Conversational Analysis to Recommend Collaborative Learning in Distance Education

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Abstract: Conversational agents can recommend interactions among students in a Virtual Learning Environment (VLE) for the purpose of supporting collaborative learning, an important approach to improve online education. This paper describes the current position of a research that addresses the implementation of Conversational Analysis (CA) in order to make recommendations through chatbots for promoting collaborative learning among students in a VLE. Based on an experiment, the authors propose a CA strategy to determine the level of collaboration among students, point out possibilities for chatbot's intervention in favor of collaborative learning, and present the results obtained in the current stage of the research.

1 INTRODUCTION

Conversational Analysis (CA) offers a way to analyze the understanding produced through interaction, focusing on the methods by which interactants build sense collaboratively, with the aim of producing a report on how understanding was achieved in the conversation (Koschmann, 2013). A CA methodological approach can assess not only the content, but also the structure, nature of roles, and relationships within students' conversations (Abraham et al., 2016).

The characterization of the online conversation provided by CA can be used in Virtual Learning Environments (VLEs) in order to better identify where social interaction occurs and how it takes place, indicating possibilities for collaboration. It can also help indicate where no collaboration has taken place, but possibilities exist for interactions and to promote collaborative learning, in which students do not depend only on direct interaction with the content and teachers since the possibilities are expanded through the student-student connection. Thus, they learn through their doubts and interests, teaching each other. At the same time, they can visualize how others are learning as well as their difficulties, which demands a computational support oriented to productive interaction in a motivating way (Stahl et al., 2005).

Chatbot as a pedagogical tool offers opportunities to support learning in adaptive and personalized environments (Zawacki-Richter et al., 2019). For example, a chatbot integrated into a VLE can provide predefined feedback during the chat in order to intervene and encourage students' engagement in the conversation, and keep focus on one aspect of the task at hand (Tawfik et al., 2020). Therefore, chatbots can be used to instigate debate among students in a VLE and, in case there is interaction or the absence of it, indicate to the teacher where the collaboration is occurring or could occur. In addition, chatbots can suggest actions to stimulate collaborative learning.

Considering this potential for the application of Artificial Intelligence in Education (AIEd), establishing a method to measure collaboration among students is relevant. In this paper this authors discuss a methodology to measure collaboration levels based on what students write in discussion

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forums, so as to make recommendations to students, teachers, and tutors in order to promote collaborative learning in VLEs.

2 RESEARCH AIMS

The main objective of the research is the implementation of a chatbot adopting CA to make recommendations in order to promote collaborative learning in a VLE. The specific objectives are: (1) to analyze aspects of students' interactions that may indicate the collaboration among them in the discussion forums appointed by the teacher as those which are to be monitored; (2) to model knowledge on the level of collaboration among students in the monitored forums; (3) to model the dialogue base in an available chatbot architecture, that can be integrated into a VLE, to structure the conversations with students, teachers, and tutors; and (4) to make recommendations to the participants, focusing on questions that encourage feedback and on topics under discussion, in order to promote the collaboration among students in the monitored discussion forums.

The research hypothesis is that adopting CA with a chatbot makes it possible to make recommendations to students, teachers, and tutors, in order to promote collaborative learning in distance education. The following research questions are associated with this hypothesis: (1) how can one characterize students' interactions through a CA in monitored discussion forums?; (2) what knowledge can be modeled in regards to the level of collaboration among students in monitored discussion forums?; (3) in which architecture that can be integrated into a VLE is it possible to model the chatbot dialogue with students, teachers, and tutors?; and (4) what recommendations should the chatbot make to students, teachers, and tutors, focusing on questions that encourage feedback and on topics under discussion, to promote the collaboration among students in monitored discussion forums?

Moodle[1], an acronym for Modular Object-Oriented Dynamic Learning Environment, is a free software VLE and was chosen as the ET development platform, as it is the most prevalent VLE in higher-education institutions in the Portuguese language context. In this environment, a teacher will define which forums will be monitored. Moreover, the ET processing will be done only once for each post made in a monitored discussion forum.

