Ranking Learner Collaboration according to their Interactions

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Abstract— **Collaboration is supposed to be easily implemented in Learning management systems (LMS). Usually the basic functionalities in that respect support grouping students and providing communication features so that they are able to communicate with each other. However, related collaborative learning and CSCL studies and developments, which have been investigating how to manage, promote, analyze and evaluate collaborative features for decades conclude that there is no easy way, and much less standards-based approaches to support effective collaboration. The mere use of a typical set of communication services (such as forums, chat, etc.) does not guarantee collaborative learning. Further, managing collaborative settings in those LMS approaches is usually a time consuming task, especially considering that a frequent and regular analysis of the group's collaboration process is advisable when following and managing the collaborative processes. To improve collaborative learning in those situations we provide tutors and learners with timely information on learners' collaboration in a domain independent way so that the model can be transferred to other domains and educational environments. After setting a collaborative experience in an open and standards-based LMS, we have analyzed, through various data mining techniques, the learners' interaction in forums during three consecutive academic years. From that analysis we have built a metric with statistical indicators to rank learners' according to their collaboration. We have shown that this rank helps learners and tutors to evaluate the collaborative work and identify possible problems as they arise.**

Keywords- Collaboration, Data Mining, Distance Education Learners

I. INTRODUCTION

The current web-based Information and Communication technologies (ICT) bring people closer together. In particular, Learning Management Systems (LMSs) use the ICT's so that learners can interact with educational contents and other learners. Collaborative strategy can be implemented in those LMSs to improve the learning and mitigates the typical conditioning factors (loss of communication quality with fellow students and teachers) of the distance education [2]. Even AI techniques have been applied to model mainly learners and their knowledge [7]. However, collaboration so widely used and useful in educational environments has not been deeply researched and a standard method to analyze collaboration has not been established [24]. Although some research works have focused on collaboration [25], the proposed methods are difficult to transfer to other educational environments [21].

Moreover some researches claim that collaboration analysis is necessary to verify that collaborative learning takes place [14] and the metacognitive information on collaboration, which is obtained from the analysis, helps learners to improve the control on the learning and collaborative process [10].

In this paper we propose an approach to rank learners' collaboration according to their interactions. The objective is to help learners to improve the collaboration process through a method that both provides information on learners' collaboration, and can be used in others LMSs. Accordingly we focus our approach on a quantitative analysis of interaction data in an open-collaboration learning environment.

The educational context of our research is suitable for collaborative learning, because our learners at UNED (The National University for Distance Education in Spain) are used to the distance learning model. UNED's students are mainly adults with responsibilities other than learning. For this reason UNED's students cannot be forced to collaborate in a typical CSCL where they are requested to meet demanding time restrictions and fixed collaboration patterns [12]. We have solved this problem by providing learners with an open collaborative learning experience supported by an LMS, where students could manage their own collaborative learning process. We designed a long-term collaborative learning experience with 4th-year Artificial Intelligence and Knowledge-based Engineering (AI-KE) students. This experience consisted of 2 main phases within a step-wise approach: the first phase covered 3 consecutive weeks and the second phase covered 10 weeks. It was enough time for students to complete the collaborative work and be able to manage their collaborative process. We offered the collaborative learning experience during the academic years 2006-07, 2007-08 and 2008-09, and more than 100 learners every year participated in the experiences.

To cover the objectives, we proposed an approach based on quantitative analysis of the learner interactions in forums. Forums are a very common service in a collaborative environment and the statistics from forums can be obtained just after the interaction has occurred. We propose building a metric with statistical indicators, which are related to learner's collaboration. First we suggest some statistical indicators, which describe the initiative, activity, learner constancy and activity caused by learners. As the relation between statistical indicators and collaboration is unknown, we have used machine learning algorithms to reveal the relation. After the machine learning analysis, we found that the most collaborative learners are learners with high and constant initiative, high and constant activity, and they caused more activity than others. After the machine learning algorithms had selected the statistical indicators, we built a metric to rank learners according to their collaboration. We conclude that the ranking is an approximation of learner collaboration.

A short overview of methods already used in evaluating the collaboration process is given below. We describe the collaborative learning experience and the inferring method. Next we show the results obtained afterwards by applying the inferring method and we explain in depth how the inferring information has been shown to learners. Finally, we conclude with the discussion and future works.

