Toward Criteria-Based Automatic Group Formation in MOOCs

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Abstract. Effective use of Collaborative Learning in MOOC contexts faces many challenges. One of them regards the possibility to create groups according to a set of criteria, which is not currentlly supported by MOOC platforms. This paper presents our work in progress on this problem. We introduce the design and initial results of an experiment where groups based on homogeneous levels of activity, as creation criteria, are compared with randomly created control groups. The preliminary results provide initial evidence about the feasibility and eventual advantages of using criteria-based group formation in MOOCs.

Keywords: MOOCs, collaboration, CL, teams, group formation.

1 Introduction

The emergence and popularity of MOOCs have fostered many discussions in the educational technology community regarding, among others, their instructional quality and their high dropout rates [2]. Active learning and peer interaction can promote students' engagement [4], and collaboration can enrich learning through the achievement of social and cognitive competences [9]. Therefore, many authors are trying to include Collaborative Learning (CL) in MOOCs identifying important research challenges related to promotion of social interactions that generate knowledge [5].

One of the challenges of including CL in MOOCs, given their massive and variable scale, is the management of groups of students [10]. Moreover, in MOOCs, the notable differences between the students' engagement levels and their learning paces strongly affect the composition and structure of teams. Furthermore, the teachers' orchestration tasks become more complex and the information they need to be aware of the groups' progress is significantly increased, and therefore manual group management becomes infeasible. All these reasons prompted us to gain insight on *how we can support MOOC teachers in the management of groups to perform CL*.

A few MOOC hosting platforms incorporate features for group management (e.g. Canvas Network, NovoEd), but they only allow student's self-selected groups, automatically created random groups or groups created manually by the instructors. Hence, the first research objective we want to accomplish is to provide support in the creation of criteria-based groups so that teachers can select pedagogical or pragmatic criteria such as those they would apply in a non massive context. Furthermore, we want to test the utility for the group formation of the information registered in the platform about the students's activity. This type of dynamic data could reflect relevant features of this context, such as the variable level of students' engagement, the high dropout rate, or the differences between learning paces [10].

To reach this goal, our initial step has been to intervene in a MOOC using a research prototype that creates groups based on data collected by the system about the students' registered activity. Then, the interactions and performance of the criteria-based groups will be compared with those in the control groups (formed using the random group creation feature provided by the platform). Such study may allow us to extract conclusions about the convenience or not of using criteria-based groups in MOOC contexts.

The rest of the paper is organized as follows. Firstly, the research design is presented including the experiment carried out. Finally, some provisional conclusions are presented together with the short term and longer term future work.

2 Research Design

2.1 Context: The TraduEco MOOC

The course topic is an introduction to translation from Spanish to English over economical and financial texts. It was originally conceived as an instructor-led MOOC of seven weeks. We formed a co-design team composed of instructors and researchers, and such team redesigned the course to incorporate CL activities to identify the challenges it faces [7]. Therefore, a compulsory collaborative task was included on weeks four and six. The task consists in extracting terminology from some given texts in teams of six members. Each team has to create a group artifact including 20 economical or financial English terms and their corresponding Spanish translation. The teams should use the group forums for sharing opinions, discussing and reaching agreements in order to select the wanted terms and choose a spokesman who will be in charge of the task submission. Finally, the activity can be considered as having been completed, when each member performs an individual revision of the artifact produced by another team.

The course was deployed in the Canvas Network platform and began on Feb the 6th. The total number of students enrolled at the time of writing this paper was 1025, but only 909 remain still registered.

2.2 Methods

The primary research methodology adopted to conduct our work is based on the Design Science Research Methodology (DSRM) [8]. The study reported in this paper is part of the iterations defined in DSRM, and has as main goal to contribute to evaluate initial ideas of the proposal in order to improve them in the next iterations.

We collected data from questionnaires, interviews and meetings with the MOOC's teachers to codesign the compulsory collaborative activity, which is the basis of the grouping experiment. The Canvas LMS REST API provides us with information for the analysis of the experiment results. We will combine the quantitative data obtained from the platform with a qualitative analysis of: (a) communications between teachers and students in Canvas during the mandatory collaborative activity, and (b) a final student satisfaction survey.

We will analyze this information to find out the differences between the experimental (criteria-based) and the control (random) groups (see section 2.3) regarding: (i) active teams, (ii) active participants per team, (iii) interactions within a team, (iv) task completion rate, (v) student complaints, and (vi) student satisfaction level. This analysis may provide initial evidences about the benefits and drawbacks of using criteria-based teams to perform effective CL in MOOC contexts.

2.3 The experiment

The learning design of the course includes, on the fourth week, a mandatory collaborative activity that has to be performed in groups of six members. Our experiment consists in the automatic creation of teams using homogeneous criteria over the students' activity, and their comparison with a baseline of random teams used as control group.

There were several decisions that conditioned the experiment development. One of the most important was the selection of the criteria to be used for creating the experimental groups. We used dynamic factors (i.e., data from the activity of the students in the platform) to respond to our research question regarding the relevance of these data to reflect some peculiarities of the context (i.e. the variable engagement level). Therefore we choose three variables to cover three aspects regarding the students' engagement level: (i) page views, as a reflection of their activity, (ii) submitted tasks (both mandatory and optional), as a measure of their commitment, and (iii) posted messages on discussion forums, to reveal their active participation [3]. Another major decision was the application of homogeneity over the criteria instead of heterogeneity. The underlying reason was that, taking into account the group size (six members) and MOOC statistics in literature (5-15% of completion rates), heterogeneity over students' activity criteria could be very similar to a random grouping (feature covered in the Canvas platform) and could result in many teams with only one active student.

