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Towards a User Model for Personalized Recommendations in Work-Integrated Learning: A Report on an Experimental Study with a Collaborative Tagging System

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Abstract

The informal setting of learning at work give rise for unique challenges to the field of technology enhanced learning systems. Personalized recommendations taking into account the current context of the individual knowledge worker are a powerful approach to overcome those challenges and effectively support the knowledge workers to meet their individual information needs. Basis for these recommendations to adopt to the current context of a knowledge worker can be provided by user models which reflects the topics knowledge workers are dealing with and their corresponding knowledge levels, but research has only focused on user modeling in settings with a static underlying domain model so far. We suggest to model the users' context based on the emergent topics they are dealing with and their individual current knowledge levels within these topics by extracting the necessary information from the user's past activities within the system. Based on data from an experiment with students learning a new topic with the help of a collaborative tagging system, we started to evaluate this approach and report on first results.
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1. Introduction

Within the last decade, there is an increasing interest in the research community to study technology enhanced learning not only in formal settings, e.g. students trying to achieve a deeper knowledge to pass a university course by using an intelligent tutoring system, but also in informal settings, e.g. learning at work, where learning is directly integrated into the daily routines and processes of a knowledge worker. Learning at work takes mainly place as a by-product of work processes and practices rather than as a result of explicit learning actions the knowledge worker performs [1]. This concept of seamlessly integrated working and learning is described by [2] as work-integrated learning (WIL) and makes great demands on the designers and developers of systems supporting knowledge workers at their workplaces as compared to traditional learning systems: WIL requires learning support (1) during work task execution and tightly contextualized to the work context (2) within the work environment and (3) utilizes knowledge

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artefacts available within the organizational memory for learning. Furthermore, knowledge workers need to compensate with information overload and time pressure for finding relevant information to meet their current information needs.

Therefore, intelligent automated support for individual knowledge workers is needed to capture the challenges in work-integrated learning. An appropriate approach for automated support is for example in form of personalized recommendations which take into account the users' context. If for example the users experience a certain information need, the context to support information retrieval can be given by the topics they are currently dealing with or their individual knowledge levels within these topics. Personalized recommendations, adapted to the current context of the users, are a powerful tool for supporting the knowledge workers during their work processes to meet their needs and requirements. [3] identified a representation of the users (a user model) in terms of their interests and skills as one of the main aspects for providing personalization in work-integrated learning.

The purpose of the paper at hand is to to suggest a user modeling approach for representing the users context in terms of their topics of interest and corresponding knowledge levels which is based on naturally occurring events within the work-integrated learning system. This user model can then be used to provide personalized recommendation to support work-integrated learning in various dimensions. Our suggestion for a user model is based on and extends the approach of [4]. In this approach a user model is designed by interpreting usage data from the system in the context of enterprise models and utilize heuristics to determine user specific knowledge levels for topics available in a static knowledge domain model. We are looking for an approach to extend this user model for being able to apply it to a more dynamic setting, where the topics are not static, rather emerge during usage of the system.

As a first step towards modeling the users profile in dynamic, adaptive WIL systems, we have chosen to use a collaborative tagging system, a system which shows highly dynamic user behavior and emerging topics of interest. Collaborative tagging describes the process by which many users add freely chosen keywords (tags) to shared content (such as webpages, photos, ...) and in the last years, collaborative tagging systems emerged as a popular tool supporting knowledge workers such as researchers or students in managing their own resources and finding relevant material based on keywords assigned to them. We report on the analysis of a dataset from a collaborative tagging system as a test bed for our user modeling approach to find out (a) if and how users change their activities over time in these dynamic systems and (b) try to investigate whether specific activities provide good indications for being able to determine the knowledge level of users related to specific topics.

In the following, we will clarify our understanding and the special needs of personalization for work-integrated learning as compared to traditional areas for personalization and personalized recommendations. We will then present in more detail examples of user modeling approaches and report in detail about the experimental study to analyze our ideas for unobtrusive user modeling in WIL within a dynamic setting of collaborative tagging. Finally, we discuss implications of our results for designing personalized recommendations based on our model and present an outlook for further research directions.

