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HSI’09

2nd International Conference on Human System Interaction

Catania, Italy, May 21-23, 2009

Proceedings

Edited by Lucia Lo Bello and Giancarlo Iannizzotto

IEEE Catalog Number: CFP0921D-USB
ISBN: 978-1-4244-3960-7
Library of Congress: 2009900916

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Modeling a publication sharing system 2.0

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Abstract — **Current publication sharing systems inherit from the Web 2.0 philosophy the idea that users can add reusable information to support other peers, enabling them to insert new resources and to tag the existing ones; but, in their current form, these systems suffer of some limitations, such as the lack of tools for supporting users during the creation and organization of their personal concept spaces, and the poor utilization of tags as information sources for producing personalized recommendations.**
In this paper we propose a model for organizing dynamic and customizable concept spaces, based on innovative structures, and we introduce a mechanism for recommendation, based on tags and mainly on the way in which users connect resources in their concept spaces. Adaptive recommendations are generated analyzing the users' concept spaces, and evaluating the similarities among them in order to reveal the similarity among their goals and perspectives.

Keywords — **Publication sharing systems, personal concept spaces, recommender systems, zigzag structures.**

I.INTRODUCTION

As digital libraries become a commonplace for finding new useful information, their users become more sophisticated and need new intelligent services, able to improve the usage of these environments: users require quick and personalized responses, and wish to avoid boring searches over increasing and heterogeneous collections of resources.
Traditional digital libraries support the user searches sorting the resources on the basis of some not-adaptive methodologies [1]; so, they manage in the same way queries created from different users and do not consider that different users have different goals, interests and needs [2]. This approach frustrates the users, forced to try many different combinations of keywords for finding the desired documents.
In order to tackle these issues, a class of systems, known as *recommender systems* [3], model the users, compare their profiles to some reference features, seek to predict the rating that they would give to a resource they had not yet considered, and offer personalized suggestions.
More specifically, *collaborative filtering* is indicated as the process of filtering or evaluating items through the opinions of other people [4]. Collaborative filtering methodologies are based on the idea that users with similar interests and needs express similar preferences about the same resources; following this idea, a recommendation engine can predict if a user will like or dislike a specific document considering the opinions expressed by similar users, technically known as *neighbours*. For this reason, these systems store information about users' interactions in order to understand their preferences, compare them and find good neighbours.
Recommender systems help users to detect useful resources in large repositories, and in particular, collaborative recommender systems work well when there are a lot of users, since they need to consider an appropriate set of people to calculate effective suggestions.
Only recently, in the area of recommender systems an important role is played by tags; using a tag, the users express a subjective and free description of a resource, based on their sense of values [5]; a tag represents a potential mean for deriving personalized recommendations, since, by means of it, it becomes possible to establish a sort of affinity among a user and a group of other (unknown) users.

The studies on the users' tagging activity are still in their initial phase; some open issues need attention:

1. User concept spaces are flat and static.
   Several Web 2.0 applications, such as bookmarking (like del.ici.ous [6]) or publication sharing systems (like Bibsonomy [7], CiteSeer [8] , CiteULike [9] or Connotea [10]) enable user to tag resources, but they weakly support creation and personalization of customized user concept spaces [11], in which the user can organize his/her resources, receive support for search, and take effective advantage of the shared use of tagging. Generally, user concept spaces are poorly structured and show static views on resources.

2. Using tags for personalized recommendation is still an open challenge.
   Although many social networks store and make (partially) available a huge amount of tags, the use of these tags for personalized suggestions is still difficult and there is not a reference model to apply: often different users assign different meaning to the same tag and, moreover, they have different goals in mind when tag-

ging.

In this work, we focus our attention of both these aspects, proposing, in our publication sharing system, called SharingPapers,

- a dynamic and customizable way to organize the user concept space, using graph-based structures, the zz-structures [12];
- a mechanism for recommendation, based on tags and mainly on the way in which users connect resources in their concept spaces. Adaptive recommendations are generated analyzing the user's concept space, and evaluating the similarities among them in order to reveal the similarity among goals and perspectives.

