Group Formation in a Cross-Classroom Collaborative Project-Based Learning Environment

Gail L. Rolle-Greenidge
The University of the West Indies, Cave Hill Campus
gail.rolle@mycavehill.uwi.edu

Paul A. Walcott*
The University of the West Indies, Cave Hill Campus
paul.walcott@cavehill.uwi.edu

ABSTRACT

Cross-Classroom Collaborative Project-Based Learning (C3PjBL) requires the formation of project-groups by pairing student-groups across classrooms. Unfortunately, due to the configuration of these groups, the group formation techniques found in the literature are unable to automatically create project-groups for C3PjBL. This paper describes an automatic project-group formation technique for C3PjBL which utilizes clustering to create homogeneous student-groups, based on the students' perceived technological and higher-order thinking skills (student characteristics). Student-groups, from different classrooms, are then paired using an optimization technique to form project-groups. In our results, we present a comparison of the performance of a random group formation technique and our technique. We observed that automatic group formation using an n-dimensional space of student characteristics and k-means clustering is more effective than random group formation and, the strategy of forming homogeneous student-groups and heterogeneous project-group for C3PjBL creates more compatible group compositions than random grouping.

CCS CONCEPTS

• **Human-centered computing**; • **Collaborative and social computing**; • **Collaborative and social computing systems and tools**;

KEYWORDS

Collaborative and social computing, Group formation, Clustering, Cross-classroom collaborative project-based learning, C3PjBL, G2Group

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*Corresponding author

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1 INTRODUCTION

Cross-classroom collaborative project-based learning (C3PjBL) is a teaching and learning strategy that requires student-groups from one classroom to work collaboratively with student-groups from another to complete curriculum-based activities using wikis [1, 20]. Before collaboration can occur however, a project-group must be formed by pairing a student-group from one classroom with a student-group from another. Although manual group formation is possible in this environment, it is time-consuming and error prone. Due to this complexity, group formation in C3PjBL needs to be automated if teachers are expected to effectively work in this environment [1].

Recently, factors that impact automatic group formation in online collaborative environments have been the focus of several researchers. These factors include: students' characteristics and learning attributes [2]; optimization for group formation [3]; and, attributes of group formation and grouping techniques [4]. Through the process of selecting students to participate in a group, teachers can combine several factors to form collaborative groups that will foster meaningful interactions and desired learning outcomes [4]. However, creating these complex groups often necessitates computational backing to be successful [5]. Two automatic group creation approaches are presented in the literature: the random selection method and computational techniques (namely algorithms). Although the random selection method has been preferred for online group formation due to its simplicity, Cruz and Isotani [6], indicated that randomly created groups often pose challenges such as "disproportional participation of individuals, demotivation, and resistance to group work in futures [sic] activities". [2], also added that groups that are randomly created could result in groups being homogenous instead of heterogeneous.

To the best of our knowledge, no existing open project-based learning systems support cross-classroom collaboration and project-group creation for C3PjBL. In this paper, we describe an automatic project-group formation technique for C3PjBL which utilizes clustering to create homogeneous groups, based on students' perceived technological and higher-order thinking skills [7]. Homogeneous student-groups, from different classrooms are then paired using an optimization technique to form project-groups. We present a comparison of the performance of a random group formation technique and our computational technique.

Our research expands the current research on automatic group formation and brings to the fore effective heterogeneous and homogenous grouping for C3PjBL based on students' technological and higher-order thinking skills. Combining these skills to group students creates a balance in the groups which can improve group performance and create a positive synergy among group members, thus improving their higher-order thinking skills.

Without automatic group formation in C3PjBL, teachers may be unwilling to engage in C3PjBL [1] thus not benefiting from Collaborative PjBL. Also, manual group formation is tedious and time-consuming and may lead to incompatible groups.

In the next section of the paper, the research literature is reviewed, followed by a discussion of the novelty of the proposed approach, a description of the present study, the results, discussion and conclusion.

2 BACKGROUND

2.1 Group formation

Group formation in online collaboration can be either manual or automatic [9]. Manual group formation can be achieved either by self-selection or instructor assigned. The self-selection approach does not guarantee a balanced group, since learners choose to join a group that is most suitable for them. This may lead to a less than ideal group [10]. Although the instructor assigned grouping technique guarantees a more balanced grouping, it becomes complex when large number of students must be grouped manually [11].

