Towards a transferable and domain-independent reputation indicator to group students in the Collaborative Logical Framework approach

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Abstract. Collaborative indicators derived from quantitative statistical indicators of students' interactions in forums can be used by e-learning systems in order to support the collaborative behaviour and motivation of students. The main objective of this research is to achieve a transferable and domain-independent reputation indicator, considering the information extracted from social network analysis, statistical indicators, and opinions received by students in terms of ratings. This paper describes how to consider the reputation indicator in a collaborative environment in order to group students (distributing the most prominent students into different groups) aimed to improve the collaborative indicators (such as initiative, activity, regularity).

Keywords: Collaborative indicators, Reputation indicator, Forum interactions, Grouping students, Social Network Analysis, Collaborative platform

1 Introduction

Providing personalised recommendations to students in order to foster their participation and increase their level of engagement in a collaborative environment is a relevant field that every e-learning system should take into consideration [1]. Collaborative learning environments have been successfully used to support student learning [2]. Using collaborative indicators derived from students' interactions might help an e-learning system in deciding whether to 1) speed up in order to reveal new educational content, 2) slow down in order to go into content in depth , 3) introduce new conversations or messages in order to stimulate new debates and a better understanding of the content, and 4) identify recommendations opportunities that guide students in performing specific actions intended to help their mates on a given task, encouraging participation and improving team work [3].

From previous research [3, 4, 5] carried out by aDeNu research group on collaborative indicators for e-learning environments, statistical indicators (such as number of threads started, number of messages sent, number of replies, etc.) have been proposed as relevant to evaluate the collaboration process. These statistical indicators were collected by a collaborative platform that implemented the CLF (Collaborative Logical Framework) approach on top of dotLRN Learning Management System (LMS) [6] and show their capacity to reveal students' collaboration quality in terms of several students characteristics such as initiative, activity, reputation and regularity [5]. The CLF has been proposed to provide real collaboration in the Logical Framework Approach, and is aimed to facilitate an efficient collaboration among students, grouping them in small clusters for effective collaboration (typically, 4 students per group). Under this framework, three stages have been defined [7]: 1) *Individual stage*: each student works individually to produce his contribution on a given problem; 2) *Collaboration stage*: students have access to the solutions of their mates and must comment (by answering the corresponding forum thread), and rate them; and 3) *Agreement stage*: taking into account the interactions in the two previous stages, a moderator is selected for the group, who is responsible for providing the agreed solution of the group based on the best rated works of the group.

In [3], it was suggested that from forum interactions analysis, those students whose messages receive more replies indicated more interest by fellow students, and this, can be considered a proof of acknowledgment, and thus, of student's reputation. The reputation is a relevant measure of the degree of prominence of an actor in a social network. In turn, [8, 9] showed that reputation was one of the most important attributes for predicting final student performance on the basis of the use of data from online discussion forums.

In this context, this research work aims to complete previous reputation indicator in terms of three different types of analytic data, which are based on forum activity: 1) quantitative information that uses statistical indicators (number of received messages in the threads started by a student and the number of received answers in messages sent by a student), 2) qualitative information that uses the average score of opinions received by the rest of students (rating), and 3) social network information (SNA) and hyperlink analysis [10, 11] that uses the ratio of students' in-links (when a student receives a response from another student). Using the reputation indicator as a reference to form collaborative groups in courses, an e-learning platform that keeps track of the collaboration process and the students' behaviours in terms of the collaborative indicators, could group the most prominent students with those less prominent with the intention of fostering engagement and improving the students' performance. In this way, the collaboration process is expected to be improved [12, 13], and thus, the statistical indicators that reflect student's collaborative characteristics (initiative, activity, regularity).

The work carried out in this research also aims to prove the transferability and domain-independence of the proposal. For this, the CLF approach will be deployed in another e-learning platform (Moodle) showing the transferable characteristic of the collaborative indicators, and also their domain-independence when free-content interaction variables are computed in the same way using the specific interaction data gathered in each environment.

The paper is structured as follows. First, a way to compute the reputation indicator from statistical indicators, rating of students, and social network information is presented. Next, the focus is put on describing how the CLF runs on Moodle Finally, ongoing works are outlined.

