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A visual recommender tool in a collaborative learning experience

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ABSTRACT

Collaborative learning incorporates a social component in distance education to minimize the disadvantages of studying in solitude. Frequent analysis of student interactions is required for assessing collaboration. Collaboration analytics arose as a discipline to study student interactions and to promote active participation in e-learning environments. Unfortunately, researchers have been more focused on finding methods to solve collaboration problems than on explaining the results to tutors and students. Yet if students do not understand the results of collaboration analysis methods, they will rarely follow their advice. In this paper we propose a tool that analyzes student interactions and visually explains the collaboration circumstances to provoke the self-reflection and promote the sensemaking about collaboration. The tool presents a visual explanatory decision tree that graphically highlights student collaboration circumstances and helps to understand the reasoning followed by the tool when prescribing a recommendation. An assessment of the tool has demonstrated: (1) the students collaboration circumstances showed by the tool are easy to understand and (2) the students could realize the possible actions to improve the collaboration process.

1. Introduction

In recent years, collaborative learning has become an appropriate pedagogical strategy for minimizing the disadvantages of distance education because the social component has been incorporated into e-learning environments (Barkley, Cross, & Major, 2004). However, frequent and regular analysis of student actions is necessary so that tutors know that collaborative learning is taking place (Johnson & Johnson, 2004).

Moreover, the lack of standards and comparative studies in the collaboration analytics field is a drawback (Strijbos, 2011). Some approaches have focused on student monitoring and participant assessments to analyze collaboration (Martinez-Maldonado, Dimitriadis, Martinez-Monés, Kay, & Yacef, 2013). Other approaches have focused on data mining (DM) techniques to carry out collaboration analytics (Gaudioso, Montero, Talavera, & del Olmo, 2009; Romero, Espejo, Zafra, Romero, & Ventura, 2011). Some approaches have also proposed comparing a student's collaboration model with an a priori model to infer the student's state (Chronopoulos & Hatzilygeroudis, 2012).

Despite the increasing interest in collaboration analytics in the e-learning community (Wang, Jin, & Liu, 2010), there is no common strategy to improve the collaborative process, as we mentioned above. We warn that, in addition to the corrective actions that the different researchers have proposed to improve collaboration, student self-reflection and self-regulation can only be enhanced if the results are clearly shown to the students, according to the open learner model strategy (Bull & Kay, 2010). Therefore, the open learner model strategy requires that the information shown is self-explanatory. So, the development of explanation facilities is crucial for the acceptance of expert systems (Lacave, Luque, & Díez, 2007). Humans do not usually accept the advice provided by a computer if they cannot understand how the system reasoned to reach the conclusions. Thus, the system must communicate the knowledge in a way that is easily understandable to a person without any expertise in the inference methods utilized.

The motivation of our research is to develop a tool that offers recommendations to students to improve their collaboration process. The tool has the following functionalities: (1) tracking and analysis of the students interactions in a collaborative learning experience; (2) warnings about possible problematic collaboration circumstances of the students and (3) guiding the process to create a recommendation and make it understandable. We would like to point out this issue. The objective of the tool is not to offer a recommendation such as a learning object or an exercise, which the students could study or make; that is the typical objective of recommender systems in other learning experiences (Drachsler, Verbert, Santos, & Manouselis, 2015). The objective of the tool proposed in this paper is to show

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the analysis to promote the sensemaking of the students and teachers. According to Knight, Buckingham Shum, and Littleton (2013) exploring the sensemaking process offers opportunity to understand how learners, and educators, identify the value of learning through data, and the best ways to support this. Once the tutor understands the students collaboration circumstances, which the tool shows, s/he could make a personal recommendation to one student. Once the students understand their collaboration circumstances, they could follow the recommendation because they understand the reasons of the recommendation.

In a previous research (Anaya, Luque, & García-Saiz, 2013) we used the visual features of a decision tree (Quinlan, 1986) to explain the pedagogical implications of the proposed analysis method. In this paper we propose a tool that performs collaboration analytics and visually explains the results to students to enhance their self-reflection about collaboration and promote the students and tutor sensemaking. The tool guides tutors so that they can create a personal recommendation to a student who could need a recommendation and explains the reason for the recommendation showing the student's collaboration circumstances. The tool presents to the student a *visual explanatory decision tree* (VEDT), which is a graphic representation highlighting the student's personal circumstances in the collaboration process. We hypothesize that visually showing metainformation about the collaboration process eases the understanding of the problem and encourages students to think about how they are collaborating, thus provoking self-reflection (Klerkx, Verbert, & Duval, 2014) and sensemaking (Knight et al., 2013). The tool shows the collaboration circumstances as a route in a hierarchical logical tree. The nodes, which represent collaboration indicators order in the hierarchical logical tree, help to focus student attention on the indicators that are more important for prescribing the recommendation (Klerkx et al., 2014). Each route is labeled to advise the tutor in the process of making, or not, the recommendation. The tool does not require human intervention so tutor and student workloads are not increased during the collaboration learning experience.

