A FUZZY MODEL FOR REPRESENTING LEARNING
BEHAVIORS IN COLLABORATIVE ACTIVITIES IN LMSs

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ABSTRACT
Collaborative learning in the context of Learning Management Systems (LMSs) deals with a collection of tools and activities which learners can use to interact in a process of constructing a shared meaning of their knowledge. To support an effective and successful collaborative learning process it is especially important to correctly design the activities and to report the instructor how the collaboration is performing in the collaborative activities. Analysis of interaction in these activities can serve both to the support of learners’ self-regulation, as well as to task monitoring and evaluation on the part of the instructor. This paper proposes a fuzzy model for the representation and the description of the learning behaviors of learners and groups in the collaborative activities of a LMS, by monitoring and evaluating the collaborative learning process across several dimensions. The model aims to support the analysis of the collaborative learning process and also to help the tutor and the learners to deal with quantitative and qualitative information on the collaboration process, in an easy-interpretable way.

KEYWORDS
Fuzzy models, fuzzy rules, collaborative activities.

1. INTRODUCTION
Collaborative learning refers to teaching methodologies and learning environments in which students work in groups assisting each other, towards a common goal of their learning like an understanding of a meaning, a solution or the creation of an artefact.

Many researchers have shown that there exist various kinds of positive features in collaborative learning such as building self-esteem in students, stimulating learning, increasing motivation, promoting feelings of belonging to a team, promoting a positive attitude toward the subject matter, encouraging creativity, easing communication and enhancing student satisfaction with the learning experience. [1]

Most of the Learning Management Systems (LMSs) enable collaborative learning by organising students in groups, and by engaging them in collaborative activities based on communication tools, such as forums and chats, and on several collaborative tools for concurrent manipulation of simulations, cooperative writing or application sharing.

Teachers in LMSs support activities, through authoring, management and monitoring environments which allow them to design, organize and supervise the learning activities by posing tasks, formulating the groups, assigning roles to their members, uploading learning material and answering questions.

The use of all those tools in the collaborative learning approaches of LMSs, does not guarantee an effective and successful collaborative learning and therefore a frequent and regular analysis of the
individual’s and group’s collaboration process is needed to follow and manage the collaborative settings, which is usually a time consuming task for the tutor.

In our previous work [2] we developed an intelligent system that aims to assist teachers to supervise the learning process and the collaboration in a lesson of a LMS. The system analyzes the individual’s performance in the activities regarding the group work and a participation model, and by that provides awareness information to the learners and issues evaluation reports for the teacher.

A main drawback of the model used in that architecture is that it assigns learners to stereotypes based on their performance, so the evaluation reports that issues are difficult to be interpreted by the instructor. Moreover, the ranges of values that are used for the discretization process in this system are consecutive and so the labels (linguistic values) that are assigned are not so valuable and realistic.

To support the collaboration management in LMSs without such limitations, we propose, in this work, a fuzzy model to represent the collaborative learning behaviors and to evaluate the performance of the learners and the groups in the collaborative activities of a LMS. The model aims to enrich the analysis of the collaboration process in the activities of a LMS using fuzzy techniques to deal with quantitative and qualitative information and presenting it to the learners and to the teacher, in a user-friendly way.

The term ‘learning behavior’ has been introduced in this study to describe the performance of individual learners and groups in collaborative activities of a LMS through the analysis of the collaborative learning process, regarding several dimensions such as the participation, the interaction, the social and cognitive presence of the learners and their groups in those activities. The description of those variables is made using fuzzy sets [3], because they are very effective in treating uncertainty of collaboration analysis indicators [4].

We claim that the evaluation of the learning behaviors of the participants in those activities, concerning the level of their participation and their performance, characterize the learners and groups and could assist the instructor and the learners to understand the collaborative learning process taking part in the activity. This understanding could further help the teachers to intervene effectively in the design of those activities and also the learners to self-regulate their learning behavior in order to fulfill the goals of the lesson.