2 Reputation basis

As [3] suggested, a reputation indicator should provide information on target student collaboration. Although previous researches [3, 4, 5] took into consideration the reputation indicator from a statistical point of view (*N_r_thrd* as the number of replies to threads started by a student, and *N_r_msg* as the number of replies to messages sent by a student), *N_r_thrd* could be further investigated as one of the most significant indicators to assess student collaboration [3]. For this reason, and being aware of the importance of the reputation in collaboration processes [14], it is of interest to consider a richer definition of this indicator. Additionally, taking into account the results obtained in [9], this research proposes to explore the extension of previous reputation indicator in terms of three different types of analytic data. Grouping students according to this extended reputation indicator could improve the collaboration process, which is expected to improve the computation of the statistical indicators on which initiative, activity and regularity indicators are based. Following a similar approach as [15], which took into consideration several sources of information to define the reputation in terms of a social and scientific scores, the proposed reputation indicator has been composed of three different sources of information: 1) statistical indicators (SI) as quantitative information, 2) rating information (RI) as qualitative information, and 3) information provided by SNA (SNI). Following a similar methodology [3, 5], each of these sources can be normalized between 0 and 1 [9], and computed using a metric to assign a reputation value (Rep) to each student. Different weights (a, b, c) can be used when combining the three sources in the case of correcting some deviations or subjective connotations. A machine learning method, such as linear regression, could learn these weights and automatically compute their relevance:

$$\mathrm{Rep} = \frac{\mathrm{aSI} + \mathrm{bRI} + \mathrm{cSNI}}{\mathrm{a} + \mathrm{b} + \mathrm{c}} \tag{1}$$

For the experiment carried out (see section 4), initially weights used are $a=b=c=1$, as tentative value to start this first experiment.

Reputation has allowed to group students according to its value, pursuing an improvement of the collaborative indicators, and if the experiment shows the expected importance of the reputation indicator, it could be another relevant source of data for the e-learning systems to suggest tailored recommendations and favoring the engagement. The reputation indicator could reflect popularity connotations, above all when one of its three sources (SNI) is based on students' networks and interactions. But the reputation indicator is composed by two other elements (SI and RI) in order to be able to balance the final score in this respect.

2.1 The statistical indicators as quantitative information

The evaluation of information gathered in previous pilot experiences [4] showed that some indicators might have overlapped the description of others, and it was considered the possibility of setting up a range of three values for labelling each indicator instead of using its absolute label. In particular, this research proposes three values to rank initiative, activity, regularity and reputation, namely: improvable, moderate and notable.

The statistical indicators for activity, initiative, regularity and reputation (based on forum conversations started, forum messages sent and replies to student interactions) are calculated following the results of previous works carried out by aDeNu [5]. In the case of reputation and as anticipated above, in [3] two indicators were proposed: the number of replies to threads started by a student (*N_r_thrd*) with respect to the total replies to threads started (*Total_r_thrd*), and the number of replies to messages sent by a student (*N_r_msg*) with respect to the total replies to messages sent (*Total_r_msg*). This work hypothesised that more replies indicated more interest by fellow students, which is proof of acknowledgement. The statistical indicators (SI) can be calculated as follows:

$$\mathrm{SI} = \frac{\mathrm{N\_r\_thrd} + \mathrm{N\_r\_msg}}{Total\_r\_thrd + Total\_r\_msg} \tag{2}$$

2.2 The rating as qualitative information

The instructor is faced with the difficulty of interpreting and evaluating the quality of the participation reflected through students' contributions, considering that current e-learning systems do not provide explicitly many indicators regarding this qualitative information. A reasonable information source to tackle this issue can be to use a rating system, in which students are able to grade the messages of the rest of students according to different values [9]. Each student can set an evaluation or score for the usefulness of each message: non-relevant, interesting, or totally relevant. Following a similar method for computing reputation from the rating point of view [16], but giving different importance to each type of opinion, it can be calculated the rating information (RI) by taking into account the number of non-relevant opinions (NR), the number of interesting opinions (I), and the number of totally relevant opinions (TR). The relevance of the opinions can be weighted by giving 1 point to *NR*, 2 to *I* and 3 to *RT*. The rating information is calculated as follows:

$$\mathrm{RI} = \frac{\mathrm{NR} + 2\mathrm{I} + 3\mathrm{RT}}{3\mathrm{r}} \tag{3}$$

where *r* is the total number of opinions received by the student.

2.3 SNA as social information

There is a recent line of research on applying social network analysis (SNA) techniques to study the interactions among students in e-learning platforms, for example [17, 18, 19, 20], and it has already been investigated the practicability of SNA in evaluating participation of students [11, 21, 22]. Exploiting SNA techniques it is possible to discover relevant structures in social networks generated from student communications [23]. With visualization of these discovered relevant structures and the automated identification of central and peripheral students, an e-learning system could be provided with better means to assess participation in the online discussions. The practicality of SNA methods in computer supported collaborative learning is demonstrated in [24, 25], using methods for extracting social networks from asynchronous discussion forums, finding appropriate indicators for evaluating participation, and measuring these indicators using social network analysis. A previous work of aDeNu research group [3] suggested the similarity between SNA techniques and the statistical indicators to measure student perceived reputation. As [9] showed, the social network information (SNI) can be calculated as the normalized node in-degree of that student:

$$\text{SNI} = \frac{Z}{p} \tag{4}$$

where Z is the number of in-links and p is the number of students. This research uses Meerkat-ED[1] [26], a specific and practical toolbox for analyzing interactions of students in asynchronous discussion forums of online courses.