The paper is organized as follows: in Section II we discuss related work. In Section III we describe the general architecture of SharingPapers; then, we deepen the discussion about the organization of user concept spaces in Section IV, and we propose our recommendation mechanism in Section V. Finally, Section VI concludes the paper.

II. Related Work

The amount of the available documents on the Web, and in particular the growth of publication sharing systems, highlights the importance of a personalized access in order to grant an effective information retrieval and usage.

Collaborative [4], content [13] and hybrid [14] recommendation systems are implemented for improving Web searches over scientific information bases. For example, a collaborative recommendation engine is described in [15] where a modified version of the Expectation Maximization algorithm is used for calculating the expected users' rating for the unseen items considering their past ratings; in [16], the authors propose a content-based recommender system that represents user profiles as trees of concepts and applies an algorithm for computing similarity between the user and document profiles using a tree distance measure; in [17], the authors present a hybrid recommender system; they use a content based algorithm, based on the cosine similarity measure, and a collaborative filtering algorithm, that uses the traditional K-nearest neighbours approach, for generating recommendations in scientific digital libraries starting from a list of citations.

These strategies improve Web usage by filtering available resources in accordance with a set of features extracted from the user behavior. Nevertheless, they model users as a *passive* entity able only to consume the available contents; in fact, in order to model the users, these frameworks consider only the set of resources that users *visited* or *rated* .

But, in new Web 2.0 philosophy, users became *prosumers*, because they can both consume and produce information adding, for example, tags, annotations, reviews, comments.

These changes offer great opportunities for a new generation of digital libraries, known as digital libraries 2.0, providing people with new ways to communicate, interact, acquire and share knowledge, search, investigate, and participate in the creation and re-mixing of new content [18].

User attitude for knowledge construction is recognized in current publication sharing systems, like Bibsonomy [7], CiteSeer [8] or CiteULike [9]; in fact, they provide users with tools for tagging documents.

Tags can help users to organize resources or retrieve previously visited documents, but they can also reveal existing communities, groups with common interests, or show similarities among different users. Using the tagging activity provided by the users in Web 2.0 systems, a recommendation system can produce customized suggestions, although it needs to take into account that tags are often applied only for a personal consumption and that folksonomies donot use controlled vocabularies [19].

An attempt to use tagging for improving resource discovery has been proposed in [20], where an interesting variation of the PageRank algorithm is used for ranking resources, tags and users in a folksonomy. The algorithm, named FolkRank, incorporates the idea that a node is important if there are many edges from other important nodes pointing to it, and applies this principle to the tripartite graph representing the folksonomy. The FolkRank algorithm is then used to assign a non-adaptive score to users, tags, and resources.

An adaptive recommendation framework based on a hierarchical clustering of tags is presented in [21]. This framework models user interests considering the most accessed clusters of tags in order to recommend documents close to these clusters. Users' tagging behavior is also considered in the approach defined in [22], in which the authors measure the users' similarity considering their past tagging activity and inferring relationships among tags; but, in this way, they throw away information about resources, keeping only information about what tags a user has used and how often.

In [23], the initial set of resources (that collaborative recommendation frameworks have to consider in order to enhance the accuracy of their prediction) is filtered using tags; the authors underlie that traditional collaborative filtering engines work well when all resources belong to the same domain.

However, if there are more domains, two users that have similar preferences in a specific domain, may be very different in another one or they may have other different domain of interests.

III. SharingPapers

SharingPapers presents an agent-based architecture shown in Figure 1.

