Artificial Intelligence to Improve Learning Outcomes Through Online Collaborative Activities

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Abstract: A key strategic objective of the University courses is the promotion and development of new and innovative teaching activities, also through the e-learning environment, with the aim of providing students with direct involvement in the learning process. Collaborative activities represent important and effective teaching methodologies that allow the improvements of learning outcomes through active learning. Furthermore, they can allow the development of soft skills because they enable learners to work together and practice critical reflection and conflict negotiation. Recently, online learning environments are being used to design and deliver assignments based on student work groups. Indeed, the development of digital technologies allows the organization of these online activities in a flexible way for both students and teachers. The goal of this work is to develop successful collaborative activities for undergraduate students to ensure the improvement of knowledge and soft skills on a specific topic. One of the fundamental factors that influence the success of collaborative learning is the students' group formation, which consists in the realization of heterogeneous groups in terms of cognitive resources, characteristics, and behaviors, composed by four or five students. However, the correct implementation of groups requires careful profiling of each student's behavior which can be difficult for the teacher to detect. In this work an intelligent software, developed using Artificial Intelligence algorithms, was used to assist the teacher in the realization of heterogeneous groups of students. It is composed of a Machine Learning model, consisting in clustering techniques applied to Moodle learning analytics performed to return clusters that identifies different students' profiles, and a specific algorithm that automatically organizes the groups, ensuring the heterogeneity including at least one student from each cluster. At the end of the execution the software returns the list of the heterogeneous groups to the teacher. The software was applied to assignments that required working group within a specific online course for university students, using a Moodle e-learning platform. The quantitative analysis demonstrated the effectiveness of the numerical method for group composition proposed in this work to ensure successful collaborative activities, confirmed also by the perceptions of the students on the course.

Keywords: collaborative activities, machine learning, Moodle, e-learning

1. Introduction

Collaborative activities are important and effective teaching methodologies that enable active learning to improve learning outcomes.

Research experiences demonstrate how the use of digital technologies help the realisation of on-line collaborative learning using activities such as gamification (Hasan, 2019), peer assessment (Badea, 2019), collaborative writing (Biasutti, 2017) and led teachers to organise online collaborative activities in a very flexible way using e-learning platforms such as Moodle (Abedin, 2012). Several authors have compared learning outcomes in online courses between students who worked in groups and students who worked individually, demonstrating the effectiveness of collaborative activities (Van Eijl et al, 2005), which lead to an improvement in higher cognitive abilities and excellent results.

However, collaborative online activities do not always improve student performance. Factor that influences the success of collaborative learning is the creation of heterogeneous groups, both in terms of cognitive resources, characteristics, and behaviours (Nijstad et al., 2002), and in the realisation of groups, which tend to be effective if composed of 4-5 members, as confirmed by research evidence (Burke, 2011). Detecting students' behaviour is a fundamental requirement to create heterogeneous courses, but it's not always easy for instructors, in particular when they have to manage a large number of students. (Hieu, L. T. et al, 2021). Due to these difficulties, teachers tend to create random groups, hoping to achieve heterogeneity within the groups (Bacon, 2001) but this approach it's not always effective. In Wiki activities, random groups can reduce their engagement in the topic affecting the achievement of their learning outcomes. (Sun, 2014).

Even though researchers attempted to overcome these limitations by using Artificial Intelligence to automatically create heterogeneous groups using data extracted from students' interactions with Forum (Maina et al., 2017), the need to identify students' behaviour in a specific online course led us to execute an intelligent software using Clustering to create heterogeneous groups applied to Moodle Log data to achieve this goal.

The goal of this project was to create effective heterogeneous groups for collaborative writing activity (Wiki) in order to meet the requirements for obtaining a successful teaching methodology that would benefit university students in terms of learning and soft skills.

This work entails the creation of a collaborative writing activity that allows groups of students to improve the learning experience of students enrolled in the "User Experience (UX) Design" blended course of the Computer Science degree programme, which consisted of an individual and a group project component, which included collaborative writing.

The obtained clusters were used for the group composition, inserting at least one student belonged to different clusters to the same group, guaranteeing heterogeneity.

Before creating the groups, a further verification of the clusters obtained was performed to confirm the similarity of the students within the same cluster and the differences with the members of the other clusters. For this purpose, the types of the students belonging to each cluster were compared with the evaluations obtained by them during an individual task, requested of them in the first phase of the course in order to check if there was a correspondence between cluster type and evaluation score.

