Helping the tutor to manage a collaborative task in a web-based learning environment

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Abstract. Collaborative learning environments are mainly based on constructivist instructional design theories where students construct their own knowledge by interacting with their environment. The so-called virtual communities constitute and approach that facilitates the constructivist learning within these environments. In this context, the learning process consists of authentic participation in the activities of the community in a level appropriate to the student's current competency. Nevertheless, due to the great amount of students in web-based courses, it is necessary to help the tutor to correctly design and manage the collaborative activities in the learning community. Furthermore, the tutor should be provided with certain information about how the collaboration is performing in the collaborative activity in order to detect potential problematic situations. In this paper we propose a scenario for a collaborative task to be carried out in a web-based collaborative learning environment. This scenario can be supported by intelligent learning management systems and applied in a variety of domains. The collaborative task described here can be used to build a collaboration model from students' interactions, which can help the tutor to manage the collaboration activity itself. This task is being implemented on a web-based collaborative environment called aLF through user modelling based on a machine learning multiagent approach.

1. Introduction

In the constructivist learning approach to teaching, students construct their own knowledge by interacting with their environment. In this situation, people learn best when they are active [4]. Nowadays, the constructivist learning approach is specially benefiting from the boom of the so-called web-based learning communities [12], mainly due to the availability of the communication and collaboration services. Thus, many opportunities for constructivist learning are now available in web-based learning.

In this context, the learning process consists of authentic participation in the activities of the community at a level appropriate to the student's current competency. According to the constructivist learning approach, students learn by fitting new information together with what they already know [4]. For this reason, it is advisable that the student participates in more central practice as the student's understanding and competence increase. In this way, the student can become an acculturated member of the community. To achieve this, the tutor has to be able to guide students as they engage in open-ended activities. Moreover, s/he has to be able to help students to establish and maintain fruitful learning conversations about the collaborative activities they are performing.

However, there are some drawbacks for this approach in web-based environments. In these environments there is often a great amount of students with very diverse characteristics.

This makes very difficult for the tutor to manage the task conveniently (e.g. assigning the appropriate level of expertise to certain students according to the activities done). Thus, it is necessary to help the tutor to correctly design and manage the collaborative activities in the learning community. This must be achieved by designing a collaborative activity that can be applied on a variety of domains and that can take advantage of the constructive learning approach. Furthermore, it is needed to provide the tutor with certain information about how the collaboration is performing in the collaborative activity in order to detect potential problematic situations.

We propose a scenario for a collaborative task based on a well-known workgroup activity called ***L**ogical **F**ramework **A**pproach* (LFA) [1] to be discussed in this workshop. This scenario can be supported by intelligent learning management systems and applied in a variety of domains. The collaborative task is designed to be carried out in a web-based collaborative environment called aLF (***a**ctive **L**earning **F**ramework*) [3,6].

We have already implemented a LFA in aLF in the course "*Planificación y Gestión de Proyectos de Cooperación al Desarrollo - COPEDESA*"[1] (*Planning and Management of Cooperation to Development Projects*) organized by the OEI[2], MECD[3], CIDEAL[4] and UNED[5] during the school year 2001-2002. In this experience, we have detected that the way this activity is designed does not allow a real collaboration among the students, since each phase in the LFA is done individually by each user. Therefore, we have extended the LFA to promote collaboration, which is the scenario discussed in this workshop. This new approach is currently being implemented in aLF integrating user modelling, machine learning techniques and a multiagent architecture. The followed procedure is similar to the one used in several adaptation tasks already implemented on aLF [14].

To support the management of this collaborative task, a quantitative and a qualitative analysis automatically performed from the interaction data is presented to the tutor. Thus, problematic situations in the collaboration can be detected at the start of the course.

In this paper we describe this collaborative task and the collaboration data that can be obtained. We also show how these data allow us to obtain a collaboration model that can be used to help the tutor in the management of the group and the collaborative activities.

2. Fundamental points

To guarantee a successful constructivist learning process it is specially important to correctly design the activities and to report the tutor how the collaboration is performing in the collaborative activity in order to detect potential problematic situations.

In this context, CSCL (Computer Support Cooperative Learning) environments support the collaboration between students and tutor [8]. However, from our point of view, one of the greatest constraints of the systems developed within the CSCL area is that they are limited to restricted environments. Thus, the interactions between students and tutors are based on restricted data, e.g. tagged dialogs [2] or shared workspace actions [9]. These approaches have two main disadvantages: students have to explicit label the contributions they made and the collaboration is often focused on a particular task in a certain domain [9].

