Overview and Analysis of Personal and Social Tagging Context to construct User Models

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ABSTRACT
The quality and user acceptance of personalized services such as personalized information retrieval and navigation or content recommendation depends depends besides the personalization mechanism on the quality, validity and accuracy of the employed user model. In literature a variety of user model construction methods based on tagging activity in social tagging systems (STS) are presented, relying on different user contexts, e.g., the personal or social context. But up to now there is neither a concise overview of existing construction methods available nor a deeper analysis and discussion of the differences between these models. Such an analysis would for example ease evaluation but also enable system designers to choose the most appropriate one. Our work tackles this problem by providing a short overview of state-of-the art user model construction methods which employ social tags. This is followed by a statistical comparison of four different user model construction methods for STS based on tag-frequency. This analysis unveils that depending on the method chosen (based user's personal tagging behavior as well as community-based social strategies), the user model consists of different tags and tag frequency rankings, thus services employing different models will lead to different results.

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User Modeling, Social Tagging, Recommender Systems, Personalized Information Retrieval

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Algorithms, Human Factors.

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INTRODUCTION
In the last years the web has witnessed an explosion of information created and shared, by individuals and through social interaction, such as for example in social tagging systems or social streams. This amount of information has generated a huge need for more effective access to the information, especially since each user has different expectations, goals, knowledge, information needs and desires to be satisfied. One way to ease the access is by personalization. To enable a system to adapt to e.g. the user's interests, the system usually builds a user model, an accurate machine-readable representation of the user. In social tagging systems, which enable a user to annotate a resource with a freely chosen keyword (tag) for later reuse and sharing, the user's interests are commonly modeled by using the tags available in the system.

In literature, a variety of user model construction methods have been presented but to the best of our knowledge, there is yet no concise overview of common techniques available. E.g. several methods build the user model solely based on the personal tagging context (only the tags the person used) or the social context (the tags all users used for a specific user's resources). Thus, in the first part of this work we present a literature overview and based on that, we present four typical user model construction methods and variations of it which can be used to enhance personalization in a social tagging system. Each of these models can be used for example to personalize resource ranking for retrieval with the FolkRank algorithm [13]. FolkRank provides the possibility to adapt the preference vector for a random surfer component to express user preferences by giving a higher weight to components that represents the user's preferences. It is expected that different user models (based on their context) lead to differently ranked results. This raises the question whether typical UM techniques lead to similar user model representations or whether they exhibit a different user model depending on what technique is chosen; which in turn is expected to lead to different search result rankings. Thus, in a second part, we present and discuss a statistical analysis of the comparison of the four chosen user model construction methods. We thereby focus on general statistics such as the 'tag richness' of a user model, the similarity between different possible models for one user as well as the correlation between the similarity of the possible user models for one user and the resource sharedness of this user.

Contribution of this work is the following:

- We provide a short overview of user model construction methods in Social Tagging Systems.
- We present a set of four possible and popular user modeling strategies to personalize services in STS. Two models are based solely on the user's tagging behavior, two represent the user model based on the tagging behavior of the community (userbase of the system).
- We show that the more tags are assumed to be part of a tag-based user model, the more specific a user model becomes and the different the four possible user models become. For personalized information retrieval a rich, specific user model is preferred, thus it plays an important role which user model is chosen to be fed into the personalization mechanism.
- We furthermore show that the more resources a user shares with the community, the more the personal and community-based profiles differ. For these users, it needs to be further investigated which user model is the most useful one, depending on the use case (e.g. personalized IR, expertise search, navigation).

SOCIAL TAGGING

Tagging has gained a major success in the web 2.0 as it plays an important role of helping user manage their resources. Users are encouraged to add tags to describe a website, a publication, a music track, a picture, etc. and to share these resources tags with other people. These tags indirectly reflect a user's interests, concerned topics, activities in daily life, and many more. Thus social tagging activities can serve as as an interesting source of information to build a user representation for any kind of personalized service.

Definitions

In the following we describe a few definitions of terms that are used throughout this work.

