

# Semantic Collaborative Filtering for Learning Objects Recommendation

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**Keywords:** Online Communities of Practice, Learning Resources, Recommendation System, Ontologies, Semantic Filtering, Collaborative Filtering.

**Abstract:** The present paper proposes a personalized recommendation approach of learning objects (LOs) within an online Community of Practice (CoP). Three strategies of recommendation have been proposed: (1) a semantic filtering (SemF) by member's interests; (2) a collaborative filtering (CF) based on the member's expertise level; and (3) a semantic collaborative filtering combining in different ways the two approaches. The expertise level of a member is calculated in relation to all of his domains of expertise using the domain knowledge ontology (DKOnto). A similarity measure is proposed based on a set of rules which cover all the possible cases for the relative positions of two domains in DKOnto. In order to illustrate our work, some preliminary results of experimentation have been presented.

## 1 INTRODUCTION

The great expansion and explosive use of the Internet has created new ways of collaboration between people as well as exchange and sharing of knowledge. A vast number of learning object repositories are made available to any user searching for educational content on various topics (Tzikopoulos et al., 2007). However, one of the main problems encountered actually is the selection of the appropriate resources. Accordingly, to deal with the problem of information overload, the need for recommender systems is more than necessary.

The main objective of our research is to facilitate access and reuse of knowledge within a CoP of teachers. The main objective of this community is to promote e-learning in higher education context applied to the domain of computer science.

We propose in this paper a personalized recommendation approach of learning objects (LOs) for members of this CoP, based on the semantic collaborative information filtering approach. Three strategies of recommendation have been proposed: (1) a semantic filtering (SemF) by member's interests; (2) a collaborative filtering (CF) based on the member's expertise; and (3) a semantic collaborative filtering combining in different ways

the two approaches. These strategies are based respectively on the following member's objective: specialization ; learning; or both, specialization and learning. The CF is used to predict the utility of LOs for members based on the similarity among their preferences and the preferences of other members. The SemF is used, to take advantage of the enhanced semantics representation.

The main contribution of this paper concerns: (1) the proposition of a set of rules to calculate the similarity between the domains of interests of the member and each of the domains of the LO; and (2) the proposition of a pseudo usage matrix for the prediction of evaluations using the CF approach, which is based, both, on the members' evaluations and on the members' expertise levels and importance degrees of the domains of the LOs.

The remainder of this paper is organized as follows: Section 2 presents a literature review about recommendation systems and approaches in the technology enhanced learning. Section 3 proposes a personalized recommendation approach of LOs within an online CoP. A prototype of the proposed recommendation system and the experimental results are presented in Section 4. Finally, the main contribution and some future perspectives are discussed in the conclusion.

## 2 LITTERATURE REVIEW

Recommender systems aim to generate suggestions about new items or to predict the utility of a specific item for a particular user.

### 2.1 Recommendation Approaches

Three types of approaches are distinguished: (1) the content-based filtering (CBF) recommenders, are built on the assumption that a person likes items with similar features to those of other items he preferred in the past (Peis et al., 2008); (2) the CF recommenders, generates suggestions about data items that users with similar tastes and preferences liked in the past (Shafer et al., 2007); and (3) the hybrid recommenders try to overcome the shortcomings of the two previous approaches by combining them in different methods (Burke, 2007).

With the advent of the semantic web, a new generation of recommender systems based on ontologies has emerged. These approaches take advantage of the enhanced semantics representation.

### 2.2 Related Work

The state of the art shows a large number of recommendation systems proposed in the context of formal education, i.e. including learning offered from educational institutions (e.g. universities, schools) (Manouselis et al., 2009). A discussion of the advantages and limitations of different techniques applied in this context was presented in (Drachsler et al., 2008). However, few works have been proposed in an informal setting (Ziovas et al., 2010).

As reported by Manouselis et al. (2009) an informal setting is described in the literature as a learning phase of so-called lifelong learners who are not participating in any formal learning and are responsible for their own learning pace and path (Colley et al., 2002; Longworth, 2003). Online communities and social networks are examples of such contexts.

We mention for example the following recommendation systems proposed in an informal setting: (1) the QSIA system (Questions Sharing and Interactive Assignments) to share educational resources, evaluation and recommendation in the context of online communities (Rafaeli et al., 2004). (2) The ReMashed system for learners in informal learning network (Drachsler et al., 2009). The main objective of this system is to offer personalized

recommendations from the emerging information space of a community.