2. Personalization for Work-Integrated Learning

The terms personalization and personalized recommendations have mainly been coined in two different research areas: First, personalization in the web; typical examples here are personalized recommendation in portals for e-commerce (for example [5]) or personalized information retrieval in search engines (for example [6]). And second, in technology enhanced learning; typical examples here are personalization in adaptive hypermedia (for example [7]) or personalized recommendations in intelligent tutoring systems. Both approaches have in common that the systems often maintain a user model to enable personalization. In e-commerce or for search, previous user activities and their preferences (e.g.. What products did a user buy? What information needs does a user have?) are analyzed to infer a user model unobtrusively, in traditional technology enhanced learning systems student or learner models are generated based on explicit assessments to derive the user's knowledge state for personalization of the system.

In our view, personalization for WIL based on user modeling combines the best of the two traditional approaches for personalization to fit the needs of knowledge workers during their daily tasks. Personalization should be an adaptation of the system towards individual knowledge workers and their current context. Implicit user modeling is preferable as testing, assessments or explicit feedback about interests or preferences is not very suitable in WIL. For effective knowledge work, recommendations and information provided to the user should also be based on the

knowledge a user already has about a certain topic (experts might have different information needs for a certain topic as compared to a novice) and thus, the user model should also incorporate knowledge diagnosis. Personalized recommendations for WIL can not only be useful for recommendations of suitable resources to meet the individual information needs of knowledge workers but also for example to recommend knowledgeable people for certain topics if someone is seeking explicit help or to ask for performing a specific activity.

3. Examples of User Modeling Approaches to represent the User's Context for Personalized Recommendations in Work-Integrated Learning

In the field of work-integrated learning systems, an approach for unobtrusive user modeling based on topic-specific individual knowledge levels has already been developed in APOSDLE [4], where the individual knowledge levels (novice, advanced, expert) for topics within the domain ontology were extracted by analyzing so called Knowledge-Indicating Events (KIE). KIE refer to user activities which indicate that the user has knowledge about a certain topic or a certain skill, e.g. being asked for help about a certain topic versus to ask for help about a certain topic are contrary actions performed by persons supposed to be knowledgeable versus being a novice in this area. Furthermore, activities indicating that a user has knowledge about a certain topic in APOSDLE are of general nature, relating to a range of possible actions that are available in a system specifically designed to support learning at work. Examples for those actions are 'Contacting A Person', 'Selecting A Learning Goal', 'Performing A Task', 'Getting Learning Hints For A Topic'. This approach is especially interesting, as it does not depend on explicit feedback from the users (e.g.. testing their knowledge levels for certain topics) to model their profiles. Explicit feedback is highly obtrusive, it would even prevent the knowledge workers from performing their tasks effectively and thus are not appropriate for informal settings such as systems for work-integrated learning.

As we apply our user modeling approach prototypically to the dynamic setting of collaborative tagging systems, is is also interesting to investigate user modeling and detecting knowledgeable users (experts) not only in the context of work-integrated learning systems but also to the general area of these kind of emergent systems. User modeling itself has already has a long tradition, but has not not been explicitly and extensively tackled in the field of collaborative tagging yet. [8] for example tried to investigate how user tags can affect user modeling and [9] researched user models based on tagging data for personalization in tagging systems. User models based on emergent semantics are often developed implicitly for tag or resource recommendation in those systems, for example in [10] or for studying the intent behind tagging, [11] analyzed personomies (as a result of individual tagging versus folksonomies as a result from collaborative tagging) to classify the individual users based on their tagging behavior and [12] studied user profile generation from personomies for recommendation of webpages by identifying the user's multiple interests. In order to support knowledge workers with adequate information based on their context (current information need and individual knowledge level), our main intent is not only to detect the user's interests, but also their individual knowledge level (level of expertise varying from novice, e.g.. someone that has just started to research a certain topic, to expert, e.g.. someone that has extensively studied the topic in question). In collaborative tagging systems, some work is also available which tries to measure not only interest, but also the user's overall expertise in a global setting ([13], [14]) and in an enterprise setting [15].