- A *User Library* $ULib(u)$ is the set of all resources a user u has annotated within a social tagging system.
- An *Author Library* $ALib(u)$ is the set of resources who are authored by a specific user u. E.g. an academic publication annotated with 'myown' in Bibsonomy [1] or added to the folder 'My Publications' in Mendeley[2]. Usually, $ALib(u) \subset ULib(u)$ and one resource r can have more than one author.
- A *Folksonomy* $F(R;U;T;TAS)$ is the central data structure of a social tagging system like Bibsonomy (academic publications as well as web resources), which is commonly seen as a lightweight classification structure built from so called tag annotations (TAS) added by different users to their resources. A folksonomy consists thus of a set of users U, a set of tags (i.e. freely chosen keywords) T, and a set of resources R with $ULib(u) \subseteq R \forall u \in U$, together with a ternary relation $TAS \subseteq U \times T \times R$ between them.
- A *Personomy* $P(u) = F(ULib(u);u;T(u);TAS), u \in U$ is a subset of $F(R;U;T;TAS)$, built only from tag annotations of a single user (person).
- The *Tag Sharedness* $TS(t)$ of a tag $t \in T$ is given by $|\{u \in U | t \in T(u)\}|$, thus is the amount of users who used a specific tag t . If we limit the tags of $F(R;U;T)$ to $F_2(R;U;T_2]$ where $T_2 = \{t \in T | TS(t) \geq 2\}$ is the set of tags with tag sharedness greater than 1, this eliminates on the one hand e.g. typical problems of a tag vocabulary such as misspellings etc. but also on the other hand increase the 'information value' of a tag in a user model.
- The *Resource sharedness* $RS(r)$ of a resource $r \in R$ is given by $|\{u \in U | r \in ULib(u)\}|$, thus is the amount of users who have a specific resource r in their library.

[1]http://www.bibsonomy.org

[2]http://www.mendeley.com

OVERVIEW OF USER MODELING APPROACHES FOR SOCIAL TAGGING SYSTEMS

In social tagging systems, it is generally assumed that annotating a resource is a good indicator for the current interests of a user. E.g. if a large number of a user's tagging activities include the tag 'sports', the user is likely to be interested in sports-related content. Some work also models the user's expertise- or knowledge-based on the user's tagging behavior ([14], [28], [4]).

A categorization of the user model construction is usually somehow problematic as some approaches apply more than one construction technique. For example, in concept-based methods often clustering is applied to identify clusters representing one concept. Also, this is not a complete overview but we rather aim at presenting the most common methods together with some prime examples.

Tag-Frequency-based User Modeling

In most approaches presented in literature, a tag-based user model representing the user's interests or expertise is usually provided in form of a weighted tag vector. In its simplest form, a weight is given by the frequency of the tag in the user's personomy. Tag-frequency-based user models are constructed in different ways, the following two main approaches can be distinguished:

Firstly, the user model is based on *tags extracted from a user's personomy*, thus on the tags the user has directly assigned to annotate resources. The work of [18] or [3] follow the naive approach which simply represents the user in form of a tag (frequency) vector which indicates that user u has used a tag t (a certain number of times) to annotate an item.

The personomy-based user model depends on the fact that the user has to collect a sufficient amount of annotation data such that the system can infer a useful user model. [1] present a more lightweight approach which builds the user model based upon *the tags that other users have added* to the resource the specific user clicks on. Similarly, in the work of [9] or [12] a personalization strategy for IR based on folksonomy data is presented, the user model is enriched with the tags other users added to the resources of the user's library. In the recommendation research literature, tag-frequency-based user models are for example presented in [11] or [29].

An additional approach for user modeling can be based on *the tags chosen by a user from a list of suggested tags* as for example described in [6]. [15] enriches tagging activities with explicit ratings from users to model their likes and dislikes based on other similar users. More formally, a user is modeled as two tag vectors, on vector of tags denotes those tags a user is interested in another vector denotes the tags irrelevant for this user.