3 CLF running on Moodle

The transferable feature of the collaborative indicators emphasized in [3] is demonstrated in this research by deploying the CLF approach on Moodle. Moodle has already been explored as collaborative tool [27, 28], and fits perfectly the purposes of this research. For this, the first step is to see how the CLF functionality can be provided in Moodle. This mapping is compiled in Table 1.

CLF Features	.LRN	MOODLE
Proposing a solution	Survey (for quiz solutions) or file storage area (to upload a solution document) + forum (for discussing the proposed solution)	Q and A forum + assignment + forum in a blog format, to capture students' interactions. Survey for quiz solutions and file storage area are also available.

[1] http://webdocs.cs.ualberta.ca/~rabbanyk/MeerkatED/

CLF Features	.LRN	MOODLE
Management of the CLF stages and timing control	Workflow mechanism	Workflow mechanism
Grouping students	Groups functionality (for manually grouping) and clustering methods provided by Weka data mining suite (for automatic grouping)	Manual groups' functionality, based on reputation. Also an automatic functionality based on the number of groups or number of students per group.
Students' ratings collection	Rating functionality	Rating system based on tailored scales
Reputation estimation	n/a (requires development)	Manual, based on statistical indicators, rating and SNA
Meta-cognitive tools	CLF computed indicators with Weka shown in a customised portlet	Blocks showing information for students. Collaborative information has to be provided manually to be displayed.

Table 1. Comparison between the CLF deployment in dotLRN and Moodle

4 Ongoing work

Previous experiments were carried out by the aDeNu group in 2009, 2012 and 2013, testing the CLF and the collaborative indicators [4]. Now, we are testing the reputation indicator to group participants, looking for an improvement of the collaborative indicators (initiative, activity, regularity).

The research is focused on several aspects, altogether aimed to compute the students' reputation in a domain independent collaborative task called CLF. It is grounded in 1) gathering statistical indicators based on forums interactions, 2) extracting SNA information from the links created among students and 3) considering qualitative data from students' ratings.

An experiment with 23 users was carried out in April with some workers of Tecnalia Research & Innovation[2] centre. They were asked to solve two riddle placed in forums. Previous researches carried out in Madrid Science Week (2009, 2012, 2013) showed the importance of the engagement component in collaborative experiences to get a representative number of participants. For 3 days, the participants collaborated in each stage of the CLF (individual, collaboration, and agreement stage) to find the solution to the first riddle. Next 3 days, they were asked to solve the second riddle. In order to evaluate the benefit of taking into account the reputation indicator in creating

[2] http://www.tecnalia.com/en/

the groups within the CLF, a 'between- subject' experiment (i.e., participants were randomly assigned either to the control group, where the CLF grouping was not informed by the reputation indicator and the experimental group, where the CLF grouping considered the reputation indicator by separating the students with higher reputation among the groups, so each group had at least a high reputation participant) was carried out.

Currently, the indicators obtained from the students' interactions are being analyzed to identify the benefits of taking the reputation indicator into account when making the groups of students. This data analysis can be used to determine required changes in a collaboration process, such as grouping students according to the reputation indicator so as to distribute the students with higher reputation among the groups. This information could also be used by e-learning systems to make tailored recommendations and favouring the engagement, trying to increase the reputation of students less prominent, and improving the collaboration process.

This research also takes the advantage to explore some additional advanced features provided by Moodle, such as learning analytics or the possibility of incorporating meta-cognitive tools [5], automatically calculating the collaborative indicators and displaying the current value of indicators in each stage of the CLF.

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References

1. Kumar, V. S.: Computer-supported collaborative learning: issues for research. In Eighth Annual Graduate Symposium on Computer Science, University of Saskatchewan (1996)
2. Barkley, E. F., Cross, K. P., Major, C. H.: Collaborative learning techniques: A handbook for college faculty. John Wiley and Sons (2004)
3. Anaya, A. R., Boticario, J. G.: A domain-independent, transferable and timely analysis approach to assess student collaboration. International Journal on Artificial Intelligence Tools, 22(04) (2013)
4. Santos, O. C., Boticario, J. G.: Involving Users to Improve the Collaborative Logical Framework. The Scientific World Journal (2014)
5. Anaya, A., Boticario, J.: Content-free collaborative learning modeling using data mining. User Modeling and User-Adapted Interaction, 21(1), 181–216 (2011)
6. Bayón, A., Santos, O. C., Boticario, J. G.: A component to carry out the Logical Framework Approach in dotLRN. In dotLRN. 7th OpenACS/. LRN conference (2008)
7. Santos, O. C., Rodríguez, A., Gaudioso, E., Boticario, J. G. (2003, July). Helping the tutor to manage a collaborative task in a web-based learning environment. In AIED2003 Supplementary Proceedings (Vol. 4, pp. 153-162).