The paper is structured as follows. Section 2 presents a short review on methodologies that have been used to support monitoring and evaluation of online collaborative learning processes in web based environments. Additionally, in this section, some tools are presented which use fuzzy logic for the analysis of the interaction among the members of a group in Computer Supported Collaborative Learning (CSCL) systems. In section 3, a fuzzy model for the representation of the learning behaviors of learners and groups in the collaborative activities of a LMS is presented. Section 4 refers to a case study of the fuzzy model on the learning behaviors of the participants in a forum activity and the generation of evaluation reports, to the users of the activity. Finally, some concluding remarks are pointed out.

2. RELATED WORK

Collaborative learning as a teaching method has been mostly used in the classroom, but is now becoming increasingly used in higher education and in distance education settings through the advent of web based collaborative learning systems and LMSs. The idea that collaborative learning is the development of shared meaning among group members through negotiation among them emphasises the social creation of knowledge as the basis of learning [5].

The important components of collaborative learning in web-based environments are how to realize social context, group learning process, communication with each other and performance evaluation. Collaboration and interaction analysis can be used for representing and studying users’ behaviors within computer-supported collaborative learning (CSCL) environments through appropriate indicators. The analysis aims at evaluating and understanding the learners’ activity and contribution to the collaborative learning process to support the teacher and/or the collaboration between students [5].

There have been several proposals for methodologies or tools to support monitoring and/or evaluation of online collaborative learning processes. Some of them rely on models that have been proposed to analyze online interaction, as a form of discourse.

Henri [6] proposes a framework for analysing the content of online discussions integrating quantitative and qualitative methods. Her model includes five dimensions for the analysis of online discussion: the participative, interactive, social, cognitive and meta-cognitive dimensions.
Garrison and Anderson [7] propose a model for the monitoring of the learning processes that occur in asynchronous-based learning environments tracking indicators of social, cognitive and teaching presence within students’ and tutors’ messages, using text analysis.

Pozzi et al [8] adapted Garrison and Anderson’s model in a framework for analysing the learning processes that take place in a CSCL environment through inquiry-based processes. They have considered four main dimensions as the most relevant for characterizing an online collaborative activity, namely the participative, cognitive, social and teaching dimensions. In this model, each dimension is characterized by a set of relevant indicators that can be used for monitoring, evaluation or assessment purposes.

Daradoumis et al [9] propose a framework for the evaluation of online collaborative learning interactions which separates the evaluation of the process (or group functioning) from the evaluation of the product (or task performance) of collaboration. Their analysis framework targets on: task performance (or learning outcome), group functioning (or participation/interaction behaviour), social support, and help supply (or task/process scaffolding). To measure and evaluate each level, they have defined generic evaluation criteria with assigned weights that describe and capture its important features as fully as possible. Each criterion is also assigned a specific weight.

All those studies specify four important levels or aspects in the evaluation, monitoring or assessment of online collaborative learning activities: the participative, interactive, social and the cognitive one. We have also found in the literature several efforts regarding systems or tools that use fuzzy logic in order to allow detailed analysis of the interaction that takes place among the members of a group in CSCL systems in order to determine or characterize situations of effective and non-effective learning.

Barros and Verdejo [10], in DEGREE, characterize the collaboration process by means of variables that they define in qualitative terms. They model them as fuzzy sets using linguistic values. With the definition of the variables and with a group of rules, a fuzzy inference process is carried out providing conclusions about an individual student’s way of working (i.e. modeling, revision, critic, justification and participation) and about a group behavior (work, argument, coordination, cooperation and collaboration).

Redondo et al [11], in their Domosic-TPC system, propose the use of fuzzy sets to describe concepts about the collaboration such as, communication, cooperation, agreement, or participation. In the DomoSim-TPC system automatic methods have been outlined and applied, considering the model of learning activities defined in, that aim to allow teachers to analyze the results from those activities. The methods study the dialogue of the participants as well as the design models they build.

The data used in those studies come from the representation and organization of the information about the discussion process and/or the domain aspects through structured interfaces. Those systems register this information from user interaction.