Graph-based User Modeling
The assumption behind a graph-based approach presented in [18] is that, if two tags co-occur in a user's tag annotation, there is some kind of relationship and the more often two tags are used together by a user, the stronger is this relationship. The top-k edges of the personomy graph representation with the highest weights (number of co-occurrences) and their incident nodes (tags) are chosen to represent the user model. A variant of this algorithm includes time-based information: every time the user adds another tag annotation, the current edge weights are decreased by a small percentage of their value. This technique is commonly known as evaporation from ant algorithms [10]. Another graph-based approach is for example described in [7] where a user model is constructed to enhance resource retrieval. Information from tagging as well as rating activities are used to personalize search results.

Clustering-based User Modeling
[27] constructs sets of tags which represent different interests of a user, they apply a community-detection algorithm on the tag-document network of a user's personomy. From the derived document clusters, a set of tags which appear on more than f% of the documents in the cluster are chosen. The final user model is a collection of those sets. One major drawback of this approach is that the user profiles are created solely on the basis of a specific personomy, thus the user models representing the interests of more users are not easily comparable. [25] proposes a method to map individual personomies on the corresponding folksonomy. They also presented how the model can be applied to services such as tag recommendations and tag-based social search. The authors of [16] propose besides topic-based clustering also a time-based clustering.

Concept-based User Modeling
In tag-based user modeling, the user model is often built solely on top of the user's personomy. While this approach meet individual needs and preferences, the differences between the users individual tag vocabularies creates discrepancies. E.g., when mapping for example a user model to an item representations (= a tag frequency vector containing tags all users have added to this item) for search or recommendation services or when identifying similar users based on their user models. This can be avoided if a user model contains concepts representing a set of tags rather than individual tags from this user. In the work of [24], the system gathers tag annotations of a specific user from a range of applications, then the user's tags are mapped onto a multi-domain model (provided by Wikipedia categories and their relationships) to filter tags and create a more structured interest vector as a user model. In [21], a hierarchical tag clustering approach is applied to the overall folksonomy where each cluster represents a concept. The user model for his/her interests is then a set of concepts where the user's interest in a specific cluster is given by the number of times the user annotated a resource with a tag from the cluster divided by the total number of the user's tag annotations. [26] introduce a novel user-centric tag model that enables a mappings between personal tag vocabularies and the underlying common folksonomy. An approach to map multilingual tags in a folksonomy is presented in [19] where two tags are considered as a valid translations if they expose similar global tag co-occurrence patterns.

Classifier-based User Modeling
A different approach for user modeling based on tagging data has been taken up in [8], who built a classifier-based user model for each user to recommend tags for when annotating new resources. Given the set of all tags in the user's personomy, binary classifiers are trained where each classifier corresponds to a specific tag in the user's personomy. Positive examples for training are those resources which have been tagged by the user with the corresponding tag and negative examples those which have not been annotated with that tag. In this sense, the user model construction is reduced to a binary text categorization task where each document has to be classified as interesting or not with respect to the user preferences provided by previous tag assignments.

User Modeling based on enriched tag information
A combination of tag annotations and content ratings are used to build a user model in [20]. The strength of an interests for a specific tag is a result of the ratings for items provided by the user which is tagged with that tag. In addition, their framework infers higher preference for those tags a user has applied, tags for which a user has searched as well as a third implicit tag signal, the quality of a tag which in turn is a measure depending on how often tags have been used for search and annotations etc. A tag categorization scheme such as presented in [5] could also be used to understand the meaning behind tags to map different user models and/or resource models. The authors utilize the multi-domain YAGO ontology ([23], a Semantic Web knowledge base with structured information extracted from WordNet and Wikipedia) to classify tags based on the intent of the tag.

USER MODELING: PERSONAL-, SOCIAL- AND AUTHOR-BASED STRATEGIES

As presented in section , tag-frequency-based vectors in the form of

$$UM(u) = <(t_1, f_1), (t_2, f_2), ... > \quad (1)$$

are the most common user models for STS. We present four user modeling construction methods to realize a user model as a tag vector, which we aim to analyze and discuss. Our main intent is not to study all possible user model construction methods (as presented in section), but to use basic ones to illustrate that even in this rather simple setting, different construction methods lead to different user models and that this has to be carefully taken into account when to apply which user model construction method to which personalization service. The analysis in section shows insight into the differences.