[1] Moodle website: https://moodle.org/?lang=en.

3 LITERATURE REVIEW

The literature review were carried out both by focusing on conceptual aspects and methodological emphasis. The first part relates to chatbots, collaborative learning, and CA. The results indicated that CA to identify collaboration in VLE and possibilities of chatbot's intervention in favor of collaborative learning is a promising research area for AIEd.

CA offers a way to analyze the understanding produced through interaction, focusing on the methods by which interactants build sense collaboratively. It can also provide insight on how understanding was achieved in the conversation (Koschmann, 2013). CA focuses on the sequential nature of thinking, which is lost in most statistical coding analyses, where individual statements are encoded and then accounted for, without regard to their sequential response order (Stahl, 2012). The adoption of CA is relevant when considering the characteristics of online conversations, whose grammar is comparatively informal and unstructured, with users involved in a tone of conversation, compared to other texts (Uthus & Aha, 2013).

From the analysis of conversation logs, it is possible to adopt a methodology to detect and classify student interaction behavior (Procter et al., 2018). In order to assess collaboration among students, it is necessary to use interaction analysis techniques that identify some of the processes used by groups to create meaning and build knowledge, providing an insight into collaboration according to the sequential flow of students' statements. As students are solving problems together, they necessarily express their thoughts to each other and this data is available for analysis in VLE logs. Moreover, the flow of proposals, responses, questions, agreements, etc. is available for analysis as an extended cognitive process (Stahl, 2012). In order to analyze this data it is necessary to adopt preprocessing practices that avoid overly optimistic results in the analysis of discussion forums (Farrow et al., 2019).

Some aspects related to the assessment of collaboration among students deserve to be highlighted in the context of this research. In the literature on classroom discourse, the adjacent pair becomes a 'utterance-triad', question-answer-comment, which is commonly described as the sequence IRE (Inquiry, Response, Evaluation), the latter referring to the sufficiency of that answer. This indicates that the basic and minimum form of a sequence is two turns of conversation and that the sequences composed of more turns are expansions, which can produce an assessment of conversation, positive or not, in the third round (Koschmann, 2013). To identify questioning, Lu et al. (2011) propose that this is a type of statement that seeks factual information, including words such as "what", "which", "where" and "when", or one that seeks explanation, including words such as "why" and "how". To identify questions, the Linguistic Inquiry and Word Count (LIWC) software package, which is based on empirical research, can be used to extract word counts indicative of different psychological processes, such as affective, cognitive, social and perceptual (Farrow et al., 2019). Its core is based on a lexical resource, called the LIWC dictionary, which is also available in Portuguese (Cavalcanti et al., 2020).

The quality of engagement in educational tasks is measured by the number of responses to posts, and not by the number of posts initiated by an individual student, that is, responses demonstrate engagement (Lyndall & Elspeth, 2015). The number of debating students also influences the quality of their interactions, ideally being organized in small groups, ranging from 3 to 6 participants, which positively impacts the value of the discussions (Saqr et al., 2019). Social Network Analysis (SNA) makes it possible to record the number of interactions among students as an indicator of quality in collaboration. The use of SNA has played a prominent role in the analysis of learning in order to indicate collaborative learning (Dascalu et al., 2018). It is also important to note that the benefit of measuring the quality of collaboration for individual students is the recognition of their proactive and effective collaboration (Lyndall & Elspeth, 2015).

Regarding topic detection, the repetition of keywords in statements by different students is an indicator of which topics are under discussion (Allaymoun & Trausan-Matu, 2015). To this end, topic modeling, a text mining tool frequently used to discovery hidden semantic structures in a corpus, can be adopted to identify keywords in student statements. Based on this identification, Epistemic Network Analysis (ENA) combined with SNA can detect information about the student performance in the perspective of identifying a set of cognitive and social dimensions, which is marked by interaction with the appropriate people on the appropriate content (Farrow et al., 2019).

