Journal of Web Engineering, Vol. 12, No.5 (2013) 383-402

USING HYBRID SEMANTIC INFORMATION FILTERING APPROACH IN COMMUNITIES OF PRACTICE OF E-LEARNING

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Received November 8, 2012
Revised April 29, 2013

The paper discusses the application of the Information Filtering (IF) approach in Communities of Practice of E-learning (CoPEs). We identify the main characteristics of CoPEs and show how the integration of the IF techniques can be useful in this context as a technology support for members of CoPEs. A personalized recommendation approach is proposed for CoPEs based on the hybrid semantic IF, integrating the content-based filtering, the collaborative filtering and the ontology-based filtering approaches. Three strategies of recommendation have been proposed: (1) a semantic recommendation by specialty; (2) a semantic content-based recommendation by domains of interests; and (3) a semantic collaborative recommendation by domains of interests. We have developed a prototype of a recommendation system called ReCoPESyst, based on the recommendation approach. In order to evaluate our system, we considered a community of teachers from a higher education context. A preliminary tests and experimentation of ReCoPESyst conducted within this community show its advantage and benefit for members.

Key words: Communities of Practice of e-learning, recommendation system, information filtering, ontologies, semantic filtering, learning resource, profile.

1 Introduction

One of the most important concepts in social or situated learning theory is the notion of a community of practice. According to Wenger [1], Communities of Practice (CoPs) are "*groups of people who share a concern, a set of problems, or a passion about a topic, and who deepen their knowledge and expertise in this area by interacting on an ongoing basis*". CoPs are seen as a new organizational structure offering innovative means for creating and sharing knowledge.

The authors in [2, 3] extended the application of CoPs to the domain of e-learning. They considered CoPs of e-learning (CoPEs) as a virtual framework for exchanging and sharing techno-pedagogic knowledge and know-how between actors of e-learning. CoPEs can have different objectives, for instance: the CoP of tutors Learn-Nett (Learning Network for Teachers and Trainers – http://learn-nett.org), which is focused on a shared course and aims at preparing future teachers or trainers for educative uses of Information and Communication Technologies; the CoP of e-learning at Luxembourg - CoPe-L (http://www.allaboutelearning.lu), that aims to share practices and promote e learning activities; and the eLearning Guild community (http://www.elearningGuild.com/), which is specialized in instructional engineering.

By using advanced technology, CoPEs have the potential to bring members together virtually, to learn from each other, collaborate and share expertise and techno-pedagogic knowledge. However, the key question is how technology might support CoPEs and what kind of techniques is necessary for supporting members of CoPEs in their activities efficiently?

The aim of this paper is to explore and discuss the use of Information Filtering (IF) approach in CoPEs as a technology support to assist members to find the appropriate learning resources. A personalized recommendation approach is proposed based on the hybrid semantic IF, integrating the content-based filtering, the collaborative filtering and the ontology-based filtering approaches. Three strategies of recommendation have been proposed: (1) a semantic recommendation by specialty; (2) a semantic content-based recommendation by domains of interests; and (3) a semantic collaborative recommendation by domains of interests.

The remainder of this paper is organized as follows: Section 2 presents the main characteristics and needs of CoPEs and then introduces the problem statement of our research work. Section 3 presents the background and related work about IF approaches. Section 4 discusses the application of IF in CoPEs and proposes a hybrid semantic IF approach for the recommendation of learning resources in CoPEs. A prototype of a recommendation system, called ReCoPESyst, is presented in Section 5 through an exemplification scenario to illustrate its main functionalities. Furthermore, we present in the same section an experimental study conducted within a community of teachers from a higher education context. The results of a qualitative evaluation are presented and discussed. Finally, the conclusion includes some important results of our contribution and future work.

2 The main characteristics and needs of CoPEs

In this section we briefly present CoPEs as well as their main characteristics and needs. Then, we introduce the problem statement of our research work.

2.1 Communities of Practice of E-learning (CoPEs)

CoPEs are defined in [2, 3] as a group of professionals in e-learning who gather, collaborate, and organize themselves in order to: (i) share information and experiences related to e-learning development and use; (ii) collaborate in order to solve together e-learning problems and to build techno-pedagogic knowledge and best practices; (iii) learn from each other and develop their competences and skills in their domain of expertise. Members of CoPEs are working in the e-learning domain like teachers, pedagogues, tutors, administrators, etc., having different levels of skills and knowledge based on their training and experience in the field. They can organize themselves in groups on the basis of their objectives and concerns.

Taking into account socio-cultural theories [4], learning in a community is facilitated by some conditions. First, members have to define individual objectives (What do I want to learn?) and common ones (What do we want to learn together?). Then, they have to participate in regular and rich interactions. Different forms of members' interactions can be distinguished in a CoPE: starting from a simple access to knowledge resources (e.g. learning resources, learning scenarios); to formal or informal exchanges between members (e.g. discussion using a forum or a chat); until participating in collaborative activities (e.g. collaborative problem solving process or collaborative design). When performing collaborative activities, members exchange knowledge (tacit and explicit) and, in turn, these can lead to the construction of new knowledge (e.g. identify the best practices to formulate a requirements document). It can also conduct to the proposition of new approaches, methods and techniques that will improve the quality of online learning (e.g. how to evaluate learners in collaborative activities or to test their understanding according to their behaviour).

