

A general framework for testing different student team formation strategies

Juan M. Alberola¹, Elena del Val¹, and Victor Sanchez-Anguix² and Vicente Julián¹

¹Universitat Politècnica de València, Valencia, Spain
{jalberola, edelval}@dsic.upv.es

²Coventry University, Department of Computing, Gulson Road, CV1 2JH
ac0872@coventry.ac.uk

Abstract. One of the most important problems faced by teachers is grouping students into proper teams. The task is complex, as many technical and interpersonal factors could affect team dynamics, with no clear indication of which factors may be more relevant. Not only the problem is conceptually complex, but its computational complexity is also exponential, which precludes teachers from optimally applying strategies by hand. The tool presented in this paper aims to cover both gaps: first, it provides a range of grouping strategies for testing, and second, it provides artificial intelligence mechanisms that in practice tone down the computational cost of the problem.

Keywords: team formation, teamwork, education, artificial intelligence

1 Introduction

A recent graduate has just been hired by an e-commerce company after finishing her degree in Computer Science. In the first day in the job, she is introduced to her team, which is composed by a variety of profiles. Let us be honest, it did not matter if the student had finished a degree in Computer Science, Statistics, Literature, or Ecology. It also did not matter whether she was going to be part of an e-commerce company, a manufacturing company, a bank, or a retail shop. The scenario will be in all cases similar, as the problems faced by these organizations will be so complex that they will require the action of teams [15, 13].

Despite the ability for teams to tackle complex problems, it has also been documented that teamwork is by no means a trivial soft skill and it requires to be polished. If team dynamics are not adequate, the results can be totally opposite to those intended when the team was formed [6, 3]. Given these circumstances, teamwork has been introduced in Higher Education as one of the core general competences in the course programmes [4, 14]. Nevertheless, a very unsatisfactory team experience may preclude team members from adequately polishing their teamwork skills, and it may overly emphasize the negative experiences in future scenarios. Therefore, for students to correctly sharpen their team skills, it is necessary to create an adequate environment in educational settings.

The aforementioned problem has no straightforward solution. First of all, there are many criteria that could affect team dynamics inside a team: technical skills, soft skills, knowledge distribution, personality, friendship, common interests, goals' compatibility, languages, schedule's compatibility, and so forth. As the reader can imagine, the range of possible grouping strategies is almost infinite and there is not a clear indication of which strategies may outperform others in terms of facilitating teamwork. Secondly, even if the best grouping criteria was clear, the problem of optimally allocating students into groups is exponential with the number of students, which precludes lecturers from optimally applying these strategies by hand. Therefore, computational tools may be necessary to provide support to lecturers in that task.

The tool that we present in this paper aims to cover such gap. First of all, lecturers can employ multiple defined grouping strategies to test with their own students. Second, the tool applies artificial intelligence optimization methods to provide an optimal solution for the grouping problem, which tones down the exponential cost in practice. The tool is an evolution of our previous work [1, 16], where we offered a grouping method for students based on Belbin's role taxonomy. The remainder of this paper is organized as follows. First, Section 2 describes the proposal in detail. Section 3 shows how the proposed tool has been applied to test several team formation strategies in a real educational environment. Finally, Section 4 presents some concluding remarks and future work.

2 Framework design

In this section, we describe in detail the team formation tool (Figure 1). The tool's core components can be grouped into three different functionalities: information gathering, team formation, and feedback and analysis.

2.1 Information gathering

All team formation activities to be supported by the tool always start with some information gathering. To begin with, all the users (lecturer and students) must be registered and logged into the system. The first time that a specific team activity is created, the teacher needs to specify some required information about the activity (e.g. description, start date, end date, etc.).

From the students perspective, some extra information may be required depending on the team formation strategy. Thus, some initial questionnaires may be prepared to be filled by the students. The current version of the framework provides the Belbin Self-Perception Inventory for those strategies based on Belbin's model [7] and the Myers-Briggs Type Indicator (MBTI) personality test for the strategy based on the MBTI model [8]. Apart from these questionnaires, some information about the students can also be introduced such as their concerns, their academic performance (e.g. marks). The tool may also use information from past team activities registered in the systems.