The review of the literature shows that most systems provide resources (Tang and McCalla, 2003) and / or individuals (Recker and Wiley, 2003), which can help in a learning activity. Other systems recommend courses, offering some advices to learners for their registration in training sessions (Garcia-Molina, 2008), or appropriate activities and their execution sequences, allowing learners the selection of the appropriate activities to achieve some educational objectives (Hummel et al., 2007).

The lack of work in an informal education motivated us to apply this approach in the context of online CoPs. Our goal is to propose a personalized recommendation approach taking into account the advantages of existing hybrid systems, especially in the domain of e-learning which is very close to our context of study.

The proposition of a recommendation approach in CoPs 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. In addition, the representation of the resource will also take into account the evaluation aspect according to several dimensions: feedback, results, analysis, etc. We will focus in this paper on the members' profile, taking into account some specific dimensions that are important in the context of a CoP such as the member's objective, his interests and expertise.

## 3 A RECOMMENDATION SYSTEM FOR COPS

We propose in this section a personalized recommendation system for CoPs of teachers.

### 3.1 Recommendation Strategies

As illustrated in the Figure 1, three recommendation strategies are proposed, according to the member's objective:

1. Strategy 1: If the objective is a "Specialization", then the system applies a SemF by domains of interests.
2. Strategy 2: If the objective is a "Learning", then if there are enough ratings the system applies a CF,

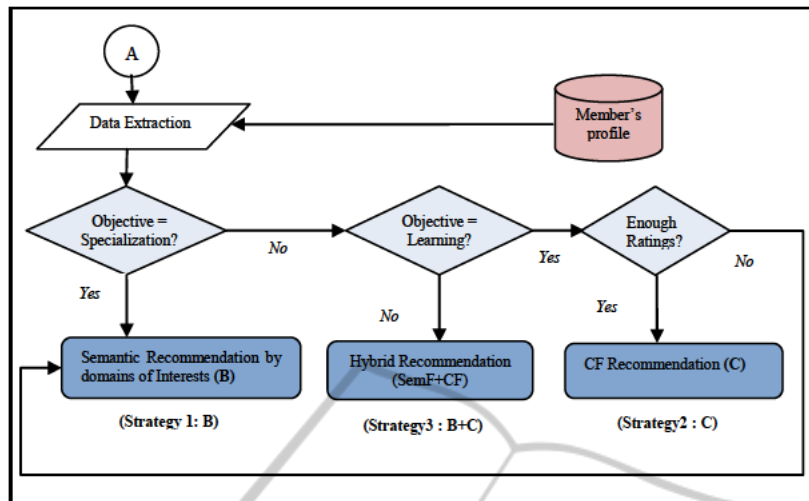


Figure 1: The proposed recommendation strategies.

otherwise, the system applies the strategy1 (i.e. considers a specialization rather than learning).

3. Strategy 3: If the objective is a “Specialization and Learning”, then if there are enough ratings, the system applies a hybrid recommendation, where two techniques of hybridization are proposed: (1) a SemF boosted CF approach; and (2) a feature combination approach. Otherwise, if there are not enough ratings, the system applies the strategy1.

## 3.2 Semantic Filtering Approach

We present in this section the domain knowledge ontology, the conceptual models of members’ profiles and LOs and the SemF approach.

### 3.2.1 Domain Knowledge Ontology

We consider in our research a hierarchical ontology of the computer science domain which is derived from the well-known ACM taxonomy (<http://www.acm.org/class/1998/>). Figure2 illustrates the domain knowledge ontology (DKOnto).

However, taking into account that each domain has a degree of importance in the CoP, we have enriched in earlier work (Berkani and Chikh, 2013) this ontology with weights (see Figure 2). These weights reflect the importance of the corresponding domains and relevance to the exchanges within the CoP. The leaf nodes directly reflect this relevance while each parent’s weight is obtained by summing up those of its children nodes (a parent has a higher weight as it covers more domains). The weights may be updated automatically by observing the members’ interactions within the community. For instance, if

members capitalize and evaluate a high number of LOs related to the domain  $D_i$  which may have a low weight at some specific time, then this domain will get its weight increased to reflect the relevance of  $D_i$ .

### 3.2.2 Semantic Representation of Resource and Profile

We have proposed in earlier works, an ontology dedicated for CoPs of e-learning (Berkani and Chikh, 2009). This ontology is used and enriched in other works such as (Berkani et al., 2013). Figure 3 and Figure 4 illustrate the resource and profile conceptual models.

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.