Some collaborative learning factors relevant to chatbot performance are characterized regarding the effectiveness of immediate feedback, more appropriate in verbal learning tasks, and delayed feedback, advantageous in learning concepts because it allows more time for students' metacognition; being careful not to interrupt or disturb when there are interactions among students during their learning activities; and the benefit more focused on interactions among students than on their learning performance (Hayashi, 2019).

Hayashi (2019) implemented the following three-steps chatbot structure: (1) two chatbots were designed to facilitate requests based on types of functions: the *communication consultant* to answer about the efficiency of communication and the *tutor of explanations* to generate answers on how to think about a topic that triggers metacognition; (2) the system detected keywords in an inserted sentence and classifies them by type; (3) the system generates responses based on detected keywords and number of turns taken in conversation. Each chatbot, therefore, responded to students when it detected any of the keywords, whether they are related to important phrases or communication problems (Hayashi, 2019).

Classification processes have been implemented through machine learning algorithms, which is a sub-field of AI capable of recognizing patterns, making predictions and applying newly discovered patterns in situations that were not initially included or covered. Zawacki-Richter et al. (2019) identified, in a review of 58 studies in this area, that all of them applied machine learning methods to recognize and classify patterns and model student profiles. To evaluate the accuracy of classifiers, the authors used statistical measures that demonstrated their high ability to predict the performance in a student group from participating in online discussion.

With regard to recommendation systems, Chatbots can play an effective role in distance education, having been identified as an ET that may contribute to the acceleration of the learning process, facilitate access to educational contents and enrich the learning environment by supporting students and teachers (Liu et al., 2019). It is also relevant to highlight that in knowledge-based recommendation systems, recommendations are suggested based on the specified requirements, and not on the learner's interaction history (Aggarwal, 2016).

Chatbot intervention strategies can be defined based on the Academically Productive Talk (APT) structure, designed to encourage discussion in an educational context from social interaction to the construction of mental processes, with an emphasis on valuable interaction (Tegos et al., 2020). APT proposes tools to be adopted by the teacher in order to encourage discussion in the classroom in which students expose their reasoning, listen deeply and critically to the contributions of others, and thus interact collaboratively (Michaels & O'Connor, 2015). It is also important to note that when students post their participation in forums and their partners receive invitations to comment on them, this results in a smaller number of fragmented topics, but with a greater number of participations per topic (Oliveira et al., 2011).

In conclusion, the adoption of a ET in order to carry out the recommendation of collaborative learning in distance education starts with the CA to identify the possibility of collaboration. A chatbot, whose architecture includes CA and machine learning, in addition to providing technical information and educational content, can promote collaborative learning in VLE through interventions that contribute to the construction of students' knowledge. Thus, this application of AIEd can act as a recommendation system when it is implemented as a resource that makes feasible the debate among students, providing knowledge about the domain, supporting the affective and social experience, and contributing to the proper usability of VLE, which can occur even through mobile devices.

4 RESEARCH METHOD

The methodological approach takes place in three stages: conversational analysis; assessment to determine collaboration level; and implementation of the chatbot to make recommendations to students, teachers, and tutors in the monitored discussion forums. Accordingly, the development of the ET has been taking place in the stages shown in Figure 1.

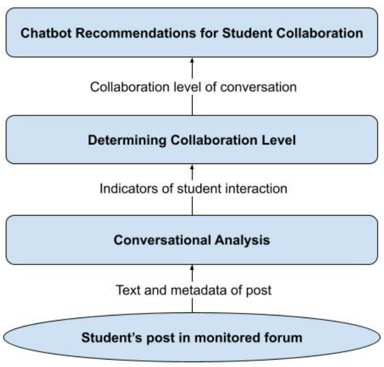

Figure 1: Three stages of the methodological approach.

