

Recommendation Strategies for Promoting eLearning Performance Factors for All

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Abstract

Personalized inclusive eLearning requires a dynamic support in terms of recommendation strategies that combines design time and runtime approaches. This support is to be provided by standard-based open learning management systems. In this paper, we identify different situations during the delivery of a course based on the Collaborative Logical Framework approach and propose when to recommend and what recommendations are to be provided to the learners to improve their performance by addressing eLearning critical factors. Expert evaluations and empirical studies maintain this work.

Introduction

Due to the increasing complexity of products and services, new demands for recommender systems have appeared. Moreover, there are specific contexts in which recommender systems have particularities that have to be addressed independently. That is the case of learning scenarios, and more specifically, those focused on the lifelong learning paradigm.

Although recommender systems support users in finding their way through the possibilities offered in web-based settings by pre-selecting information a user might be interested in, there are several distinct differences for recommendations to consumers in contrast to recommendations to learners, which are translated into specific demands for these systems. In particular, recommender systems in the eLearning field need to improve the learning effectiveness and do not depend just on the user's tastes. For instance, the preferred activity by a learner might not be pedagogically adequate (Tang and McCalla 2003).

Moreover, the lifelong learning paradigm recognizes that, in a knowledge based society, education and work are integrated throughout people's lives. In this context, technology is expected to attend the learning needs of the students in a personalized way. This personalization can be supported by the emergent field called 'web intelligence'.

In this paper, we focus on how to provide this personalized and inclusive support by proposing recommendation strategies for different situations during the delivery of a collaborative course in a standard-based learning management system (LMS). The goal is to identify when and what recommendations are to be provided to the learners to improve their performance by addressing critical eLearning factors. Expert evaluations and empirical studies have been carried out to sustain our approach and are presented. We have surveyed the critical factors that affect the eLearning among accessibility and psycho-pedagogical experts from aDeNu group research projects. In addition experiments have been run on an open source standard based LMS with high adaptation, accessibility and usability features called dotLRN (Santos et al. 2007). For the experiments, the Collaborative Logical Framework approach (see section 'Improving the learning performance in a collaborative task' for details) has been applied to a course on Learning to Teach through Internet. The results of our experiments suggest the validity of our approach, although further studies are still to be carried out since the number of users considered for this preliminary experiment is not large enough to be representative.

This paper first described some existing related works and introduces the foundations of our work. Next, the survey among experts to identify critical factors for eLearning is presented. Then, the results from an empirical evaluation are shown. Finally, conclusions and future works are summarized.

Existing related work

Personalized eLearning in web-based environments combine efforts from related areas such as Adaptive Hypermedia, Intelligent Tutoring Systems, Computer Supported Collaborative Learning and User Modeling. State of the art research shows advances in them that provide a diverse range of solutions (Cristea and Garzotto 2004) and (Brusilovsky 2004a).

However, these systems do not fully address the problem of personalized and inclusive eLearning in scalable open architectures. Some rely on designing in advance the diverse learning routes the different types of learners will require in the different situations learners may

encounter. This approach is time-consuming, provides partial solutions due to the variety of situations to cope with, and does not consider unforeseeable circumstances (Carro et al. 2004). General solutions extending existing educational standards to support personalized course delivery addressing students' individual needs are also provided (Paramythis, Loidl, Reisinger and Kepler 2004). An alternative line of developments is to incorporate, through the usage of educational specifications and standards (IMS¹, SCORM²), personalized processes into modern large-scale web based education, where current LMS are applied (Baldoni et al., 2004) and (Boticario and Santos 2007). Others, apply intelligent support for the authoring process. For instance, there are rule-based adaptation approaches with selection of stability (DeBra, Smits and Stash 2006), authoring of adaptive hyperbooks (Murray 2003), re-using educational activities through distributed servers (Brusilosky 2004b), dynamic course generation through planning techniques (Brusilovsky and Vassileva 2003), etc.