Figure 4 describes a generic member profile model that can be used for the representation of both individuals and group members (Berkani et al., 2010). This model is based on some existing approaches (PAPI, 2000; IMS LIP, 2001; Evangelou et al., 2006). The proposed model is based on two types of information:

- *Static information*, including personal characteristics such as name, contact details (email, Tel, fax), academic background, working experience, languages, friend’s list.
- *Dynamic information*, including different dimensions such as “Preferences”; “Expertise” and “Interests” about a specific domain; and “Objectives”.

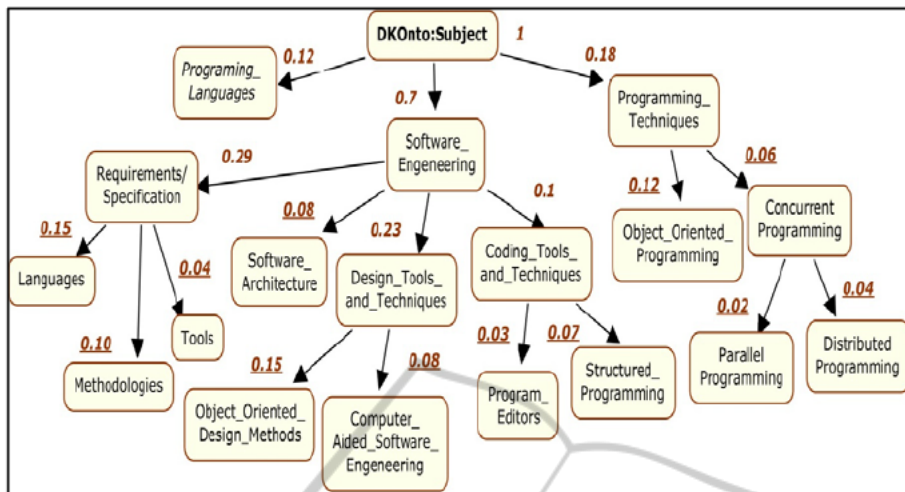


Figure 2: Example of a DKOnto ontology, from (Berkani et al., 2013).

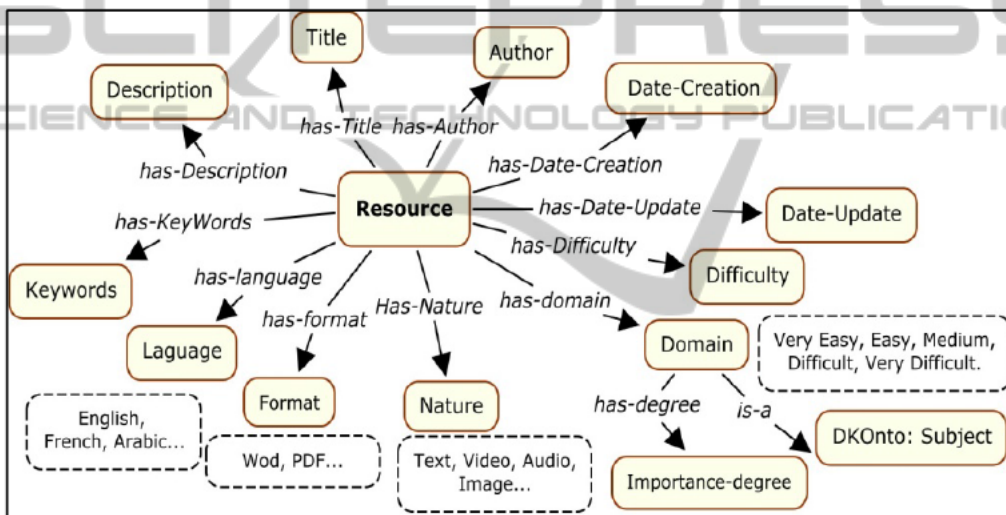


Figure 3: The resource conceptual model, from (Berkani and Chikh, 2013).

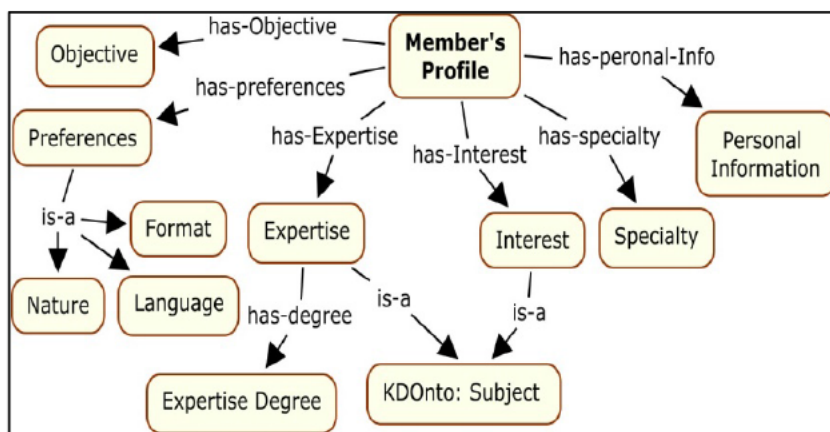


Figure 4: The profile conceptual model, adapted from (Berkani and Chikh, 2013).