In the following description of the four construction methods chosen, the notation $MethodName(u)$ refers to the corresponding user model for user u u, created with construction method $MethodName$. The notation $ModelName(u).tags$ refers to the set of tags in the corresponding user model for user u.

- In *US(u)*, the tag frequency is based on the amount of tag assignments of a single user u (the user's personomy).
- In *UF(u)*, the tag frequency is based on the tag assignments complete folksonomy, limited to the resources in $ULib(u)$.
- *AS(u)* is based on the tags chosen by a single user u to annotate his/her own publications, thus $AS(u).tags$ it is a subset of $US(u).tags$.
- *AF(u)* is based on the tagging activities of all users for the authored documents of one specific user u to represent the 'author model' of this user.

Each of the four methods UF, AF, US and AS represent different dimensions of a user model: First they are either based on the tagging vocabulary of a single user (US, AS) or the tag vocabulary of the community (UF, AF). And second, besides utilizing all resources in a user's library (US,UF), we analyze user modeling based on the user's authored documents in his/her library (AS,AF) as in literature authorship is assumed to represent the expertise of a user (see e.g. [22]). In addition to the presented four construction methods (presented below), we compare variants where each user model is required to contain exactly the top-k most frequent tags of the corresponding complete user model.These user models can for example be fed into an STS ranking algorithm such as the FolkRank algorithm [13] which provides the possibility to adapt ranking results based on the preference vector for a random surfer component.

Each of the above presented construction methods UF, US, AF or AS generate user models based on a different amount of information as for example the author's publications $ALib(u)$ is usually a subset of the user's library $ULib(u)$. Table 1 presents as an example four possible user models based for one selected user. It can be easily seen, that for this specific user the different user models not only contain some different tags, but also that the frequency-based rankings of the same tags are different in the four models.

Examples of UF,US,AF and AS for one specific user	
(UF)	(US)
toread (121)	studienarbeit (36)
bibsonomy (124)	www2009 (37)
web (141)	ontology (41)
semantic (167)	kassel (44)
web2.0 (172)	folksonomy (48)
ontology (188)	tool (50)
social (218)	online (52)
tagging (542)	toread (60)
folksonomy (564)	diploma_tesis (71)
(AF)	(AS)
2008 (17)	evidence_networks (2)
2009 (20)	www2009 (2)
social (20)	ibm-kde-tagging (3)
similarity (22)	studienarbeit (3)
bibsonomy (23)	2008 (4)
itegpub (23)	2009 (4)
semantic (24)	www2010 (4)
folksonomy (25)	tagorapub (6)
tagging (50)	itegpub (17)

Table 1. Example of different user model representations for one specific user based on 4 different construction methods. In this table the top-k (k=9) most frequent tags with their frequencies in the UM are shown. Details about the dataset are presented in section .

STATISTICAL ANALYSIS OF DERIVED USER MODELS

Dataset

In this work we will concentrate our analysis on Bibsonomy [2], an social bookmark and publication sharing system. The data set (available after signing a license agreement [1]). Some necessary preprocessing has been done before using the data. For example, to identify the semantic relationship between identical tags, we ignored capital letters and used stemming to such that 'Book', 'book', or 'Books' refers to the same tag 'book'. The dataset after preprocessing consists of 2.434.387 tag assignments by 6.463 users of the tagging system with 192.445 distinct tags for 551.540 resources. Out of the overall amount of users, 98 users used the tag 'myown' to tag their own publications. These tag annotations were used to identify a user's authored publications. The dataset shows the following statistics for tag sharedness (the number of users per of a tag) and resource sharedness (the number of users of a resource):

- Tag Sharedness (TS): On average each tag is used by 2.622 users (variance 90.84; Median is 1.0) and there are 60079 tags with $TS(t) > 1$. The highest ranked tags are: web (709), software (599), social (554), internet (484), search (467), blog (463), design (444), web2.0 (430), semantic (425) and research (405).
- Resource Sharedness (RS): On average there are 1.153 users per resource (variance 0.61; Median is 1.0) with a maximum sharedness of 84 users for a specific resource.