[1] COPEDESA: http://www.campus-oei.org/cooperacion/experto
[2] OEI: http://www.oei.es/
[3] MECD: http://www.mecd.es
[4] CIDEAL: http://www.cideal.org
[5] UNED: http://www.uned.es

If the collaboration is not allowed to be restricted by dialog tags, it is necessary to guarantee that the conversations and interactions between students are fruitful for the task. In this respect, several types of conversations have been identified [10]: *social*, *procedural*, *expository* and *cognitive*. In social conversations, students discuss elements of a social nature and not directly associated with the lesson (e.g. 'What course are you studying?'). In procedural conversations students discuss matters relating to procedures and steps associated with the learning materials (e.g. 'What do we need to do here?'). In expository conversations students exchange knowledge with little further elaboration or discussion (e.g. 'Your work seems to me very useful.'). Finally, in cognitive conversations students discuss issues directly related with the contents and demonstrate critical thinking and reflection (e.g. 'I think the point 1 is very useful to make the first assignment because ...').

Expository and cognitive conversations are the more worthwhile ones. Nevertheless, experiments performed in [10] shown that in all groups there were considerably more procedural interactions than expected. In some cases, this was brought about by student uncertainty in the unfamiliar environment. In addition, [10] found the following factors as the causes why there were fewer cognitive interactions than expected and why the number and forms of interactions varied within the different groups: *group composition* (inappropriate composition of groups can lead to non-collaborative environments); *inappropriate design for collaborative learning activities* (both activities need to be designed specifically with collaborative components and suggested roles for group members that encourage discussion and articulation have to be defined in collaborative settings); *lack of learning goals* (students were not guided by any particular goals).

Although we cannot completely avoid these circumstances, they can be loosen if we design the collaborative task so that social and procedural interactions take place in the early stages of the task. In this sense, we have desigened the collaborative task described in this paper through several phases with concrete activities to be performed and roles to be played.

The courses where we apply our research experiences at aDeNu Group have more than a hundred students. However, to achieve an efficient collaboration among them, it is advisable to divide the students in small subgroups of peers [7]. Due to the large number of students, a hand-made subgrouping is not easy-to-handle at all. To help the tutor in the management of the group, the subgrouping is done automatically. In these subgroups, it is important to choose a moderator that promotes the collaboration and communication.

Forming an effective group for the collaborative learning is critical to ensure educational benefit to the members. In our case, the automatic subgrouping is performed according to the interaction profiles of the users. However there are several criteria to form the groups in collaborative activities. If several learning theories are used (e.g. observational learning, self-regulated learning, situated learning, coginitive apprenticeship, distributed cognition, cognitive flexibility theory, etc.) different learning groups according to these theories should be formed. In this case, the research described in [15] proposes a learning group formation built by combining multiple learning theories. Although we are currently focusing on the constructivism theory, we may in the future include other learning theories.

To help the tutor to manage the collaborative tasks a quantitative and qualitative analysis of the interactions taken place in the tasks have to be shown to the tutor. In this way, problematic situations in the group collaboration can be detected. To really help the tutor, these analysis is performed automatically, too [2]. The collaborative task is designed for a web-based system particularly indicated for collaboration and communication. In this system, the users are grouped into workgroups and can use all the services available, such as forums, chats, shared file storage areas, surveys, etc. This learning environment is called aLF (***a**ctive **L**earning **F**ramework*) [3,6] and gives support to the development of virtual communities. aLF strength is that interactions done in any of the platform services are exhaustively controlled by the platform and stored in a database [6]. Explicit user collaboration models can be obtained. These models are dynamically updated from the users' interaction data gathered from the collaboration services and shown to the administrator when required [5].

To construct such user collaboration models we are using a machine learning multiagent approach which has already been applied to related tasks in this context by our research group [13, 14]. The main feature of the architecture proposed is that it allows us to combine several techniques for representation and inference in user modelling. Part of the model can be constructed from predefined rules, while the other part can be constructed and dynamically updated from user behaviour using machine learning techniques. However, no machine learning algorithm is better than other but it depends on the machine learning task. This poses a problem in our environment where different machine learning tasks are needed and very heterogeneous data are used. We have implemented a machine learning multiagent architecture to avoid these inconveniences, This multiagent architecture can combine the results of different machine learning algorithms and chose the best response for each machine learning task.