Moreover, other systems focus on the runtime part, analyzing the users's interactions to provide a dynamic support. Within this approach, there is an increasing interest in developing recommender systems in education, but they usually provide solutions to specific problems, e.g. selection of papers (Tang and McCalla 2003) without considering their integration with other solutions in a standard-based LMS. Some recommender systems consider a hybrid approach with a part based on knowledge (the filter) and a part based on learning (the guide) (Burke 2002). There are systems that emphasize the collaboration among users through tagged dialogs (Barros and Verdejo 2000) or shared workspace actions (Muehlenbrock and Hoppe 2001). Others capture and analyze student actions to create collaborative tutors (Harrer et al. 2006). Some have tried to combine design and runtime adaptation by applying machine learning techniques for user modeling based on an extensive use of educational standards (Boticario and Santos 2007). However, till very recently there have not been general approaches that consider learners and their evolving circumstances (i.e. prior knowledge, preferences, learning style, learning activities, learning goals, learning context...) (Drachsler, Hummel and Koper 2007). Moreover, most of the personalized systems do not address the accessibility requirements, which are of major importance to provide an inclusive support. On the other hand, those which address accessibility requirements, do not take into account the users' interactions during run-time in order to enrich the user model and adapt the interface (Cudd et al. 2004), (Alexandraki et al. 2004) and (Velasco et al. 2004).

Our research directions

With this context in mind, our research deals with the management and integration of different types of

recommendations in standard-based LMS, so that it can be easily reutilized in any of the current open LMS. Our experience is framed within several R&D projects, namely aLFanet (IST-2001-33288), EU4ALL (IST-2006-034778) and ALPE (eTen 2005- 029328). The most salient aspects of our work are:

- 1) Universal design philosophy based on the pervasive usage of standards and specifications for contents, users and devices.
- 2) Dynamic support at runtime based on a hybrid approach combining knowledge based and machine learning techniques, which complements the above universal design when this design does not suffice.
- 3) Open architecture that provide interoperable services along the full life cycle of eLearning.
- 4) Lifelong learning approach to cope with an increasing demand for a continuous updating of knowledge.

In this context, we propose the utilization of various recommendation techniques supported by a multi-agent architecture, where different types of agents interact with each other to give the corresponding recommendation to the learner (Hernandez et al., 2003; Boticario and Santos 2007). The main advantage of the multi-agent architecture is its flexibility, which is based on combining different techniques via autonomous agents that provide their list of recommendations according to the technique used. The foundations of this approach relays on the well known fact that there is no single technique to be applied to a wide range of problems.

Improving the learning performance in a collaborative task

The goal of this work is to provide a personalized and inclusive support through dynamic recommendations during the course execution. Our work hypothesis is that during the learners' experience in an eLearning scenario there are different factors that affect the learning performance, and different situations take place, which are not dependant of all the factors at the same time. If this hypothesis is valid, we could identify different types of recommendations relative to these factors, and define which are more suitable in each situation to improve the performance. Initial works are described in (Santos and Boticario 2008).

For the works described in this paper, first we have identified which are the critical factors for eLearning by surveying accessibility and psychopedagoical experts. Then, we defined a learning scenario (that involves a collaborative activity with a wide variety of situations) and run an experiment with two different groups of learners (study group and control group). The first group performed a predefined set of tasks without receiving any recommendation from the system. The second group was told to perform the same set of tasks but was provided with recommendations. Both groups have never used the platform before this experience nor followed a collaborative activity of this type.

¹ IMS: <http://www.imsglobal.org/>

² SCORM: <http://www.adlnet.gov/scorm/>

Our experience with this collaborative setting over the years (Gaudioso and Boticario 2003) has shown that the different nature of the situations involved in the eLearning scenario (getting familiar with the platform, getting familiar with the collaborative activity methodology, performing the collaborative activity) influence learners' performance. Following the experts opinion, we consider that each situation is more likely to be affected by some of the eLearning factors that by others. Therefore, we propose to distinguish different types of recommendations for each of the different situations in the scenario. These recommendations (see below) were given to the second group. By comparing the performance of both groups regarding the resources consumption, we were able to check our work hypothesis. Several assumptions were made:

- The performance is measured as tasks accomplished against resources used. Additional measures to be considered are actual learning gain, time on task and learner satisfaction.
- For this experiment, resources are meant the time spent in getting to do each task, but without computing the time spent in the task. In other words, the time spent since the user clicks on the action to do (e.g. post a message in the forum) till the user clicks on the accept button (e.g. to post the message) is not computed. Thus, we do not consider the time for writing the message, which may depend on many non observable factors (e.g. network conditions and human writing capabilities).
- We are aware that time can be considered as a partial indicator for measuring performance, so we are currently investigating how we can relate the learning performance to the usage of platform resources, such as number of threads created, threads that have been answered, etc., which are observable features we previously utilized to infer collaboration indicators (e.g., student with initiative) (Santos et al. 2003). Actually, the usage of the platform resources is very much related to the nature of the collaborative task selected (see below).
- Learners are told to focus in the tasks provided and to consider the recommendations when they appear. We want to check if the recommendations we have defined in each situation improve the learning. If succeeded, future works will focus on tuning when it is more appropriate to offer them and identifying which of them are more valuable.