II. Related Works

There have been various experiments to measure or identify the collaboration that is taking place between users of a system, although the methodology and standards are scant to analyze collaborative educational environments [24]. We mention two main points of research works, which focus on collaboration: data acquisition and inferring methods.

We can identify three data acquisition methods: 1) Qualitative [18, 15]: where participants are asked directly or experts evaluate the activities of the participants. 2) Quantitative [25, 21, 13, 5], which collects statistical information on the activities of the participants. 3) Mixed [8, 9, 17, 19]: the use of both methods simultaneously.

After the data had been collected, they were then analyzed using several techniques. These systems can be characterized by the inferring methods used. The methods may include: 1) Analysis by an expert [18, 15]. 2) Comparison with a pre-existing model using machine learning methods [21]. 3) Different statistical techniques [13, 9, 17, 5], or machine learning, such as clustering [25, 19], fuzzy logic [21], sequential pattern mining [19]; 4) Systems can even be characterized by not using any inference method [8, 9, 17].

Some research works focused on the experts' analysis to obtain evaluations of the collaboration [18, 15], others monitored learner interaction to improve collaboration knowledge but they did not obtain any evaluation of the collaboration [8, 13, 9, 17, 5] and some others used machine learning algorithms to analyze collaboration, although the expert's analysis is necessary [25, 21]. For this reason the regular and frequent evaluation of the learners' collaboration are delayed or the approach cannot be transferred to other learning environments.

We propose an approach to obtain evaluation of the learners' collaboration in a frequent and regular way, and reusable in other collaboration environments. This evaluation rank learners according to their collaboration. The approach uses both statistical indicators of learner interaction without semantic information and also the expert's analysis of collaboration as a data source, and machine learning algorithms to relate the statistical indicators to the expert's analysis of collaboration. With the statistical indicators most related to the expert's analysis we propose building the metric to rank learners.

III. Collaborative Learning Experience

The loss of communication quality that usually affects the distance education environment can be solved, if collaborative learning strategy is used [2]. However, the collaborative learning strategy must be focused on the learner to use all advantage of collaboration [11]. The distance education learners can be characterized by their diversity (different ages, residence, background, objectives, experience, etc) [4]. These learners are used to managing their own learning process, because they have responsibilities other than learning. Thus, a collaborative learning experience must allow the learners to manage their own collaboration process.

We offered learners a long-term collaborative learning experience during three consecutive academic years; 2006-07, 2007-08 and 2008-09. The collaborative learning experience provided learners with enough time to perform the tasks without the typical time restrictions of CSCL systems.

The learning experience consisted of practical collaborative tasks, which covered 3 months of an annual subject on AI at the Computer Science School. The activity structure was divided into 2 main phases within a step-wise approach. The collaborative learning experience was offered to all students enrolled in the subject. The Figure 1 shows the learning experience schema.

