Ontology-Based User Profiling for Personalized Acces to Information within Collaborative Learning System

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The use of modern educational technology methods has become an important area of research in order to support learning as well as collaboration. This is especially evident with the rise of internet and web 2.0 platforms that have transformed users' role from mere content consumers to fully content consumers-producers. Furthermore, people engaged in collaborative learning capitalize on one another's resources and skills, unlike individual learning. This paper proceeds with a categorization of the main tools and functions that characterize the personalization learning aspect, in order to discuss their trade-offs with collaborative learning systems. It proposes a framework of a personalized information research (IR) within a collaborative learning system, incorporating the characterization of the research type carried by the query, as well as modeling and constructing semantic users' profiles. We use the context of the user query into a prediction mechanism of the search type, based on a previous identification of users' levels and interests. The paper is concluded by presenting experiment results, revealing that the use of the subject ontology extension approach satisfyingly contributes to improvement in the accuracy of system recommendations.

Key Words: information technology, collaborative learning, ontology, information research, user profile

INTRODUCTION

Nowadays learning is being developed and applied in new ways. Its goal is transforming learning to meet learners' lifelong needs.

This adequacy/personalization will accompany learners during their professional careers. Moreover, it will promote both, social and economic goals through its contribution to preventing skill mismatches, boosting productivity and also addressing social equity and social inclusion (ELGPN 2012). This new learning context implies a different role for learners. They need to keep up to date with new knowledge, which needs in turn to promote professional networks and learning organizations. Thus, learning becomes more collaborative and personalized at the same time. In IT environments, there are many tools to support collaborative web which is a part of novelties brought by Web 2.0. By using these tools, the user has the opportunity to participate, share and search the content corresponding to his needs. However, the research task is the most important step towards the support of learner during his learning process. It enables the provision of the most adequate content to him, which in turn leads to the development of his knowledge level. In fact, the overloading data would make learners feel lost and frustrated when they search for relevant information on websites. In general, learners prefer and are more comfortable with websites that present the right content in ways that correspond to their preference (Aragonees and Hart-Davidson 2002, 375–88). The objective of a personalized collaborative learning system is to optimize the management of knowledge exchange. Indeed, each contribution or research activity of the learner, is used on one hand to construct his own profile, and on the other hand his contributions will be recommended to all other learners with similar profiles. According to Tang, Yao and Zhang (2010) the user profiling forms are the basis of the main techniques related to most recommender systems. Profiling of a Web user is the key process that allows the personalization of the information looked for by him. Considerable efforts have been made to find the user's interests. Some applications directly involve user data through surveys, questionnaires, submitting personal information during registration, and so on. In this case, the type of content may be provided for users according to their choices and preferences (Cheng et al. 2009). Some other applications, building user profiles in accordance with log files, are engaged without the user direct involvement (Liu and Keselj 2007). It's still insufficient for modeling and understanding users' behaviors. The major limitation of the classical profiling is that it is based on a general approach that consistently evaluates user requests and delivers results without considering the context of research. However, the utilization of ontologies in user profiling techniques has gained much attention since it allows inference to be employed, enabling interests to be discovered that were not directly observed in the user's behavior (Wu, Zeng, and Hu 2009). In this way, the profile of each learner is described by annotations in accordance with ontology. This allows the system to 'know' at a given time, the learner's needs in order to promote the success of his learning. Furthermore, once profiles are represented using ontology, they can communicate with other ontologies and share similar concepts, which contributes to knowledge reuse (Felden and Linden 2007). In this paper, we propose a refined ontological profiling method based on user's information search within a collaborative learning system. According to learners' profiles, the most relevant contributions of other learners will be proposed to them, which will take into account the explicit and implicit interests of the learners, and will also reduce the total reasoning time of the system by searching only in similar profiles contributions.