LMSs, on the other hand, track through unstructured interfaces heterogeneous data about learners’ interactions with the activities and provide to their users a rather quantitative evaluation of the collaboration processes and the learning experiences of the learners, through learner and monitoring environments.

In this study, we propose the use of a collaboration analysis framework based on a fuzzy model, to represent in a more easily interpretable way the learning behaviors of the users of collaborative activities in a LMS and also to treat the uncertainty of some collaboration analysis indicators. The model provides some variables that describe what the learner has done and how the learner collaborates across the participative and interactive dimensions and also his social and cognitive presence. Each variable is analysed through a set of indicators that have been tracked by the LMS. The objective of using those variables is to characterise the learner’s and group’s collaborative learning behaviors. We consider that the instructor in this framework can more easily obtain information about the way students are taking part in a collaboration task and detect in a quick and easy manner several problems in the collaboration process such as, poor collaboration of specific students, failure of a collaborative task or conflicts within the groups. Such a representation based on the information of their learning behavior might also be helpful for the learners in order to self regulate and adapt it towards the learning goals of the teacher and/or the group work.

3. A FUZZY MODEL FOR REPRESENTING LEARNING BEHAVIORS IN COLLABORATIVE ACTIVITIES
In this work, we propose a fuzzy model that represents the online collaborative interactions and processes that occur in the collaborative activities of a lesson of a LMS through the description of the learning behaviours of learners and groups based on several factors of the collaborative learning process like, the attendance, the participation, the interaction, the social presence and the cognitive presence. We refer to them as collaboration variables.

The values of the collaboration variables are estimated based on the analysis indicators. Analysis indicators are metrics that estimation of the values of collaboration variables is based on and are related to the process or the product of collaboration. Therefore, they are elements of central importance within collaborative learning systems. Some of those indicators can be obtained directly from LMS’ database while others have to be calculated. Dimitrakopoulou et al. in [12] classify analysis indicators according to their interpretative value (high, intermediate and low level indicators), purpose (cognitive, social and affective), scope of analysis (related to the process or to the product) and point of view (concerning learners or groups). Barros and Verdejo in [10] describe three types of indicators: (a) calculated indicators that take the form of numeric variables, (b) subjective indicators that are qualitative indicators computed using calculated indicators and the evaluator’s assessment of the process and product and (c) inferred indicators that are generated from calculated and subjective indicators, from other inferred indicators and from information about the learning activity.

The level of learners’ participation in a collaborative activity gives an indication of their involvement in the process so, it might help the tutor to regulate the activities and also be used for the evaluation of the learning experience. The participative dimension in our framework is defined through the variables 'attendance' and 'participation' of the learner or a group in a collaborative activity. 'Attendance' is based on indicators such as, the number of the accesses of the learner in the activity and the total time he has participated in. 'Participation' is evaluated e.g. by the new posts one has made in the forum and also by the replies to others' posts. The social presence is defined in our model by the variable 'sociality' and concerns whatever is not related to the subject matter. We have selected to be evaluated by the total number and also by the average size of the messages that a learner has sent in a chat activity.

In CSCL contexts, interaction refers to the relationships that participants build during the learning processes, so the interactive dimension in our model (variable ‘interactivity’) should be addressed by aspects such as the number of messages in the chat and the replies to others’ posts in the forum activity. The cognitive dimension is defined in our model by the variable ‘contribution’. This variable's value is based on the participation of a learner in the activity and by the mark that the teacher has set.

The variables and the associated indicators that we have used for the representation of the learning behaviors of learners and groups in a forum activity in a lesson of a LMS are shown in Table 1.

<table>
<thead>
<tr>
<th>Number of accesses in the forum activity</th>
<th>Total time in forum</th>
<th>Average size of messages in chat</th>
<th>Number of messages</th>
<th>Number of replies to posts</th>
<th>Number of new posts</th>
<th>Mark of the teacher</th>
<th>Participation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attendance</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Sociality</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Interactivity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Participation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contribution</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Determining values of the collaboration variables using linguistic terms (like e.g. low, average, high etc) to evaluate collaboration aspects of a collaborative activity, is not a clear-cut case. For example, in order to evaluate 'Interactivity' you need to take into account the 'number of replies to posts' and 'the number of new posts'. It is not clear for any combination of those numbers to which linguistic term of 'Interactivity' corresponds. Fuzzy sets and fuzzy rules are a suitable tool for representing this kind of uncertainty.