### 3.2.3 A New Similarity Measure

We have proposed in (Berkani and Chikh, 2013) a set of rules to calculate the similarity between each of the member's domains of interests and each of the domains of the LO. These rules cover all the possible cases for the relative positions of two domains in DKOnto.

The similarity between the member  $M$  and the resource  $R$  represents the degree of closeness of  $R$  for the domains of interests of  $M$ . We define this similarity as the Mean Similarity.

where:

$D$  is one of the member's domains of interests,  
 $D'$  is one of the LO domains,  
 $D_c$  is the closest (parent) domain common to  $D$  and  $D'$ , and

$\Delta Depth$  is the difference between the depths of  $D$  and  $D'$  in the ontology.

The mean similarity between  $M$  and  $R$  is expressed as follows:

$$Similarity(M, R) = \frac{1}{N} \sum_{i=1}^m Sim(D_i, D_j), j=1, n \quad (1)$$

where:

$Sim(D_i, D_j)$  is the similarity between the domain  $D_i$  of  $M$  and the domain  $D_j$  of  $R$

$N$  is the number of similarities ( $n \times m$ )

The Figure 5 below describes an example of use of the similarity measure. Let  $M$  be a member and  $R$  a LO. Let  $M$ 's domains of interests be the following:  $D_1, D_2$  and  $D_3$  and let  $R$ 's relevant domains be the following:  $D_4$  and  $D_5$ .

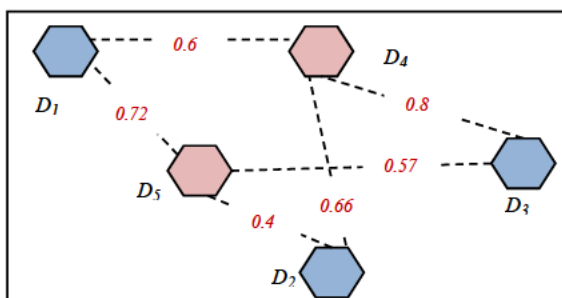


Figure 5: Example of a similarity measure.

We define the similarity matrix of  $M$ 's domains of interests with respect to  $R$  as an ( $m \times n$ ) matrix as follows:

$$Similarity(M, R) = \begin{pmatrix} 0.6 & 0.72 \\ 0.66 & 0.4 \\ 0.8 & 0.57 \end{pmatrix}$$

The Mean Similarity  $(M, R) = 0.625$ .

Finally, a set of suggested resources  $R$  will be recommended for  $M$ , according to a predefined threshold  $t$ : If the  $Similarity(M, R) > t$ , then the resource  $R$  is recommended for  $M$ . For example if  $t$  is equal to 0.5 then all the resources  $R$  where the  $Similarity(M, R)$  is greater than or equal to  $t$  will be recommended for  $M$ .

The proposed SemF algorithm is as follows:

**SemF Algorithm (Input:  $M$ , Output: suggested  $R$ )**

**BEGIN**

- Extract the domains of Interests of the member  $M$  from his Profile

- Localize the domains of Interests from DKOnto

- Make a pre-filtering

**For each selected Resource  $R_i$ , do**

**Begin**

Calculate the similarity  $Sim$  between  $M$  and  $R_i$

**If  $Sim(M, R_i) > t$  Then**

Recommend  $R_i$  for  $M$

**End**

Filter the resources by assigning priorities according to the Profile of  $M$

Display the list of commended resources for  $M$

**End**

**END**

The pre-filtering process 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 other resources (that are not in English or French

Table 1: The proposed similarity rules.

	Description	Similarity
Rule1	D corresponds to $D'$	$Sim(D, D') = 1$
Rule2	D (direct or indirect) parent of $D'$	$Sim(D, D') = 1$
Rule3	D (direct/indirect) son of $D'$	$Sim(D, D') = \frac{ weight(D) - weight(D') }{\Delta Depth}$
Rule4	D and $D'$ are independent	$Sim(D, D') = \begin{cases} weight(D_c) & \text{if D and D' at the same depth} \\ \frac{weight(D_c)}{\Delta Depth} & \text{otherwise} \end{cases}$

language). Similarly, if the member prefers textual resources, then the system will remove the multimedia resources, etc.