This approach has already been used in aLF in the construction of individual user models to provide certain adaptation tasks, such as prediction of the level of activity of a specific user in the platform, automatic grouping of users within the same community or analysis of the messages sent to the forums [13, 14].

3. A web-based collaborative task

The collaborative task described in this paper is based on a well-known activity for workgroups, the ***L**ogical **F**ramework **A**pproach* [1]. The LFA is an activity for conceptualizing, designing, implementing, monitoring and evaluating projects. It provides structure to the project planning process and helps to communicate essential information about the project.

The LFA is currently implemented in aLF as follows: for each phase to be performed and in order to gather the students' solutions for a particular phase, the tutor activates a survey during a period of time. Once the period of the phase has finished, the tutor deactivates it and makes the solution available to the students. Due to the monitoring process taking place in aLF, for each student and for each phase only the tutor can see the responses given by the students. Although the tutors in the course are satisfied with the LFA in aLF, students complaint from the lack of collaboration among them, since the only way in which students can collaborate with each other is through messages on a forum.

In the proposed scenario, we have extended this LFA to allow a real collaboration among the students who are taking part on it. Thus, students can collaborate to perform each of the phases of the LFA. In this respect, a student can only collaborate with his/her partners if they have already finished an initial individual work. Thus, each student learns by fitting potential new knowledge together with what s/he has already learned during the individual work previously done. We will see that this is possible thanks to the use of several roles in the group.

Four stages have been defined for the collaborative LFA extension: interaction stage, individual stage, collaboration stage and agreement stage. The interaction stage is previous to the LFA beginning, but the other three (individual stage, collaboration stage and agreement stage) are done in each of the phases of the LFA. A brief description is shown below:

- ***Interaction stage:*** It deals with the organizational tasks regarding the LFA. The goal is two fold: to show the students the LFA methodology and to allow the system to acquire useful data from the students' interactions in order to automatically make the subgroups and select the moderator for each one. The subgroup moderator is one of the students of the subgroup whose features indicate that s/he can lead the agreement stage. The way these features are obtained is described in subsection 4.1.

- ***Individual stage:***. From the tutors formulation of the problem, each student works by his/her own in solving each of the LFA phases, and provides the solution by filling in the corresponding survey. The only help students receive comes from messages in the forum for doubts resolution. To provide real collaboration to the LFA, students have also to start a new thread in the forum, where the initial message has to be the justification of the solution provided for that phase.
- ***Collaboration stage:*** Once a student has given his/her solution to a phase of the LFA (has finished his/her survey) and started his/her thread, s/he may be allowed (depending on his/her current role) to:
    - Access the solutions given by the other students of his/her subgroup.
    - Rate all the surveys s/he can access to.
    - Comment the surveys.
    - Rate new solutions. New solutions are automatically notified by the system when they are provided.
    - Collaborate through discussions in the forum. Since there is a thread for each of the surveys discussions regarding each survey are separately done.
    - Change his/her answer as result of the discussions in the forum. A new version of the survey is created and the rest of students of the subgroup are notified that there is a new version of the survey that has to be rated again.
    - Create a subthread for each new version of the survey.
- ***Agreement stage:*** The subgroup moderator plays his/her role in this stage. S/he is responsible of providing a unique solution accepted by the subgroup. Up to now, students have been interacting and collaborating by posing messages to the forum, versioning his/her surveys and rating others'. As a result, there are some surveys with higher rates than others. The goal of this stage is to produce a new survey which include the strong points of these surveys but avoid their weak ones. The procedure is similar to the one described in the collaborative stage. Students rate the new survey, they discuss in the survey thread the possible changes, the moderator creates a new version of the survey with the changes agreed, the survey is rated again, if the rating is lower, the old version is retrieved, and so on until the deadline arrives, and the latest version is handed in as the subgroup solution.

It is important to highlight that the roles a student plays in each stage have to be explicitly controlled, since students are allowed to do different interactions depending on their situation in the LFA. Any student, no matter whether s/he has been selected as moderator or not, plays the following roles:

- ***Individual working student:*** the student fills his/her survey for the first time and has no access to the other students solutions (at the individual stage).
- ***Passive collaborating student:*** the student has already given his/her solution and s/he is now rating the other students solutions for the first time, but s/he is not allowed to pose messages on the forum nor change his/her survey yet (at the collaboration stage).
- ***Active collaborating student:*** the student has already rated all students solution and can actively collaborate with them. S/he can participate in forum discussions and change his/her survey answers according to them. Ratings can also be done for the

new versions of the solutions, as in the passive collaborating student role (at the collaboration stage).