In the next subsections, the authors present the results obtained in these stages, not only describing the conceptual model, but also showing some relevant aspects for its implementation.

4.1 Conversational Analysis

The adopted CA seeks to identify interactions among students from the text and metadata of each post obtained in the monitored discussion forums, whose implementation is described in the steps below. The CA layer applied in the context of research's architectural flow is shown in Figure 2.

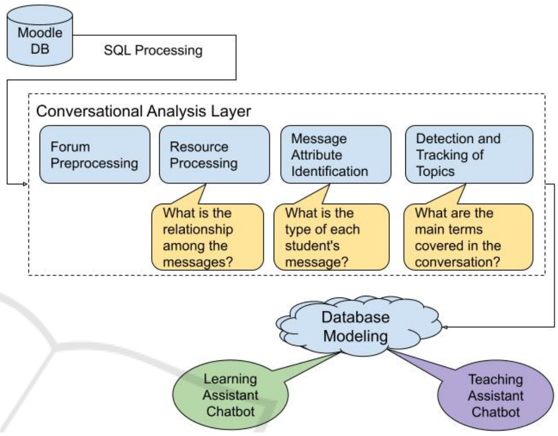

Figure 2: Architectural flow for the research.

For each message posted by a participant, the CA steps must be performed, whose resulting information must persist in a relational Database Management System (DBMS). The set of data was obtained via SQL, from read-only access to the VLE database of a vocational education school, from which two online courses were offered. The posts obtained are exclusively from the discussion forums, without participant identification, as only messages and forums are assessed in order to generate recommendations. From the available 20,976 messages, 15,703 were posted by students.

Preprocessing is the CA step in which specific techniques of Natural Language Processing (NLP) are applied, without which the quality of the results will be compromised. First, it is important to clean up the obtained data, such as deleting HTML tags and punctuation marks used on web addresses, and formatting numeric fields. Subsequently, NLP techniques take place, as lemmatization, mapping inflected forms of word to a common root; stemming, removing the ending of words to find their base form; and phonetic mapping that addresses features rarely seen in formal texts, which can be applied to words and numbers to define the meaning of words with unusual spellings. In this research some NLP techniques are adopted in step Detection and Tracking of Topics, described below.

Resource processing is the CA step in which the characterization of social dynamics occurs through SNA, carried out by the Cytoscape[2] open source software platform, in order to identify interactions among students in each forum. To this end, SNA provides insights into dimensions such as cohesion, centralization, and prominence. Centrality measures seek to identify the extent to which the network depends on a certain number of interactants. Thus, the Weighted Degree Centrality (WDC) is responsible for the weight of the edges that a node has in the network, being the sum of the edges weights connected to the node. SNA also provides in- and out-degree (OD) metrics, which are scores that correspond to the in-and-out edges of a given node calculated from the sociogram (Pereira, 2018).

In this research, each node corresponds to a message in the forum. Therefore, WDC characterizes the number of student responses, as the weight of their messages is one and that of the other interactors is zero. When OD is zero, then there was no response for the given message, but if it is greater than zero, then it is because there were that specific number of responses for the message.

Identification of the message attribute is the CA step that allows identifying characteristics of the statements, specifically the questions, through NLP, using LIWC[3]. Based on the total words count (WC), LIWC informs percentages such as Interrog and QMark, related to question words and question mark respectively.

This research is developed in a Portuguese language context, and, considering the results obtained from the LIWC Portuguese dictionary, only the presence of the question mark was effective to identify the questions, that is, it was not possible to identify any question message without the QMark percentage was grater than zero.