The recommended resources will be assigned with priorities taking into account different parameters, such as: the difficulty of the resource and the expertise degree of the member; see if the resource has been visited or not, evaluated or not (i.e. resources that are not yet visited have more priority).

### 3.3 Collaborative Filtering

In the context of a CoP, 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 LOs. The expertise level of a member is calculated in relation to all of his domains of expertise using the ontology DKOnto (see Figure 2). We formulate the problem as follows:

Let  $M$  be a member and  $R$  a LO. Let  $M$ 's domains of expertise be defined as a vector  $E_M = [E_1, E_2, \dots, E_m]$ . We associate with this vector a vector  $D_M = [d_1, d_2, \dots, d_m]$  (with same size as  $E_M$ ) meaning that  $M$  has a degree of expertise  $d_i$  in the domain  $E_i$ , where  $0 \leq d_i \leq 1$ . (It should be noted that 'm' can be strictly smaller than the total number of domains in the ontology.) Each resource has a set of relevant domains denoted by vector  $D_R = [D_{R_1}, D_{R_2}, \dots, D_{R_k}]$ .

The idea behind this formalization of the problem is that each domain of expertise  $E_i$  of  $M$  is similar to a certain degree to each domain  $D_{R_j}$  of  $R$ .

Thus, we define the similarity matrix of  $M$ 's expertise with respect to  $R$  as an  $(m \times R_k)$  matrix as follows:

$$\text{Similarity}(M,R) = \begin{pmatrix} \text{Sim}(E_1, D_{R_1}) & \dots & \text{Sim}(E_1, D_{R_k}) \\ \vdots & \text{Sim}(E_i, D_{R_j}) & \vdots \\ \text{Sim}(E_m, D_{R_1}) & \dots & \text{Sim}(E_m, D_{R_k}) \end{pmatrix} \quad (2)$$

where:

$0 \leq \text{Sim}(E_i, D_{R_j}) \leq 1$  is the similarity between  $M$ 's domain of expertise  $E_i$  and the domain  $D_{R_j}$  of  $R$ .

We know that each domain  $D_{R_j}$  of  $R$  has a weight  $0 \leq p_{R_j} \leq 1$  for this resource. Each member  $M$  has a degree of expertise  $0 \leq d_i \leq 1$  with respect to his domain of expertise  $E_i$ . We define the degree of expertise of  $M$  with respect to  $D_{R_j}$  (domain  $j$  of  $R$ ) as

follows:

$$\text{Expertise}(M, D_{R_j}) = \sum_{i=1}^m d_i \times \text{Sim}(E_i, D_{R_j}) \quad (3)$$

We define an overall degree of expertise of  $M$  with respect to  $R$  as being:

$$\text{Expertise}(M,R) = \sum_{j=1}^k p_{R_j} \times \text{Expertise}(M, D_{R_j}) \quad (4)$$

We finally calculate the interpreted usage matrix, by considering only the evaluations of members having an expertise degree greater than or equal to 0.5 for  $R$ , as follows:

$$v'_{ij} = \begin{cases} v_{ij} & \text{if } \text{Expertise}(M,R) \geq 0,5 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

The obtained matrix will be used in the two steps of the CF: (1) to calculate the similarity between the members and infer communities, and (2) predict notes for 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 correlation, for the prediction of the evaluations.

### 3.4 Hybrid Filtering

We have proposed different methods combining the semantic and the CF approaches. We present in this paper two algorithms of hybridization as follows:

#### 3.4.1 A Semantic Boosted CF Approach

The main idea is to apply a SemF, then provide suggestions through a CF. The SemF is applied to each row of the matrix and gradually generates a pseudo matrix,  $PV$ . Each row,  $i$ , of this matrix includes the evaluations given by the member  $M_i$ , if they are available; otherwise the predictions calculated using the SemF are considered:

$$pv_{ij} = \begin{cases} v_{ij}, & \text{if } M_i \text{ has evaluated } R_j \\ s_{ij}, & \text{otherwise} \end{cases} \quad (6)$$

where:

$v_{ij}$  refers to the score given by the member  $M_i$  on the resource  $R_j$ ,

$s_{ij}$  refers to the score calculated using the SemF.