2.2 CoPEs' characteristics and needs

In order to achieve their objectives, the most important needs of members of CoPs can be summarized by the following elements [5]:

- Facilitate direct exchanges (through conversation between members participating in a discussion) and indirect exchanges (through the community memory);
- Formalize tacit knowledge;
- Archive common resources and make them retrievable and reusable.

Accordingly, important questions arise about the management of knowledge resources and the technological services that could support the knowledge management and learning processes in a CoPE. As stated by Preece, the technology configuration for CoPs should provide distinctive technological services to support learning, knowledge sharing and creation, as well as sociability and participation [6]. In the PALETTE project [7] that aims at facilitating and augmenting individual and organizational learning in CoPs, three kinds of technological services are developed: (1) Services for producing, reusing and sharing information; (2) Services for reification of knowledge about practices; and (3) Services for supporting collaborative learning.

Hoadley and Kilner, identify three areas of technology affordance relevant to CoPs including content, process, and context [8]. Hoadley described in [9] four techniques in which technology is used to foster learning in CoPs, including: (1) linking others with similar practices; (2) providing access to shared repositories; (3) supporting conversation within a community; and (4) providing awareness of the context of information resources. These four strategies follow four of the target areas in the C4P model of CoPs identified in [8]. This model is described as a way of understanding how knowledge is created and disseminated by participants in an online CoP. It envisions its structure as consisting of four factors: Content, Conversation, Connections, and information Context, supporting a common purpose. According to the authors, content refers to explicit knowledge resources such as documents, whereas conversation refers to face-to-face or online discussions. Connections refer to interpersonal contacts between community members that involve some level of relationship. Information context is the "who", "what", "where", "when", "why", and "how" that enables community members to assess whether and how information is relevant to them. This context provides the richness of detail that makes information meaningful and memorable. Finally, purpose is the reason for which the members come together in the community.

Figure 1 represents a framework for CoPs, we have adapted from the C4P model [8] and from the work presented in [9] describing some techniques used to support CoPs through technology. The framework seems to be interesting for CoPs as it provides a mean for knowledge creation and sharing, social negotiation of meaning and learning through the collective participation of their members. Thus, we'll use this framework for CoPEs according to the research issues identified in the following sub-section.

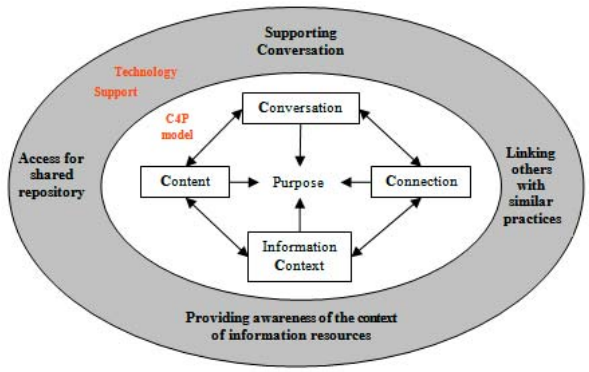


Figure 1 Framework for CoPs adapted from [8, 9].

2.3 Research issues

In order to participate effectively to the knowledge management and learning processes in a CoPE, members need guidance to find and access the adequate information. Our objective is to provide them with a suitable technology support to foster learning and help them in their activities during the different interactions using the CoPE environment. After analyzing some existing communities (e.g. CoP of tutors Learn-Nett, CoPe-L and eLearning Guild community), we identified the following issues:

1) First, with the increasing number of member's interactions, the memory size becomes very important and therefore it is difficult to find and access the adequate knowledge resources according to the members' needs and profiles.

2) Second, with the increasing number of members belonging to the community, and because they are geographically distributed (are not physically co-located), it is difficult to find members with similar profiles, to localize experts or to identify the groups of members according to their interests.

Accordingly, there is a need to support members of a CoPE to find and access the adequate knowledge resources and to enhance the relationship among them. On the other hand, members need a support to select suitable activities and in which sequence they should be performed in order to attain certain learning goals according to their personal objectives. For instance, one member interested to software engineering and who wishes to perform his skills, needs for example to be informed about the new asked problems related to this domain, in order to participate in the problem solving processes. Moreover, members need a support in selecting the suitable services according to their activities (e.g. a forum related to a specific topic).

In order to address these issues, we argue that this could be provided using personalized recommender systems. We identify four categories of recommendation within the CoPE corresponding to the four aforementioned needs, as shown in Figure 2:

1) The members' recommendation: in this category, members with similar interests are suggested for a given member *M*.
2) The resources' recommendation: in this category, a set of appropriate resources are suggested for a member *M* according to his interests and expertise level.
3) The activities' recommendation: concerns the suggestion of one or more activities for a given member *M* according to his needs, interests and expertise level. For instance, if *M* has a high degree of expertise in a given domain D_i and as he wants to share his knowledge with others, accordingly the system will recommend him, for example, to participate in a decision making process related to D_i.
4) The services' recommendation: concerns the suggestion of one or more services for a given member *M* according to his needs and interests in order to perform his activities.