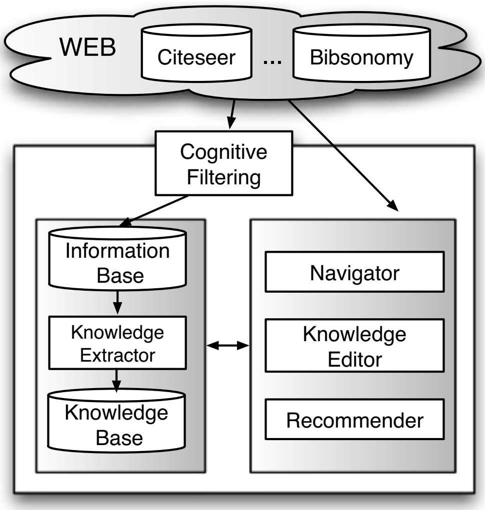

Fig. 1: System architecture.

The main modules are:

- The *Cognitive Filtering* module uses the IFT algorithm [24] [25] and specialized agents for browsing and accessing a set of external sources (such as Web sites and digital libraries), looking for relevant documents.
  The filtering operation is performed according to a set of defined information needs and populates the *Information Base*.
- The *Knowledge Extractor* module is specialized in extracting, from documents present in the Information Base, attributes (such as the title of a paper, its authors, its year of publication) and relations (such as the network constituted by co-authors, or by people having a same affiliation, etc.), in order to populate the *Knowledge Base*: it is used to store the entities constituting the data-structure layer and the relations among them; these relations are defined or automatically or by users' interaction with the system. More specifically the Knowledge Base stores the users' concept space, containing both the network of documents and the social network related to the specific user. A detailed description of this module is proposed in next Section IV.
- The *Navigator* module provides views on the Knowledge Base, enabling users to navigate among documents and social networks. Examples of views have been proposed in [26].
- The *Knowledge Editor* module implements the features users can invoke in order to manually modify and re-arrange their personal spaces, defined as concept space (see definition in Section IV); more specifically, each agent keeps track of the interaction of each user and translates performed actions into a set of operations on his/her concept space: users can create new entities, add them to their concept spaces, or connect them with existing entities.
- The *Recommender* module suggests tags, recommends to visit parts of concept spaces (belonging to other users) and calculates personalized rankings on papers. The recommendation model is described in the Section V.

IV. Organizing the knowledge base

In our system, users are represented by their *concept space*, which contains a collection of *papers* and a *social network*.
Papers are connected in an innovative structure by links (indicating, for example, common keywords or tags), while the social network is constituted by users sharing interests and/or contents. A user concept space presents a dynamic structure, evolving in accordance to the user behavior (new searches, adding-deleting new contents or tags, etc.).

The **concept space** (Map) related to the user u is formally defined by the agent $M_u = (S_u, En_u, Re_u, Ac_u)$ where:

- S_u represents its *topological structure*;
- $En_u = \{\eta_{1_u}, \eta_{2_u}, \ldots\}$ defines its local *environment*;
- $Re_u = \{\rho_{1_u}, \rho_{2_u}, \ldots\}$ is the finite set of incoming *requests*;
- $Ac_u = \{\alpha_{1_u}, \alpha_{2_u}, \ldots\}$ is the discrete, finite set of possible *actions*.

S_u and En_u represent the passive part of the agent, while Re_u and Ac_u its active part. In particular, $S_u = (MG_u, T_u, t)$ is a zz-structure, an *edge-colored multigraph*, where

- $MG_u = (V_u, E_u, f)$[1] is a multigraph;
- T_u is a set of colors (T refers to Tag);

1 Multigraph definition: $MG_u = (V_u, E_u, f)$ is a multigraph composed of a set of *vertices* V_u, a set of *edges* E_u and a surjective function $f : E_u \to \{\{v, v'\} \mid v, v' \in V_u, v \neq v'\}$.

- $t : E_u \rightarrow T_u$ is an assignment of colors (tags) to edges of the multigraph;

- $\forall x \in V_u,\ \forall k = 1, 2, ..., |T_u|,\ deg^k(x) = 0, 1, 2^2$.