The system applies a semantic recommendation and then the similarity results are converted into a set of scores from 1 to 5, as follows:

If  $\text{Similarity}(M_b, R_j) \in [0, 0.2]$  then score =1  
 Elseif  $\text{Similarity}(M_b, R_j) \in [0.2, 0.4]$  then score =2  
 Elseif  $\text{Similarity}(M_b, R_j) \in [0.4, 0.6]$  then score =3  
 Elseif  $\text{Similarity}(M_b, R_j) \in [0.6, 0.8]$  then score =4  
 Elseif  $\text{Similarity}(M_b, R_j) \in [0.8, 1]$  then score =5  
 Finally, the CF is applied using the  $PV$  matrix.

### 3.4.2 A Feature Combination Approach

We propose an approach which combines the CF and the SemF approaches using a distance formula. The collaborative distance represents the correlation between resources using the Pearson function, while the semantic distance represents the similarity between the resources using the "similarity rules", we have proposed in section 3.2.3.

We adopt a combination method to enrich the neighborhood, combining both semantic and collaborative distances, using the following formula:

$$Distance = (Col-Distance + Sem-Distance) / 2 \quad (7)$$

where:

Col-Distance refers to the collaborative distance, Sem-Distance refers to the semantic distance, Distance represents the distance between the resources.

The recommendation will be based on the value of a predefined threshold,  $t$ . A set of resources will be suggested to the member where the value of "Distance" is greater than or equal to " $t$ ".

## 4 RESULTS AND EVALUATION

### 4.1 ReCoPSyst: A Prototype of a Recommendation System

In order to illustrate our work, we have developed a personalized recommendation system called "ReCoPSyst", based on the proposed approach. In order to evaluate this system, we considered a CoP called CoPHeduc (CoP Higher Education), made up of actors who are interested to teaching in computer science in the university.

Figure 6 shows a screenshot of the proposed recommendation system for this community. The prototype ReCoPSyst was included in the CoPHeduc portal. We can see the personalized space of the member *MI*, offering for instance the following functionalities:

- Personalized recommendation of LOs and members.
- Last visited LOs.
- Notifications about new added members, new LOs, etc.

ReCoPSyst offers different recommendation services based on the proposed approaches:

- A Semantic recommendation service based on the similarity measures. Furthermore, we have developed other similarity recommendation

services using some existing metrics such as Wu and Palmer (1994).

- A collaborative recommendation services using different similarity functions (Pearson, cosine...) and according to different recommendation types (user-user or item-item).
- Hybrid recommendation services using the above mentioned algorithms (e.g. a semantic boosted collaborative approach and a feature combination approach).

We can see in Figure 7 an example of a collaborative recommendation service. The member can see the description of each recommended resource, download or evaluate it. Furthermore, the system proposes additional information about the evaluations made by other members for each resource (e.g. the average resource assessment, the number of evaluators).

### 4.2 Tests and Evaluation

We present in this section the results of two experimentations: (1) a qualitative evaluation; and (2) an offline evaluation, using some existing datasets.

#### 4.2.1 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 ReCoPSyst prototype. Fifteen teachers from the community were asked to use ReCoPSyst and then each one provided us with a detailed feedback of use. We have gathered more than 350 resources from different websites such as Amazon. Furthermore more than 300 resources were captured by members using the system. The resources are related to some domains of our DKOnto. The distribution of the domains of relevance of resources and domains of interests of members by the selected domains is described in the table 2 below. 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.

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



Figure 6: A personalized recommendation system.



Figure 7: Example of a CF recommendation.

Table 2: Distribution rates for the selected domains.

Domains	Rates	
	Res.	Mem.
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%

of results; (3) *usefulness*, in terms of members' learning satisfaction; and (4) *willingness*, to reuse ReCoPSyst in the future. The questions are as

follows:

- Q1: I found ReCoPSyst 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 SemF very appropriate to my interests.
- Q5: I found the results recommended using the CF very appropriate to my interests.
- Q6: I found the results recommended using the Hybrid recommendation very appropriate to my interests.



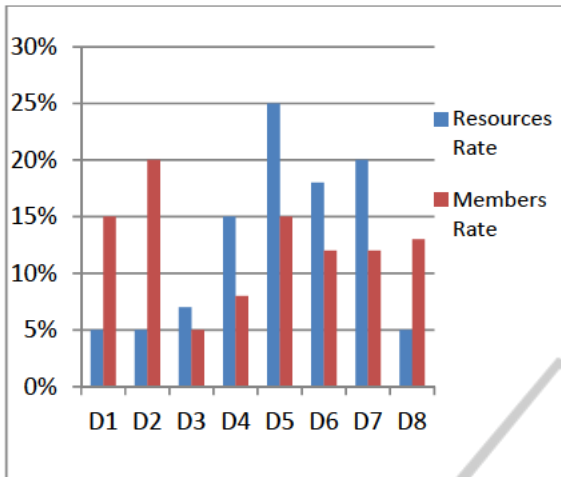


Figure 8: Members and resources distribution by domains.