4. A Report on First Results

Collaborative tagging systems are becoming more and more popular, not only for the web community but also for our daily knowledge work, such that these systems provide an interesting area for research in WIL: They can support the knowledge workers to effectively organize, share and retrieve information, for individual but also for collaborative purposes and have already been applied in several enterprise systems and used in organizational settings for different purposes, examples are [16], [17] for knowledge management and sharing or [18] and [19] for social networking and competence management.

The assumption in the following is, that the users are using those systems in their daily work for example to retrieve, store and manage knowledge artifacts or to keep and maintain a common lightweight ontology of tags/concepts or competencies. Using the KIE approach presented in section 3 within systems knowledge workers are usually dealing with, enable user modeling unobtrusively: It is based solely on the activities of the users within those systems and no explicit user interaction is needed to infer the user's interests and topic-specific knowledge levels.

The application of the KIE approach to model individual knowledge levels includes the need for analysis of the mapping between possible KIEs and knowledge levels (e.g.. Do some KIE occur more frequently for persons assumed to be an expert or for persons assumed to be rather an expert?). KIE and the mapping to different levels of knowledge (expertise) need to be adapted to the activities that are relevant in the context of the specific collaborative tagging system with the goal of fulfilling the needs of knowledge workers. [4] suggest a simple heuristic to implement the KIE approach into a software system for evaluation and analysis purposes. Therefore, we were interested to analyze two different hypothesis: Firstly, we assume that users change their behavior within the system the more familiar they become with a topic and secondly, we assume that certain activities within the system give indications for different knowledge levels that can be mapped with an explicit measure of the 'real' knowledge level of a user.

For this study we used log-data that was collected by [20] who researched the Basic Level Effect in Collaborative Tagging. In their experiment groups of students collected and structured web resources to gain knowledge about a certain topic with the help of a social semantic bookmarking system. After the end of the course, the students performed association tests, where they were presented tags from their corresponding tag space and were asked to write down associations. We assume at that point, that the number of associations provides a relation to the real knowledge level of a user.

In the following, we first present the experimental setting from which we gained the log-data and present overall characteristics of activities within the system and finally report on results of the analysis of the two mentioned hypothesis to answer our research questions mentioned in the introduction: (a) that users change their types of activities over time in these dynamic systems as a result of more experience with a certain topic and (b) that specific activities can provide indications to determine the 'real' knowledge level of users related to specific topics.

4.1. Experimental Setting

The log-data used for evaluation are the result of an experiment, which took place in the context of a university course on cognitive models in technology enhanced learning at the University of Graz. Psychology students (N=25, mean age M=23.3, SD=1.2) collaboratively collected bookmarks related to their course subject and described them with tags within a Social Semantic Bookmarking system (SOBOLEO, [21]). The main difference between this social semantic bookmarking system and collaborative tagging systems in general is that the users do not only add tags to resources for later retrieval and sharing but they also collaboratively develop a semantic structure of the tags and their concepts they used. The main benefit is that this help to overcome the problems that typically arise by using only user created tags. In SOBOLEO, the tags and the lightweight semantic structure that is collaboratively created are shared by all users of the system.

Two groups of students had to work on a topic for the whole duration of the semester (4 months; referred to ld groups in the following), the other two groups switched their topic at half time (2 months; referred to sd groups in the following). Two groups of students were asked to research the topic 'the use of Wikis in enterprises', the other two groups 'the use of Weblogs in universities'. They were asked to prepare these topics as if they were collaboratively working on a report of presentation. Both topics were chosen because they were related to the course subject and because we expected the participants to have only little prior knowledge about them. During the whole duration of the study (ten weeks) each student was expected to post two relevant bookmarks per week to the SOBOLEO environment and describe them with meaningful tags. The students were also required to collaboratively organize their tag collection with the help of the SOBOLEO taxonomy editor. To facilitate the emergence of consensus, the students were also encouraged to utilize the chat provided by the tagging system and an external discussion forum.At the end of the semester, an association test was conducted which elicits implicit knowledge about concepts underlying verbal representations. Therefore, the users were presented 19 concepts/topics from their corresponding SOBOLEO system as stimulus words and were asked to write down all associations coming to their mind. Response time was confined to 30 seconds. By counting the number of associations, the test informs about the strength of representation of concepts in memory. For a more detailed description of the methods, we want to refer the reader to [20].