In each of these stages one of the conversations types (social, procedural, expository and cognitive) identified in [10] predominates. Thanks to the design of the stages, procedural and social conversations occur mainly in the first stage (interaction stage), while expository and cognitive conversations take place in the other three (individual stage, collaboration stage and agreement stage). Procedural conversations take place in the interaction stage due to one of the objectives of the stage is to show the students the methodology of the task. Social conversations appear in this stage, too, since it is the first stage of the task and students do not know each other.

4. The collaboration model

Since aLF traces all what has been going on during the students' interaction, collaboration data can be obtained and collaboration indicators can be inferred [5], which are used to build the collaboration model. At the interaction stage, collaboration indicators (based mainly on social conversations) are learned to select the moderators and to divide the students into subgroups. The collaboration model is acquired from the collaboration indicators obtained in the individual, collaboration and agreement stages which, in turn, are a refinement of the collaboration indicators initially obtained in the interaction stage. The collaboration indicators are related to the students' performance and compose the so-called student reputation of the collaborative task and allow us to characterize the students as:

- ***Participative student:*** This indicator measures the activity of the student in the different platform services. A student is participative if it produces lots of contributions. However, we are not interested in those students who simply contribute, but in those that their contributions are useful. Thus, a student contributions are useful if, at least, they are worth to be replied, so a student is really participative if s/he sends lots of messages to the forum threads and his/her messages are replied by other (as many as possible) students. Regarding participation, it can be distinguished between impulsive participative students, those who send messages (and get responses back) to most of the threads, and selective participative students, those who only send messages to mainly certain threads and subthreads.
- ***Insightful student:*** An insightful student is a selective participative student that most of his/her rates coincide to the afterwards computed mode and that from the beginning has given high rates to those surveys that were the highest ones rated in the end.
- ***Useful student:*** A useful student is a selective participative student that has strongly participated in the discussions of the threads of the finally highest rated surveys and in the threads that made the user create a new version of his/her survey (and this new version is not rejected by the subsequent ratings).
- ***Non-collaborative student:*** A non-collaborative student behaves as if there is no collaboration among students. For instance, a student of this type may reply messages to him/herself, produce a new version of his/her survey although there are no messages in the corresponding thread, keep the new version of his/her survey although this late version is rated lower than the previous one.
- ***Student with Initiative:*** If a student performs new tasks like sending new messages to the forums, mailing to other users or suggesting new solutions, it can be said that s/he

has great initiative. The student initiative may be the first step to achieve collaboration between the subgroup members.

- ***Communicative student:*** This indicator infers the student facility or ability to transmit information to other group members. However, it does not consider if the information contents are related to the LFA task or not. It is very important to pay special attention to the replies made by other students to see the effect of his/her actions to the rest.

Failure prediction can be done once students have finished the LFA taking into account the initial collaboration indicators obtained from the interaction stage and the collaboration model obtained at the end. Correlations between the initial indicators and the final collaboration model should be found, that can help to predict students failure in future interactions of the LFA with different students and the same or different LFA problem formulation. In this way, problematic situations in the collaboration can be detected in early stages of the course.

Moreover, to help the tutor in the management of the group, students are subgrouped automatically. This subgrouping is done just after the interaction stage, and is based on the collaboration indicators obtained at this stage. One of the students in each subgroup is selected to play the moderator role, taking into account the collaboration model just obtained. In the next subsections we describe how to select the moderator and make the subgroups. Next, we suggest how the student reputation can be obtained from the collaboration indicators.

4.1 Moderator selection

The goal of subgrouping is not to create subgroups based on the knowledge possessed by each member, but the composition of the group is such that collaboration is promoted. For this reason, the moderator should not be the student who has the greatest knowledge on the task to be performed, but the one who is likely to communicate easily with the rest of the students of the subgroup. As in the interaction stage communications are mainly social and procedural, this stage is the most indicated to discover the communication skills and, therefore, to identify the moderators. According to the collaboration indicators previously described, a moderator has to be a participative, communicative and with initiative student, and his/her answers in the initial survey have to be appropriate to become a candidate to take on the moderator role.