For the composition of the control group, we chose random grouping because it can be performed automatically in Canvas and guarantees that all students will be included in a group. However, the fact that in our approach the students with an activity profile type of *no-shows* [1] were clustered together could be a big advantage over the random teams, where the *no-shows* students would be spread over the teams. Therefore, we decided to improve the baseline to compare with in order to obtain richer conclusions about the advantages of using a criteria-based approach for grouping. Hence, in the control group, we grouped together the students with zero page views prior to the creation of the random teams.

The algorithm selected for implementing the homogeneous grouping was k-means clustering because it is a well known, effective technique that works with big datasets [11]. We combined it with a balancing algorithm to obtain clusters with exactly the same number of members (same size k-means variation[1]).

To carry out the experiment the following steps were followed:

- Data preprocessing. Prior to the clustering process the data was standardized in order to assign the same weight to the three selected variables (page views had a dimension much bigger than the other two) as recommended in [6].

- Finding out the statistical distribution of the selected variables (page views, task submitted and forum messages). We used the Kolmogorov & Smirnov, and the D'Agostino & Pearson tests, resulting a non-gaussian distribution of the three variables.

- Creation of two subsets (the experimental group and the control group) checking their uniformity regarding the variables used as grouping criteria. As a consequence of the non-gaussian distribution of the variables, a Wilcoxon test was selected to verify that the subsets do not differ regarding the variables. The array of students was shuffled and splitted in two equal size subsets until the Wilcoxon test returned a p value greater than 0.5 in the three variables used as grouping criteria (if $p < 0.05$, the samples would be different with 95% confidence; if $p >= 0.05$ we cannot state that the samples differ; we required a $p > 0.5$ to strengthen the non-difference between samples).

- Creation of the teams in the control group. Firstly, students with zero page views were grouped together and then, the rest of the students in the control group were distributed randomly in six-members teams.

- Creation of the teams in the experimental group. The selected clustering algorithms were used to obtain clusters of six members based on homogeneity on the three standardized variables.

- Monitoring of teams' activity. We retrieved data about: (i) number of messages in each group discussion forum, (ii) number of different participants in each team, and (iii) teams that complete the task submission.

- Analysis of gathered data. Quantitative data about the students' activity, and qualitative data collected from students messages and a final satisfaction survey will serve to obtain conclusions about the eventual advantages of homogeneous-activity criteria-based teams.

2.4 Preliminary Results

At the time of writing this paper there were 18 experimental vs. 39 control teams with registered activity. The total number of messages registered in the homogeneous-activity teams was 167 versus the 143 registered in the random teams. In Figure 1 (left) we can appreciate that there are less active teams in the

[1] https://elki-project.github.io/tutorial/same-size_k_means

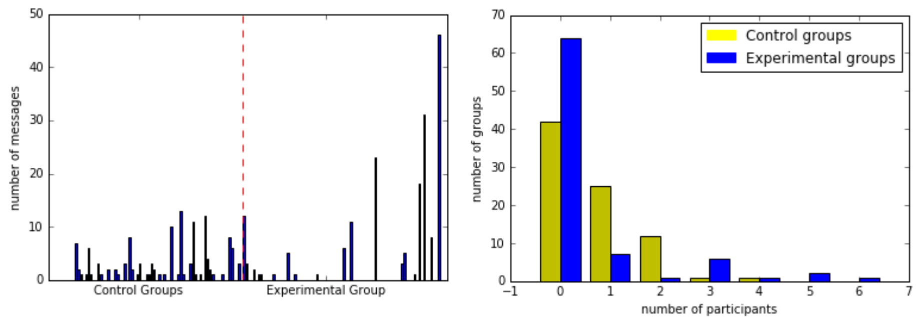

Fig. 1. Messages exchanged in the teams forums (left side) and number of teams with a certain number of active members (right side)

experimental groups, but they have a high number of messages exchanged. Figure 1 (right) shows 64 non-active experimental teams versus 42 non-active control groups, due to the fact that in experimental teams the students with a very low level of activity during the course were grouped together. Furthermore, in this figure we can also observe that the number of teams with a single one active student is more than a quadruple in the control groups than in the homogeneous-activity ones. The number of teams with two active participants is also much higher in the control groups (12 versus 2). However, the number of teams with more than two participants is greater (or equal in the case of four participants) in the homogeneous-activity teams. We can also apreciate that there are only full active teams (with five or six active members) in the experimental group.

3 Conclusions and Future Work

Due to the dispersion of active students in the control group we can observe a higher number of active teams in it, but many of them are teams with only one active participant. The number of teams with an isolated participant is more than a quadruple in the random groups than in the homogeneous-activity ones. Taking into account that we adopt the decision of segregating the students with zero page views in the control group to improve the baseline to compare with, this result suggest that our approach presents advantages regarding students isolation. Moreover, we can only find teams with five or six active members in the experimental group, and the interactions and number of messages exchanged within the them are more numerous. Therefore, at the moment of writing this paper, the preliminary results suggests that there is more collaboration in the experimental groups than in the control groups.

In the short term our work is focused on supporting and gathering data while the experiment of the fourth week is taking place. Then, we will repeat the experiment in the sixth week in order to compare and analyze the evolution of data and the results. In the long term, we plan new iterations of DSRM with an evolution of the tool prototype including different types of grouping criteria and new experiments to evaluate it.

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