The authors of the study report the following results, contrary to their hypothesis: the sd groups developed a taxonomic structure with which they felt more comfortable, the students in this group developed a stronger internal representation of the topic and the underlying knowledge domain and finally developed a better common understanding of the topic.

4.2. Results

In this section we report on the results of an analysis of a dataset from a collaborative tagging system from the experiment described in section 4.1. This data resulted from groups of students using four different instances of the SOBOLEO systems, in the following referred as SOBOLEO Instances SI1 - SI4. Our intention with this work was to find out (a) if and how users change their activities over time in these dynamic systems and (b) try to investigate whether specific activities provide good indications for being able to determine the knowledge level of users related to specific topics.

Table 1 gives an overview of the general statistics and number of activities available in the data sets of SI1 -SI4 for analysis and research purposes at the end of the semester. Students who used SI1 and SI3 spent a shorter period of time (sd groups) and students who used SI2 and SI4 spent a longer period of time (ld groups) with one of the two general topics.

Table 1: General statistics of the data from the four SOBOLEO instances SI1 - SI4 at the end of the semester.

Details	SI1	SI2	SI3	SI4
Number of users	8	8	5	8
Number of resources	56	104	51	67
Number of distinct tags	59	49	34	71
Overall number of activities	851	1776	708	1776

In order to test our two hypotheses, we collected activities available in the log-data which can help to infer the individual knowledge levels of users for certain topics, and thus define a suitable KIE. These activity types vary in type of purpose,from purely generating data in form of tag assignments which can be done very easily without the need to having already developed a very good understanding of the domain up to changing the taxonomic structures, which require already a certain level of knowledge about the domain in order to perform this activity successfully. In more detail, activities within the social bookmarking system SOBOLEO included activities concerning the five main activity types:

- Generation of data: Assigning keywords (tags, topics) to a resource

- Generating a taxonomy of tags/topics: Adding a new sub/super concept relationship (e.g.. the concept 'wiki' is a sub-concept of 'web2.0') and adding similar or related concepts (e.g.. 'wiki' is similar to 'Wiki').

- Performing changes within the taxonomic structure (e.g.. changing a certain sub/super concept relationship)

- Getting an overview of the generated taxonomy or exploring a concept

- Changing data: Renaming a concept or deleting a tag assignment

4.2.1. Temporal Patterns

Our first hypothesis is that the kinds of activities users perform within the system are changing over time. An example would be that the longer they are working with the system and the more familiar they become with the general topic of the group work (two groups dealt with 'the use of Wikis in enterprises', the other two groups with 'the use of Weblogs in universities') by using the system to organize web resources, the more are they able or willing to generate the underlying taxonomic relationships between sub-concepts of the topic. Figure 1 shows the number of activities of the five activity classes over time. For this plot we took four snapshots of the system, each of the snapshots represents the activities within the system for a period of a month. In SOBOLEO instance 2 and 4 there are four snapshots (as these were the instances used longer by the students) and in SOBOLEO instances 1 and 3 there are two snapshots of the activities (as these instances were used only during a period of two months).

It can be clearly seen that in all 4 instances, generating data in form of tag assignments is the most dominant activity, followed by getting an overview of the taxonomic structure and generating the taxonomic structure, whereas students did rarely contribute to change the collaborative generated data or taxonomic structure. Contrary to our hypothesis, that the behavior of students within the system would change the longer they use the system and become
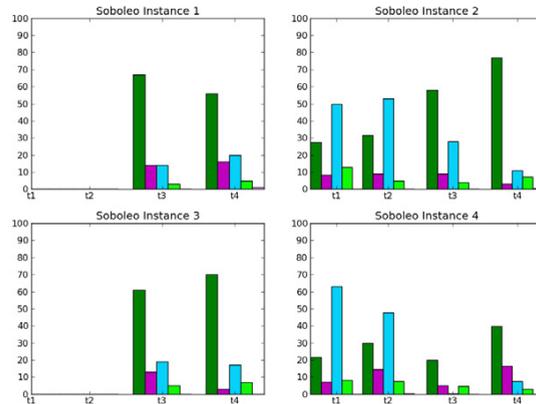
Figure 1: Different activities over time in the four SOBOLEO instances. Different colours indicate different activity classes (green: 'Generation of data',blue: 'Generating the taxonomy', purple: 'Getting an overview of the generated taxonomy' activities, light green: 'Changing of data' and finally, the light purple (did occur rarely): 'Performing changes within the taxonomic structure.'). Specific activities are presented as a percentage of the overall activities within the SOBOLEO instance for each snapshot period (t1, t2, t3 and t4).