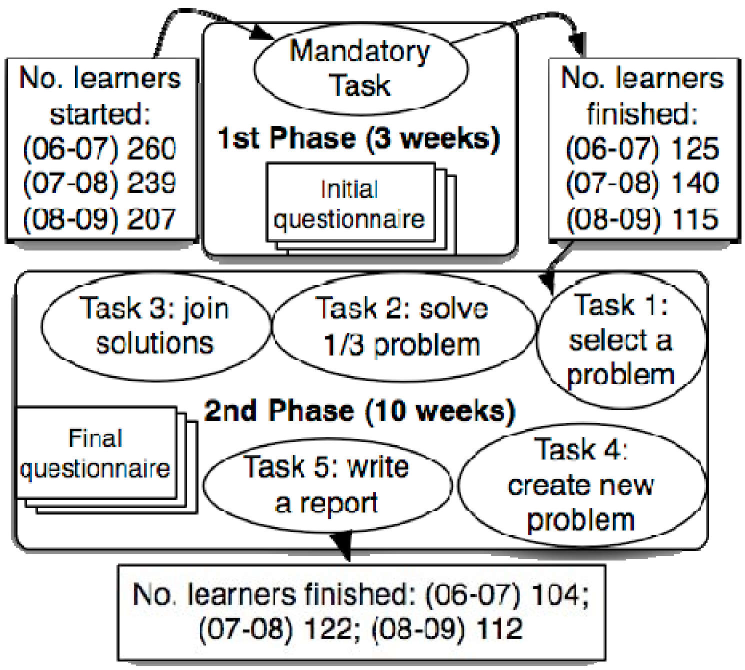

Figure 1. Learning experience schema

The first phase went on for 3 consecutive weeks where the main learner tasks were answering an initial questionnaire and solving an individual task. The questionnaire asked personal data and information about their willingness and availability to collaborate with one another. The individual task was mandatory and its results had to be integrated with the collaborative work to be performed during the second phase.

The second phase covered 10 weeks and the learners were grouped in 3-member teams. The team members had to follow 5 consecutive tasks throughout the collaborative experience. (1) In the forums teams discuss which problem they are going to address from the ones that are given to them. (2) This task is mainly individual work and consists of each team member solving one of the three different subproblems. (3) The team members have to integrate their previously generated individual solutions. (4) The experimental task takes place in this phase and here the team has to create other related planning problems that are based on the original one. (5) Finally, the team has to provide a report that covers all the activities and their corresponding results. At the end, the learners were asked to fill in a final questionnaire, which includes several topics with valuable information associated with the collaboration results. The team-work increases the difficulties depending of the done tasks, from the easiest (Task 1) to the most difficult (Task 4). Thus, the learners can be developed and improved the collaboration skills [16].

The whole range of activities included in the collaborative learning experience was supported by the open and standards-based learning platform dotLRN [23]. This learning platform stores all the interactions, which take place on the platform, in a relation database. During the first phase a general virtual environment was open for all students. The general virtual space included several services to support their collaboration needs, such as the file storage area, FAQs, news, surveys, calendar and forums. During the second phase a virtual spaces were opened for each 3-member team, where they could perform the tasks. The specific virtual spaces included documents, surveys, news, task manager and forums.

IV. METHOD

To know the collaboration learning happens, a frequent and regular analysis of the collaboration is needed [14]. In the aforementioned collaborative learning experience the learners have the control of the collaboration process. The tutor has difficulties to analyze the collaboration of all learners and teams in these circumstances. However, machine learning techniques can be used to analyze the learners' interactions to infer evaluations of the learners' collaboration.

The research objectives were twofold. Firstly, to build a domain independent method, which was capable of identifying the interaction features that were more relevant to support learner collaboration. Secondly, providing collaboration managers with timely results so that they could provide corrective actions wherever appropriate. We argue that quantitative data can support the overlapping required between user interactions and corrective actions. Besides, quantitative data without domain information (for instance, quantitative data without semantic analysis of forum messages) make it easier to transfer the method to other environments, because the data are domain independent. Our hypothesis was that the statistical indicators derived from learner interactions in forums could support both requirements, i.e. domain independency and simultaneousness.

We proposed a set of statistical indicators to characterize the forum interactions. We built datasets with these indicators and the dataset was labeled with information on learner collaboration. An expert, who was the tutor throughout the whole collaboration experience, supplied this information. We used machine learning algorithms [3], decision trees, to infer the relation between the statistical indicators and learner collaboration. The decision tree algorithms classify the given dataset instances according to the students' collaboration label, which corresponds to their level of collaboration. These algorithms provide a logic tree, which shows the dataset attributes used in the classification process (i.e., those that were more discriminatory). As we know the logic and theoretical difficulties (what the collaboration is, how to collaborate, what indicates the best way of collaboration [14]) of finding a model describing learner collaboration, we did not look for a model, which indicated how people collaborate. We looked for an estimate of indicators, which describe the collaboration in some way. This estimation is provided by decision tree algorithms, which link a model with the dataset attributes. Other methods like Bagging [6], whose approach is similar to the method being described here, improve the learnt model. As we did not look for the best model learned, we did not use those approaches. The decision tree algorithms are very sensitive to small changes in the instances. Accordingly, all dataset attributes should be used in the logic tree of some decision tree algorithm. However, the attributes that were most related to the collaboration should appear more than others and thus the machine learning algorithm bias is removed or alleviated.