STATE OF THE ART

User Profiling and Related Work

Whatever the approach of personalization, we still need to collect and save data describing users in profile classes. These profiles are defined by contextual elements directly related to the user, such as his interests, his search preferences, etc. In fact, interest profiles satisfyingly contribute to improvement in the accuracy of recommendation. Their construction is presented on a rather fine granularity level. Generally, there are several methods to extract the contextual elements characterizing the user profile. In web-based social networks such as MySpace and YouTube, the user has to enter the profile by her/him-self. Unfortunately, the information obtained solely from the user entering profile is sometimes incomplete or inconsistent (Tang and Zeng 2012). The need for a profile that supports reasoning is stressed out in (Rich 1983). An overview of methods for building a user profile semantically is presented in (Rich 1983). The user modeling knowledge plans, and preferences

in a domain are presented in (Kobsa 1993). In this context a wide variety of Artificial Intelligence techniques have been used for user profiling, such as case-based reasoning, Bayesian networks, association rules, genetic algorithms, neural networks, among others (Schiaffino and Amandi 2009, 193–216). The purpose of obtaining user profiles is also different in the various areas that use them. But, to keep the reasoning side in the profiles' construction, all purposes should refer to ontologies. Nonetheless, most existing models based on ontology only consider the importance of the concepts in capturing user interests. Although some models (Vallet et al. 2007) used semantic relations for user modeling, these relations are merely used to indicate that certain concepts are connected, and semantics of the relations are not considered. To build more precise user profiles, it is essencial to explore effective ways of combining semantic relations with concepts for representing a user's interests (Xing and Tan 2009). The implicit profiles are acquired on the basis of correlative relationships among topic nodes. Inside this semantic context, there are two main strategies to build user profiles: document-based and concept-based approaches. Document-based user profiling methods aim at capturing users' clicking and browsing behaviors. This approach is based on measuring the occurrence of click through data through user's activity, before being represented as a set of weighted features. Secondly, concept-based user profiling methods aim at classifying users browsed documents and search histories to a set of topical categories. Then, users' profiles are categorized in the extracted topical categories. However, the most existing user profiling strategies only consider documents that users are interested in (i. e. users' positive preferences) but ignore documents that users dislike (i. e. users' negative preferences). While Profiles built on both positive and negative user preferences can represent user interests at finer details, personalization strategies that include negative preferences in the personalization process are all document-based, and thus, cannot reflect users' general topical interests (Leung and Lee 2010). Practically, the most common representation of user interests are keyword-based models. Those interests are represented by weighted keywords representing users' interest-topic relevance. The main problem of this represen- tation is that keywords contained in users' requests/posts present high diversity and nearly no overlapping that prevents from achieving an accurate profiling. In literature, there are some propositions to solve this problem. Ebner et al. (2010) argue that a knowledge-based semantic analysis is needed to deal with the high keyword diversity, they propose to manually link each keyword with its related category. Zoltan and Johann (2011) leverage the contribution of extracted information to the user profile according to their degree of occurrence with respect to the linked categories. They characterize users' profiles according to a set of weighted categories. Bernstein et al. (2010) present a new approach based on transforming noun phrases found in each user's message (composed usually of compressed similar words to gain space) posted on Twitter (or other web 2.0 application) in a set of web search queries, to retrieve documents that help to expand the original message context. To affect the topic to the original message, authors apply a term co-occurrence techniques. The main problems of this technique are related to the execution time and ambiguity derived from querying keyword-base search engines (Alexandre, Sánchez, and Roca 2012). To overcome the difficulties presented in these last methods, we will make use of the benefits offered by collaborative learning systems. Much of researches on collaborative learning were been based on the idea that peer interaction can be a powerful means for learning if and when peers engage in collaborative sense-making processes (Asterhan, Schwarz, and Eliyahu 2014). Indeed, we will benefit from contributions of other users with a similar profile to resolve requests with the appropriate content. These contributions can also be feedbacks on outcomes correctness expected through collaborative reasoning, since it provides an answer/proposition about users' knowledge domain. In summary, computer Supported Collaborative Work (CSCW) systems provide the necessary support in the use of communication services for sharing information and finding appropriate users to collaborate (Agustin, Amandi, and Campo 2009).