familiar with the general topic assigned to the group, all four instances of SOBOLEO do not show a switch to less activities for generating data and more activities creating and/or changing the taxonomic structure. In SOBOLEO instance 2 the inverse case occurred, the relative proportion between activities for generating data and generating structure even increased instead of decreased. Thus, it is not the case that users first add data to the system and then try to collaboratively create and refine the emerging taxonomic structure at a later stage. It can be observed that there is a time-based relationship between tag assignments and activities performed for generating the taxonomic structure: As soon as new concepts were added to describe documents, these concepts were added to the lightweight taxonomy and these relations were not subject to change afterwards.

Figures 2 and 4 visualize in a detailed manner the performed activities over time, for two of the systems in general and figures 3 and 5 for two specific, rather active users of the corresponding SOBOLEO instances where the time-based relation to the activities for generating data and the activities for generating structure can be clearly seen.

Our assumption that the activities performed would change from actions that do not need a very deep understanding of the knowledge domain to actions that would actually need more experienced users with the topic did not hold in this case. And though the users were unsatisfied with the collaboratively generated structure (especially the ld groups in SOBOLEO instance 2 and 4), they did not take actions to change the generated taxonomic structure. We take this as an indication that an average user might feel uncomfortable with changing parts of the collaboratively generated structure, furthermore we could in addition to the above mentioned temporal patterns identify that only a small number of the overall users contributed to the creation of the taxonomic structure (data not shown.) Identifying knowledgeable users for certain parts of the taxonomy and give them recommendations to check and maintain this part of the structure would support the maturing of the semantic model represented by the taxonomy.

4.2.2. Relation between User Activities and Associations

The second hypothesis that we wanted to investigate is, that there is a relationship between the different activities of the users within the system and their 'real' knowledge level. As reported in section 4.1, at the end of the experiment each user was provided with 19 different topics from the SOBOLEO system and was asked to write down within 30 seconds the associations that came to his/her mind, which relate to the given topic. The association test is supposed to give an implicit measure for the strength of representation of a concept in the user's memory, and thus we can assume that this indicates a relationship to the user's knowledge level about the given concept.
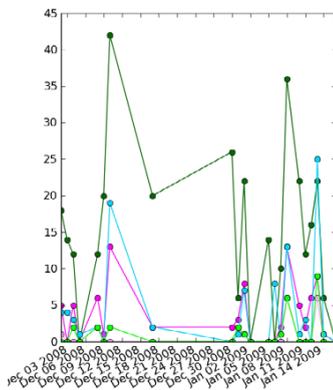
Figure 2: Detailed overview of different activities within SI1 performed by all users during usage time.
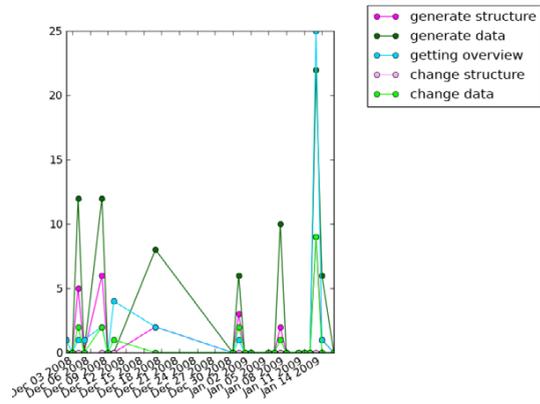

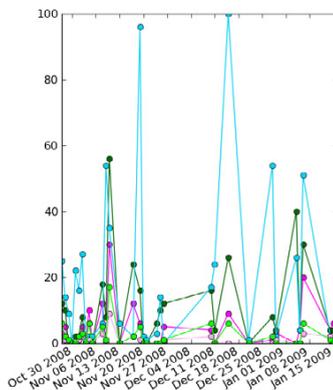Figure 3: Detailed overview of activities performed by an active user of SI1.

