Towards web-based adaptive learning communities

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Abstract

Nowadays, with the improvement of communication and collaboration services, the web-based educational systems have evolutionated towards systems based on the so-called virtual learning communities, where students and tutors collaborate each other in order to acquire the desired learning goals. In this situation, the mere fact of setting up an environment for students and lecturers does not guarantee mutual collaboration or succcesful student learning. This is partly due to the fact that just one response is given to users with changing needs depending on their level of experience in the use of the resources available on the website. Thus, it is desirable to provide some adaptation to the students. Nevertheless the intensive use of the communication and collaboration services and thus the new kind of input data for adaptation has forced a change in the user models, which are used as the basis for adaptation in these systems. In this paper we will describe the basis of a user model within a web-based collaborative learning environment. We will describe some adaptation tasks developed and that are based on that user model. At the end the empirical evaluation carried out on the system will be shown.

Keywords: Learning systems plaforms and architectures, web-based adaptive collaborative environments, modelling and representation, adaptive collaboration and navigation support, machine learning, user modelling.

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Abstract.
Nowadays, with the improvement of communication and collaboration services, the web-based educational systems have evolutionated towards systems based on the so-called virtual learning communities, where students and tutors collaborate each other in order to acquire the desired learning goals. In this situation, the mere fact of setting up an environment for students and lecturers does not guarantee mutual collaboration or succcesful student learning. This is partly due to the fact that just one response is given to users with changing needs depending on their level of experience in the use of the resources available on the website. Thus, it is desirable to provide some adaptation to the students. Nevertheless the intensive use of the communication and collaboration services and thus the new kind of input data for adaptation has forced a change in the user models, which are used as the basis for adaptation in these systems. In this paper we will describe the basis of a user model within a web-based collaborative learning environment. We will describe some adaptation tasks developed and that are based on that user model. At the end the empirical evaluation carried out on the system will be shown.

1 Introduction

Nowadays the proliferation of accesses to the Internet has made the World Wide Web (WWW) an ideal environment for communication between a lecturer and students overcoming time and space constraints. This development is changing the teaching model, and nowadays lecturers and students are becoming active members of virtual educational communities. However, the mere fact of setting up an environment for students and lecturers does not guarantee mutual collaboration or successful student learning. In fact, in many instances a significant number of students are reluctant to actively participate in collaborative course activities. This is partly due to the fact that just one response is given to users with changing needs depending on their level of experience in the use of the resources available on the website. Thus, certain adaptation to the student is desirable. In this situation, the adaptation tasks must help both the student in his/her collaboration in the course and the tutor in the management of the community. In addition, in order to make possible the use of a collaborative environment on a variety of courses, it is neccesary to guarantee that these tasks will be domain independent.

Normally the adaptation tasks usually applied in educational systems are based on users models. Nevertheless in virtual communities, the intensive use of the communication and collaboration services and thus the new kind of input data for adaptation has forced a change in the user models, which are used as the basis for adaptation in these systems. Now, these models must be extended so that they can gather and consider data on users' collaboration with one another.

This circumstance imposes a requirement on the representation and inference mechanisms of the user models. These mechanisms must be able to represent and dynamically update the user and usage data contained in the models. In addition, as described in the field of user modelling ([13], [14] and [21]) user models must be explicit so that they can be explored by users. This requirement is especially important in the educational sphere, where it is necessary for the tutors to know the information that the system has on the students.

Following these ideas, in this paper we will describe the basis of a user model in an web-based adaptive collaborative environment. We will describe some domain independent adaptation tasks developed and that are based on that user model. At the end the empirical evaluation carried out on the system will be shown.

2 A Web-based collaborative learning environment

The personalization that we pose is set in a web-based system particularly indicated for cooperation and communication. It is called aLF [11]. Users in aLF are grouped into workgroups, each one with its own services such as, forums, chats rooms and file storage areas. The information on each interaction done by the user is stored in the database.

In this framework we use both personal data on the users gathered from explicit forms (e.g. name), user preferences (e.g.if the user is interested in tele-education) and background knowledge (e.g. experience with computers), and user interaction data with the platform (number of messages sent, alerts activated in the forum, etc). The use of the aLF database enables us to have a more exhaustive control of the interactions done in any of the platform services [11]. For example, for every user, the number of threads that have initiated, the number of threads that have finished, . . . are gathered. A full description of the data gathered can be found at [12].