Automatic group formation provides the option of group creation with or without instructor input [12]. Random selection and computational techniques (for example, algorithms) are two techniques used to achieve automatic group formation. Random group formation is the approach most frequently used by instructors because of its simplified implementation, whereby social and academic heterogeneity can possibly be achieved given that students have an equal opportunity of being a member of any group [2]. The authors further point out that although this grouping method is popular in learning management systems, such as Moodle, the level of heterogeneity may not match the diversity in learning capabilities which is required for effective grouping. Authors like Maqtary and his colleagues [4] caution that randomly forming groups for collaboration often results in a mismatch of students' skills and characteristics, and a group composition that poorly represents the structure of successful groups [9].

Group formation in the form of heterogenous and homogeneous groups is a topic of interest in recent research. A study was conducted by Wichmann et al. [8] to determine whether groups formed based on learner behavior impacted productivity when students who were classified as either high, average, or low-level were randomly assigned to heterogeneous or homogenous groups.

2.2 Clustering

Clustering is used to find groups of objects with related characteristics [2]. Romero et al [13] defined clustering based on the premise of maximizing the similarity among the object groups in a cluster while minimizing the similarity between the object groups in different clusters. In online collaborative learning, clustering has been used to group students according to their collaboration competence level [2], predict students' academic performance [14] and group students to give them differentiated guidance according to their learning skills and other characteristics [15].

Maina et al. [2], in their work, applied an intelligent grouping clustering algorithm to automatically form heterogeneous groups using students' collaboration competence levels. Similar work has also been done by Valetts and Gesa [14], however, they proposed a different clustering method to group students using their collaboration competences. In another work, Tang and McCalla [16], employed a clustering technique to group students with similar learning characteristics to promote group-based collaborative learning. Anaya and Boticario [15] also applied a clustering algorithm to group students according to their collaboration level (high, low, or medium) to evaluate student interactions.

2.2.1 K-means clustering. K-means is an unsupervised learning algorithm used for clustering. K-means clustering works by partitioning "n" objects into k clusters in which each object belongs to the cluster with the closest mean [17], thus, each cluster formed is associated with a centroid. The K-means algorithm minimizes the sum of distances between the points and their respective cluster centroid [18]. Drake and Gyimah [19] developed a simple algorithm (Algorithm 1) to perform K-means clustering which can be extended or modified to implement user characteristics and attributes for group formation [19].

Algorithm 1 K-means Clustering Algorithm

a. Clusters the data into k groups where k is predefined.
b. Select k points at random as cluster centers.
c. Assign objects to their closest cluster center according to the *Euclidean distance* function.
d. Calculate the centroid or mean of all objects in each cluster.
e. These centroids form the new cluster centers.
f. Repeat steps c, d, and e until the same points are assigned to each cluster in consecutive rounds.

3 NOVELTY OF GROUP FORMATION FOR C3PJBL IN G2GCOLLABORATE

G2GCollaborate is a web-based platform that implements the C3PjBL environment [1]. It provides a robust method for the creation of institutions which are managed by institutional administrators (IAs). These administrators are responsible for the creation of project originators (POs) and project coordinators (PCs). POs create projects and are responsible for project-group formation, while the PCs create student-groups and guide them through the project. To encourage collaboration and the growth of a learning community, G2GCollaborate features: project creation; automatic student-group, and project-group formation; wikis (G2GWiki); user profiles; messaging; notifications; scaffolding (through project-roles and wiki templates); and, wiki publishing and search through a RESTful API [1, 20].

In G2GCollaborate, student-groups are formed in the classrooms participating in the C3PjBL project. Students are grouped based on their perceived technological skills and their higher-order thinking (HOT) skills. Once the student-groups are created, an optimization technique is employed to create project-groups by pairing student-groups from the participating classrooms. There are two main approaches to group formation in G2GCollaborate: instructor group selection (that is, groups created manually by the project coordinators (PCs) and project originators (POs)) and automatic group creation using an extended K-means clustering algorithm.