A variant of using the complete folksonomy F for analysis is to limit it to tags with a certain tag sharedness threshold. This eliminates tags that are used very rarely or might be the result of misspelling etc. For our dataset F_2, we set the tag sharedness threshold to value 2.

[1]http://www.kde.cs.uni-kassel.de/bibsonomy/dumps

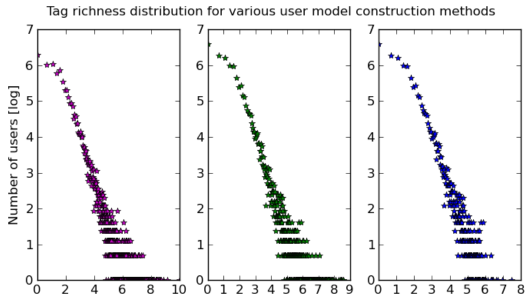

Figure 1. Tag Richness (= number of distinct tags in a personomy; on the x-axis) distribution for different user models UF (plot on the left), US for F (plot in the middle) and US for F2 (plot on the right). It can be seen that only a small number of users have a very rich user model (which is independent of construction method), although UF provides a richer user model than US.

Tag Richness of different User Models				
User Model Construction Method	Min	Max	Mean	Median
$UF(UF_2)$	1(1)	25879 (21742)	140.9 (104.0)	12.0 (10.0)
$US(US_2)$	1(1)	21381 (18829)	78.1 (57.4)	8.0 (7.0)
$AF(AF_2)$	1(1)	637 (510)	65.4 (51.1)	28.0 (23.0)
$AS(AS_2)$	1(1)	294 (265)	29.6 (24.0)	17.0 (14.5)

Table 2. Analysis of Tag Richness (= number of distinct tags) for different user models. Measures are provided for the TR vector containing the TR of each user for which the corresponding user model. User models based on tags from all users (UF,AF) are richer than those derived from the the user's tags (US,AS).

Amount and Richness of derived User Models

We define the Tag Richness of a user model as the number of distinct tags in a user model. The richer in tags a user model is, either the more specific the user interests are described or the more different interests a user has. Figure 1 shows the tag richness distribution for different user modeling construction methods, namely (UF and US) for folksonomy F as well as US for Folksonomy F_2. Data for author-based models is not visualized as they contain only a small amount of users. Table 2 presents the details about the tag richness for user models constructed by the four methods in more detail.

Impact of k on the amount of possible user models that can be constructed

The tag richness distribution follows a power-law distribution (independent on the user model construction method chosen), thus the number of users with a large amount of tags in their complete user model is rather small compared to the overall number of users. For 98 users, author-based models $AF(u)$ and $AF(u)$ can be constructed; if we set $k = 15$, there are only 71 users left for which $AF(u)$ and 51 for which $AS(u)$ can be constructed. In addition, it seems that users who manage their own publication in the tagging system by using the tag 'myown' show a higher TR, which might be the result of the fact that those users are in general more active taggers.

Impact of tag sharedness on the amount of possible user models that can be constructed

Using dataset F_2 instead of F decreases the number of possible user models that can be constructed as well as the tag richness of the user models. For example, if we apply restriction 2 to construct $UF(u)$, this reduces the number of user models from 6463 users to 6176 users.

$$TR(t) \geq 2 \forall t \in UF(u).tags. \quad (2)$$

Impact of single- vs. community-based user modeling method

User models based on tags from all users of the system (UF) and (AF) are richer in terms of tags than the user models derived from the user's personomy (US) or a subset of the personomy (AS). Ideally, if the view of a user u on the resources in $ULib(u)$ corresponds to the view of the community on these resources, the models $UF(u)$ and $US(u)$ would result in the same set of distinct tags and an equal tag ranking. But neither do all users have the same expertise and motivation for tagging, nor do users usually use the same tags for one and the same concept, thus the user models contain different (number of) tags. If the view of a user differs significantly from the view of the community, then the most appropriate user model for information retrieval or recommendation of new resources would be the a community-based one (either UF or AF), whilst for tag recommendation and navigation in one's own library, the most appropriate user model would be the personal one (either US or AS). If the author-based representation differs significantly from the user-based representation, then the user's expertise is best represented by the author-based one (e.g. for expertise search) and the user's interests might be best modeled by the user-based one (for personalized IR or recommendations).