With this information it is possible to do some adaptation tasks that facilitate the use of the services by the user and navigation of the contents available. Thus for example, from the level of activity of the user in the use of a specific service we can recommend him/her to interact more or less with this service, or from the last page accessed we can recommend the next suitable page to visit.

The main goal of this paper is to describe the user model that we propose for certain adaptation tasks and that takes as input data all these interaction and personal data. Following we present the adaptation tasks considered in the system.

3 Adaptation tasks

In the beginning, research in the area of adaptive web-based educational systems focused on the adaptation of course contents. One of the most salient examples is AHA [3]. Nowadays, the approach has changed because it requires too much work on the contents and in most instances the advantages of the services offered by the Internet were not being fully exploited. In addition, in collaborative environments the fundamental tasks that should be offered are the tasks that provide adaptive collaboration support [4, 5]. Conversely, adaptive navigation support [4] should be applied to offer the user a personalised navigation of all the contents available on the system.

Our fundamental objective is therefore to enhance user access to the services offered (forums, information sources, ...) as well as facilitating collaboration between members in the same group.

Following these ideas, we consider, on the one hand, the following adaptive collaboration support tasks:

- Predict the level of activity of a specific user: this task is useful for those systems where all the activities are done via the course platform.
- Automatic grouping of users within a same community: although a community groups users with a common objective, when doing the group work it will be useful to form some subgroups bearing in mind common or differentiating student aspects.
- Analysis of the messages sent to the forums: this task can be extremely useful for the tutor when administering a specific group, identifying topics of interest that can be used to add categories to the forum.

On the other hand, and at the moment we consider the following adaptive navigation support tasks:

- Provide some pages describing the course information. The route of these pages will be personalised to each user.
- Provide links to the information sources, (web addresses, file-storage area, forum message), which may be interesting (according to user interests, the profile of the person that has provided this source of information, etc.).

It is important to point out that our goal is not a deep description of the adaptation tasks that can be carried out in a web-based collaborative environment. On the contrary, we aim to present certain adaptation tasks that allow us to highlight the model proposed. Within the adaptation tasks proposed, the adaptative collaboration support tasks are resolved by machine learning techniques. Besides, the adaptative navigation support tasks are resolved by knowledge based techniques (i.e. rules). In this context, we will see that the user model proposed allows us to easily combine both types of inference mechanisms.

4 User model representation and inference: An hybrid approach

As we have previously mentioned, the user interaction data that we have considered are fully described in [12]. Although the information gathered on the user is very exhaustive, the user model contains attributes that are not directly observable from the data gathered by the system. Since these attributes are not directly observable from the data, the system must infer them [14]. This inference can be done by imposing predefined rules and machine learning techniques. The main disadvantage of the rule-based approach is that the rules have to be predefined, and so all the process is very static. Conversely, the machine learning techniques process training input and infer the required values based on this input. The main advantage of these learned models is that they can be automatically updated. The main disadvantage is that these models are implicit and that they are often not directly observed. To take advantage of both approaches, a hybrid approach [18] combining these two different techniques is desirable [11].

In order to construct our user models, we have chosen a representation and inference mechanism called THEO [16]. It allows us to obtain the values of the attributes in the model combining both rules and machine learning techniques. A model represented in THEO is composed of several entities. Each entity in the knowledge base has several attributes describing the entity, for example, we can define an entity named `user` which will have several attributes such as `name` or `address`. The value of these attributes can be defined in three different ways:

- The value is directly assigned by the user or the tutor (for example, the name) or it is the result of a particular function (for example, the age of the student is determined from the date of birth and the date of the interaction).
- The value can be determined by applying a specific rule predefined by the tutor. The syntax of these rules is similar to PROLOG logical programming language rules.
- The value can be the result of a machine learning task. When an attribute is dependent on a machine learning task, THEO sends a request to a special module in charge of executing this task.

From a minimum model begun using preliminary surveys and forms completed by the user, we aim to increase and dynamically update these models from the interaction data. In [1] a more compete description of this model's composition can be seen. From this user model representation and inference, in the following sections we will see how we can perform the adaptation tasks mentioned before.

5 Adaptative collaboration and navigation support tasks

In this section we will describe how we perform the adaptative collaboration and navigation support tasks outlined in section 3. As we have mentioned before, the adaptative collaboration support tasks are based on machine learning techniques, on the contrary the adaptative navigation support tasks are based on rules.