4 PRESENT STUDY

In C3PjBL, an environment is created that promotes collaboration within student- and project-groups. Given that the group formation approach can impact the effectiveness of the group, C3PjBL has drawn on the research literature to inform the approach used. Wichmann et al. [8], noting that heterogeneous group composition is beneficial for learning in small-group tasks, studied 120 students placed in 29 small groups. These students were classified as low-, average- or high-level based on the number of characters they contributed to an essay assignment. They concluded that high-level students were more productive in heterogeneous groups, low-level students were more productive in homogeneous groups (since social loafing was reduced) and, overall, heterogeneous groups were better for learning communities. As such, C3PjBL forms small, homogeneous student-groups in each classroom to ensure that low-level students are grouped together; and, heterogeneous project-groups to ensure that high-level students are productive.

In the present study, we explore the efficiency of G2GCollaborate's group formation approach using a Social Studies research project designed for Caribbean Class 3 primary school students, based on their technological skills and Social Studies knowledge. The objective of the project was for students to create a wiki that discussed the construction of canoes by indigenous Caribbean people (of note however, due to the devastation left by a Category 5 hurricane, the project was never completed). The experiment presented here compares whether randomly formed groups or groups formed using G2GCollaborate automatic group formation approach, produced the more desirable group compositions [8].

4.1 Technology and knowledge skills

The technology and knowledge skills of 330 Class 3 students were determined during a survey conducted at nine Caribbean primary schools. The Instruments used were a Social Studies test (a national assessment) and a technology skills survey which queried students' perceptions of their ability to complete 12 technology skills (students indicated that they could either complete the skill or not). These technical skills included: searching for files on a computer, searching the Internet for information, creating web pages, downloading files, and uploading files. These instruments were administered by the class teachers and one of the researchers during school hours.

Of these 330 students, data from N=60 were selected for use in this experiment. These data represented N=26 students from a rural primary school and N=34 from an urban primary school. Parental consent was received from all participants.

4.2 Group formation

In C3PjBL, student characteristics are captured using an n-dimensional space. In the present experiment, a two-dimensional space (Search Skills, Social Studies Knowledge) was employed based on Social Studies Knowledge and Search Skills. The Search Skill dimension was created using a combination of the "searching for files on a computer" and "searching the Internet for information" survey items, converted to a percentage; and, the score on the Social Studies assessment, which was also converted to a percentage, was used as the Social Studies Knowledge dimension. These values were scaled to create a (1000,1000) two-dimensional space.

Since C3PjBL utilizes an n-dimensional space for student characteristics, if the behavior of learners was also recorded using learning analytics (for example), then these behaviors would simply become dimensions in the n-dimensional space.

K-means clustering [19] was used to cluster students into student-groups. For C3PjBL, two such student-groups needed to be created from collaborating classes and joined to create a project-group. An optimization technique was used to join student-groups from Class A (for example) to student-groups from Class B so that the most dissimilar student-group pairs were joined together. Essentially, this technique created heterogeneous project-groups as advocated by [13].

4.3 Comparison of group formation approaches

To determine the efficacy of the automatic group formation technique, we created N=6 student-groups each for Class A and Class B by randomly assigning students to each of the groups. Class A comprised N=34 students, while Class B comprised N=26 students. Next, for each student-group in Class A, we randomly selected a student-group in Class B to join it to, thus creating six project-groups. We then used the automatic group formation feature (called G2Group) in G2GCollaborate to create six student-groups (each) in Class A and Class B and the six project-groups and compared the results of the two approaches.

To determine which approach produced the better groupings, the Euclidean distance between the centroids of the two student-groups comprising the project-group were calculated for each project-group. The approach that maximized the sum of these distances was deemed better given that this ensured group heterogeneity.

5 RESULTS

The sizes of the student-groups generated by the Random and G2Group group formation approaches are presented in Table 1. Of note, the sizes of the student-groups created by G2Group vary from, as low as, one student (Group 1 in Class B; and, Group 6 in Class A) to, as high as, 18 students (Group 3 in Class A).

Table 2 shows the centroid (and Standard Deviation (SD)) in the two-dimensional space (Search Skills, Social Studies Knowledge) of each student-group in Class A and Class B, using the Random and G2Group group formation approaches. Student-group centroids with small SDs indicate closely packed clusters (for example, Group 5, Class B for the G2Group approach). The size of this two-dimensional space is (1000,1000) as described in Section 4.2.