The second phase involved analysing the students' perceptions to determine whether there were any benefits in terms of learning and soft skills.

2. Methodological aspects

The course is part of the undergraduate degree in Computer Science and it involves students enrolled to the last year of the degree programme. It was delivered in a blended learning format via the University's Moodle e-learning platform with the participation of 111 international (mainly composed of European, African, Arab, Indian And Asian) students taking part, characterised by 90 men and 21 women.

It aims to guide students to gain an understanding of underpinning theoretical concepts and practical techniques relevant when considering humans, both in the organisation of design and design processes, and as a way of incorporating a user perspective in the design of products and services.

Students' knowledge was assessed firstly across an individual task through multiple choice quiz (used as part of assessment for undergraduate courses in computer science (Roberts, 2006) and then through collaborative writing activity based on the practical work undertaken.

The on-line multiplechoice quiz consisted of 25 questions of 35 minutes duration based on the topics included in the on-line pathway performed in the e-learning platform supervised by the teacher in class.

In the collaborative group coursework, students are tasked to research, design, and evaluate an interactive system using an iterative ‘user-centred design’ approach. Students are expected to contribute equally to their group work.

For group formation, an intelligent software, based on Clustering techniques using K-means algorithm applied to Moodle log data, creates firstly clusters of students with the similar characteristics and then heterogeneous groups distributing students of the same clusters into different groups (Nalli et al. 2021). Moodle log data extracted by the e-learning platform allows for the calculation of various aspects of the student learning process, as well as the identification of students' behaviour using clustering techniques. Specific log data were carefully chosen to create the input dataset for the clustering process.

Research shows that log data extracted from the Moodle platform, properly selected, allow the calculation of different aspects of the student learning process, such as “presence coefficient”, “study coefficient”, and “activity coefficient”, and therefore permit the identification of online user behaviour, using clustering techniques. Different Moodle log data needed are used in this work, consisting of login frequency, last login, total time spent online, number and frequency of video viewed, number and frequency of files opened (Bovo, 2013).

In this work, that was the first step of the research process, the Pre-experimental design was used, where subjects or groups were observed after a treatment had been applied, in order to test whether the treatment had the potential to cause change (Frey, 2018). Because of the pre-experimental design no control group was applied to this work. (Thyer, 2012).

Finally, the course provided an anonymous questionnaire based on past tested similar investigations related to the students’ perception about collaborative activities (Landry et al.,2015) (Amendola et al., 2016). It consisted of 18 questions divided into behaviours, opinions, and comments, characterised by open and closed-ended questions using Likert Scale, related to the online course, in terms of advantages and disadvantages of collaborative activities based on working groups, and improvements of learning outcomes and soft skills.

3. Results

Once the dataset was identified, it was possible to run the software, which used the K-Means algorithm in addition to the Elbow method to generate four clusters.

Each cluster determined identifies different behavioural profiles of students basing on the interaction on the platform.

Table 1: Details of analysed features (average values) for each cluster

	Cluster 0	**Cluster 1**	**Cluster 2**	**Cluster 3**
Students	9	23	26	53
total logins	17,5	14	16	12
total files	3	1,6	1,2	0,9
frequency of files viewed	10,5	4,9	5,1	2,7
total videos	6,7	5,6	5,1	3,4
frequency of videos viewed	1,1	1,3	1,1	1,2

The students in Cluster 3 (53 members) were either inactive or had low interaction levels. This is evident by the low number of accesses to the course, with an average of 12, and low viewing of files (average of 0.9) and videos (average of 3.4).Cluster 2 (26 members) and Cluster 1 (23 members) represents students with average participation on the online course, demonstrating by the higher values compared Cluster 3 in file (average 1,2 and 1,6 respectively) and videos (average 5,6 and 5,1 respectively) viewing and the total access on the course (14 and 16 respectively).Cluster 0 (9 members) instead includes students with high interaction reported by the highest values in terms of access to the course (17,5) files (3) and videos (6,7).

The correspondence with the grade obtained by the students in the individual part of the course confirms the differences between students belonging to different clusters. This correspondence suggests how the level of interaction on the platform had feedback in terms of performance, with cluster 3 that got a very low score equal to 63, Cluster 1 and Cluster 2 that received good scores equal to 71 and 72, and Cluster 0, which represented students with high activity on the platform, achieving an excellent score average equal to 78.