During the interaction stage, the tutor is monitoring the students. It can be a very hard task to ask the tutor to select the moderator for each subgroup. However, it will not be difficult for the tutor to select some students that may seem valuable candidates to take on the moderator role. In this way, the tutor can easily label certain students as moderators to help the system to select the rest. Machine learning can be used to train the system to select the moderators from these labelled samples and the collaboration indicators mentioned above. We have already used several machine learning techniques for different user modelling tasks [5]. Regarding the collaborative task described in this paper, we consider Naive Bayes is an appropriate machine learning algorithm since it does not require too many training examples and it has been proven its success in other user modelling tasks [10]. This algorithm returns the student probability to be a moderator and the system selects the 'n' students with the highest moderator probabilities, where 'n' is the number of subgroups defined by the tutor.

4.2 Automatic subgrouping

In the aLF platform, both the interactions of the users and their personal data are stored in the database [5]. To make the automatic subgrouping, we can use the same indicators as the ones used to select the moderator, plus communication suitable conditions such as students who are usually in the platform at the same time, students who share the same geographical location, coincidence in certain personal data (e.g. age or language), list of students to whom the student has had a communication act, etc.

All these data can be provided to a clustering algorithm. Once the subgroups are made, the tutor assigns a moderator to each subgroup. 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, the tutor is allowed to reorganise the groups according to his/her restrictions, but the model learnt for the clustering algorithm is not modified for subsequent automatic subgrouping.

4.3. Students' Reputation

The reputation that a student has can be achieved by considering the quality in the collaboration interactions with the system and the other students. In this case, the reputation is an indicator that considers mainly the knowledge of the student, the ability to share it and the utility for the rest of students. The reputation can be obtained from those indicators that allow us to characterize the users as participative, insightful, useful, non-collaborative, with initiative, and communicative which have already been described above.

The reputation of a student is very useful to determine how trustful can be the responses given by this student. For instance, an answer to a message given by a student with a strong reputation should be more seriously taken into account than a message sent by another student with worse reputation.

We are currently working on defining in more detail how the student's reputation can be obtained from the collaborative indicators just defined.

5. Conclusions and Future Work

In this paper, we have shown how a well-designed collaborative task can be easily managed by the tutor thanks to the collaboration model build from the students interactions. We have proposed a scenario that can be supported by intelligent learning management systems for a collaborative task based on the LFA workgroup activity. This task is carried out in aLF web-based collaborative environment and implemented by a user modelling based on a machine learning multiagent approach. Thus, it can be applied in a variety of domains and takes advantage of the principles of the constructivist learning approach since the students learn as they interact with their environment and with their partners. Students are allowed to participate in a more central practice as their understanding and competence increases and are helped to maintain fruitful conversations about the collaborative activities they are performing. With the collaboration indicators acquired, problematic situations in the collaboration can be detected in the early stages of the course. That is, once a particular phase has been activated, if a student still has the role of individual working student, it means that his/her is not really collaboratively working in the task. On the contrary, if a student has the role of active collaborating student but s/he has not been considered a participative student (i.e. his/her contributions have not been replied), the tutor can detect that this student is not collaborating properly although his/her is actually working in the task. Moreover, to help the tutor in the management of the group, students are subgrouped automatically where one of the students in each subgroup plays the moderator role.

A simplified version of the collaborative task has already been implemented in aLF and tested with experimental small groups of students. A preliminary study has shown the effectiveness of this approach. As a result, it is being applied in several postgraduate courses in our distance learning university (UNED) since January 2003. These courses have over one hundred students, which allows us to gather data to construct the collaboration models. We are simultaneously enhancing this simplified implementation with the functionalities defined in this paper for the collaborative extension to the LFA, so richer types of data can be obtained. In this sense, our goal is to strongly bind the individual work performed by each student with the interactions in the forums, and to effectively manage the roles described in this paper.

In addition, we are asking the tutors to explicitly label several reputation indicators of the students for the first courses performing this task (e.g. communication-ability, utility-of-contributions, etc.) in order to acquire the students reputations. In this way, we use supervised machine learning techniques to predict the reputation for the students in the early stages of the cooperative LFA on subsequent courses.

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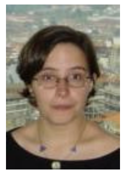
PhD on Artificial Intelligence at the Artificial Intelligence Department in the Computer Science School at the Spanish National University for Distance Education, UNED. Researcher on User Modeling at the aDeNu Research Group. Her main research area focus on the application of machine learning on the user modeling specially in web-based collaborative adaptive systems. Currently, she is involved in ALFANET and SAMAP Projects.	 ***Elena Gaudioso***
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