5.1 Adaptive collaboration support tasks

5.1.1 Prediction of the level of activity

In this subsection we will describe how we can predict the levels of activity for a specific user of the platform services from his/her initial interactions. The objective of these learning tasks is to predict each user's level of activity of the general platform and specific individual services. Specifically we will focus in the prediction of the level of activity in the forum of the course.

To learn this attribute and like any learning task [21], it is necessary to determine what the input attributes are going to be for each instance in the training examples. By extracting and preparing data from the aLF database, we composed a set of training instances as input data to the learning algorithm. Each instance corresponds to a user and includes information about

Algorithm	Accuracy (eagerness bboard)
C4.5	83.98
Naive Bayes	77.76
LTree	88.79
MAI (15 classifiers)	86.41.5

Table 1: Summary of the results of the experiments done

his/her behaviour in his/her first one or two interactions (in [12] a detailed description of this attributes can be found). From this process we obtained a dataset of 125 instances, each with 21 attributes, and labelled with a class value indicating the level of forum, chat and general activity on the course (these training data were constructed taking into account the labelled data constructed by the external course tutors).

Once the training examples was prepared it was neccessary to determine an adequate machine learning algorithm for this task. However, in a web environment there is a wide variety of interaction data and this makes that single classifiers would fail in some regions of the training data or would be accurate in others (competence region). If we have classifiers with different competence regions, we can combine them in order to enhance performance. This combination is usually called *ensemble of classifiers* [2, 12].

For our experiments we therefore consider three classifiers; a decision tree learner (C4.5), a Bayesian learner (Naive Bayes) and two well-known ensembles (MAI [17] and Ltree [10]). In order to assess the individual performance of each of the algorithms, we performed a 10-fold cross validation test. The experiments [12] show that the algorithm Ltree [10] performs slightly better than the others (in the table 1) there is a summary of the experiments done). In addition, as it is proved in [10] the model learnt by the Ltree algorithm remains explicit and simplified (the decision tree generated is reduced in aproximately 50%).

Although the improvement is not very significant at the moment, we found that algoritms similar to Ltree will be beneficial for certain user modelling tasks similar to the ones presented here and it is an important starting point on which to continue working.

5.1.2 Automatic subgrouping of users

Our objective with this task is to group users into subgroups to facilitate collaboration among them with the course tools. We have posed this task as a non-supervised learning task. In our case we have opted for the clustering algorithm EM (*Expectation Maximization*) [8].

Once the groups have been formed, if we have some interaction data on a specific user the system automatically assigns him/her to a group. The user will then be advised to contact members of that group. In our case a tutor can change students in a group for no set reason, just to evenly distribute the number of students, or because the tutor wants a student to be with another, etc. If this is the case reorganise the groups according to their restrictions, but we do not modify the model learnt for the clustering algorithm.

In this instance, we have presented the subgroups obtained from the course tutors, which the tutors have validated for the most part. Nevertheless, we think that obtaining groups based solely on interaction profile is limited. Furthermore, although the task has been well received by the tutors, we think that there is still a lot of work to be done in this direction, and new attributes have to be identified for forming subgroups.

5.1.3 Automatic allocation of categories on forum messages

The automatic classification of texts [9] is an important component in any organisation and automatic knowledge management task. To perform this task, it is necessary to predefine some vocabulary containing all the possible *categories*, and these categories are used to classify the input documents. In this respect, there are text classification systems, which incorporate the data preprocessing for facilitating the final learning mechanisms that can be applied for document classification. Thus, in the forum messages, you just have to provide the system with a set of messages and the system does the rest. This is the case of the Rainbow system [15], which classifies texts mainly using a bayesian classifier, Naive Bayes.

In our case, we planned this task in the following manner. Although the course forums provide categories for organising the forum messages, users very often do not assign these categories to their messages. The direct consequence of this situation is that there are more and more sets of unclassified messages (in this instance the messages would belong to the category *no categorie*). This hampers access to the forum messages of interest. The purpose of this learning task is therefore to provide the course tutor with new categories not initially considered (from those existing) for unclassified messages.

For this task we have used the RAINBOW system [15] with a training set consisting of 247 messages in three different categories. As we have mentioned, the Rainbow system constructs a model from a set of categorised messages. This model is used for classifying the other unclassified messages. We did a 10-fold cross validation. With these tests the system has an average success rate of 80.53%. These results allow us to integrate this message classification mechanism into our model.

5.2 Adaptive navigation support tasks

At the moment we consider the following adaptative navigation support tasks: personalization of the navigation path of the course information pages and providing interesting links.