The statistical indicators considered in datasets were as follows. We selected the statistical indicators to describe learner initiative, activity, constancy and regularity, and their acknowledgement by their fellow students, which are suitable for collaboration according to [22]). The statistical indicators considered in datasets were: number of threads or conversations that the learner started (num_thrd), and their average, square variance and the number of threads divided by their variance; the number of messages sent (num_msg), and their average, square variance and the number of messages divided by their variance; the number of replies in the thread started by the user (num_reply_thrd), and divided by the number of user threads; the number of replies to messages sent by the user (num_reply_msg), and divided by the number of user messages. The indicator number of threads started and its associated indicators are related to learner initiative. The square variance of the indicator number of threads is related to the constancy of the initiative. The indicator number of messages sent and its associated indicators are related to learner activity and constancy of activity. The indicator number of replies to messages sent and its associated indicators are related to the activity caused by the learner.

The statistical indicators are grouped into datasets expressed in tables where each row refers to the twelve statistical indicators of a student's interactions. Datasets were constructed with the indicator values for each academic year.

The doubt arose as to whether it was necessary to filter the datasets as some teams participated little in the forums because of coordination problems or they used other means of communication. Thus other datasets were created with the same data but without the students in the teams with little interaction. In other words, the students in teams with little activity were eliminated from the original dataset. The criterion for filtering was: eliminating students from a team, whose interaction was below half the average interaction of all the teams. During all the collaboration period these team members sent an average of 65 messages in the academic year 2006/2007, 73 in the academic year 2007/2008 and 87 in 2008/2009. In the academic year 2006-07 12 teams were filtered, 11 in the academic year 2007-08, and 8 in the academic year 2008-09.

The machine learning algorithms were trained to provide the validity of the different indicators. Then the datasets were labeled with a list of learner collaboration levels. An expert, who read the forums messages of each team and gave one value for the collaboration level to each learner in comparison with the other team members, supplied this list. The expert used a scale of 9 values (1 very collaborative, 9 not very collaborative, although the label "9" was used only to label students who did not send any messages).

Finally 2 dataset were built with the students' statistical indicators of every academic year. Thus, the non-filtered datasets were D-I-06-07 (104 labeled instances), D-I-07-08 (124 labeled instances) and D-I-08-09 (107 labeled instances), and the filtered datasets were D-II-06-07 (79 labeled instances), D-II-07-08 (97 labeled instances) and D-II-08-09 (88 labeled instances).

We needed machine learning algorithms that could classify learners according to their collaboration level. We used decision tree algorithms, because they return a logical tree, where each tree node is an attribute of the dataset. The logical tree informed us of the statistical indicator in relation to the labeled learners' collaboration. Instead of choosing the best learning algorithm for a given dataset, we experimented with several. There was no criterion to say which algorithm was the most appropriate taking into account that some decision tree algorithms classify all instances correctly but the tree is very complex, and others return a simple logic tree, although the logic tree does not classify all instances correctly [21]. For this reason there was no suitable criterion to choose only one decision tree algorithm. We used the data mining software WEKA [25], which includes several decision tree algorithms. We proposed the following working method: 1) Train all possible decision tree algorithms, which return a logical tree. 2) Identify the statistical indicators used from each logical tree. 3) Counting up how many decision tree algorithms use the identified indicator in every dataset. 4) Construct a metric with the most used statistical indicators. 5) Relate the metric to the collaboration level provided by the expert.

V. RESULTS

We trained the decision tree algorithms with the labeled datasets and counted the number of decision tree algorithms that used some statistical indicator in the logical tree. The decision tree algorithms used were: Best first decision tree, DecisionStump, Functional trees, J48, Logistic model trees, Naïve Bayes tree, Random tree, REPTree, Simple Cart. Table I shows these results.

TABLE I. NUMBER OF DECISION TREE ALGORITHMS THAT USED SOME STATISTICAL INDICATORS IN EVERY DATASET.