The reason for selecting an elaborated collaborative activity for our experiment is based on a number of reasons. Firstly, following a constructivist approach (Edelson, Pea and Gomez 1996) we aim at improving learnability of concepts through learners' active participation (Barkley, Cross and Major 2004). Secondly, teaching a collaborative task that has shown its value in a wide variety of areas (Santos et al. 2003).

In particular, we have selected for our work the Collaborative extension of the Logical Framework methodology (CLF) which is a domain independent

activity supported by a user model built from learners' interactions. It consists of 4 basic stages (interaction, individual, collaboration and agreement), where the three last are repeated along several phases, usually 6.

The Logic Framework methodology can be applied in many settings where activities such as conceptualizing, designing, implementing, monitoring and evaluating are required. Traditionally, the methodology was defined for cooperation projects to be carried out by international development agencies, but it can be applied in very different domains, such as clinic use cases in Medicine, practical cases in Laws or building collaboratively websites. In essence, it provides structure to the planning process to solve the problem and helps to communicate essential information about the problem to be solved. The collaborative extension (CLF) can be represented as follows:

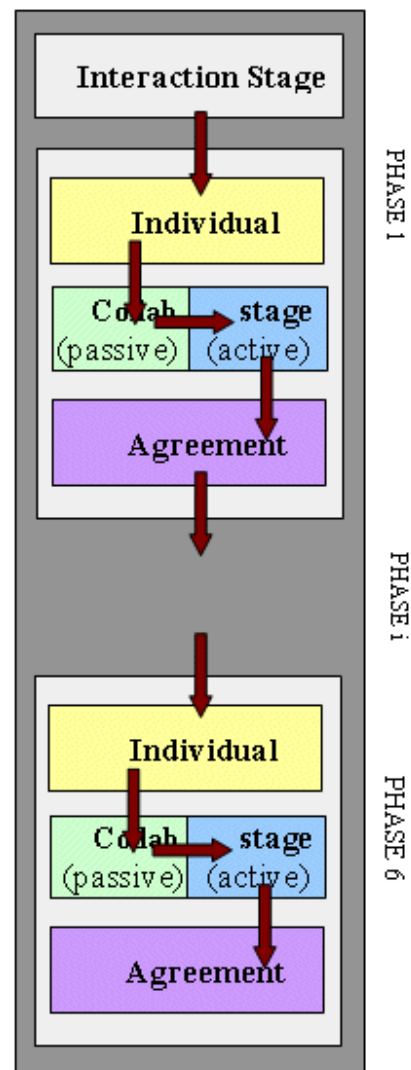


Fig. 1 Phases and stages of the CLF

The details of the different phases are provided elsewhere (Santos et al. 2003) and here we focus on the 4 basic stages. The goal is that learners work collaboratively to provide an agreed solution. The interaction stage simulates a small CLF to teach its methodology. Afterwards, 6 phases are defined to solve different problems, where three stages (individual, collaboration and agreement) take place. The process is as follows:

- Individual stage: each learner works individually and fills in a survey with the solution. When finished, she must start a thread in the forum justifying the solution. During this stage, learners can solve doubts in the forum.
- Collaboration stage: learners have access to the solutions of their mates and must comment and rate them (passive collaboration). Once they have analyzed the work of the other learners, each learner creates a new version of his/her work taking into account the comments and ratings given by his/her mates, and start a new thread in the forum (active collaboration). Learners can also reject their new version if they are rated lower than the previous one. The other mates receive a notification of the new version and have to comment and rate it, as before. In any case, discussions take place in the thread corresponding to the appropriate survey and version.
- Agreement stage: the moderator of the group is responsible of providing the agreed solution of the group. She has to propose a solution based on the best rated works of the group and make it available to its members. The procedure is similar to the one described in the previous stage.