As we have mentioned before these tasks are resolved by means of rules predefined by the tutor at the early stages of the course (see Figure 1 for an example). A fully description of these tasks are fully described in [1].

```
(next-link-advised *novalue*
    (all.prolog.clauses (
        ((next-link-advised ?r ?value):
            (id-user ?r ?user)
            (eval (visited-page ’?user ”bases.html”) nil)
            (eval ”fundamentos” ?value))
            ..))))
```

Figure 1: Example of a partial rule in the user model. The attribue next-link-advised indicates the next link that the user should visit according to the pages that he/she has visit before.

6 Empirical Evaluation

In order to validate the adaptative system described in this paper, we have carried out an empirical evaluation of the system and the adaptation tasks presented. Logically, since some

	Without adaptation		With adaptation	
Variable	***Tutor***	***Student***	***Tutor***	***Student***
Satisfaction^a	6.33 (0.51)	6.28 (1.25)	8.33 (0.52)	8.14 (0.20)
Impression^b	5.00 (0.00)	5.42 (0.53)	6.33 (0.82)	6.28 (0.76)
Ease of use ^{c}	7.00 (2.68)	7.14 (2.03)	7.00 (2.68)	7.14 (2.03)

Table 2: Means and standard desviations for the dependant variables. *Note*: a, b and c are the maximun values for each variable: $a = 9, b = 7$ y $c = 10$

of the adaptation tasks were specially indicated for tutors and some for students, we have asked a group of users and a group of tutors for their participation in the experiments.

In the evaluation process, one of the courses delivered in aLF and described in [11] was taken as a reference. The main characteristics of these courses was that the students were given a series of activities to solve in the forums. Therefore, the level of activity in forum use is a fundamental characteristic when promoting work on the course and the realization of the activities.

To evaluate that the adaptation in the system is useful for the student we need to obtain the users satisfaction level and the global impression of the system with and without adaptation. To this end, *Questionnaries of User Interface Satisfaction* [7] are usually presented to the user using both the system with and without adaptation [20]. Once the experiments have finished it is needed to verify that the variance on the responses given by the users are really a consequence of the adaptation tasks. To this end, variance analysis (ANOVA) tests are usually used [19].

Due to the characteristics of the students with little experience on web-based learning communities we decide to design the experiments with cross designs [6]. In this way the same participants participated in the experiments done with and without adaptation. The number of participants in the experiments were 13 out from a total of 73 students in a web-based course in aLF. From the users arbitrary chosen for the experiments, 8 were women and 5 were men. Generally the level of the use of computers and Internet services was medium-low and none of the participants have earlier experience with web-based educational systems. In addition from the users participating in the experiments 6 were tutors and 7 were students.

In the ANOVA test mentioned we considered the following independent variables: type of program (with and without adaptation) and the group (tutor or student). The dependant variables considered were: *level of satisfaction*, *global impression of the system* and *ease of use*. In table 2 are shown the means and variances obtained for these variables.

From the results obtained the ease of use of the system is not influenced by the adaptation tasks. This is obvious due the type of adaptation tasks considered. Regarding the other two factors (satisfaction and impression) the results obtained show that adaptation influences positively in both variables. However the only factor whose improvement is significative (with a confidence level of 95%) is the global impression of the system. From users informal comments we find out that a reason for this circumstance is that the users have a better global impression of the system due to the recommendations presented. However, at the moment the adaptation level of the system is not significative and that provoques a minor improvement in the level of satisifaction of the users.

Regarding the adaptation tasks foreseen for the tutors and that have been described in sections 5.1.2 and 5.1.3, and with the goal of validate these tasks, we present the tutors a questionnarie which intends to validate these tasks. Results showed that almost every tutor consider these tasks as mandatory or very important. Only one tutor considers that these tasks have less importance.

7 Conclusiones and Future Work

In this paper we have described a user model and several domain independent adaptation tasks within a web-based adaptive learning community. The main feature of the user model presented is that it allow us to combine machine learning and knowledge based techniques for representation and inference. This circumstance allow us to construct and dynamically update user models from user and usage data. The adaptation tasks described are domain independent and the empirical evaluation carried out shows the general users satisfaction with them.

Since at the moment the adaptation tasks are simple the results obtained should be considered as preliminary. Nevertheless, the results obtained indicate that the model and adaptation tasks proposed, are appropriate and will act as a basis for defining, some time in the future, more complex collaboration tasks that we hope to be able to pose this academic year.

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