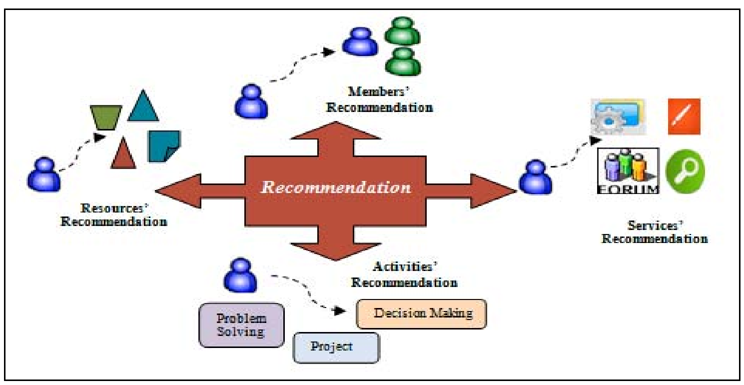


Figure 2 Recommendation categories in a CoPE.

In this paper, we'll focus on the recommendation of knowledge resources using IF approach that will attempt to present to the member information items, the member is interested in.

3 Personalized recommendation

This section describes the different types of recommender systems and presents some related works.

3.1 Background

Information filtering (IF) is the process allowing, starting from an incoming volume of dynamic information, to extract and present the only information interesting either a user or a group of users having relatively similar interests. The filtering system makes a "prediction" about the usefulness of the information to the user. This prediction is based on the "profile" of the user and leads to a decision-making: "recommend" or "don't recommend" information [10].

The recommendation problem can be formulated as follows [12]: let $U=(u_1,u_2,...,u_M)$ be the set of all users, and let $I=(i_1,i_2,...,i_N)$ be the set of all possible items that can be recommended. Let $g(u_m,i_n)$ be a utility function that measures the gain or usefulness of item $i \in I$ to user $u \in U$, i.e., $g: U \times I \rightarrow R$ where R is a totally ordered set. Then for each user $u \in U$, we aim to choose the item $i' \in I$ that maximizes the user's utility. More formally:

$$\forall\ u_m \in U,\ i'_u = \arg\max_{i \in I} g(u_m,i_n)$$

3.1.1 Content-based recommender systems

Content-based recommendation approaches are built on the assumption that a person likes items with features similar to those of other items he liked in the past [11]. In this approach, items are suggested according to a comparison between their descriptions and the user profiles, which contain information about the users' preferences, interests, and needs introduced explicitly (e.g. through a questionnaire) or implicitly (through a behavior supervision) [12].

3.1.2 Collaborative filtering or social recommender systems

Collaborative filtering approaches recommend data items to a user by taking into account the opinions of other users [13]. Instead of recommending data items because they are similar to items the user preferred in the past (content-based recommendation), collaborative approaches generate recommendations about data items that users with similar interests liked in the past. In order to estimate user's preference for an item, collaborative filtering systems collect ratings through explicit means (e.g. the user is asked to rate the item), implicit means (e.g. the system infers user's preference by observing user's actions) or both.

There are two main categories of collaborative filtering techniques: user-based and item-based approaches. User-based collaborative filtering approaches compare the active user's ratings with those of other users to identify a group of similar persons. The highest rated items of that group will be recommended to that user. Item-based collaborative filtering approaches, on the other hand, take each item of the active user's list of rated items, and recommend other items that seem to be similar to that item according to other users' ratings.

3.1.3 Hybrid recommender systems

Hybrid recommender approaches try to overcome the shortcomings of the two previous approaches, where several limitations have been identified [14; 15; 16]: the "cold start" problem when there are not enough ratings, the inability to recommend non-textual items that do not have information about their content, quality criteria and reliability of the source that are not considered in the content-based systems, etc.

3.1.4 Other recommender systems

Recently, with the emergence of the semantic web, a new generation of recommender systems has emerged [17]: *(1) the ontology-based IF systems,* allowing *a* conversion from a description of items by key words to a semantic description based on concepts; *(2) the collaborative annotations systems*, assigning to resources a set of words called tags or annotations to describe their content or provide a more contextual and semantic information; *(3) the social networks-based IF systems*, managing the friends lists and expressing their interests (e.g. Facebook, MySpace, and LinkedIn). The great success of these services, encouraged the reuse of this social data in IF systems.

3.2 Related work

The sate of the art shows an important number of proposed recommender systems in educational settings [18; 19]. However, little work has been proposed in the context of online communities [20]. For instance the QSIA (Questions Sharing and Interactive Assignments) for learning resources sharing, assessing and recommendation used in the context of online communities [21]. ReMashed is a recommender system that addresses learners in informal learning networks [22; 23]. The authors created an environment that combines sources of users from different Web2.0 services and applied a hybrid recommender system that takes advantage of the tag and rating data of the combined web2.0 sources. Recent works use semantic approaches for the recommendation, taking advantage of the enhanced semantics representation. Brut and Sèdes [24] presented a personalized recommendation approach to monitor user activity in terms of topics of interest inferred from his conceptual navigation. Cantador et al. [25] presented an approach to automatically identify Communities of Interest from ontology-based user profiles.