Collaborative Web and Tools

Collaborative work is work performed in general by several people leading to a common task. It assumes that people interact to accomplish a fixed goal, according to their skills and role in the group dynamics. If the goal is the acquisition of skills, we will call it a cooperative work or cooperative learning. According to (Lopriore 1999) cooperative learning, which is a kind of collaborative learning, it is a learning group activity, organized in a way that learning will be dependent on the socially structured exchange of information between learners in the group. It is also an activity in which the learner is responsible for his own learning and motivated to participate in the learning of others. Once the internet media is used we talk about collaborative web, which is one of innovations introduced by Web 2.0. This web technology allows every user to become an actor, not a spectator.

Actually, with the development of new educational technologies the constructivist approach has led to the use of online learning communities in educational settings. In this way, De Wever et al. (2006) argue that CSCL environments provide a richer learning experience because inputs explain personal learning elements (memory recall) and consecutively order knowledge elements during social interaction. In addition to this main advantage of CSCL environment, they still benefit from functionalities offered by online learning environments, which led to the higher quality of knowledge exchange and important enhancement of mutual interactions. In fact, learners play an active and constructive role by providing contributions and during their interactions in CSCL (Dewiyanti et al. 2007). However, these rich learning environments are becoming more important qualitatively and functionally. In the opposite way, an environment structured by considering these elements can significantly influence learners' contributions as well as the effectiveness of the environment (Akgün and Akkoyunlu 2013).

Collaboration services are present on both, intranet and extranet. More broadly, there are many tools to support collaborative web:

- Communication tools: e-mail, forum, chat, video conferencing services, user directories, etc.
- Content sharing tools: wiki, blog, file libraries, virtual whiteboard, etc.
- Organizational tools: shared diaries, todo-list (task list), etc.

Among the software/websites the most known include: Wikipedia, Google Docs, Lotus Note, Microsoft Exchange. There are also content management systems (CMS or CMS) to create their own tools, such as MediaWiki which is the engine used to manage Wikipedia.

In all educational systems, learner interests and goals have been raised to guide learning development, in order to make learning practice aligned with objectives and strategic plans of learning systems. However, it will be more effective to reveal these interests through the use of ontologies within CSCL systems.

User Interests and Ontology

User interests are among the most important parts of user's profile in information retrieval, filtering systems, recommender systems, some interface agents, and adaptive systems that are information-driven such as encyclopedias, museum guides, and news systems (Brusilovsky and Millán 2007, 3–53). The most common representation of user interests are keyword-based models, which are extracted from his search requests or his contributions within the collaborative learning system. However, the ontology is used as the reference to construct a user interest profile. It serves to share common understanding of the information structure among the community (human or artificial agents) and to enable reuse of domain knowledge (Noy and McGuinness 2001). The ontology also plays a principal role in the construction of learners' profiles. For this purpose, the user profile modeling in our approach is characterized by a semantic representation based on a set of semantically-related concepts via the reference ontology used. In addition, several areas of applications are using users' profiles, for reasons related to personalization, with different needs. Depending on the area, personalization consists of one or more of the following tasks: filtering a flow of information,

guiding the search in an wide information space, recommending a set of information to the user, adjusting results of a request to the profile, adapting the interaction to the user situation (interface, interaction) (Daoud 2009). Whatever the area of application, the notion of the user profile is defined according to dimensions related to the system purpose.

Exploitation of the User Profile in the Information Research Process

The notion of a user profile is the heart of personalization in information research (IR). It is exploited in the rescheduling of the search results of queries dealing with the same information need. It is assumed that the profile has a more invariant character compared to the task context even if interests and search preferences evolve over time. Several definitions of the profile have been discussed in literature of personalized IR. The following can be distinguished:

- The cognitive profile exploited in several personalized works (Lieberman 1995, 924–29; Leung, Chan, and Chung 2006, 357–81; Pazzani, Muramatsu, and Billsus 1996, 54–61) is analog to the cognitive context of users.
- The qualitative profile in (Harrathi and Calabretto 2006, 299–304) related to the search preferences of users relatively to the quality of information returned by the system (fresh, credible sources of information, consistency, etc.).
- The multidimensional profile (Kostadinov 2003) characterizing the environment and the system.

However, the framework we propose considers both, cognitive and qualitative sides of profiles due to the exploitation of CSCL systems in a semantic way. This will allow automatic discovering of profiles and interests, which will lead in turn to adapted and suitable recommendations.