eLearning Factors

There is ample literature regarding the factors that affect the performance in eLearning settings. In Mungania (2003), an empirical study was done to determine barriers experienced by employee e-learners, those that are more likely to follow lifelong learning approaches. The findings of the report reveal that eLearning barriers are heterogeneous encompassing seven types of barriers, namely:

- 1) personal or dispositional (e.g. attitude towards eLearning, lack of appropriate skills and knowledge)
- 2) learning style (e.g. preference for other instructional delivery)
- 3) instructional (e.g. access and navigation problems, information overload, lack of instructor presence/interaction, support and experience sharing)
- 4) situational (e.g. time for study)
- 5) organizational (e.g. cultural problems concerning credibility of eLearning)
- 6) content suitability (e.g. irrelevant content)
- 7) technological barriers (e.g. lack of training)

To confirm these results (5 years from the previous report and within higher educational inclusive settings), we asked 12 experts on psychopedagogy and accessibility from

aDeNu group projects to identify relevant factors that may affect the performance in eLearning. First a brainstorming took place to identify a list of candidate factors. The selected factors were:

- F1. Motivation for performing the tasks
- F2. Platform usage (and technological support required)
- F3. Collaboration with the class mates
- F4. Accessibility considerations when contributing
- F5. Learning Styles adaptations
- F6. Previous knowledge considered

Once identified and agreed, the experts were asked to rate them with the Likert scale.

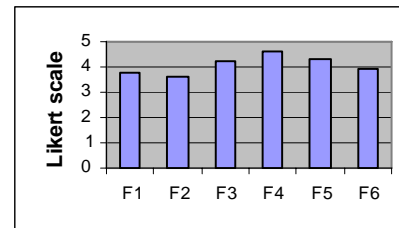


Fig. 2 Relevance of the factors (average computed from the experts' answers)

The result of this survey (see Fig. 1) shows that for these experts the factors identified were strongly relevant in eLearning. They are also related to the barriers defined in the report, which justify that unfortunately, those barriers still exist and the suggestions presented there to remove them are still valid. Thus, it is advisable that recommender systems take these factors into account when providing the dynamic support if we are committed to remove them and help to improve the learning performance.

Experimental study

The experiment was designed to model typical situations encountered when carrying out course activities. In each of the situations, learners were asked to do specific tasks. First, learners need to get familiarized with the learning platform, to be aware of the available resources and make a proper use of them. Second, they have to get used to the operative framework of the course. Finally, they have to carry out the learning tasks of the course using the available resources and following the course design.

We identified three different situations. For each of them, we defined several objectives (i.e. tasks that the learners should carry out) and computed their performance as the percentage of the resources used (for the time being, the percentage spent of the available time). We run the experiment twice with two different groups (study and control) of 10 learners each, where none of the learners had used the platform nor followed a CLF course. We focused on the performance of the non-moderator learners. Thus we computed only the results of the nine learners. The contents of the course were extracted from an existing course on 'Teaching to Learn through Internet' being run

at UNED from 1999 by some members of aDeNu group under the on-going education program of this university.

Performance of the learners in the course

The results from the first group (no recommendations given) for each of the three situations are shown in the following graphics (Fig. 2 to Fig. 5). The graphics show the percentage of available time spent by average by the 9 users to perform the selected tasks to reach the corresponding percentage of objective achievement.

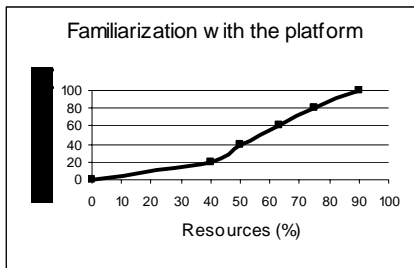


Fig. 3. Performance results for the platform familiarization

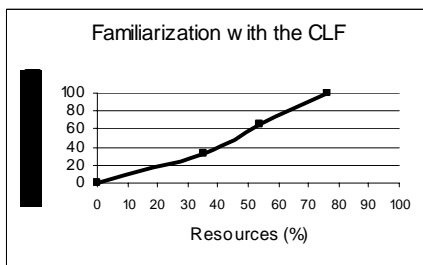


Fig. 4. Performance results for the CLF familiarization

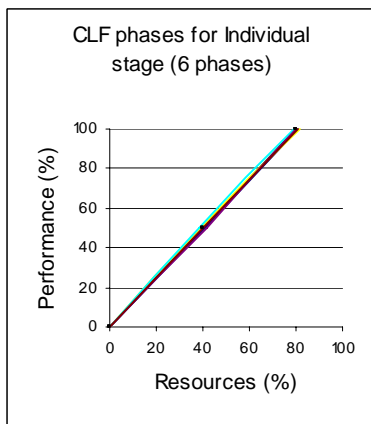


Fig. 5. Performance results for the 6 phases of the CLF along the individual stage