A fuzzy model consists of a collection of fuzzy rules. The fuzzy rules comply with the general form:

\[ IF \langle \text{Antecedent} \rangle \ THEN \langle \text{Consequent} \rangle. \]

A fuzzy model can be viewed as a knowledge based representation of the functional relationships among analysis indicators and collaboration variables expresses as fuzzy (or linguistic) variables. The antecedent of
a fuzzy rule is a conjunction of fuzzy memberships of some analysis indicators' values, while the consequent is a fuzzy set representing the linguistic value of a collaboration variable. The rules in our fuzzy system infer linguistic values for each collaboration variable. Based on them, the learning behavior of a learner or a group is characterized.

More specifically, our fuzzy model consists of a collection of n rules of the form

\[ \text{If } V_1 \text{ is } A_{1j} \text{ and } V_2 \text{ is } A_{2j} \text{ and } \ldots \text{ and } V_n \text{ is } A_{nj} \text{ then } Y \text{ is } B_i \]

where \( A_{ij} \) and \( B_i \) are linguistic values (or labels) internally represented as fuzzy (sub)sets over the domain of the corresponding indicator or collaboration variable. The purpose of the fuzzy model is to determine the value of the consequent (collaboration) variable \( Y \), for a given combination of values of the antecedent (indicator or collaboration) variables \( V_1, V_2, \ldots, V_n \).

Each linguistic variable can take one or more of its values, which are determined by the designer and cover the domain of the variable. Each linguistic value, which has a label, corresponds to a fuzzy set, which is represented by a membership function \( \mu(x) \), which can be of any shape (e.g., triangular, trapezoid, Z, S etc). Membership functions can take values between 0 and 1 (included). For example, if \( \mu_{\text{low}}(x) = 0.4 \), it means that the degree of participation of \( x \) to fuzzy set/value 'low' is 0.4.

In our system, we have considered a fixed number of five fuzzy linguistic values, for all variables, corresponding to the following labels: Very-Low (VL), Low (L), Normal (N), High (H) and Very-High (VH), which are represented by triangular membership functions. For example, the indicator \( \text{mark} \) is modeled as a fuzzy variable using the membership functions of Fig.1 and so it could be assigned the following linguistic values: \{VL, L, N, H and VH\}. The method requires the instructor to define the numeric ranges for each membership functions.

Figure 1. The membership function used for the the indicator \( \text{mark} \)

The values of the collaboration variables of the fuzzy model are inferred using fuzzy rules that have been designed by an expert. Each fuzzy rule relates some indicators (antecedents) with a collaboration variable (consequent).

Our methodology also specifies, by the same process, the learning behaviors of the groups and of the whole class in the collaborative activities of the LMS by calculating and taking into account the mean values of participation and performance indicators of the group or of the whole class.

4. A CASE IMPLEMENTATION

We have implemented a prototype of the fuzzy model for representing the collaborative learning behaviors of the users of a forum activity, in the environment of the Learning Activity Management System (LAMS) [13].

Before using the system, the instructor has to define the numeric ranges for the linguistic values (membership functions) of the indicators: number of replies to posts, number of new posts and \( \text{mark} \). In Figure 1, the numeric ranges that have been set by the instructor for the membership functions of indicator \( \text{mark} \), are displayed.

The fuzzy model includes also several fuzzy rules that are being used to infer the linguistic values for each collaboration variable.

An example of a fuzzy rule used to infer the linguistic value of the variable ‘contribution’ is:

\[ \text{IF } \text{participation IS normal AND mark IS low THEN contribution IS low} \]
Table 2 presents the whole set of 25 fuzzy rules, that has been designed by experts and is used for inferring the values of the variable ‘contribution’ from the values of the fuzzy variables mark (an indicator variable) and participation (a collaboration variable), as follows from Table 1.