3.3 Discussion

The literature review shows that few studies have focused on the recommendation in an informal setting. This lack of related work motivates us to apply this approach in the context of CoPEs, as addressed in our previous works [26 and 27]. Moreover, the proposition of a recommendation approach in CoPEs is necessary because existing systems in e-learning, for example, can not be used directly in the community. Learning is informal, participation being unsupervised and the objectives and constraints are different. In our case, the personalization will take into account other parameters linked, for example, to member's expertise, skills, purpose, etc. Accordingly, we will focus in this paper on the members’ profile, taking into account some specific dimensions that are important in the context of a community such as the member’s objective, his interests and expertise.

Our objective is to propose a personalized recommendation approach for CoPEs taking advantage from the existing works concerning, particularly: (1) the hybrid recommender systems proposed in the context of technology enhanced learning, and (2) the semantic approaches offering the advantage of the enhanced semantics representation (i.e. user profiles, items and capability of inferring knowledge from the relations defined in the ontologies).

4 Contribution

In this section, we describe first some situations in which members of CoPEs need suggestions of items. Then, we propose a recommendation approach for CoPEs based on the hybrid semantic IF.

4.1 Overview of the recommendation within CoPEs

We describe in this section, the recommendation during the following situations:

The member's personal space: once the member has authenticated, the system suggests him resources according to his profile (specialty, interests, preferences, expertise degree…). The suggested resources are related to the member's specialty or domain of interest, inferring also other similar resources. The recommendation may take into account the evaluations of other members having the same profile. Furthermore, the recommendation system will assign a higher priority to new resources than those already visited by the member. Moreover, resources that are not appreciated by the member (evaluated with a low score), will not be suggested for him another time.

During an explicit search: the member expresses his request to the semantic search engine, which proposes him a set of resources that meet his need. The semantic search selects also similar resources, by inferring other resources' domains. Furthermore, in order to enhance the search feature, the recommendation system may be exploited for providing information related to the member's profile, as well as the evaluations made by other members about the selected resources. For example, the search engine will propose for the member resources that have been appreciated by other members having the same profile (i.e. belong to the same community).

During a learning activity: the recommendation system suggests resources for members in order to support them in their activities. For example, members need recommendations of resources during a problem solving process. In this case, resources are related to the problem, and taking into account the member's interests, his preferences, etc.

When a new resource is added to the CoPE memory or when a new member joins the community: the system recommends the new resource to all members having a specialty or domain(s) of interests related or similar to the resource's domain(s). Once the resource is evaluated, it may be recommended to other members who belong to the same community of members who appreciated it (i.e. who have evaluated the resource with a high score). Similarly, when a new member is coming to the CoPE, the system recommends this member to all members having the same or similar specialty or domains of interests.

4.2 Recommendation approach for CoPEs

We propose a recommendation approach based on the hybrid semantic IF, integrating the content-based filtering (CBF), the collaborative filtering (CF) and the semantic filtering (SemF) approaches. The SemF is integrated in our solution as it offers the advantage of the enhanced semantics representation. Before describing in more detail the different recommendation strategies, we present first the knowledge representation aspect.

4.2.1 Knowledge representation

Resources and member profiles are represented semantically using OntoCoPE [28], an ontology dedicated for CoPEs. Figure 3 illustrates the resource conceptual model, where a set of concepts are proposed to describe the resource. These concepts will be used later to express the member's needs and preferences to search about or recommend the resource. For instance, the "nature", "language", and "format" concepts will be used in the pre-filtering process; the "knowledge domain" will be used in the recommendation. Furthermore, we have added the "difficulty" concept for a personalized recommendation according to the member's expertise level (e.g. if the member has a high degree of expertise in a given domain, the recommendation system will suggest him resources with high a degree of difficulty). In addition, the recommended resources will be ordered according to their difficulty degrees.

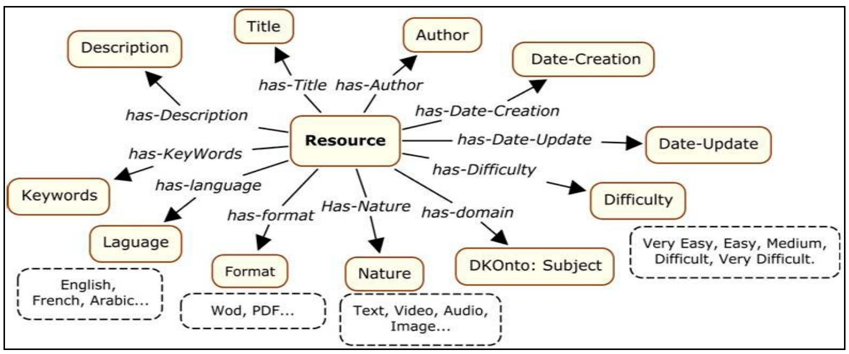


Figure 3 The resource conceptual model.

DKOnto refers to the Domain Knowledge Ontology, which describes the concepts related to the domain of interest (e.g. software engineering, networking, etc.). We consider in our research the hierarchical ontology of computer science domain, which derives from the well-known ACM taxonomy: (http://www.acm.org/class/1998/). We present in Figure 4 an excerpt of this ontology, which is used in our experimentation.