Based on these observations we analyze in the following the similarity between between various possible models for one user and the correlation between similarity and resource sharedness.

Vocabulary Overlap in derived User Models

For one specific user, different user model construction methods lead to user models for this user which consist of a different amount of tags. E.g., comparing two models for one user, there might be additional tags in $UF(u).tags$ which are not contained in $US(u).tags$. Thus, in a next step we analyze the similarity between the different user model construction methods. As a comparison measure, we use the Vocabulary Overlap coefficient [17], which is for example for a user u and the two user-based models calculated as follows:

$$VOC(UF(u), US(u)) = \frac{|UF(u) \cap US(u)|}{min(|UF(u)|, |US(u)|)}, \quad (3)$$

where VOC takes a value in $[0, 1]$ and $VOC = 1.0$ means that all tags of the smaller set are contained in the larger set. Due to better readability, we wrote $UF(u)$ instead of $UF(u).tags$. We consider a VOC value in the range of $[0.8, 1]$ as a good indicator for similarity. We do not use more common set overlap metrics such as the Dice Coefficient because this or related metrics are sensitive to the relative size of the two sets of tag vocabularies; in addition, if a user model representation is of a fixed size k as it is the case when limiting a user model to the top-k most frequent tags, then the Dice coefficient is equal to VOC.

Clearly, for the pairs $(AS(u).tags, AF(u).tags)$, $(US(u).tags, UF(u).tags)$ and $(AS(u).tags, UF(u).tags)$ with no limitation to the top-k most frequent tags, VOC equals 1.0 as these are subsets of each other. The mean of the VOC for pairs $(AF(u).tags, US(u).tags)$ for all users u is 0.78 with a variance of 0.05 and a median of 0.84. This means that for half of the authors, at least 84% of the tags in $AF(u).tags$ are contained in $US(u).tags$, thus in general these two construction methods overlap quite well.

Figure 2 shows the VOC distribution for the folksonomies F as well as F_2 for various values of k, where k limits the user model to the top-k most frequent tags (and it also means that the initial user model has to contain at least k tags and thus, the less users exist for which this model can be constructed). The distributions do not change significantly for the two different folksonomies F and F_2. First, it can be seen, that the lower k is chosen, the more users exist for which the tag sets in e.g. $(UF(u).tags, US(u).tags)$ or in $(AF(u).tags, AS(u).tags)$ overlap; the higher k is chosen, the more 'specialized' the user models becomes (as more more users exist for which the possible user models for this specific user contain different tags). Second, in general it is clear that the more similar $UF(u)$ and $US(u)$ are, the more similar is the view of one person on his/her library to the view of the community on this set of resources. Based on the figure we can conclude that for 40-50% of users these two views show a good overlap (depending on the value chosen for k). It can be seen that the amount of users with a higher overlap between (UF) and (US) decreases the higher k is (and thus the more tags are in the user model). This means that for higher ranked tags the vocabulary overlap is larger than for lower ranked tags. In general, the tag vocabulary overlap is for a large number of users below 0.8.

Figure 3 shows the comparison of tag overlap between various combinations of user model construction methods for $k = 15$. As we compare with author models and the number of authors in our dataset is limited, the number of user models to compare is rather small. Nonetheless, it is obvious that the VOC distribution (with a coefficient between 0.4 an 1.0) seems rather uniform.

Tag Overlap between user-based and community-based User Models and Resource Sharedness

In the previous section, we have shown that depending on the k-value chosen for the profile construction, for about half of the users the personal tagging behavior matches the community tagging behavior quite well. For the rest, the community-based user models do not overlap very well with the personal

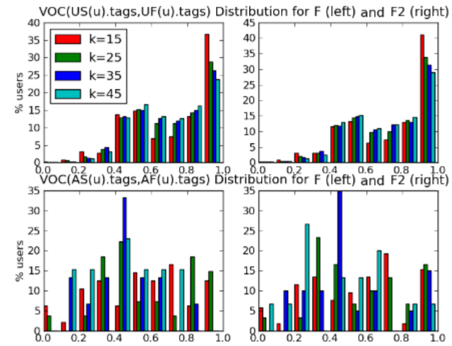

Figure 2. Tag vocabulary overlap distribution for (UF,US) in upper row and for (AF, AS) in lower row various values of k; Left column shows data for folksonomy F, right column for F_2 The x-axis shows the VOC value, the y-axis the % of users with this VOC. The higher k, the more less frequent tags are part of the user model.