	D-I-06-07	**D-II-06-07**	**D-I-07-08**	**D-II-07-08**	**D-I-08-09**	**D-II-08-09**
Num_thrd	4	3	3	2	**7**	**8**
Med_thrd	2	2	3	2	3	4
Var_thrd	4	3	4	3	4	5
Level_thrd	**5**	4	4	4	5	4
Num_msg	**5**	4	**5**	4	2	5
Med_msg	2	2	2	1	3	4
Var_msg	4	4	4	3	5	5
Level_msg	4	**5**	4	**5**	4	**8**
Num_reply_thrd	3	3	3	2	4	4
Med_reply_thrd	2	3	4	4	2	5
Num_reply_msg	4	3	**5**	**5**	3	**8**
Med_reply_msg	3	3	**5**	**5**	5	5
No. algorithms used	6	6	7	7	7	9

Each column represents the number of decision tree algorithms that used the statistical indicator (first column) in their logical tree with each dataset (first row), and therefore the importance of a given statistical indicator in relation to collaboration. For example, four (see column 2 and row 2 in Table I) decision tree algorithms (J48, Logistic model trees, Random tree, REPTree), which were trained with the dataset D-I-06-07 (2006-07 dataset without filtering non-active teams), used the statistical indicator "num_thrd" in their logical trees. However seven decision tree algorithms, which were trained with dataset D-I-08-09 (2008-09 dataset without filtering non-active teams), used the statistical indicator "num_thrd". We note that some decision tree algorithms did not return any logical tree in some cases, but in other cases they returned the logical tree. This is the reason for the last row in the table above. Slight differences can be observed between the unfiltered datasets of teams with little activity (D-I-XX-YY) and the filtered datasets of teams with little activity (D-II-XX-YY). The differences are due to the sensitivity of these algorithms to small changes in the data provided [20]. Adding the filtered datasets, in this instance, the number of trials is increased, so each decision tree algorithm's bias can be reduced.

To better identify the relationship between the indicators and collaboration, we added up the number of uses for each statistical indicator. As the number of decision tree algorithms were different depending on the datasets (see the last row of the Table I), we weighted the addition with two criteria: I) Each value in the table above is divided by the maximum value in the column and then the values are added up in each row. II) Each value in the table above is divided by the number of algorithms used (the value of the last row) and then the values in each row are added up. The results are shown in Table II.

TABLE II. WEIGHTED ADDITIONS ACCORDING TO CRITERIA TO IDENTIFY THE MOST RELATED INDICATORS TO COLLABORATION.

	Addition I	**Addition II**
Num_thrd	4.40	3.77
Med_thrd	2.73	2.25
Var_thrd	4.00	3.29
Level_thrd	4.61	3.80
Num_msg	4.51	3.63
Med_msg	2.33	1.97
Var_msg	4.34	3.60
Level_msg	5.17	4.25
Num_reply_thrd	3.27	2.73
Med_reply_thrd	3.51	2.82
Num_reply_msg	4.83	3.91
Med_reply_msg	4.54	3.70

From the table above we conclude that the statistical indicators most related to the collaboration level are: **level_msg**, **num_reply_msg** and **level_thrd**. With these statistical indicators we have created this metric:

$$\text{Metric I} = \alpha(\text{level\_msg}/\max(\text{level\_msg})) + \beta(\text{num\_reply\_msg}/\max(\text{num\_reply\_msg})) + \gamma(\text{level\_thrd}/\max(\text{level\_thrd}))$$

We note that the statistical indicators are normalized. The possible values of the statistical indicators are between 1 and 0. We normalize because the "level_msg" is always higher than "num_reply_msg" and "level_thrd" values and the effect of the "level_msg" on the metric would be too high. We introduced the constants α, β and γ to weight the metric. In this experiment we did not weight the metric, thus α, β, $\gamma = 1$.

Finally, we related the metric to the collaboration level list. We calculated the value of the metric in each dataset. Then we grouped the instances according to their collaboration level, which was provided by the expert, and we measured the average metric of each group. The results are shown in Table III.

TABLE III. METRIC I AVERAGES FOR EACH COLLABORATION LEVEL IN EACH DATASET.