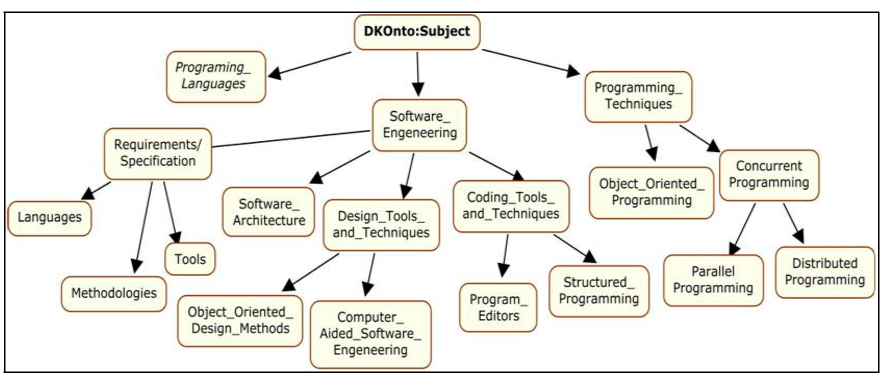


Figure 4 Excerpt of the computer science domain ontology.

Figure 5 describes a generic member profile model that can be used for the representation of both individuals and group members [29]. This model is based on some existing approaches [30; 31; and 32].

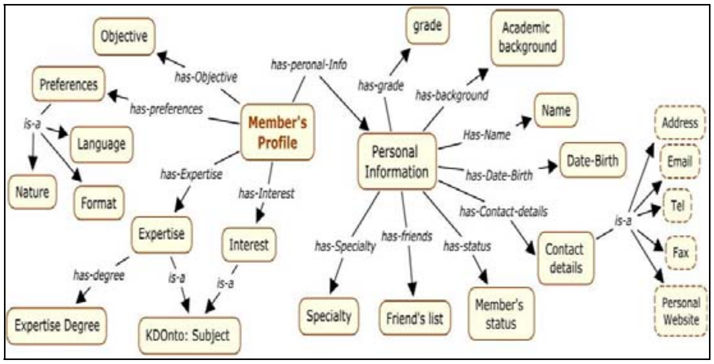


Figure 5 The profile conceptual model.

As shown in Figure 5, the member's profile is based on two types of information:

- *Static information:* including personal characteristics of the member such as his name, contact details, academic background, working experience, member status (e.g. expert, novice), qualification (e.g. technical, pedagogical), specialty, languages, friend's list, etc.
- *Dynamic information:* including different dimensions such as "Preferences" regarding the use of learning resources; "Expertise" and "Interests" about a specific domain; and "Objectives". This information will be used in order to recommend the adequate resources for members. For instance, the "Preferences" concept will be used in the pre-filtering process which consists to eliminate the resources that are not adapted to the profile of *M* (i.e. remove the resources that don't correspond to the preferences of *M*, such as the language, format and nature of the resource). For example, if the member has a preference for English and French languages, then the system will remove all the resources that are not written in English or French language. Similarly, if the member prefers textual resources, then the system will remove the multimedia resources, etc.

4.2.2 Recommendation strategies

Adding a new resource implies its semantic representation according to the conceptual model presented in Figure 3. Similarly, adding a new member within the CoPE, implies a profile acquisition according to the conceptual model presented in Figure 5. We consider that the specialty is required information, while the member's interests are considered as optional (i.e. the member may complete his profile later). Furthermore, the member's profile can be updated automatically, explicitly (e.g. using questionnaires) or implicitly (through a behaviour supervision).

Our recommendation approach is based on the hybrid semantic IF, integrating the content-based filtering, the collaborative filtering and the ontology-based filtering approaches. We have considered three recommendation strategies: (1) the semantic recommendation by specialty; (2) the semantic

Content-based recommendation by domains of interests; and (3) the semantic collaborative recommendation by domains of interests. Figure 6 illustrates the proposed recommendation strategies.

The recommendation system extracts data from the profile of the member *M*, and then proceeds as following:

(1) If the system hasn't found any information about the interests of the member *M*, in this case, the system applies a SemF by specialty (i.e. Strategy1).

(2) Otherwise, if the member *M* has Interests then the system applies first a SemF by interests, and then verifies the usage matrix if there are enough ratings to apply a collaborative recommendation (i.e. Strategy3), otherwise, the system applies a content-based recommendation (i.e. Strategy2).

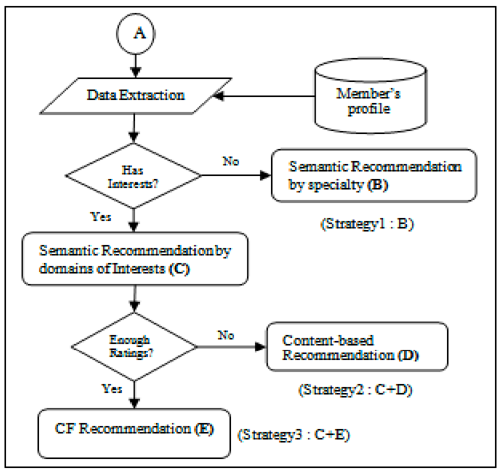


Figure 6 The proposed recommendation strategies.