The set of vertices is $V_u = \{P_u, U_u\}$, where P_u is the collection of papers of the user u, while U_u the set of users connected to u.
Interested readers will find a deeper discussion about zz-structures in [12], [11], and [26].
In Figure 2 is shown a graphical example of a generic M_u.

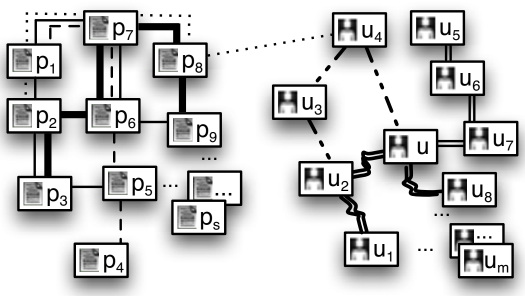

Fig. 2: An example of user concept space.

$P_u = \{p_1, \ldots, p_s\}$ contains papers of interest for u, while $U_u = \{u, u_1, \ldots, u_m\}$ contains his/her social network; 7 different colors-tags (identified with different types of line style - normal, thick, dashed, double, etc.) are associated to the edges. Each tag identifies a link among vertices; for example, the tag (dashed line) connecting p_1, p_7, p_6, p_5, p_4 represents papers sharing a same topic; the tag (double line) connecting u, u_7, u_6, u_5 indicates co-authors of one or more papers; the tag (dashed-dotted line) connecting users u, u_4, u_3, u_2 groups members of the same research group; the tag (dotted line) connecting users and papers in u_4, p_8, p_7, p_1, p_2 identifies the author and a set of his/her papers.
For each color t_k, we can isolate a specific sub-graph of M_u, constituted by the set of vertices V_u and edges $E_u^k \subseteq E_u$, containing edges of the unique color t_k.
Each sub-graph of M_u is called *dimension* of color t_k and is denoted by D_u^k. Formally, a dimension $D_u^k = (V_u, E_u^k, f, \{t_k\}, t_u)$, with $k = 1, ..., |T_u|$, is a graph such that (1) $E_u^k \neq \emptyset$; (2) $\forall x \in V_u, deg_u^k(x) = 0, 1, 2$.
Using dimensions, the topological structure of M_u can be seen as $S_u = \bigcup_{k=1}^{|T_u|} D_u^k$. In this way, a dimension is defined in terms of one or more connected components. For example, four connected components, present in M_u, are shown in Figure 3.

2 $deg^k(x)$ denotes the degree (that is, the number of edges incident to x) of color t_k.

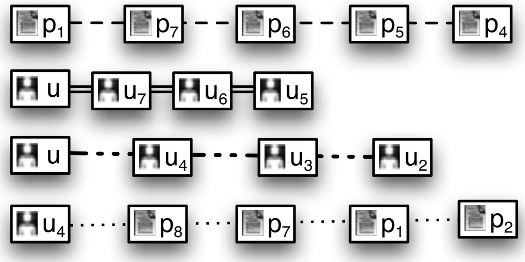

Fig. 3: Four dimensions of the previous concept space.

When the user enters in the system for first time, his/her concept space is automatically initialized by a set of dimensions. Papers that the user wrote, cited or tagged are imported in specific dimensions, as well as the papers presented in the events (conferences, journal, workshop) that (s)he attended. Similarly, co-authors and other people involved in the user research activity are also imported in the social network considering common publications, events and organizations. As second step, users can invoke the Knowledge Editor in order to manually modify and rearrange their concept space. In this way, users can create new entities, add them to their concept spaces or connect them with existing entities. The concept space represents and models the user, and evolves in function of his/her interaction with the system. Each dimension groups the resources labelled by the same tag and specifies a user interest, while sets of dimensions are used to identify his/her goals and perspectives. Specialized classes of agents manage the user model and propose personalized recommendations, as described in the next Section V.