Figure 4: Detailed overview of different activities within SI4 performed by all users during usage time.
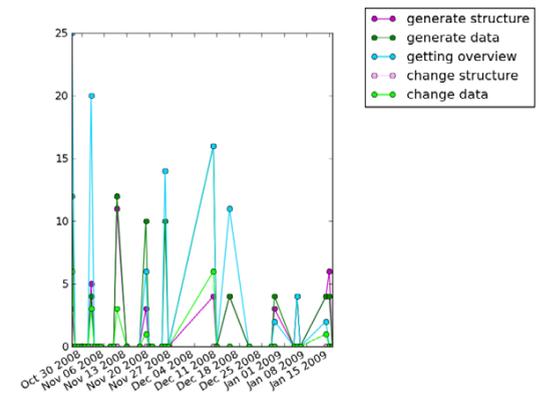

Figure 5: Detailed overview of activities performed by an active user of SI4.

To analyze the relation between activities and associations for a specific topic, we collected available information about the number of the different activities of each user for each topic. As the number of activities for changing the collaboratively created taxonomic structure are to small, we focused in this part on the following two activity types: 'Generating data' and 'Generating structure'. Table 2 shows the correlation between the activities of the two groups ld and sd for certain topics and the number of associations for those topics. To calculate the correlation we used the Spearman's correlation coefficient. It can be seen that there is a tendency for a positive monotonic relationship in the ld group between the activities for generating data and the number of associations the users had for the corresponding topics. For the activity of generating the taxonomic structure, this is cannot not be clearly shown.

Thus, we could not derive clear statistical correspondences between activities and associations, only a tendency for the ld group for 'Generating data'. This is due to several constraints: Firstly, the log-data we used for analysis is not very large as the study was not conducted in a real-world setting with hundreds of users which would lead to more stable patterns than from a few users where individual behavior has more influence on the results. We have nevertheless chosen this data to be suitable for our purposes as systems for work-integrated learning applied within an organization will not and is not supposed to be used by hundreds of users as for example in typical Web 2.0 systems. As our goal is to support knowledge workers in their daily working processes and tasks with personalized recommendations, this is an important constraint the recommendation mechanisms will have to be aware of. Secondly,

Table 2: Correlation between number of activities and number of associations of users concerning a certain topic.

Activity type	Group	ρ
Generating data	ld	0.28
Generating data	sd	0.10
Generating structure	ld	0.10
Generating structure	sd	-0.095

we presented the students 19 topics that emerged during usage of the system, but not every user had one or more performed activities related to those topics, nevertheless in the association test they could come up with associations related to that topic, resulting in rather sparse data. This is also due to the fact that the system does not represent the complete 'real' learning process and the learning experiences of each user. As a result, the system might detect that a user has less knowledge than s/he actually has (false negatives) if that person has not performed enough activities such that the system could derive the correct knowledge level.

An approach to overcome both of the problems is to incorporate external information sources in order to enrich the user data. This can happen on the on hand through human interaction with the system. It could be for example envisioned that the user can edit the automatically detected user model consisting of topics of the user's interest and related knowledge levels to avoid false negative knowledge levels for certain topics. On the other hand, which is more suitable for the context of WIL, this could be done automatically by not only taking into account one specific system as in our case the collaborative tagging system, which is due to its nature limited to certain types of activities.

5. Discussion

Personalized, context-aware recommendation mechanisms to support the information need of knowledge workers in work-integrated learning highly benefit from a suitable user model based on the user's past interaction with the system. In this work, we discussed prerequisites for effective personalization in WIL which include unobtrusive user modeling to infer the topics a user is dealing with and an appropriate modeling of the user's specific knowledge level for these topics. We presented results from an experimental study, where we adopted the KIE approach for unobtrusive user modeling from [4] for a setting where knowledge workers organize, share and retrieve information in a collaborative tagging system.