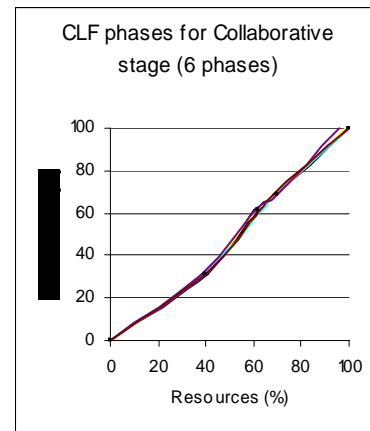


Fig. 6. Performance results for the 6 phases of the CLF along the collaborative stage

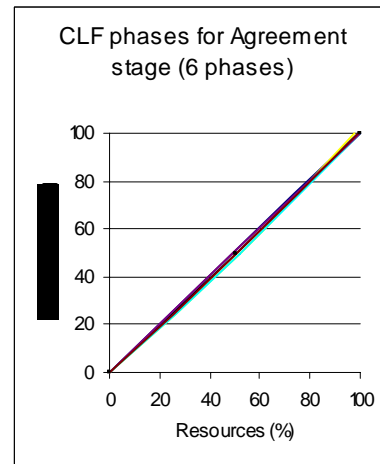


Fig. 7. Performance results for the 6 phases of the CLF along the agreement stage

Results show that learners require some initial time to get familiarized with the platform, but afterwards, they progress on the tasks linearly. There is not a significant delay when learners begin the second situation to understand the CLF methodology. That is consistent with the fact that they are getting used to other resources of the platform, but they have already been used to the way it has to be navigated. Nevertheless, there is a reduction of the performance at the beginning of the collaborative stage, since learners are not very much used to such collaborative approach. Finally, there are not significant differences in the different phases for the three stages. This can confirm again the independence from the platform familiarization, so when performing the tasks, only conceptual issues are relevant.

Dynamic support to improve performance factors

After this first round, we analyzed the results obtained and tried to find out correlations between the different situations and the factors that had been previously identified. The analysis suggested different types of recommendations that address the different factors presented in the previous sections. These recommendations are based on the suggestions provided in (Mugania 2006) and our own experience in eLearning scenarios, and we have assigned them to the three situations in which we have model the course activities. The objective is to improve the learners' performance in the tasks designed via providing support to help students better achieve their goals. In a certain way, they can be seen as feedback strategies for the learner. The assignation of recommendation types to the situations are shown in the following Table. This table is the input for the second round of the experiment.

Situations	eLearning Factors					
	F1	F2	F3	F4	F5	F6
Platform familiarization	X	X				
CLF familiarization	X	X				
Individual stage	X			X	X	X
Collaboration stage			X	X		
Agreement stage	X		X	X		

Table 1. Proposal for recommendation types more suitable for each of the situations

Before describing the second round of the experiment, here we provide some high level examples of the recommendations that have been designed. In each example, on the left hand side we present the pre-condition that should take place, which refers to the learner features or interactions, or the activity. In any of both cases, we identify the most relevant attribute that is to be considered as well as the value that should occur. The right-hand side shows the action to be done in the condition is positively evaluated.

When the user is getting familiar with the platform and the CLF she is getting used to the platform resources. If the user model (which is built from her answers to questionnaires and her past interactions) reflects that she is not comfortable with technology, motivation recommendations are offered.

Rec: if Learner.inForum → link to Forum help (platform usage)

Rec: if Learner.technology_level=low → "Seems you are getting used to the platform. Go on!" (motivation)

From the experiment done, it follows that when arriving at the individual stage the platform is no longer a barrier. So, it is not needed to offer recommendations on the platform usage, but recommendations should focus on the learning task, and deal with the lack of learners' interest, low

collaboration level and lack of previous knowledge. Four main issues have been addressed. First, if the difficulty level of the task requested by the CLF is high, motivational recommendations are given. Second, the wording of the problem may not be appropriate for the learner's learning style (e.g. inductive approach for a deductive learner). In this case, the recommendation suggests the learner a different order to read the wording. In the case presented, a global learner should be given first global information of the task to do, such as the table of contents. In turn, a sequential learner should be presented the information in linear steps.