V. Recommendations in SharingPapers

An important feature of the zz-structures is the intrinsic simplicity to contextualize information and to retrieve all documents and info related to a given resource, starting from the resource itself. On this feature is based our collaborative approach for recommendation: starting from the set of tags (that is, dimensions) that identify the current user's interests, we apply the following four steps process:

Step 1: expanding the set of tags for similarity;

Step 2: comparing the collections of documents, associated to the set of tags;

Step 3: ordering similar collections, assigning them a score of similarity;

Step 4: ordering similar papers, assigning them a score of similarity.

Each step enables the system to provide intermediate specific types of recommendation:

- Step 1 provides new tags for selected resources;
- Step 2 provides new similar users;
- Step 3 provides new collections of resources;
- Step 4 provides new specific resources.

In order to simplify our discussion, we identify the paper p as focus of attention for a user u and all the dimensions, contained in M_u, in which p appears; specifically $D_u^{1,\ldots,n}$ $=D_u^1 \cup D_u^2 \cup \ldots \cup D_u^n$.
Following the example shown in Figure 2 , if the focus of attention of the user is paper p_6, the recommender module considers the three dimensions, associated dimensions to it: $D_u^{1,2,3} = D_u^1 \cup D_u^2 \cup D_u^3$ (see Figure 4).

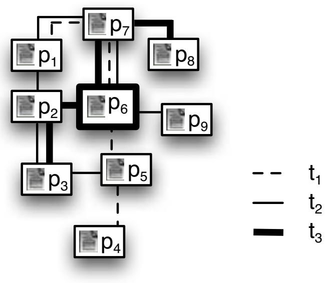

Fig. 4: The focus paper p_6 and the associated dimensions.

The recommender module uses these dimensions as the starting point to execute the four step process, described below step by step.

1. *Step 1: expanding the set of similar tags*. In order to obtain a high recall, we are interested to find tags similar to the starting tags; for this reason, we apply a non-adaptive algorithm for estimating tag similarity, which considers the frequency of association of a specific tag to a given paper.
   This step considers two tags as similar if several users applied them on the same resources, considering that, due to the lack of control during the process of tagging, different users could apply different tags for indicating the same feature.
   Let $w^k(p)$ be the number of times that the tag t_k has been associated to the paper p from all the users of the system:
   $$w^k(p) = \sum_{u' \in U} w_{u'}^k(p)$$
   where
   $$w_{u'}^k(p) = \begin{cases} 1 & \text{if } deg_{u'}^k(p) \neq 0 \\ 0 & \text{otherwise} \end{cases}$$
   $w^k(p)$ is expressed in terms of the number of times that t_k has been associated to the paper p from each generic user u' (that is, $w_{u'}^k(p)$) ; in particular, $deg_{u'}^k(p) \neq 0$ indicates that the paper p has been tagged with t_k in the concept space of user u'.
   In this way, for each generic tag t_j, we can build the vector $\bar{w}^j = (w^j(p_1), \ldots, w^j(p_N))$, if $\{p_1, \ldots, p_N\}$ is the set of all the considered papers. We use this vector for measuring the similarity between a chosen tag t_k, and another generic tag t_j, applying the cosine similarity:
   $$tag\_sim(t_k, t_j) = cos(\bar{w}^k, \bar{w}^j) = \frac{\bar{w}^k \cdot \bar{w}^j}{\|\bar{w}^k\| * \|\bar{w}^j\|}$$
   This metric assigns a similarity score to a couple of tags; but, the focus paper p could be tagged by a set of tags (referring to the example of Figure 4, the set of tags associated to p_6 is $\{t_1, t_2, t_3\}$). Each tag, associated by a user to a paper, is representative of a interest. The system can suggest to refine a query or to apply new labels to a specific resource adding one or more tags detected in this step. For this reason, we calculate the degree of similarity between the set of tags associated to a paper p, that is $T_{1,\ldots,n} = \{t_1, \ldots, t_n\}$, and the tag t_j applying the average of the previous scores:
   $$tag\_sim(T_{1,\ldots,n}, t_j) = \frac{1}{n} \sum_{i=1}^{n} tag\_sim(t_i, t_j)$$
   Selecting the top scored tags, we extend the initial set of tags, generating $T_{1,\ldots,n}^+$.
   In our example, we assume that the set of tags (similar to $\{t_1, t_2, t_3\}$) is $\{t_4, t_5, t_6\}$; in this way, $T_{1,2,3}^+ = \{t_1,$ $t_2, t_3, t_4, t_5, t_6\}$
2. *Step 2: comparing user dimensions*. As second step we compare the dimensions labelled by the extended set of tags, evaluating the number of resources that they share; in fact, as known from standard collaborative techniques [4], if two users share a lot of resources (in our system, if their concept spaces contain a common set of resources), there is a greater probability that they have a common information request.
   The Jaccard similarity coefficient is applied as user similarity metric, $\forall t_j \in T_{1,\ldots,n}^+$ and $\forall u' \in U$:
   $$user\_sim(D_u^{1,\ldots,n}, D_{u'}^j) = \frac{\left|V_u^{1,\ldots,n} \cap V_{u'}^j\right|}{\left|V_u^{1,\ldots,n} \cup V_{u'}^j\right|}$$
   where $V_u^{1,\ldots,n} = \left\{V_u^1 \cup \ldots \cup V_u^n\right\}$.
   This metric compares the initial dimensions $D_u^{1,\ldots,n}$, contained in M_u with the dimensions of other users and assigns them a score of similarity.