We could show that by analyzing user activities when trying to develop a common understanding of a specific topic by using a social semantic bookmarking system, users are motivated to contribute knowledge in form of tag annotations, but only a smaller extent of those users are willing to spend more time on creating a common lightweight ontology from related concepts based on tags they assign to resources. Though questionnaires showed that the users did not feel so comfortable with the commonly generated lightweight ontology, they did not take the time to improve it. Therefore, in order to support the users in achieving this, there is a need for the system to automatically support their learning process for a better understanding of the domain. Detecting and recommending knowledgeable users to take over the responsibility for maintaining a specific part of the collaboratively generated taxonomic structure would provide a huge benefit for this system.

We were not able to show a clear correlation between certain user activities for specific topics and the number of associations the users had for these topics, except for the activity of generating data for the group that used the system for a longer period of time. We discussed the reasons for this, which are partly a result of the fact of too sparse data (e.g. a user had associations to certain topics but did not perform any explicit activities within the system) and that the complete 'real' learning process cannot be traced by the system which then might lead to false negative detection of too low knowledge levels for certain topics though the user is experienced. In terms of recommendation mechanisms, this means that there is a need to include external information source to overcome these problems. External information can either be added manually through an editable user profile or self- or peer assessments or (which is more suitable for WIL) automatically by extending the KIE that are necessary in order to improve the ability of the system to map the 'real' knowledge levels with the user's activities. In our example we used a collaborative tagging system which offered a limited amount of activities that can be used as KIE but usually systems knowledge workers are dealing with, do offer a broader spectrum of activities.

6. Outlook

This research work presented an approach for unobtrusive user modeling for personalized recommendations in work-integrated learning based on an example with collaborative tagging systems. We provided insight how KIE can be used for inferring unobtrusively a user model based on the user's topics of interest and knowledge level but also identified several drawbacks. Thus, our future work will include a deeper investigation of the mapping between KIE of work-integrated learning systems incorporating topics that emerge from usage of the system and the user's 'real knowledge'. Based on these results, we will adopt existing recommendation mechanisms and develop new recommendation mechanisms to take full advantage of the user model in order to provide the users with personalized, context-aware recommendations based on the topics they are dealing and have dealt with and the corresponding knowledge levels. Goal is to be able to provide services that support the users in extending their knowledge and improving their knowledge levels where necessary and appropriate.The evaluation of the user model and adapted recommendation mechanisms will be performed within the MATURE project (http://mature-ip.eu/), a large-scale EU-founded project, which tries to analyse knowledge maturing processes and to develop tools and services for organizations and communities to support this process.