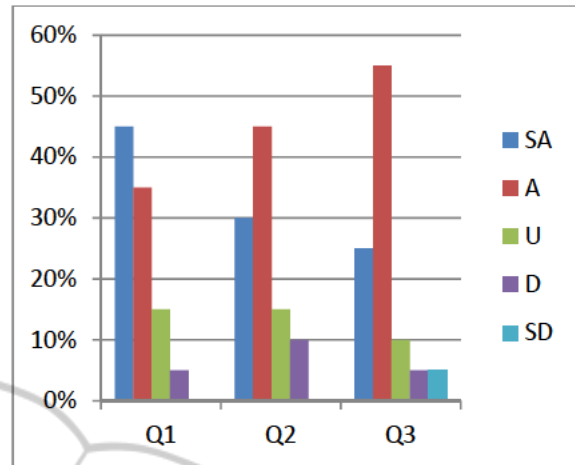


Figure 9: Usability evaluation results.

- 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 results of our investigation are summarized in the Table 3.

Table 3: Investigation Results.

Quest.	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	25%	45%	15%	10%	5%	3.75
Q5	25%	50%	10%	5%	10%	3.75
Q6	32%	55%	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

Figures 9, 10, 11 and 12 illustrate the evaluation results according to the four dimensions: (1) usability (questions 1, 2 and 3); (2) effectiveness (questions 4, 5 and 6); (3) usefulness (questions 7, 8); and (4) willingness (questions 9, 10).

The results show a high degree of interest of the evaluators for ReCoPSyst: the mean average of usability = 4.016 and the mean average of effectiveness = 3.793. This allows us to confirm the utility and effectiveness of the proposed recommendation approach. However, we notice that the results of the qualitative evaluation didn't help

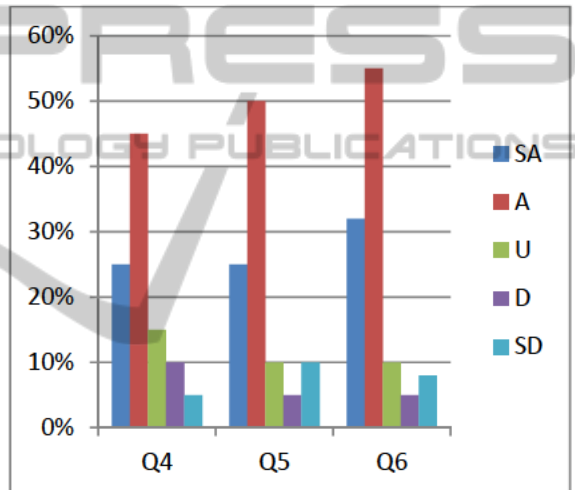


Figure 10: Effectiveness evaluation results.

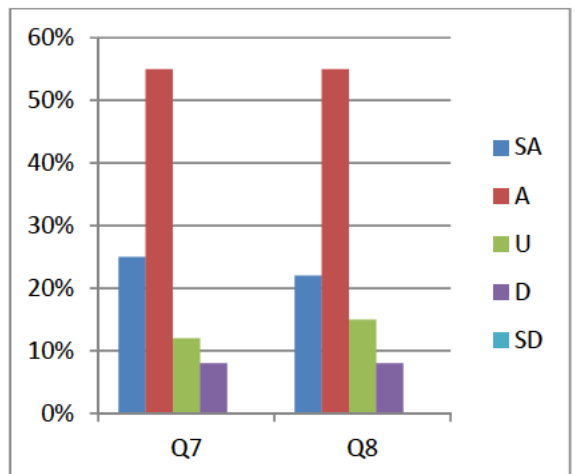


Figure 11: Usefulness evaluation Results.

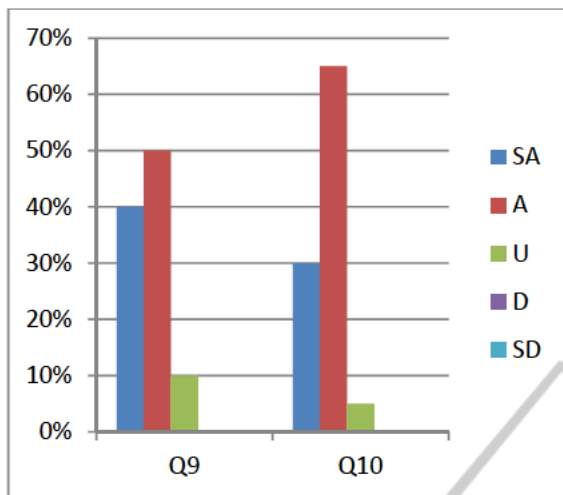


Figure 12: Willingness evaluation Results.