Framework for Generating User's Interest Profiles

In this section, we present the framework for generating user's interest profiles within online learning systems (see figure 1). This framework is able to distinguish between different contributions of the papers on the same topic to the construction of user interest profiles. Also, a part from the user profile obtained directly from the user behavior data, is applied implicitly to profiles to infer possible interests that users may develop in the future, in order to describe user interests more specifically and thereby improve recommendations.

The main components of the framework include:

- *Paper management module.* Users can upload, browse, download and comment on any research papers through the paper management module. All of the research papers are stored in the paper database. Each paper in the paper database is classified according to the reference ontology and can readily be viewed by users. The paper management module plays the role of a fundamental component in the framework.
- *User monitoring module.* This module is responsible for the background collection of the behavior data of each user. The user behavior data include searching keywords, browsing and commenting on papers, etc. The monitoring and collecting processes are totally implicit.
- *User profiling module.* The user profiling module makes use of the user behavior data recorded by the user monitoring module, the paper database and the reference ontology to create user profiles. The user profiles obtained can be used to recommend papers to them.

The term ontology seems to generate a lot of controversy in discussions. It has a long history in philosophy, in which it refers to the subject of existence. In computer science and information science, ontology is a description (like a formal specification of a program) of the concepts and relationships that can exist for an agent or a community of agents; it is defined as 'a formal, explicit specification

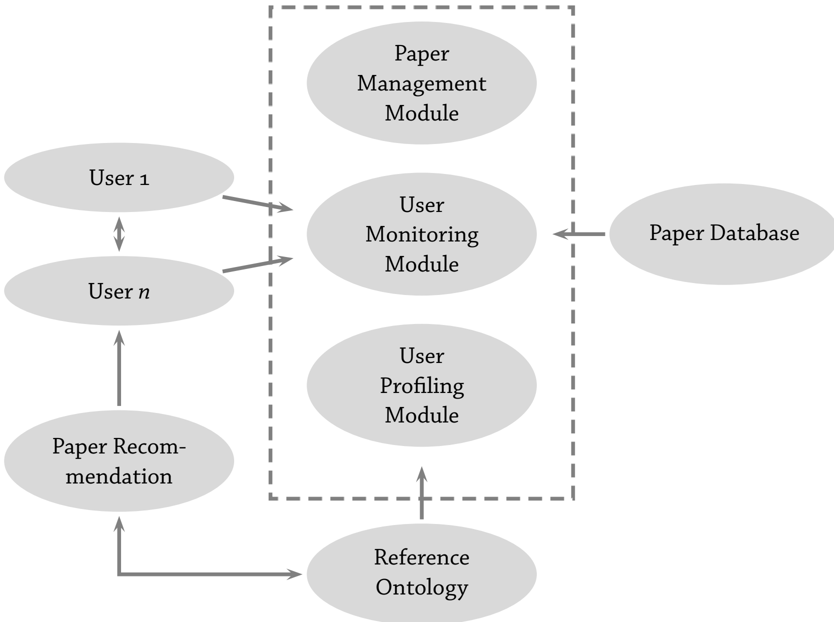

FIGURE 1 Framework for Generating User Interest Profiles

of a shared conceptualization' (Gruber 1993). Ontologies have been widely exploited in many domains (e. g., medicine, education; and logistics) using its capacity to promote and share ability of knowledge bases, knowledge organization, and interoperability between systems (Oliveira et al. 2013). In educational area, ontologies and semantic web are the backbone of e-learning; they provide mechanisms for semantic annotation of learning resources, reuse and combination of course subjects and computer-assisted open question assessment (Jia et al. 2011). Furthermore, semantic Web-based learning systems may support personalized and context-sensitive learning processes to improve learning efficiency (Gladun et al. 2009).

In summary, Chu, Lee, and Tsai (2011) offer the following reasons for developing ontology:

- To share common understanding of the structure of information among people or software agents.
- To enable the reuse of domain knowledge.
- To make domain assumptions explicit.

- To separate domain knowledge from the operational knowledge.
- To analyze the domain knowledge.