Table 3 illustrates the project-group pairings from Class A and Class B with the associated Euclidean distances between student-group centroids, using both approaches.

6 DISCUSSION

The comparatively smaller standard deviations for the student-groups created using the automatic grouping technique of G2Group indicate that these groups are homogeneous (Table 2). Conversely, the relatively large standard deviations for the randomly created student-groups suggest non-homogeneous groupings. Further, the

Table 1: Group Sizes for Student-Groups in Class A and Class B for both Group Formation Approaches

Group	Random Group Formation Approach		G2Group Group Formation Approach	
	Class A	Class B	Class A	Class B
1	6	5	3	1
2	6	5	5	5
3	6	4	18	9
4	6	4	2	6
5	5	4	5	3
6	5	4	1	2
Total	**34**	**26**	**34**	**26**

Table 2: The Characteristics of the Student-Groups Created for Class A and Class B for both Group Formation Approaches

	Random Group Formation Approach(Search Skills, Social Studies Knowledge)				G2Group Group Formation Approach(Search Skills, Social Studies Knowledge)			
	Class A		Class B		Class A		Class B	
Group	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	(733.33, 583.33)	(413.12, 220.61)	(456, 610)	(448.00, 149.67)	(40.00, 750.00)	(0.00, 50.00)	(1000.00, 841.67)	(0.00, 78.62)
2	(680.00, 658.33)	(495.74, 139.34)	(520, 630)	(391.92, 169.12)	(1000.00, 744.44)	(0.00, 81.46)	(60.00, 462.50)	(52.92, 138.63)
3	(840.00, 675.00)	(391.92, 147.48)	(320, 613)	(397.99, 96.01)	(40.00, 362.50)	(0.00, 96.01)	(1000.00, 483.33)	(0.00, 94.28)
4	(840.00, 683.33)	(391.92, 116.90)	(600, 625)	(400.00, 225.00)	(200.00, 562.50)	(0.00, 73.95)	(200.00, 533.33)	(0.00, 62.36)
5	(296.00, 510.00)	(401.60, 267.86)	(520, 488)	(480.00, 170.93)	(1000.00, 460.00)	(0.00, 96.95)	(1000.00, 633.33)	(0.00, 23.57)
6	(840.00, 710.00)	(357.77, 65.19)	(760, 675)	(415.69, 182.00)	(200.00, 800.00)	(0.00, 0.00)	(466.67, 700.00)	(377.12, 40.82)

Table 3: Project-Group Pairings with Associated Euclidean Distances between Student-Group Centroids

Random Group Formation Approach			G2Group Group Formation Approach		
Group in Class A	Group in Class B	Euclidean Distance between Student-Group Centroids	Group in Class A	Group in Class B	Euclidean Distance between Student-Group Centroids
Group 6	Group 5	389.75	Group 1	Group 3	996.35
Group 1	Group 6	95.47	Group 2	Group 2	981.37
Group 2	Group 3	362.91	Group 3	Group 1	1072.94
Group 4	Group 1	390.94	Group 4	Group 5	803.13
Group 3	Group 4	245.15	Group 5	Group 6	584.85
Group 5	Group 2	254.12	Group 6	Group 4	700.00
Mean		**289.72**			**856.44**

position of each cluster in the (Search Skills, Social Studies Knowledge) space determines if the students would be considered high-level or low-level according to [8]. Student-groups occupying the top right portion of the (Search Skills, Social Studies Knowledge) space, comprise of students who are both skillful in the search process and have tested well on the Social Studies assessment; for example, Group 1 in Class B (with a centroid of (1000.00, 841.67))(Table 2) which was generated by G2Group.

Since high-level students are best placed in heterogeneous groups [8], G2Group pairs heterogeneous student-groups, from Class A and B, into project-groups. An example of this pairing occurred between Group 3 in Class A (40.00, 362.50) and Group 1 in Class B (1000.00, 841.67) (Table 3). The Euclidean distance between their centroids in the (Search Skills, Social Studies Knowledge) space of 1072.94, demonstrates their heterogeneity.