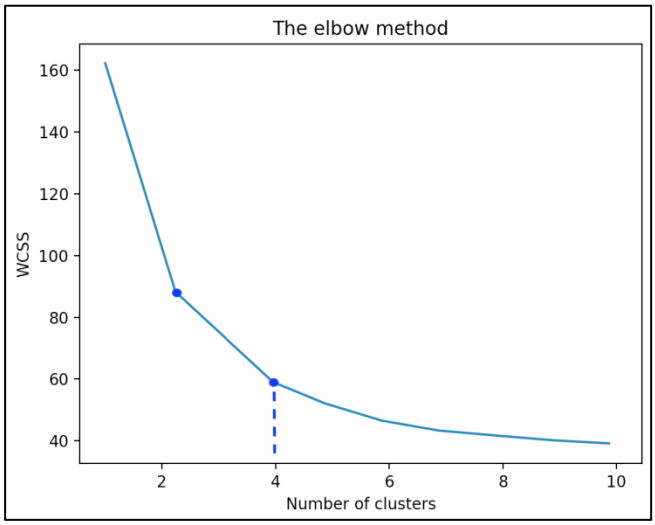

Figure 1: Elbow method plot, that allows to find the appropriate number of clusters for a specific dataset

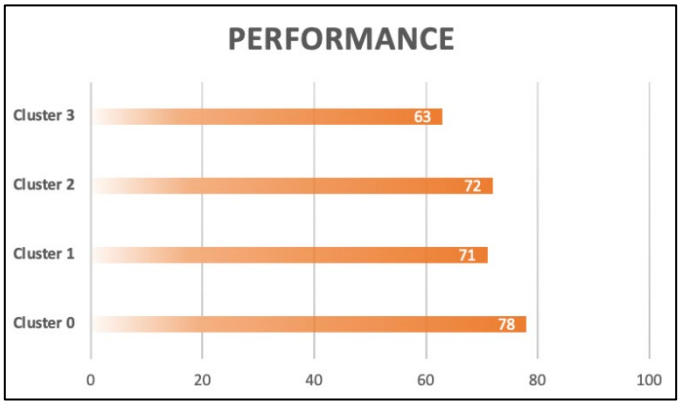

Figure 2: Correspondence between students' activity in the online pathway and individual task evaluation

This verification allows us to identify accurate profiles of homogeneous students for each cluster, ensuring heterogeneity in the building of 20 heterogeneous groups of 4-6 members, which contributes to the success of the collaborative activity. The questionnaire confirms the positive outcomes of the wiki based on heterogeneous groups, with the majority of the students believing that group members' contributions were useful for the collaborative work (78%), and the experience was motivating (75%) and increased their engagement in the study (75%). Table 2 suggests that 73% of students believe it improves learning outcomes, which is supported by open questions.

Table 2: Categories of qualitative answers extracted from the questionnaire with examples of student comment

Question	Skills	Example of positive feedback	% of students
Improvement of learning and knowledge	Teamwork	Working together has definitely helped us gain a lot of knowledge of our subject and also have a better understanding of working together.	35%
	Share information	We got to share our ideas and combine the different ideas that each one of us had.	29%
	Communication	Everyone communicated with each other and when someone didn't know about a specific topic, we would all explain that topic to them	13%
Improvement of soft skills	Communication	They allow us to be able to communicate more efficiently.	51%

Question	Skills	Example of positive feedback	% of students
	Team Work	It allows everyone to feel like a team player and having an idea on how to also give constructive feedback	8%
	Problem-Solving	It influences Problem-solving.	8%
	Time Management	It allows to manage the time efficiently	5%

4. Conclusions

The outcomes demonstrated the success of the online collaborative activity based on heterogeneous groups. The comparison of obtained clusters and grades highlighted the software's effectiveness in creating heterogeneous groups of students, which is critical for assisting students in achieving learning outcomes and developing soft skills. The quantitative and qualitative analysis, which was carried out by processing the data extracted from the final questionnaire completed by the students, revealed excellent feedback in terms of the students' perception and satisfaction, particularly in terms of group members' contributions, motivation, engagement, and improvement of learning outcomes. A future extension of this work could include an analysis of the grades earned by students in collaborative activities to test if the performance reflects the students' perceptions. Once tested the effectiveness of the software, the challenge could be applying the experimental design with a control group.

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