Practically, to implement ontology in the collaborative learning system, tools for ontology editing and visualization are necessary. In this study, Ontologies are written in Web Ontology Language (OWL), which is XML-based and recommended by the World Wide Web Consortium (W3C). OWL allows for defining classes hierarchies, relations between classes and subclasses, properties, associations between classes, properties domain and range, class instances, equivalent classes and properties, and restrictions (www.w3.org/TR/owl-ref). To support the development of ontologies and the translation in OWL, we use the open source tool Protege 4.1, which is a free open-source ontology editor developed by the Stanford Medical Informatics (SMI) at Stanford University (Rubin, Noy, and Musen 2007). It is an integrated software environment for system developers and domain experts to develop knowledge based systems.

Using Reference Ontology to Build User's Profiles

In order to solve the problems in the user profiles based on traditional ontologies, we propose the ontology for learning systems to generate the user's profiles. The simple ontology we propose consists of two levels, primary for subjects and secondary for keywords. Reference ontology presents the relationships between subjects on different levels. Each primary subject has also secondary subjects. This ontology is formed from several parts, among which are: Computer Science, Physics, Mathematics, Logistics, Chemistry, Medicine, Human Sciences, Geology, Biology and Economy.

In the paper database storing the research paper data, we associate a set of keywords to each paper. These keywords are provided by authors' contributions according to domain and level of users, and representing the keywords of each level (i.e. $level = (keyword_1 \ldots keyword_i \ldots keyword_n)$ with $1 \leq i \leq n$) as shown in figure 2.

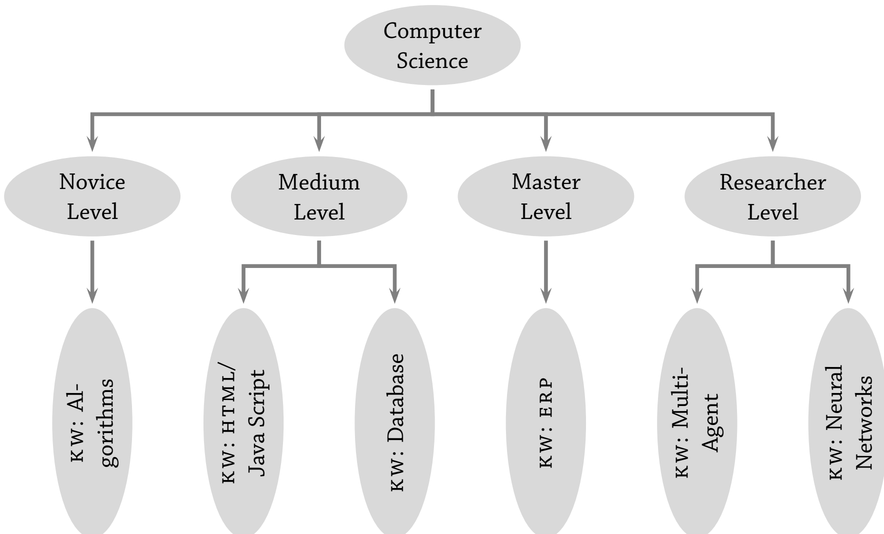

FIGURE 2 The Subject's Section 'Computer Science' in the Reference Ontology

MEASURING USERS INTERESTS BASED ON KEYWORDS

This approach is based on measuring the occurrence of keywords through user's activity in the learning system (browse, comment . . .), these measures are calculated by incrementing the counter, associated to each keyword in the ontology. Later this can show the level of interest of the user for a particular domain, and this approach can also evaluate the current level of every learner. This allows to recommend papers according to the interest centers of the user. Each keyword defined in the reference ontology belongs to a domain level, for example the keyword: 'Database,' belongs to the second level (medium level) learning in the field 'computer science.' Generalizing this process to all subjects, the system will be able to recommend papers relating to interest centers of users.

EXPERIMENTS AND RESULTS

Our experiment consists of evaluation of the system during last 60 days, with 20 users using academic learning system adopted in faculty of sciences in Tetuan, UAE/FS, browsing and commenting papers, where each field number represents one topic, as shown in table 1.