The set of all the users having in their concept space at least one of the dimensions, identified by a tag included in the set $T^+_{1,\ldots,n}$, is indicated with $U^+_{1,\ldots,n}$, while the set of papers included in these dimensions is indicated with $V^+_{1,\ldots,n}$. Finally, for each user, we indicate with $T^-_{u'} = T^+_{1,\ldots,n} \cap T_{u'}$ the set of tags that (s)he shares with $T^+_{1,\ldots,n}$.

Referring to our example, the initial set of dimensions is $D_u^{1,2,3}$, as shown in Figure 5.

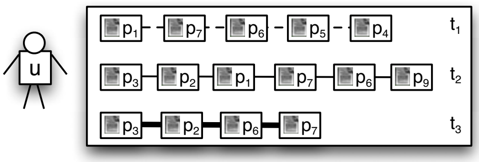

Fig. 5: The user u and his/her $D_u^{1,2,3}$.

Since the extended set of tags is $T^+_{1,2,3} = \{t_1, t_2, t_3, t_4, t_5, t_6\}$, we extract from the concept space of other users all the dimensions identified by these tags. In Figure 6, we show only a simplified case, involving two users u_2 and u_3.

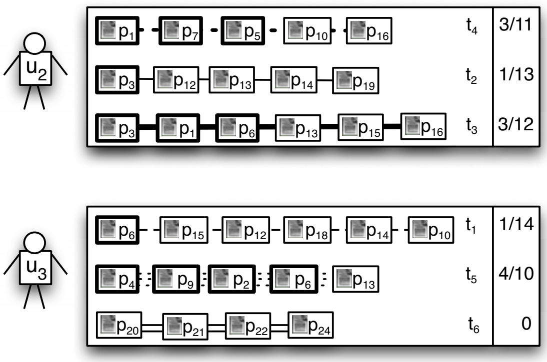

Fig. 6: The users u_2 and u_3 share with u some tags in $T^+_{1,2,3}$.

From the concept space of the user u_2, we extract three dimensions $D_{u_2}^{2,3,4}$, related to the tags t_2, t_3 and t_4. These dimensions share with $D_u^{1,2,3}$ respectively 3 papers (p_1, p_7, p_5), 1 paper (p_3) and 3 papers (p_3, p_1 and p_6). Shared papers are highlighted in Figure 6 using a bold line border.