Level	D-I-06-07	D-II-06-07	D-I-07-08	D-II-07-08	D-I-08-09	D-II-08-09
1			1.03			
2	1.89	2.10	1.89	1.64	1.83	1.83
3	1.61	1.68	1.53	1.58	1.50	1.50
4	1.37	1.54	1.50	1.49	1.27	1.33
5	1.08	1.30	1.34	1.43	0.98	1.02
6	0.78	1.21	0.95	0.97	0.93	1.12
7	0.69	1.07	0.86	0.86	0.54	
8	0.60		1.22	1.27	0.95	0.95

We note that each level has a different metric value and this value increases when collaboration increases. Only the metric predictive value is wrong in the extreme levels (1, 7 or 8), where the number of instances was small. There are cells without value, because there was no instance with this collaboration level. In other words, higher values in the student's metric mean that s/he is more collaborative than others, and lower values (but not the lowest) in the student's metric mean that s/he is less collaborative. As this metric behavior is repeated in all the datasets, it can be suggested that the metrics are related to student collaboration, so the approach was validated.

VI. CONCLUSION AND FUTURE WORK

In this paper we have proposed a data mining approach to rank learners according to their collaboration. We think that the data mining method covers the objectives needed to improve the collaboration process. The objectives are: to obtain information on learner collaboration just after the collaboration interactions have finished and to be domain independent. These objectives are needed to apply the data mining method to other open collaboration learning environments and help learners in collaboration process management.

This research focused on obtaining information on the collaboration process using the statistical indicators of learner interaction in forums. As the statistics from the forums do not give any semantic information, the statistical indicators are domain independent. We propose that the statistical indicators are related to the initiative, activity and constancy of learners and the activity caused by learners. Our first objective was to build a metric, which represented learner collaboration mathematically. This metric had to collect some proposed statistical indicators. We needed to know the relation between the statistical indicators and collaboration. We used decision tree algorithms to establish this relation. An expert's analysis labeled the statistical indicator instances of learner interaction according to learner collaboration. Thus, the decision tree algorithms relate the statistical indicator to collaboration.

To validate the approach the experimentation of his research took place over three consecutive academic years 2006-07, 2007-08 and 2008-09, and over 100 students took part in the collaborative learning experience each year (125 in 2006-07, 140 in 2007-08 and, 115 in 2008-09). We built datasets with the statistical indicators of learner interactions in forums. At the same time, an expert labeled each learner according to his/her collaboration level. The labeled datasets obtained were used to train decision tree algorithms. The logical tree algorithm offered those statistical indicators that are used to learn the classification according to collaboration. We used the statistical indicators, which were most related to collaboration, to build a metric. Finally, we checked that the metric was associated with collaboration.

We have shown that the metric proposed establishes a mathematical relation with collaboration. Therefore, learners can be ranked automatically according to their collaboration while they are in the collaboration process. This metric can be used during the collaboration process in all LMSs or collaborative environments that use forums as the main communication mean. We have observed (see Table 3) the metric represents approximately the learners' collaboration. High values in the metric mean very collaborative learners. We have checked that this behavior is equal in all datasets of the research. Thus we argue the metric I can represents the learners' collaboration in future collaborative learning experiences, and the metric can be built easily, because the metric is a mathematical relation along some statistical indicators of interactions in forums. In addition, thanks to the flexible and general nature of the approach it can be transferred to other LMSs or collaborative environments.

Moreover in terms of the metric the method informs regularity and frequently about the learners' collaboration, which is needed to ensure that the collaborative learning happens [14] and gives information on metacognitive characteristics related to their collaboration, which helps learners to improve the collaboration process [10], and from that it is expected to affect positively their learning process.

After this research, to measure the effect of using the ranking method in an educational environment we need to check the improvement of the collaboration learning in comparison to other learning experiences without the ranking method. We have considered this issue and we researched other inferring methods [1]. We obtained positive results and deduced that an inferring method on collaboration improved the collaboration process management. We have to research this issue with the ranking method in future collaborative learning experiences. Other open issue is if the current inferring method can be improved. We have researched other machine learning methods to obtain the same objectives. In [1] we described our research when we used clustering algorithms to classify learners in spite of decision tree algorithms to rank learners. Both approaches have advantages and disadvantages. We must compare both inferring methods with the same data. However since the goal of the approach is to support learners' collaboration rather than applying the more precise machine learning approach we do not expect significance variations on the method. Another related open issue is the metric itself. In this paper the results were obtained when the metric constants α, ß, γ = 1, without weighting the metric. We are currently researching with weighted metrics where the constants (α, ß, γ) have different values and from that we will be able to compare the results between weighted metrics and non-weighted metrics in order to identify which one obtains better results.

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