8. Russo, T. C., Koesten, J.: Prestige, centrality, and learning: A social network analysis of an online class. Communication Education, 54(3), 254-261 (2005)
9. Romero, C., López, M.-I., Luna, J.-M., Ventura, S.: Predicting students' final performance from participation in on-line discussion forums. Computers & Education, 68, 458–472 (2013)
10. Memon, N., Xu, J. J., Hicks, D. L., Chen, H.: Data Mining for Social Network Data. Information Systems Journal, 12, 1–7 (2010)
11. Daradoumis, T., Martínez-Monés, A., Xhafa, F.: A layered framework for evaluating online collaborative learning interactions. International Journal of Human-Computer Studies, 64(7), 622-635 (2006)
12. Alfonseca, E., Carro, R. M., Martín, E., Ortigosa, A., Paredes, P.: The impact of learning styles on student grouping for collaborative learning: a case study. User Modeling and User-Adapted Interaction, 16(3-4), 377-401 (2006)
13. Paredes, P., Rodriguez, P.: The application of learning styles in both individual and collaborative learning. In Advanced Learning Technologies. Sixth International Conference on, pp. 1141-1142. IEEE (2006)
14. Sterbini, A., Temperini, M.: Social exchange and collaboration in a reputation-based educational system. In Information Technology Based Higher Education and Training (ITHET), 9th International Conference on (pp. 201-207). IEEE (2010)
15. Clow, D., Makriyannis, E.: iSpot analysed: participatory learning and reputation. In Proceedings of the 1st International Conference on Learning Analytics and Knowledge (pp. 34-43). ACM (2011, February)
16. Tavakolifard, M., Almeroth, K. C.: Social computing: an intersection of recommender systems, trust/reputation systems, and social networks. Network, IEEE, 26(4), 53-58 (2012)
17. Durugbo, C., Hutabarat, W., Tiwari, A., Alcock, J. R.: Modelling collaboration using complex networks. Information Sciences, 181(15), 3143–3161 (2011)
18. Laat, M., Lally, V., Lipponen, L., Simons, R.-J.: Investigating patterns of interaction in networked learning and computer-supported collaborative learning: A role for Social Network Analysis. International Journal of Computer-Supported Collaborative Learning, 2(1), 87–103 (2007)
19. Martinez, A., Dimitriadis, Y., Tardajos, J., Velloso, O., Villacorta, M.: Integration of SNA in a mixed evaluation approach for the study of participatory aspects of collaboration. In W5 Moving From Analysis to Design: Social Networks in the CSCW Context), ECSCW'03 Workshop on Social Networks, pp. 14-18. (2003)
20. Yusof, N., Rahman, A. A.: Students' interactions in online asynchronous discussion forum: A Social Network Analysis. In Education Technology and Computer. ICETC'09. International Conference on (pp. 25-29). IEEE (2009)
21. Rabbany, R., Takaffoli, M., Za, O. R.: Social Network Analysis and Mining to Support the Assessment of On-line Student Participation. ACM SIGKDD Explorations Newsletter, 13(2), pp. 20-29 (2012)
22. Cuero, F. V., Collazos, C. A., Zea, N. P., Romo, J. O. Análisis y monitoreo de la interacción en entornos colaborativos, mediante el uso de SNA.
23. Rabbany, R., Takaffoli, M., Za, O. R.: Analyzing Participation of Students in Online Courses Using Social Network Analysis Techniques. In Proceedings of educational data mining (2009)
24. Nurmela, K., Lehtinen, E., Palonen, T.: Evaluating CSCL log files by social network analysis. In Proceedings of the 1999 conference on Computer support for collaborative learning (p. 54). International Society of the Learning Sciences (1999)

25. Cho, H., Gay, G., Davidson, B., Ingraffea, A.: Social networks, communication styles, and learning performance in a CSCL community. Computers and Education, 49(2), 309-329 (2007)
26. Chen, J., Fagnan, J., Goebel, R., Rabbany, R., Sangi, F., Takaffoli, M., Zaiane, O.: Meerkat: Community Mining with Dynamic Social Networks. IEEE International Conference on Data Mining Workshops, (1), 1377–1380 (2010)
27. Dougiamas, M., Taylor, P.: Moodle: Using learning communities to create an open source course management system. In World conference on educational multimedia, hypermedia and telecommunications, vol. 2003, No. 1, pp. 171-178 (2003)
28. Cavus, N., Uzunboylu, H., Ibrahim, D.: Student opinion towards using an open source learning management system together with a collaborative tool. Cypriot Journal of Educational Sciences, 3(2), 120-129 (2009)