We present below the three recommendation strategies, as following:

1) Strategy1: The semantic recommendation by specialty for the member *M*

In this algorithm, we propose a semantic recommendation by specialty, using an ontology-based filtering approach. First, the system localizes the domain of the specialty from the DKOnto and infers other similar concepts using semantic similarities between concepts of the ontology. Then, the system selects the resources that are related to the selected domains, make a pre-filtering in order to remove the resources that don't correspond to the member's preferences (e.g. according to the language, format and nature of the resource). Finally, the system assign priorities to the selected resources taking into account if the resource has been visited or not (i.e. resources that are not yet visited have more priority). The following is the proposed algorithm of recommendation for *M*:

Begin
Localize the domain of the specialty in DKOnto
Infer similar domains
Select the resources according to the selected domains
Make a pre-filtering on the selected resources according to the member's preferences
Filter the resources by assigning priorities according to the profile

Display the list of commended resources for the member M
End

2) Strategy2: The semantic content-based recommendation by domains of interests for the member *M*

In this algorithm, we propose a SemF and CBF approaches using the member's interests. The semantic recommendation using the interests returns a set of selected resources. Then the system makes a pre-filtering in order to remove the resources that don't correspond to the member's preferences. For each selected resource R_i, the system calculates the similarity between the profile and R_i using a similarity function, such as the cosine similarity:

$$Sim_{Cosine}(A,B) = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \times \sqrt{\sum_{i=1}^{n}(B_i)^2}}$$

Accordingly, the system calculates the similarity using the cosine function Sim_{cosine} (*Content-Based-Member-Profile(M),Content(R_i))*, where:

Content-based-Member-Profile(M): represents the preferences of the member *M*, i.e., a set of weighted characteristics of resources, describing the member's interests.

Content (R_i): is the content description of the resource R_i, i.e., a set of characteristics of R_i used to identify the pertinence of the resource for the different members. This description is represented as a weighted vector in which each component measures the importance of each characteristic. The contents of the resources are described using key words.

If the similarity Sim_{Cosine} *(Content-Based-Member-Profile (M), Content(R_i)> threshold1*, i.e. are similar, then the system recommends the resource R_i to the member *M*.

Finally, the system filters the resources by assigning priorities according to the profile. The following is the proposed algorithm of recommendation for the member *M*:

Begin
Order the Interests according to their position in DKOnto
For** each selected Concept C_i **do
Begin
Localize C_i in DKOnto and infer other concepts
Select the Resources related to C_i
Make a pre-filtering of the selected Resources according to the member's preferences
End
For** each selected Resource R_i **do
Begin
Calculate la similarity Sim_{Cosine} between the Profile and the Resource R_i
If** Sim_{Cosine} (Content-Based-Member-Profile (M), Content (R_i)> threshold1 **Then
Recommend the resource R_i for M
End

Filter the resources by assigning priorities according to the Profile of M
Display the list of commended resources for M
End

3) Strategy 3: The semantic CF recommendation by domains of interests for the member M

In this algorithm, we propose a SemF and CF approaches using the member's interests. The semantic recommendation using the interests returns a set of selected resources. Then the system makes a pre-filtering in order to remove the resources that don't correspond to the member's preferences. These resources will be integrated with the set of resources obtained from the CF recommendation. This later allows members to discover other domains through the evaluated resources that are appreciated by other members with similar interests.

In the context of a CoPE, members have different levels of expertise. Accordingly, we consider that the scores given to the resources based on the evaluations of members should take into account this difference of levels between members. More formally, we propose to interpret the usage matrix, *V*, taking into account the members' expertise level for the evaluated resources. The expertise level of a member is calculated in relation to all of his domains of expertise using the ontology DKOnto.

The obtained matrix will be used in the two steps of the CF process, which consist to: (1) calculate the similarity between the users and infer communities (e.g. using the K nearest neighbours), and (2) predict notes on resources and select only those with a high score. The evaluation consists to give a score (1-5) from very bad to very good. Accordingly, we chose the Pearson similarity function, for the prediction of the evaluations:

$$Sim_{pearson}(A,B) = \frac{\sum_{i=1}^{n}(A_i - \overline{A_i}) X (B_i - \overline{B_i})}{\sqrt{\sum_{i=1}^{n}(A_i - \overline{A_i})^2 \sum_{i=1}^{n}(B_i - \overline{B_i})^2}}$$

where: $\overline{A_i}, \overline{B_i}$: represent, respectively, the average of the notes contained in the vector A and B.
The following is the proposed algorithm of CF recommendation for the member *M*:

Begin
Order the Interests according to their position in DKOnto
For *each selected Concept* C_i ***do***
Begin
Localize C_i *in DKOnto and infer other concepts*
Select the Resources related to C_i
Make a pre-filtering of the selected Resources according to the member's preferences
End
Interpret the usage matrix V
Construct the similarity matrix and Infer communities of members
For *each Resource* R_i *appreciated by the other members and not yet evaluated by M* ***do***
Begin
Predict the evaluations
If *(Prediction > threshold2)* ***Then*** *Recommend the resource* R_i *to M*

End
Display the list of commended resources for M
End

5 Results and Experimentations

We have developed a prototype of a recommendation system called “ReCoPESyst”, based on the proposed recommendation approach. In order to evaluate this system, we considered a CoPE called CoPHEduc (CoP Higher Education). The main objective of this CoPE is to promote e-learning in higher education context applied to the domain of computer science. The CoPE is made up of principal actors of a university (lecturers, teaching assistants, lab assistants) as well as some pedagogues and software engineers.

In this section, we present first the recommendation system through an exemplification scenario and then we present the results of an experimentation study, based on a qualitative evaluation, conducted within CoPHEduc.