Overall, G2Group was much better at creating heterogeneous project-groups than the Random Grouping technique, based on the data presented in Table 3. The average Euclidean distance between the students-groups that were paired to form project-groups was only 289.72 for the Random Grouping technique, whereas G2Group's average Euclidean distance was 856.44. As argued in [2], the problem with the random-based approach is that homogenous groups might be created instead of heterogeneous groups (or vice-a-versa). Clearly, this was the case in our experiment.

Clustering using the standard k-means approach [19] can lead to peculiar group formations, such as groups containing one student (for example, Group 1 in Class B for G2Group (Table 1)) and very large groups (for example, Group 3 in Class A for G2Group (Table 1)) due to large numbers of students having similar technology and knowledge skills. PCs need to determine the desirability of these variations in group sizes before performing automatic group formation. For example, a PC might decide that a one-member student-group is acceptable since this group will always be joined with another student-group to form a project-group. Alternatively, PCs may choose to manually sub-divide larger groups. Another possibility is to modify the k-means approach so that it generates equal-sized groups.

The survey-based approach of acquiring student characteristics for group formation is an appropriate method for C3PjBL given that groups must be formed prior to the start of a C3PjBL activity. The presented technique of clustering in a (Search Skills, Social Studies Knowledge) space also provides great flexibility in group formation. For example, we chose the "search" technology skills from our survey data to perform group formation given that the C3PjBL activity was based on a Social Studies research project. Just as easily we could have selected word processing or communication skills as the basis for group formation. This feature makes G2Group a powerful automatic group formation tool.

The limitation of the study is that the approach used was not evaluated using control and treatment groups, however it was validated against state-of-the-art research.

7 CONCLUSION

This paper describes a novel group formation approach used in C3PjBL environments. Unlike classical group formation, C3PjBL requires both student-groups within classrooms to be created along with a project-group which is a pairing of student-groups across dispersed classrooms.

This group formation approach uses a k-means algorithm to create homogeneous student-groups based on clustering in an n-dimensional space (a two-dimensional (Search Skills, Social Studies Knowledge) space was used in the experiment presented). Subsequently, heterogeneous project-groups are created by pairing student-groups from two classrooms so that most dissimilar groups will be paired together.

The results of an experiment that compared the efficacy of a random group formation approach and the novel approach described in the present study revealed that: (1) automatic group formation using an n-dimensional space of student characteristics and k-means clustering is more effective than random group formation; (2) The strategy of forming homogeneous student-groups and heterogeneous project-group creates more compatible group compositions than random grouping; and, (3) A modified k-means clustering approach, which ensures equal group sizes, is desirable since it will ensure that student-group sizes are kept small.

Further work will explore the efficacy of creating same-sized groups versus variable-sized groups and their applicability to C3PjBL.