At this stage it is also important to consider the previous knowledge. If the system detects that the learner lacks some information, it recommends some additional material. Finally, since contributions are to be read by other learners, they should comply with accessibility guidelines. If not (e.g. information provided not properly tagged), the learner is suggested to amend it.

Rec: if CLF_task.difficulty_level=high → "you are doing great" (motivation)

Rec: if Learner.LearningStyle=global → show first the table of contents (learning style)

Rec: if Learner.PreviousKnowledge=low → give additional material (previous knowledge)

Rec: if not (learner.contribution=tagged) → alert to amend it (accessibility)

At the collaboration and agreement stage, learners continue sharing work with their fellows. Therefore, the recommendations to address accessibility issues in the learner's contributions are still required. Moreover, these two tasks are very much focused on collaboration, so the priority here will be to foster it. For instance, recommendations suggest evaluating first the contributions done for alike students. Our experience shows that motivation recommendations are not necessary at the beginning of the collaboration stage, probably because the curiosity to see other fellow's work is inherent to the human being. However, they are very useful for the agreement stage, in order to get an agreement for the final solution. For example, if two users have opposite ratings for the survey, it may be useful to recommend them to share their opinions in the forum.

Rec: if LearnerA.user_model~LearnerB.user_model → tell Learner.A to evaluate LeanerB.contributions

Rec: if LearnerA.rating=0 & LearnerB.rating=5 → tell Learner.A & LeanerB to justify rating in thread

Variations of learners' performance when recommendations are provided

In this section we present the results from the second round of the experiment (when recommendations were provided to the learners) in comparison to the previous one. The type of recommendations provided in each of the situations corresponds to the types identified in table 1. In particular,

motivation and resources usage recommendations were provided at the platform and CFL familiarization situations. Learning styles and previous knowledge recommendations were provided at the individual stage. Collaboration and accessibility recommendations were given both at the collaboration and agreement stages. Moreover, motivation recommendations were given in the agreement stage.

Graphics keep the previous results and add the new ones. If compared to the previous figures, the new results correspond to the left group of lines. Thus, it can be concluded that the provision of the recommendations has improved the performance of the learning as defined in the experiment. That is, when recommendations have been provided, the time required to perform the requested tasks (without computing the extra time required for reading the recommendation) has been reduced in average.

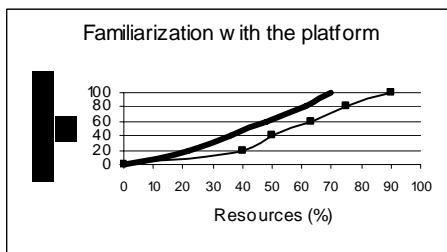


Fig. 8. Performance results for the platform familiarization both for when recommendations are provided (left, thick lines) and not provided (right, thin lines).

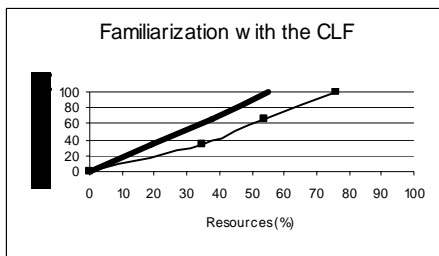


Fig. 9. Performance results for the CLF familiarization both for when recommendations are provided (left, thick lines) and not provided (right, thin lines).

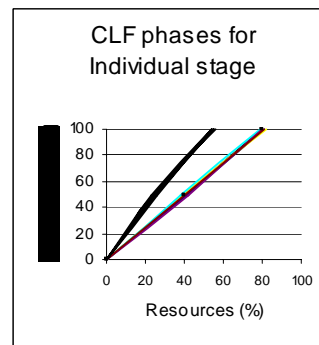


Fig. 10. Performance results for the CLF individual stage both for when recommendations are provided (left, thick lines) and not provided (right, thin lines).

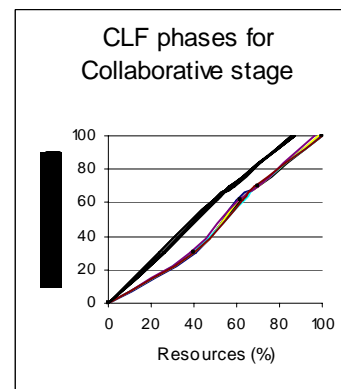


Fig. 11. Performance results for the CLF collaborative stage both for when recommendations are provided (left, thick lines) and not provided (right, thin lines).