The proposed tool consists of: (1) a data mining module, which calculates student collaboration indicators using DM techniques (Anaya & Boticario, 2011a); (2) a recommender module, which can identify students who need a recommendation according to the student collaboration indicators and an influence diagram (Anaya et al., 2013); (3) a visual recommendation module, which warns the tutor about the students who could need a recommendation, explains to the student the reasons of the warning and shows the student's collaboration circumstances visually and (4) an administration module, which helps the teacher or the tutor to configure the automatic operation of the tool and adapt it to the specific learning context. The tool has been assessed by a set of students. The assessment has informed that the students are capable to understand the collaboration circumstances showed by the tool and they could realize the possible corrective actions to improve the collaboration process.

The rest of the paper is organized as follows. The next section describes previous research that has focused on collaboration analytics. Section 3 presents the theoretical background of our research. Following, we describe the objective and structure of the tool we have developed. Section 5 illustrates how to use the tool effectively in a collaborative learning experience. An assessment of the tool is described and analyzed in Section 6. We finish this paper with the conclusions and future works.

2. Related works on collaboration analytics

Several researchers have recently studied computer support collaborative learning (CSCL). In this paper we briefly review those works on CSCL that have proposed methods for collaboration analytics. As mentioned above, frequent analysis of student actions is necessary to understand the collaboration process (Johnson & Johnson, 2004) and the usefulness of these analyses (Wang et al., 2010). For this reason, we would like to concentrate on other researchers' collaboration analytics work in the field of collaborative learning improvements and collaboration modeling.

2.1. Collaborative learning improvements

According to Soller, Martinez, Jermann, and Muehlenbrock (2005), the possible types of tools in a collaborative environment are: monitoring, metacognitive and guiding ones. We take into account the conditions of Johnson and Johnson (2004): during collaborative learning, systems should perform frequent and regular processing of collaborative teamwork. Thus, metacognitive and guiding tools are the most appropriate types of tools to improve collaboration learning as they perform inferences on student collaboration.

Metacognitive tools generally offer metainformation that students or tutors can use to understand the actual student learning process. Next, students and tutors can realize the corrective activities to improve the learning process. This fact is called self-regulated learning. Self-regulated learning is guided by metacognition (thinking about one's thinking), strategic action (planning, monitoring, and evaluating personal progress against a standard), and motivation to learn (Boekaerts & Corno, 2005). Steffens (2001) stated the advantage of also using self-regulation to improve social skills and hence the collaborative learning process.

Some research focused on analyzing collaboration to establish assessments or indicators to infer information on student collaboration (Perera, Kay, Yacef, & Koprinska, 2007; Redondo, Bravo, Bravo, & Ortega, 2003; Talavera & Gaudioso, 2004). Others researchers focused on displaying tracking or monitoring assessments (Bratitsis & Dimitracopoulou, 2006; Daradoumis, Martínez-Mónes, & Xhafa, 2006; Martínez et al., 2006). Their hypothesis was that the monitoring assessments showed could cause student self-regulation and thus improve collaborative processes. Collaboration analysis is advisable due to the self-regulation features of the information that is displayed to students. Yet this information on collaboration should enhance student self-regulation (Bull & Kay, 2010) and be self-explanatory (Lacave et al., 2007).

The third possible type of tool is the guiding one (Soller et al., 2005), also called the recommender tool. Casamayor, Amandi, and Campo (2009) proposed assistance for tutors in collaborative e-learning environments. After student participation had been assessed, the rule-based assistant warned about conflictive situations to tutors, where tutor intervention might be necessary. Chronopoulos and Hatzilygeroudis (2012) proposed a system that aims to support users by advising them on the collaborative learning process. The system made a representation of the learning behaviors of learners and groups in the collaborative activities using a fuzzy model and quantitative and qualitative data of their performance and participation. An intelligent agent, monitoring the learning behaviors, issued recommendations to the instructors. Both approaches monitored the interactions and used an a priori set of rules to infer warnings and advice.

Although recommender systems are becoming more popular with the aim of supporting learning (Drachsler et al., 2015), few approaches have been applied to the educational context of collaborative learning. (Bieliková et al., 2014) proposed the platform ALEF for adaptive collaborative learning. One of the functionalities of ALEF is to store and maintain information in the corresponding user and domain models, which can provide learners recommendations on how to achieve more successful collaboration.

2.2. How to model collaboration

Nowadays, in the e-learning and distance education field, learning analytics and collaboration analytics present important advantages to