REFERENCES

[1] Paul. A. Walcott and Gail Rolle-Greenidge. 2021. A Cross-Classroom Collaborative Project-Based Learning Management System. Proceedings of EdMedia and Innovate Learning 2021—World Conference on Educational Media and Technology. Association for the Advancement of Computing in Education (AACE), Online, 33-38.
[2] Elizaphan Maina, Robert Oboko, and Peter Waigo. 2017.Using machine learning techniques to support group formation in an online collaborative learning environment. International Journal of Intelligent Systems and Applications 9, 3 (March 2017), 26-33.https://doi.org/10.5815/ijisa.2017.03.04
[3] Hamid Sadeghi and Ahmad. A. Kardan. 2014. Toward effective group formation in computer-supported collaborative learning. Interactive Learning Environments24,3 (June 2014), 382–395. https://doi.org/10.1080/10494820.2013.851090.
[4] Naseebah Maqtary, Abdulqader Mohsen, and Kamal Bechkoum. 2017. Group formation techniques in computer-supported collaborative learning: A systematic literature review. Technology, Knowledge and Learning 24, 169-190.https://doi.org/10.1007/s10758-017-9332-1.
[5] Chinasa Odo, Judith Masthoff, and Nigel Beacham.2019. Group formation for collaborative learning. In: Isotani S., Millán E., Ogan A., Hastings P., McLaren B., Luckin R. (eds) Artificial Intelligence in Education. AIED 2019. Lecture Notes in Computer Science, vol 11626, 206-212. Springer, Cham. https://doi.org/10.1007/978-3-030-23207-8_39
[6] Wilmax. M. Cruz and SeijiIsotani. 2014. Group formation algorithms in collaborative learning contexts: A systematic mapping of the literature. Collaboration and Technology.Lecture Notes in Computer Science, vol 8658,199–214. https://doi.org/10.1007/978-3-319-10166-8_18.
[7] Paul. A. Walcott and Gail Rolle, 2014. Investigating the ICT competencies and technology access of Indigenous Dominican primary school students. In Proceedings of EdMedia 2014—World Conference on Educational Media and Technology. Association for the Advancement of Computing in Education (AACE), Finland, 948-953.
[8] Astrid Wichmann, Tobias Hecking, Malte Elson, Nina Christmann, Thomas Herrmann, and H. Ulrich Hoppe. 2016. Group formation for small-group learning: Are heterogeneous groups more productive? In Proceedings of the 12th International Symposium on Open Collaboration (OpenSym '16). Association for Computing Machinery, New York, NY, USA, Article 14, 1–4. https://doi.org/10.1145/2957792.2965662
[9] Ivan Syrba and Maria Bielikova. 2015. Dynamic group formation as an approach to collaborative learning support. IEEE Transactions on Learning Technologies8, 2 (April-June 2015), 173–186. https://doi.org/10.1109/TLT.2014.2373374
[10] Zhillin Zheng and Niels Pinkwart. 2014. A discrete particle swarm optimization approach to compose heterogeneous learning groups. In proceedings of IEEE 14th international conference on advanced learning technologies, IEEE, Athens, Greece, 49–51. https://doi.org//10.1109/ICALT.2014.24
[11] Amir Mujkanovic, David Lowe, Kieth Willey, and Christian Guetl. 2012. Unsupervised learning algorithm for adaptive group formation: Collaborative learning support in remotely accessible laboratories. In Proceedings of International conference on information society (i-Society), IEEE, London, UK, 50–57.
[12] Sofiane Amara, Joaquin Macedo, Fatima Bendella, and Alexandre Santos. 2016. Group formation in mobile computer supported collaborative learning contexts: A systematic literature review. Journal of Educational Technology & Society 19, 2 (July 2015), 258–273.
[13] Cristóbal Romero, Sebastián Ventura, and Enrique García. Data mining in course management systems: Moodle case study and tutorial. Computers & Education 51, 1 (August 2008), 368-384. https://doi.org/10.1016/j.compedu.2007.05.016
[14] Laura. M. Valetts, Silvia. B. Navarro, and Ramón. F. Gesa. Modelling collaborative competence level using machine learning techniques. E-Learning. 56-60.
[15] Anaya. R. Antonio and Jesús. G. Boticario. 2011. Application of machine learning techniques to analyse student interactions and improve the collaboration process. Expert Systems with Applications 38,2, 1171-1181. https://doi.org/10.1016/j.eswa.2010.05.010.
[16] Tiffany. Y. Tangand Gordon McCalla. 2003. Smart recommendation for an evolving e-learning system. In Proceedings of Workshop on Technologies for Electronic

Documents for Supporting Learning, International Conference on Artificial Intelligence in Education, 699-710.
[17] Hedayetul. I. Shovonand Haque Mahfuza. 2012. An approach of improving students academic performance by using k means clustering algorithm and decision tree. International Journal of Advanced Computer Science and Applications 3, 8, 46-149.
[18] Qi Jianpeng, Yanwei Yu, Lihong Wang, Jinglei Liu, and Yingjie Wang. 2017. An effective and efficient hierarchical k-means clustering algorithm. International Journal of Distributed Sensor Networks 13, 8, 1-17. https://doi.org/10.1177/1550147717728627
[19] Delali. K. Dake and Ester Gyimah. 2019. Using k-means to determine learner typologies for project-based learning: a case study of the University of Education, Winneba. International Journal of Computer Application 178, 43, 29-34. https://doi.org/105120/ijca2019919320.
[20] Gail Rolle-Greenidge and Paul. A. Walcott. 2021. Design and Evaluation of a Wiki for Cross-Classroom Collaborative Project-Based Learning. Proceedings of EdMedia and Innovate Learning 2021—World Conference on Educational Media and Technology. Association for the Advancement of Computing in Education (AACE), Online, 27-32.