The $user\_sim$ metric has been applied on $D^2_{u_2}$, $D^3_{u_2}$ and on $D^4_{u_2}$, producing the scores shown in Figure 6, on the right: in particular,
- $user\_sim(D_u^{1,2,3}, D^2_{u_2}) = 3/11$;
- $user\_sim(D_u^{1,2,3}, D^3_{u_2}) = 1/13$;
- $user\_sim(D_u^{1,2,3}, D^4_{u_2}) = 3/12$.

Similar results are shown for user u_3 in the same Figure 6.

Analogously, we calculates the similarity values for the dimensions $D^1_{u_3}$, $D^4_{u_3}$ and $D^5_{u_3}$. The similarity value grows in accordance to the number of shared resources. In fact, if two dimensions share a lot of resources then there is a greater probability that they respond to a common informative need.
In this way we can suggest to the user u, similar to him/her for behavior (tagging activity) and interests (number of papers in common).

3. *Step 3: ordering dimensions*. For obtaining an ordering, which considers both tag and user similarities, we define, $\forall t_j \in T^+_{1,\ldots,n}$, $\forall u' \in U^+_{1,\ldots,n}$, the following metric:

$$score_u(t_j, u') = tag\_sim(T_{1,\ldots,n}, t_j)*$$
$$*(user\_sim(D_u^{1,\ldots,n}, D^j_{u'})) + 1)$$

In this way we take in account the tag similarity and the number of shared resources for understanding the relevance of extracted dimensions. This value can be used for suggesting, to the user u, personalized navigation paths on dimensions defined from other users.
For example, referring to Figure 6, if we suppose that:
- $tag\_sim(T_{1,2,3}, t_4) = 0,7$
- $tag\_sim(T_{1,2,3}, t_5) = 0,6$,
since
- $user\_sim(D_u^{1,2,3}, D^4_{u_2}) = 3/11$
- $user\_sim(D_u^{1,2,3}, D^5_{u_3}) = 2/5$,
then
- $score_u(t_4, u_2) = 0,75$;
- $score_u(t_5, u_3) = 0,84$.
This result is coherent with the idea that the dimensions that share a major number of resources in the user concept spaces acquire a major score. In this case, the system can suggest to the user u to visit the dimension $D^5_{u_3}$.

4. *Step 4: ordering papers*. Finally, for each paper p *in* $V^+_{1,\ldots,n}$, we associate the score:

$$score_u(p) = \sum_{t_j, u'} score_u(t_j, u')$$

where $t_j \in T^-_{u'}$ and $u' \in U^+_{1,\ldots,n}$.
This score represents a global value to measure the relevance of a paper for a given user, comparing his/her concept space with the concept space of the other users.
Top scored resources are suggested to the user u.

VI. Conclusion

In the new Web 2.0 world users become an important source of information. They, not only, consume available documents, but they can also comment resources by tags or create new contents, such as documents or news published in blogs and forums. Current publication sharing systems recognize the users' attitude for knowledge construction allowing users to build personal collection and to attach tags to resources, but they do not offer tools able to support an effective information organization and access. Moreover, tags are an interesting source of information for improving the usage of large repositories such as publication sharing systems, for example, providing personalized recommender mechanisms.

In fact, tags incorporate useful information about social classification behaviour, which is not considered in traditional recommender systems that model users only as passive entities able to consume available contents. For these reasons, in this paper we propose a publication sharing systems able to support users in an effective way during the process of information classification and knowledge construction, allowing users to organize own concept spaces avoiding their tipical flat organization. Moreover, observing users concept spaces, the system support users by personalized recommendation reducing the effort required in order retrieve and access documents connected to their personal interests. The implementation of the proposed system is currently ongoing and experimental evaluation is planned for the next future.

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