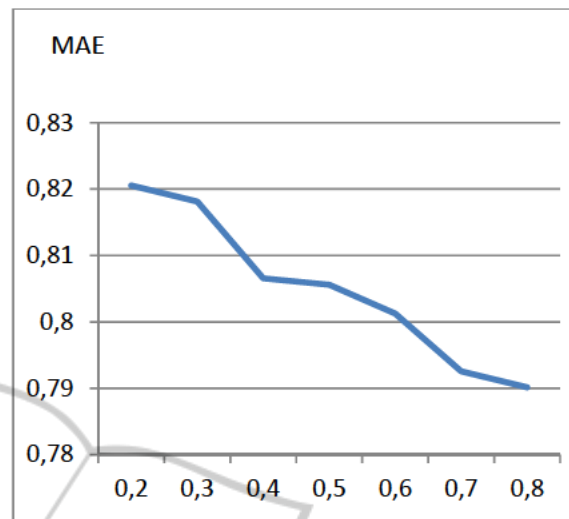


Figure 13: CF approach (classic algorithm).

us to compare the proposed strategies. Accordingly, we are currently evaluating our system using some existing datasets such as MovieLens, Book Crowsing and Amazon.

On the other side, the results show that the mean averages of usefulness and willingness are respectively 3.94 and 4.275. These results encourages us to evaluate our approach in a real community setting, asking the members of the community to use ReCoPSyst and integrate it in their daily practice.

#### 4.2.2 Offline Evaluation

In order to evaluate the different proposed approaches, we have made some experiments using two datasets: (1) the resources we have gathered; and (2) the well known dataset MovieLens. We present in this paper some results.

We have used different quality metrics for the evaluation: the Mean Absolute Error (MAE), the Precision and Recall, etc. Figure 13 and figure 14 illustrate the evaluation of the proposed CF approach using the set of learning resources we have gathered. We can see that the CF using the member's expertise is more efficient than the classic algorithm of the CF.

Figure 14 illustrates the CF approach using the member's expertise level.

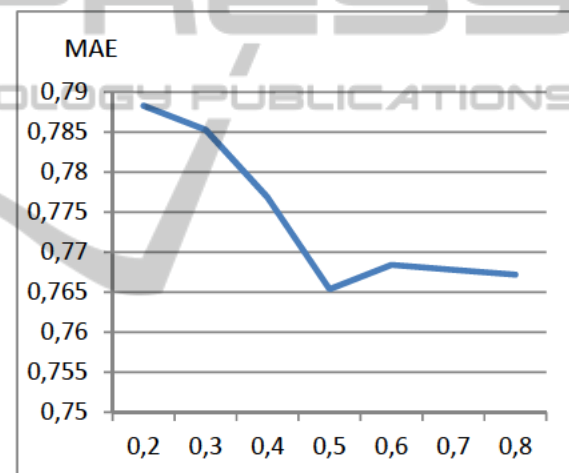


Figure 14: CF using the member's expertise.

strategies of recommendation have been proposed, according to the member's objective: (1) a SemF by member's interests; (2) a CF based on the member's expertise; and (3) a semantic collaborative filtering combining in different ways the two approaches.

The CF is based on the members' expertise level. A new similarity measure is proposed based on a set of rules which cover all the possible cases for the relative positions of two domains in the domain knowledge ontology (DKOnto).

The results of evaluation show the importance of the recommendation system for members. Furthermore, the evaluation using some datasets shows that the proposed approaches present good performance.

In our future work, we envisage to evaluate deeply the different strategies using other datasets

## 5 CONCLUSIONS

The paper proposes a personalized recommendation approach of LOs within a CoP of teachers. Three

such as Amazon, Book Crowsing and Merlot. The main objective by this evaluation is to identify which strategy is more suitable in the context of a community of practice of teachers. Furthermore, it will be necessary to validate the recommender system comparing its effectiveness with other systems on the topic such as the recommender system for CiteSeer (Kodakateri et al., 2009) or the recommender system proposed by Cobos et al. (2013).

In addition, in order to improve the response time of the proposed recommendation services, it will be interesting to enrich our approaches using the classification techniques.

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