5.1 ReCoPESyst: A Prototype of a Recommendation System for CoPEs

Figure 7 shows a screenshot of ReCoPESyst system. In order to illustrate the different functionalities proposed by the system, we present below an exemplification scenario.

Figure 7 A personalized recommendation system for CoPHEduc.

We can see the personalized space of the member “M1”, offering the following functionalities:

- Notifications about new added members, new resources, new proposed solutions and problems.
- Personalized recommendation of resources and members.
- Last visited resources.

The member *M1* has the specialty of “Programming Techniques” and the following Interests: “Concurrent Programming”; “Object Oriented Languages”; “Programming Languages”; and “Visual

Programming". Accordingly, as shown in this figure, the system suggests him a set of resources and members according to his Interests.

5.2 Qualitative Evaluation

An experimental study was conducted to explore the benefits of using the recommender system within CoPHEduc. We describe in this section the results of an investigation we have made to evaluate ReCoPESyst prototype. Fifteen teachers from the community were asked to use ReCoPESyst and then each one provided us with a detailed feedback of use. We have gathered more than 750 resources from different websites such as Amazon (http://www.Amazon.com). These resources are related to some domains of our ontology DKOnto. The distribution of the domains of relevance of resources and the domains of interests of members, regarding the selected domains, is described in the table 1 below.

Table 1 Distribution rates for the selected domains.

Domains	**Rates**	
	Resources	**Members**
D1: Requirement /Specification	5%	15%
D2: Design Tools and Techniques	5%	20%
D3: Structured Programming	7%	5%
D4: Coding Tools and Techniques	15%	8%
D5: Object Oriented Programming	25%	15%
D6: Programming Languages	18%	12%
D7: Programming Techniques	20%	12%
D8: Languages	5%	13%

Figure 8 illustrates this distribution, given that each resource may be linked to several domains, and similarly, each member may have many domains of interests. For example, there are 15% of members interested by the domain D_1 ("Requirement /Specification"), and 5 % of resources are related to this domain.

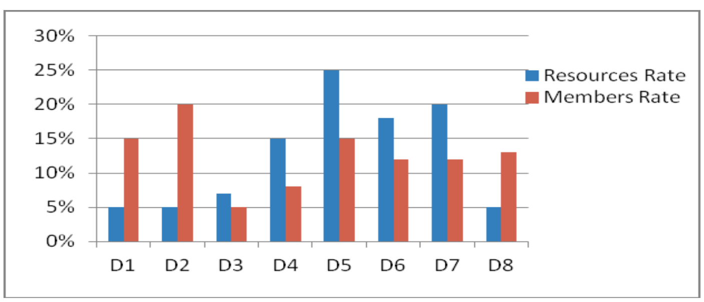


Figure 8 Members and resources distribution by domains.

The questionnaire of evaluation, we have proposed, includes ten questions using a five-point Likert scale (SA, strongly agree; A, agree; U, undecided; D, disagree; SD, strongly disagree). The questions are classified under four dimensions: (1) usability, in terms of facility of use and quality of presentation; (2) effectiveness, in terms of pertinence of results; (3) usefulness, in terms of members' learning satisfaction; and (4) willingness, to reuse ReCoPESyst in the future. The questions are as follows:

Q1: I found ReCoPESyst very easy to use.

Q2: I found the results very well presented.

Q3: I found the recommended resources correctly ordered according to the difficulty degree and the member's expertise level.

Q4: I found the results recommended using the Strategy 1 very appropriate to my interests.

Q5: I found the results recommended using the Strategy 2 very appropriate to my interests.

Q6: I found the results recommended using the Strategy 3 very appropriate to my interests.

Q7: The system helps me to carry out my pedagogical activities.

Q8: I have found the system very useful for my learning.

Q9: I would like to use this system in the future

Q10: I will recommend this system to other teachers.

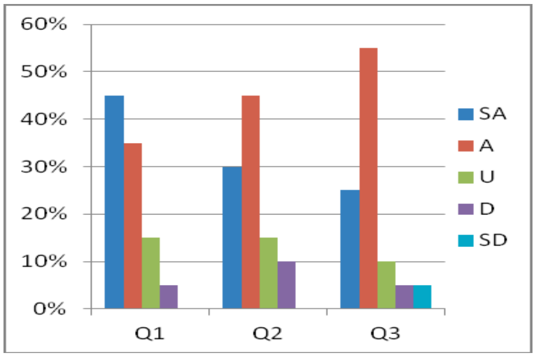
The preliminary tests and experimentations helped us to collect the member's comments about the proposed system. Some members propose to enrich the system with another service offering the suggestion of resources and members that are not necessarily related to their interests. This will help them to have general information and acquire knowledge in different domains, and this will help us to improve our system as one of the limitations of current recommendation systems is the overspecialization and domain-dependency. Other members propose to recommend the learning resources that have been visited and evaluated by the member's friends. Members who belong to the same social networks generally like the same resources and have the same tastes and objectives.

The results of our investigation are summarized in the Table 2.