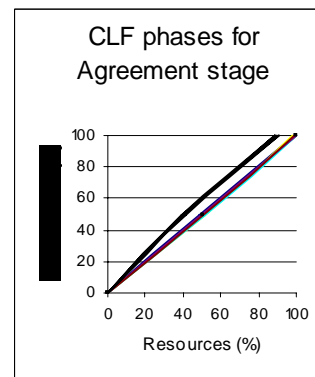


Fig. 12. Performance results for the CLF individual stage both for when recommendations are provided (left, thick lines) and not provided (right, thin lines).

Implementation issues

Current developments have focused on providing the infrastructure for the recommender system to allow offering recommendations in the LMS user interface. In particular, an open source infrastructure for open standard-based LMS has been implemented to enrich LMS functionality with a dynamic support based on users' interactions. This initial prototype has been integrated in OpenACS/dotLRN LMS (Santos et al. 2008).

Recommendations consist on links to actions to perform in the LMS, such as (see previous section) support the usages of the platform resources, suggest to post a message in the forum or recommend the reading of a particular resource of the course. So far, we have implemented the support to allow professors define at design time static recommendations to be applied in the course that are provided in terms of conditions on the user attributes and the course context. We focus on supporting different recommendation techniques and selecting the most appropriate considering the nature of the task. In this context, we are working on the utilization of various recommendation techniques supported by a multi-agent architecture, where different types of agents interact with each other to give the corresponding recommendation to the learner (Hernandez et al., 2003; Boticario and Santos 2007). The main advantage of the multi-agent architecture is its flexibility, which is based on combining different techniques via autonomous agents that provide their list of recommendations according to the technique used. The foundations of this approach relays on the well known fact that there is no single technique to be applied to a wide range of problems. Multi Agent Systems (MAS) are used due to their flexibility for combining different proposed solutions (Wooldridge 2002).

In aLFanet, we designed a two level multi-agent architecture to generate dynamic recommendations during the course execution (Boticario and Santos 2007). In this way, several agents cooperate to produce the appropriate recommendations to the learner. The low level multi-agent hierarchy was in charge of monitoring the performance of the learners in the system to update their user model by applying different machine learning algorithms. The high level one was focused on generating the recommendations to the learners based on their user model and the current learning context. This approach is being extended in the Accessible and Adaptive Module (A2M) (Santos 2007). A2M deals with supporting learners with dynamic recommendations to overcome impasses at the course execution in an inclusive way. It is in charge of providing dynamic recommendations to learners on what to do in the course. Recommendations follow different techniques such as user-based collaborative filtering, item-based collaborative filtering, case-based reasoning and attribute-based rules.

Conclusions and Future work

In this paper we have presented some preliminary results that we have obtained when trying to answer when to recommend and what recommendation type can be provided to the learners to improve their performance. We have addressed critical factors in eLearning, which have been obtained by surveying psycho-pedagogical and accessibility experts. These factors can be addressed with different types of recommendations and thus, we have defined several recommendations for each of the types. We have also modeled the course activities in typical situations.

The conclusions should be defined in terms of preferred recommendations a user may received depending on the user model and the situation in the course. For this experiment, we have proposed that not all types of recommendations have the same relevance in all the situations, and have selected those that appear to be more relevant in each of them. To validate the hypothesis, we have compared the results in two groups. Two rounds of experiments have been run to compare the performance of the learners when recommendations are provided and when they are not. Three different situations were considered: familiarization with the platform, familiarization with the operative approach of the course and the course itself, which was based on the CLF approach.

The results have shown that with the proposed recommendations, the performance has been increased. However, they have to be considered as they are, initial results produced from a reduced number of students. More experiments have to be further worked to get to global conclusions. These results support further analysis focused on determining the most appropriate recommendation types in a course depending on the learners' situations and the application of different recommendation techniques. In this sense, instead of selecting some of the recommendations for each of the situation, next experiments focus on prioritizing their relevance for each situation.

The process of results gathering has to be automated so that the size of the sample does not become a problem to compute the experiment results and a larger population of individuals can be used in next experiments.

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