After the analysis of users' topological structure by the previously introduced metrics, we may notice one or more subjects are interested in each profile. For example, user 3 is interested firstly in 'Biology' and secondly in 'Chemistry,' also user 4 is interested in 'Computer science,' 'Physics,' and 'Mathematics.' So the system will be able to recommend papers according to user interests, simply based on statistics of their keywords, and with no need to analyze their text stream. This technique enables the optimization of the time of requests' answers, by using the reference ontology, and then the facilitation of the paper recommendations.

We may notice that the results in overall show that the model enables showing users' interests: by taking user 4, for example, he has 92 keywords related to 'database subject,' 102 to 'web subject' and 33 to 'system subject.' This shows that user 4 is a 'computer science' user, especially interested in 'web subject,' so the learning system will be able to first recommend papers within 'web subject' to user 4, secondly 'database subject' and finally 'systems subject.' This means that, rather successfully, we have predicted what topics these users will potentially prefer. The new method allows optimizing the recommendation execution time, by avoiding the analysis of text generated by users, and simply still comparing similar profiles. Then, the system recommends the same papers to users with the same interest centers. In addition, this new approach provides paper recommendation according to the semantic discovering of implicit users' interests. These recommendations are presented on single pages, and users are notified about them on the homepage. They allow us to save time and effort of continuous documentary research. Finally, comparing our approach to others presented in literature, we were able to overcome some difficulties highlighted previously.

CONCLUSTION

The recommendation service on academic publications has become a very important research topic due to the development of infor-

TABLE 1 Keywords' Counters

User	Mathematics			Physics			Chemistry			Medicine			Biology			Economy			Comp. science		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
User 1	1	2	7	0	70	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
User 2	0	0	0	0	0	0	44	0	12	0	0	0	0	0	0	0	0	0	0	0	0
User 3	0	0	0	0	0	0	33	11	0	0	0	0	93	12	0	0	0	0	0	0	0
User 4	0	0	22	22	54	3	0	0	0	0	0	0	0	0	0	0	0	0	92	102	33
User 5	33	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88	30	2
User 6	0	0	0	0	0	0	0	0	0	87	0	0	0	0	0	0	0	0	0	0	0
User 7	0	22	0	0	0	87	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
User 8	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
User 9	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
User 10	0	0	0	0	0	0	0	0	0	0	0	12	6	0	0	0	0	0	0	0	0
User 11	0	0	0	0	0	0	0	0	0	0	2	0	36	0	98	0	0	0	0	0	0
User 12	12	0	65	0	0	0	0	0	0	0	0	0	0	0	0	103	88	25	0	0	0
User 13	0	0	0	0	0	0	12	43	0	0	0	0	0	0	0	0	0	0	0	0	0
User 14	0	0	0	0	0	0	0	0	0	0	0	66	3	0	0	0	0	0	0	0	0
User 15	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	60	77	4
User 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	103	0
User 17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80	67	0
User 18	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	77	23	11	0	0	0
User 19	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
User 20	11	22	33	76	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

NOTES Column headings are as follows: (1) algebra, (2) geometry, (3) analysis, (4) automatic, (5) mechanics, (6) electronics, (7) analytical, (8) solutions, (9) organic, (10) cardiology, (11) dermatology, (12) pediatrics, (13) animal, (14) vegetal, (15) zoology, (16) finance, (17) bank, (18) accounting, (19) database, (20) web, (21) systems.

mation personalization in learning systems. In this paper, we introduced a user profiling method based on ontology. The ontology we propose is based on multiple domains, and through our framework, we propose to use ontological profiling approach to provide paper recommendations to users. This method is based on measuring the occurrence of keywords through user's behavior within a collaborative learning system. Then, the system recommends papers according to interest's centers of each user. Our method also enables to identify levels of all users, and allows recommending papers according to their levels. The experiment's results reveal that the use of the subject ontology extension approach satisfyingly contributes to an improvement in the accuracy of paper recommendation. In the future, we may make improvements to the weighted keyword algorithm-based interest profiling approach and the subject ontology extension method. We will improve the keyword clustering algorithm through identifying synonyms among keywords. Furthermore, we expect to develop reference ontology using a multi-agent system, and then assess the impact of agents on the recommendation system.

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