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References

[1] M. Eraut, W. Hirsch, The significance of workplace learning for individuals, groups and organisations, SKOPE Monograph 9.
[2] S. N. Lindstaedt, P. Scheir, R. Lokaiczyk, B. Kump, G. Beham, V. Pammer, Knowledge services for work-integrated learning., in: P. Dillenbourg, M. Specht (Eds.), Proceedings of the European Conference on Technology Enhanced Learning (EC-TEL),Maastricht, The Netherlands, September 16-19, Springer, 2008, pp. 234–244.
[3] G. Fischer, User modeling in human–computer interaction, User Modeling and User-Adapted Interaction 11 (1-2) (2001) 65–86.
[4] S. N. Lindstaedt, G. Beham, B. Kump, T. Ley, Getting to know your user - unobtrusive user model maintenance within work-integrated learning environments., in: U. Cress, V. Dimitrova, M. Specht (Eds.), Proceedings of the European Conference on Technology Enhanced Learning (EC-TEL),Nice, France, September, 2009, pp. 73–87.
[5] B. Mobasher, H. Dai, T. Luo, M. Nakagawa, Discovery and evaluation of aggregate usage profiles for web personalization, Data Mining and Knowledge Discovery 6 (1) (2002) 61–82.
[6] Z. Dou, R. Song, J.-R. Wen, A large-scale evaluation and analysis of personalized search strategies, in: WWW '07: Proceedings of the 16th international conference on World Wide Web, ACM, New York, NY, USA, 2007, pp. 581–590.
[7] P. Brusilovsky, S. Sosnovsky, M. Yudelson, Adaptive hypermedia services for e-learning, in: Proceedings of the Workshop of Adaptive Hypermedia Techniques to Service Oriented Environment, AH Conference, 2004, pp. 470–479.
[8] F. Carmagnola, F. Cena, O. Cortassa, C. Gena, I. Torre, Towards a tag-based user model: How can user model benefit from tags?, in: C. Conati, K. McCoy, G. Paliouras (Eds.), User Modeling 2007, Vol. 4511, Springer, Berlin, Heidelberg, 2009, pp. 445–449.
[9] E. Michlmayr, S. Cazer, Learning user profiles from tagging data and leveraging them for personal(ized) information access, Tagging and Metadata for Social Information Organization Workshop in conjunction with the 16th International World Wide Web Conference.
[10] A. Shepitsen, J. Gemmell, B. Mobasher, R. Burke, Personalized recommendation in social tagging systems using hierarchical clustering, in: Proceedings of the 2008 ACM conference on Recommender systems, ACM, New York, NY, USA, 2008, pp. 259–266.
[11] C. Koerner, R. Kern, H. P. Grahsl, M. Strohmaier, Of categorizers and describers: An evaluation of quantitative measures for tagging motivation, in: 21st ACM SIGWEB Conference on Hypertext and Hypermedia (HT 2010), ACM, Toronto, Canada, 2010.
[12] C. man Au Yeung, N. Gibbins, N. Shadbolt, A study of user profile generation from folksonomies., in: P. Dolog, M. Krtzsch, S. Schaffert, D. Vrandecic (Eds.), SWKM, Vol. 356 of CEUR Workshop Proceedings, CEUR-WS.org, 2008.
URL http://ceur-ws.org/Vol-356/paper1.pdf
[13] A. Budura, D. Bourges-Waldegg, J. Riordan, Deriving expertise profiles from tags, in: CSE '09: Proceedings of the 2009 International Conference on Computational Science and Engineering, IEEE Computer Society, Washington, DC, USA, 2009, pp. 34–41.
[14] M. G. Noll, C. man Au Yeung, N. Gibbins, C. Meinel, N. Shadbolt, Telling experts from spammers: expertise ranking in folksonomies, in: SIGIR '09: Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval, ACM, New York, NY, USA, 2009, pp. 612–619.
[15] A. John, D. Seligmann, Collaborative tagging and expertise in the enterprise, in: Proceedings of Collaborative Web Tagging Workshop held in Conjunction with WWW 2006, Edinburgh, UK, May 22-26, 2006.

[16] D. R. Millen, J. Feinberg, B. Kerr, Dogear: Social bookmarking in the enterprise, in: CHI '06: Proceedings of the SIGCHI conference on Human Factors in computing systems, ACM, New York, NY, USA, 2006, pp. 111–120. doi:http://doi.acm.org/10.1145/1124772.1124792.

[17] I. Jumper Networks, Jumper networks press release, Website, available online at `http://www.jumpernetworks.com/NEWS-Jumper_2.0_Released_as_Open-Source.pdf` ; (March 25, 2009).

[18] S. Farrell, T. Lau, Fringe contacts: People-tagging for the enterprise, in: F. Smadja, A. Tomkins, S. Golder (Eds.), Proc. of the Collaborative Web Tagging Workshop at WWW2006, 2006.
URL `http://www.rawsugar.com/www2006/25.pdf`

[19] S. Braun, C. Kunzmann, A. Schmidt, People tagging and ontology maturing: Towards collaborative competence management, in: D. Randall, P. Salembier (Eds.), From CSCW to Web2.0: European Developments in Collaborative Design Selected Papers from COOP08, Computer Supported Cooperative Work, Springer, Berlin/Heidelberg, 2010.

[20] T. Ley, P. Seitlinger, A cognitive perspective on emergent semantics in collaborative tagging: The basic level effect, in: Proceedings of International Workshop on Adaptation in Social and Semantic Web (SAS-WEB 2010), Big Island of Hawaii, June 21, CEUR Workshop Proceedings, 2010, pp. 1–10.
URL `http://ceur-ws.org/Vol-590/sasweb10_2.pdf`

[21] S. Braun, V. Zacharias, H.-J. Happel, Social semantic bookmarking, in: Practical Aspects of Knowledge Management - 7th International Conference, PAKM2008, Yokohama, Japan, Lecture Notes in Computer Science, 2008.