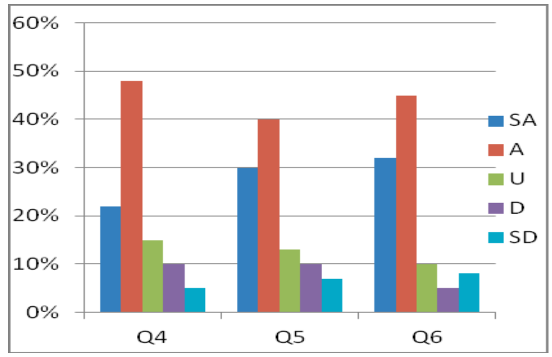
Table 2 Investigation Results.

Questions	**SA**	**A**	**U**	**D**	**SD**	**Mean**
Q1	45%	35%	15%	5%	0%	4.2
Q2	30%	45%	15%	10%	0%	3.95
Q3	25%	55%	10%	5%	5%	3.9
Q4	22%	48%	15%	10%	5%	3.72
Q5	30%	40%	13%	10%	7%	3.76
Q6	32%	45%	10%	5%	8%	3.88
Q7	25%	55%	12%	8%	0%	3.97
Q8	22%	55%	15%	8%	0%	3.91
Q9	40%	50%	10%	0%	0%	4.3
Q10	30%	65%	5%	0%	0%	4.25

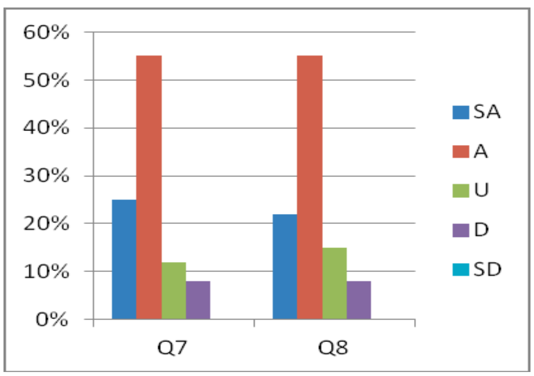
Figure 9 shows the evaluation results according to the four dimensions: (a) *usability* (questions 1, 2 and 3); (b) *effectiveness* (questions 4, 5 and 6); (c) *usefulness* (questions 7, 8); and (d) *willingness* (questions 9, 10).



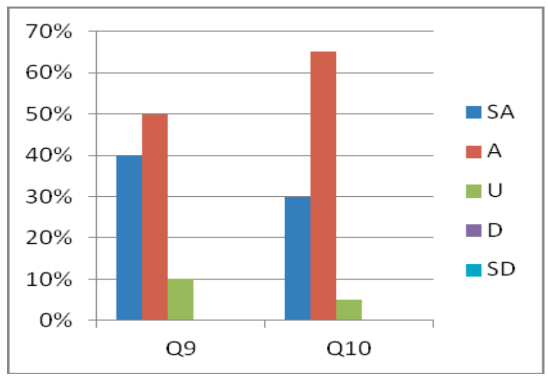
(a) Usability results



(b) Effectiveness results



(c) Usefulness results



(d) Willingness results

Figure 9 Evaluation Results.

The results show a high degree of interest of the evaluators for ReCoPESyst: the mean average of usability = 4.016 and the mean average of effectiveness = 3.786. This allows us to confirm the utility and effectiveness of the proposed recommendation approach. However, we noticed that the results of the qualitative evaluation didn't help us to compare the proposed strategies. Accordingly, we envisage in a near future to evaluate our approach using some existing datasets. Drachsler et al. [33] addressed the issue of missing data sets for recommender systems in technology enhanced learning that can be used as benchmarks to compare different recommendation approaches. Little works were interested by this issue such as: (1) the work presented by Verbert et al. [34] which provided an analysis of datasets that can be used for research on learning and knowledge analytics; and (2) the work presented by Cechinel et al. [35] which evaluated recommendations of learning resources generated by different well known CF algorithms using two databases, with implicit and explicit ratings, gathered from the popular MERLOT repository (http://www.merlot.org). These datasets and results will help us in our future work to evaluate deeply our approach.

On the other side, the results of our investigation show that the mean averages of usefulness and willingness are respectively 3.94 and 4.275. These results reflect the members' interests regarding the recommender system and, accordingly, encourages us to evaluate our approach in a real community setting, asking the member of the community to use ReCoPESyst and integrate it in their daily practice.

6 Conclusions and Future Work

The paper discusses the application of IF in CoPEs as a technology support to assist members to find the appropriate learning resources. A personalized recommendation approach is proposed based on the hybrid semantic IF, integrating the content-based filtering, the collaborative filtering and the ontology-based filtering approaches. The main contribution of this approach is the identification of three recommendation strategies: (1) the semantic recommendation by specialty; (2) the semantic Content-based recommendation by domains of interests; and (3) the semantic collaborative recommendation by domains of interests.

In order to evaluate our approach, we considered a CoPE whose main objective is to promote e-learning in higher education context applied to the domain of computer science. The first tests and experiment results show that the system is very useful for members of this community, as it provides them with a personalized access and proposes recommendations for supporting them.

In our future work, we envisage to evaluate deeply our system using an online evaluation. We'll ask members of the community to use the system and integrate it in their daily practices in order to check the usefulness and effectiveness of the recommendation system through the members' feedback. Furthermore, we envisage an offline evaluation of our system, using some existing datasets in order to evaluate the performance and effectiveness of different recommendation strategies.

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