Conclusion

Recommender systems made significant progress over the last decade when numerous content-based, collaborative, and hybrid methods were proposed and several "industrial-strength" systems have been developed. However, despite all of these advances, the current generation of recommender systems still requires further improvements to make recommendation methods more effective in a broader range of applications. With the increasing popularity of the collaborative tagging systems, surveyed in this paper, tags could be interesting and useful information to enhance recommender systems' algorithms. Besides helping user organize his or her personal collections, a tag also can be regarded as a user's personal opinion expression, while tagging can be considered as implicit rating or voting on the tagged information resources or items. Thus, the tagging information can be used to make recommendations. In this paper, we described social tagging systems which can be used for extending the capabilities of recommender systems. We presented a comprehensive survey of the state-of-the-art in collaborative tagging systems, folksonomy and tag-based recommender systems. Various limitations of the current generation of folksonomy systems and possible extensions that can provide better recommendation capabilities are also considered. We hope that the issues presented in this paper will advance the discussion in the social tagging systems community about the next generation of technologies for improving recommendation.

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