Similar sets of fuzzy rules have been designed by experts to infer the linguistic values of the rest collaboration variables, based on the dependencies of Table 1. For example, for the variable participation the values of the fuzzy variables number of replies to posts and number of new posts have been used.

Table 2. Rules for inferring the value of ‘contribution’

<table>
<thead>
<tr>
<th>mark</th>
<th>VH</th>
<th>N</th>
<th>H</th>
<th>H</th>
<th>VH</th>
<th>VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td></td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>VH</td>
<td>VH</td>
</tr>
<tr>
<td>L</td>
<td>VL</td>
<td>L</td>
<td>L</td>
<td>N</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>VL</td>
<td>VL</td>
<td>L</td>
<td>H</td>
<td>N</td>
<td>VH</td>
<td></td>
</tr>
</tbody>
</table>

After having taken the values of the analysis indicators and made corresponding inferences via the fuzzy rules, the system issues evaluation reports to the supervisor, as shown in Fig 2, that include characterisation of the learning behaviours of the learners, the groups and the whole class in a Forum Activity, named “demo forum”, across all the variables of the analysis framework. The system issues also awareness reports to each learner (Fig. 3) that describe his/her own learning behaviour in contrast to the learning behaviours of his/her group and the whole class.

![Figure 2. An evaluation report to the supervisor](image)

![Figure 3. An awareness report to the learner](image)
The evaluated learning behaviours could help the instructor in intervening efficiently in the design of the lesson in intermediate steps of the course, advising the learners, creating groups of students to perform collaborative activities or assigning roles into groups. In the following, we refer to some indicative collaborative learning cases that could be detected from the evaluated learning behaviours and the special actions that the teacher could undertake.

- Learners whose learning behaviour is characterised by a high social interaction and a high participation in collaborative activities. These learners could be assigned, by the instructor, as moderators in groups joined with students with low social interaction and participation.
- Learners are detected to exhibit high participation and high contribution but low attendance, which may mean that they try to perform tasks as fast as possible. Instructor could advise these students on trying to help and support their team-mates.
- Groups that participate and interact highly but at the same time their contributions are low. The instructor could encourage these groups that seem to be motivated, to work harder in the course contents or provide clues about how to contribute, among other actions to better exploit their interactions.

In any case the teacher’s interventions would depend on the particular pedagogical strategy that the instructor selects to apply.

5. CONCLUSIONS

In this paper, we propose a fuzzy model to represent and infer the learning behaviours of learners and groups that participate in the collaborative activities of a LMS environment. Our model consists in specifying (a) a number of fuzzy variables and (b) a number of fuzzy rules.

We distinguish two types of fuzzy variables, namely indicator variables and collaboration variables. Collaboration variables represent the five dimensions across which we examine learning behaviours, i.e. attendance, sociality, participation, interactivity and contribution (or cognitive dimension). Indicator variables represent the analysis indicators, which are the metrics dimensions, are analysed in and based on.

Fuzzy rules represent the functional relationships between indicators (in most cases as inputs, in the antecedent part) and dimensions (in most cases as outputs, in the consequent part). Those relationships have been specified by experts through a systematic way.

Our model offers an analysis or description of the learning processes in an easily interpretable and a user-friendly manner, facilitating monitoring, evaluation and assessment processes of the collaborative activities in a LMS.

We have developed a prototype of the model and applied to the LAMS environment. The prototype, after using the fuzzy inference system, returns evaluation and awareness reports to the users. This type of feedback is comprehensive and helps supervisor to easily and quickly understand the information reported and use it to effectively intervene in the learning process. Also, students that receive that feedback from the system are expected to either modify an unsatisfactory learning behaviour or recognize and reinforce a successful performance.

To fully support the above claims, we should make an adequate evaluation of our approach, which is one of our future research. Such an evaluation would give us an opportunity to revise our model, as far as either its variables are concerned or it rules. Towards that direction, a deficiency of our model is that any effort for revising it should be made manually by the expert. So, another direction for further research would be to semi-automate or even automate that process.

REFERENCES