Topic detection and tracking is the CA step in which key terms discussed in each forum are identified through topic modeling, made with the open source software Tomotopy[4], which is a topic modeling toolkit used as a Python module. Tomotopy implements one of the earliest and most widely utilized topic modeling methods called Latent Dirichlet Allocation (LDA), which defines hidden topics to capture latent semantics in text documents. With LDA, each document is represented by a probability distribution (dirichlet) over topics, which are hidden (latent), with each topic being described by a distribution over self-explanatory words (allocation). Thus, the LDA algorithm infers unobserved topics, which do not contain labels that would describe them, by assigning words to topics placing terms that often appear together in a document, it means, topics are a collection of the proportions of their contents, where word order is irrelevant (Schulte, 2021). This machine learning tool is commonly used in a few areas of focus, including document classification and recommendation of new articles that are likely to be of interest to a specific reader.

Another method implemented by Tomotopy is called the Correlated Topic Model (CTM), which is similar to LDA, but it can be used to describe the latent composition of associated topics in pairs within each document in a corpus. For LDA and CTM, the variable K defines the number of topics to be generated. The parameters φ and θ are seen as mixture weights and characterize the probability of importance of words for a given topic and the proportion of topics within a specific document, respectively. Thus, the topic modeling algorithm calculates $\varphi^{(z)}$ to represent the multinomial distribution of terms over a given topic z, and works out $\theta^{(d)}$ to represent the multinomial distribution of topics about a given document d (Vayansky & Kumar, 2020).

Within this paper, a “word” or “term” represents the fundamental unit of data, a “document” represents a message posted by one participant, and a “corpus” represents a group of documents encompassing the entire discussion forum. A “vocabulary” is the collection of all distinct words within a corpus, and a “topic” is a probability distribution spanning a given vocabulary. In this context, the LDA and CTM are being applied in order to: (1) identify the topic that has the largest number of words in the corpus associated with it; (2) classify each message according to the percentage of words associated with the identified topic; and (3) point out the most relevant terms within the corpus aiming to show some messages to which a student can post their contribution.

4.2 Determining Collaboration Level

In the present research, collaborative learning must occur from the interaction among students in a discussion forum, in which they jointly address one

[2] Cytoscape website: https://cytoscape.org/.

[3] LIWC website: http://liwc.wpengine.com/.

[4] Tomotopy: https://bab2min.github.io/tomotopy.

or more topics, through replies to previous messages, characterizing a conversation. If there is a question in any topic under discussion, it is desirable to have a colleague's response to this question, which characterizes an answer. In order to infer the level of collaboration among students in monitored discussion forums, it is necessary to:

- Create the initial database from the CA with real data, collecting information from Moodle forums for the assessment of collaboration among students, including indicators to be evaluated by teachers;
- Assessment by teachers as to which combinations of the mentioned indicators are better for classifying collaboration among students, generating a new database that will allow to learn, in an automated and intelligent way, how to classify this type of collaboration;
- Apply machine learning and other techniques to the database resulting from the evaluation by teachers in order to carry out the evaluation of collaboration among students.

The assessment of collaboration based on interaction is made through CA by the combination of variables that indicate where it occurred, including insights from the aforementioned Literature Review, to compose the following indicators:

- Identification of Students' Interactions (ISI), performed by Resource Processing, to characterize the amount of student responses to each message, which is calculate by the formula 1 below;
- Questioning Characterization (QC), carried out by the Message Attribute Identification, to point out each student message that contains a question, which is worked out by the formula 2;
- Main Topic Approached (MTA), which occurs from the Detection and Tracking of Topics, which aims to infer the topic with the highest word distribution in each discussion forum, where MTA is the value of the proportion of this topic in each message, as shown in the formula 3;
- Students Collaboration Level (SCL) of each message is formed by the average of the previous indicators, as shown in the formula 4.

$$\text{ISI} = \text{WDC} / \text{OD for OD greater than zero} \quad (1)$$

$$\text{QC} = \text{QMark} / 100 \quad (2)$$

$$\text{MTA} = \theta^{(d)} \text{ of the highest } \varphi \quad (3)$$

$$\text{SCL} = \text{ISI} + \text{QC} + \text{MTA} / 3 \quad (4)$$

In Table 1 are presented results of the CA layer in a Portuguese Language forum that took place at the beginning of the second semester of an online course, containing 47 messages, 31 of which were posted by students, 2 by the teacher, and 14 are posted by a tutor.