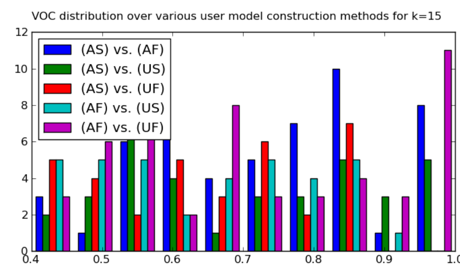

Figure 3. Tag vocabulary overlap comparison between various user models construction methods. The x-axis shows the VOC, the y-axis the amount of users. Note that the number of author models is limited, thus the amount of user models to compare is also rather small.

models. At this stage, the question arises whether there is a correlation between VOC and the overall resource sharedness $ORS(u)$ of a user. As the overall resource sharedness of a user u we define the average of the resource sharedness of the resources in a user's library; more precisely it is given by the following equation:

$$ORS(u) = \frac{\sum_{r \in ULib(u)} RS(r)}{|ULib(u)|} \tag{4}$$

where $RS(r)$ denotes the resource sharedness of resource r (see definitions in section). The correlation between $ORS(u)$ and $VOC(US(u), UF(u))$ provides an indication whether the divergence in community and personal profiles for some users emerge from the sharedness of resources. For folksonomy F the Spearman correlation has a value of -0.85 (p value 0.0) at $k = 25$ and -0.86 (p value 0.0) at $k = 45$. For F_2 the Spearman coefficient has a value of -0.82 (p value 0.0) at $k = 25$ and -0.81 (p value 0.0) at $k = 45$. Thus, there is a high negative correlation between the overall resource sharedness and the VOC of a user, the higher $ORS(u)$ the lower is the $VOC(US(u), UF(u))$ in our dataset. This means that the more resources a user shares with others, the more the community and personal profiles differ.

DISCUSSION AND FUTURE PLANS

In this work we presented a concise overview of possible user modeling methods for users, of which tag-frequency-based methods are the most common. We statistically analyzed two different versions, a community-based and single-user-based (personal) tag-frequency model and variations of those and showed that the more tags we require the user model to contain, the less user models can be constructed solely on tag annotations. For personalized IR, a rich and specific user model is preferred, thus for users with a low number of tags additional information is needed to construct a valid model. Author-based user modeling provides an alternative to library-based methods as it better reflects the expertise, whilst the user library itself might contain resources the user has tagged for different purposes; not many users provide this information in a STS. We showed that different tag-frequency-based user models for a user show a high tag overlap for about half or less of the users, but the % of users with a high VOC between community and personal models decreases the more tags a user model is required to contain. We also showed that the more resources a user shares with others, the more the community and personal profiles differ.

The derived empirical results are limited to a small-scale study, in which we wanted to find an indication if different popular user modeling construction methods lead to different user profiles (which in turn influences personalized services). These results, while not very surprising, are a first step towards a more focused work on comparing more sophisticated user models. The construction methods for comparison will includes not only tag-frequency based methods but also the graph-based, clustering-based or concept-based as presented in section . We will also expand our analysis to a larger datasets to compare author- and user-based profiles in more detail as well as enlarge the user model construction methods to more sophisticated ones: (a) as the user's interests change over time we want to take concept drift into account) and (b) as users tend to tag resources by opinion tags or use different tags to describe the same concept we want to apply preprocessing methods to filter out those tags that do not relate to topical interests and cluster those relating to the same topic.

The most important issue for future work is to test and experiment with the proposed user models in real tasks. We plan to apply the user models to a fixed set of algorithms for personalized search as well as user and item recommendations that uses theses user models. This should provide a clearer picture on the effects of the user models and its features on the selected personalization mechanisms.

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