Table 1: An example of SCL calculation.

QC	OD	WDC	ISI	MTA	SCL
0.0101	23	23	1.0	0.08369590	NA
0.0303	2	1	0.5	0.08897769	0.20642590
0.0000	2	1	0.5	0.23834153	0.24611384
0.1250	1	0	0.0	0.05000000	0.05833333

For the first message, in Table 1, SCL is equal to "NA" because the calculation is not applicable for a teacher post, which in this case was responded to directly by 23 messages (OD) all posted by students (WDC). The message corresponding to the second line got 2 responses, 1 from a student, and therefore its ISI is equal to 0.5. Its MTA corresponds to the proportion of the topic with the highest word distribution among the 20 topics generated by CTM. There is no question mark (QC) in the student message on the third line, but it still got a return from a colleague, probably because it covered the topic more than in the others posts, as its MTA indicates. In the message on the last line there is a higher QC, which can be considered a more specific question by the student, who addresses the main topic (MTA) a little, but has not yet received feedback from a colleague (WDC), but only from the teacher and so OD is equal to 1.

Thus, the three indicators of collaboration will be combined, based on real data, considering assessment of teachers. The database resulting from their assessment will be constantly updated in order to adjust the classification of collaboration among students. It is important to highlight that the intelligent processing of the mentioned indicators will occur in order to classify the conversations among students regarding their SCL. These inferences will allow chatbot recommendations to be generated for students, teachers, and tutors in order to promote collaboration among students.

4.3 Chatbot Recommendations for Student Collaboration

Chatbots to be implemented, using an existing tool, will then be able to make recommendations for each situation from the context identified in the previous stages. Based on the APT structure, recommendations to students aim:

- To suggest options for motivating student participation by prioritizing their messages with (1) questions that are still unanswered, (2) main terms under discussion, and (3) student responses to a colleague;
- To provide information about each monitored forum the student has participated in, focusing on (1) number of student messages with percentages of questions and returns, (2) indication of message collaboration level, and (3) main terms discussed.

Recommendations to teachers and tutors aim:

- To suggest options for motivating student participation, prioritizing messages (1) that contain questions which are still unanswered; (2) those messages that least cover the main terms under discussion; and (3) those messages that do not yet have responses from colleagues;
- To provide information about monitored forums, focusing on (1) number of messages from students with percentages of questions and returns, (2) amount of recommendations made, (3) percentage of recommendations that generated participation, (4) main terms discussed, and (5) classification of messages regarding the level of collaboration.

The chatbots will start the dialogue with students or teachers when they access a discussion forum that is being monitored. This agents will also send messages to the participants to specifically inform them about new conversations to participate in. A continuous mode of operation of the system will inform the evolution of the level of collaboration both for students about each forum that they participated in, and for teachers about the conversations in monitored forums.

5 CONCLUSIONS

The development described in this paper represents a new possibility for chatbot performance to promote an effective collaboration. The chatbot must be implemented in an educational context more oriented towards the construction of knowledge, which is different from the one that is traditionally adopted.

Concisely, the research presented in this paper, with the perspective of promoting collaborative learning in monitored discussion forums, has achieved the CA layer necessary to characterize the interactions among students in the discussion forums. In consonance with the research aims described in section 2, the knowledge model to classify the conversations based on the level of collaboration among students is being developed. In the next steps, the dialogue base will be modeled and the chatbots will be implemented aiming to make recommendations with suggestions and information for students, teachers, and tutors in order to promote collaboration among students. Moreover, chatbots will also inform educators about the recommendations that resulted in participation so the constant evaluation of the ET adoption is enabled.

The evaluation of the results will occur through the application of questionnaires to students and teachers who commit themselves to voluntarily using this application of AIEd, so they can assess how much the recommendations made by the chatbots contributed to collaborative learning.

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