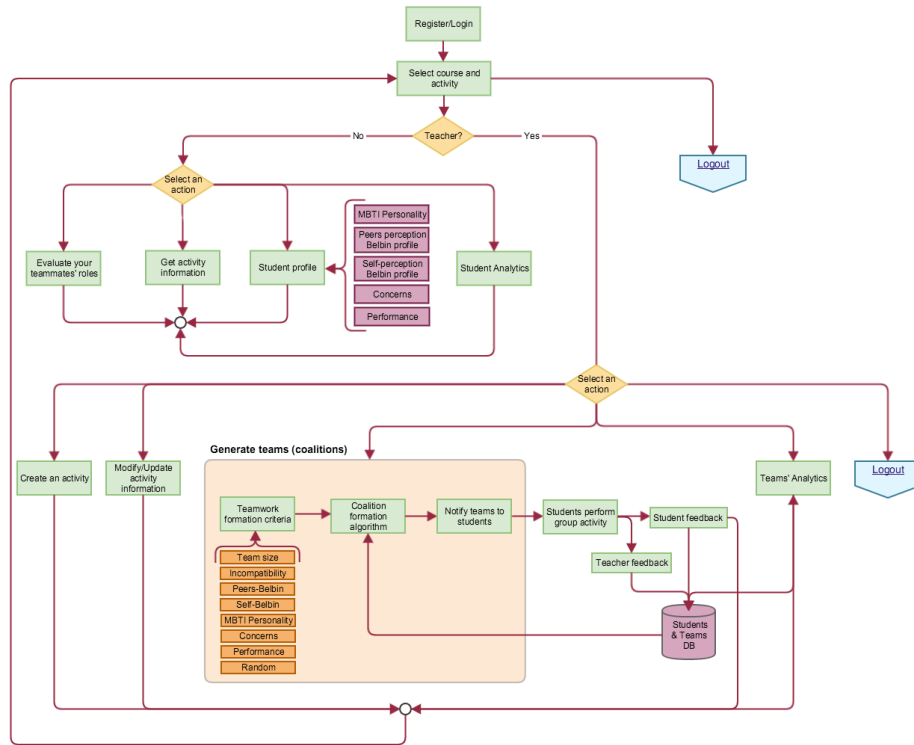


Fig. 1. Activity diagram flow for the testbed

2.2 Team formation

The information gathered in the previous component, and any other information already registered in the system is then used for creating teams in the recently created activity. For that, the lecturer should select a team formation strategy and define general parameters such as the maximum and minimum size for the teams, or any incompatibility among students (e.g., personal conflicts).

Currently, the tool supports a variety of team formation strategies: random teams, a strategy based on the students' performance, a strategy based on the students' concerns, two strategies based on Belbin's role taxonomy (by using self-perception and peers' feedback), and one strategy based on the MBTI model.

The problem of grouping students into optimal teams is equivalent to a coalition structure generation problem. The problem consists of partitioning elements from a global set into exhaustive and disjoint groups, so that the global benefits of the system are optimized. In our problem, the elements of the set are the students participating in the team activity. Let $A = \{a_i, \dots, a_n\}$ be a set of students and let $T_j \in A$ be a subset of A called *team*, the expected value of a team T_j is given by a characteristic function $v(T_j) : 2^A \rightarrow \mathbb{R}$ that assigns a

real-valued payoff to each team T_j . This expected value depends on the specific team formation strategy that is selected.

A *team structure* $S = \{T_1, T_2, \dots, T_k\}$ is a partition of teams such that $\forall i, j (i \neq j), T_j \cap T_i = \emptyset, \bigcup_{T_j \in S} T_j = A$. The expected value of a team structure is denoted by $v(S)$, which is an evaluation function for the team structure. In this work, we consider that the quality of each team is independent of other teams. Therefore, we can calculate the value of the team structure as $v(S) = \sum_{T_j \in S} v(T_j)$.

The goal of the team formation problem is to determine an optimal team structure for the classroom $\underset{S \in 2^A}{\operatorname{argmax}} v(S)$. Taking into account the specific equation, which is associated to each team formation strategy, to calculate the expected value of a given team, our team formation problem requires to solve the following expression:

$$\underset{S \in 2^A}{\operatorname{argmax}} \sum_{T_j \in S} v(T_j) \quad (1)$$

It turns out that partitioning a set of students into disjoint teams while optimizing a social welfare function corresponds to the formalization of coalition structure generation problems. In order to solve this problem, we formally define the coalition structure generation problem as a linear programming problem [9] and solve it with the commercial software *ILOG CPLEX 12.5*¹. Next, we define in general terms each of the grouping strategies.

Random strategy The random team formation strategy is mainly provided for those scenarios in which no information from students is available (cold start). Therefore, the algorithm associated to this strategy provides randomly generated teams, which may or may not be well-balanced.

Strategy based on student concerns This team formation strategy is focused on grouping students according to similar learning concerns. Concerns represent the individual achievement goals of the student in the long term. In the learning context, we focus on what students hope to accomplish during the course (i.e., learn as much as they can about a subject, personal satisfaction, doing the minimum effort to pass the course, or doing well on exams to obtain a high mark). These concerns can influence on how students approach, experience, and perform in classes [5].

Strategy based on academic performance This team formation strategy is purely based on the academic performance obtained by the students. In this approach, students are grouped according to their marks. The current implementation obtains teams whose students have the most similar academic marks (i.e. the standard deviation of their marks is minimized).

¹ <http://www.ibm.com/software/commerce/optimization/cplex-optimizer/>

Strategy based on Belbin Self-Perception This team formation strategy is based on one of the most important theories regarding successful team dynamics, which is Belbin's role taxonomy [7]. Belbin identifies eight heterogeneous behavioral patterns (or roles) that are present in many successful teams in the industry: *plant (PL)*, *resource investigator (RI)*, *coordinator (CO)*, *shaper (SH)*, *monitor evaluator (ME)*, *team worker (TW)*, *implementer (IM)*, and *completer finisher (CF)*. These roles should be played by the different team members in order to facilitate successful teamwork. This model has been widely applied to the classroom environment, where it has shown a variety of benefits [17, 11, 19]. In this approach, each student has one or several roles with a significant score according to the Belbin Self-Perception Inventory. Thus, the expected value of a team is calculated according to the role diversity within the team.

Strategy based on Belbin and peers' feedback The previous strategy may have an important shortcoming. It is based on one's self-perception, which many times may differ from the behaviour that we actually display in a team. A more educated guess on one's behavior may be to include the feedback of those that have worked with the individual. This strategy relies on that assumption.

After each activity, each student evaluates his/her peers by stating the most predominant role of each of his/her teammates. Then, the strategy calculates an estimation of the expected value of the team given the history of evaluations received for each student. After each team activity, the evaluation history grows and, therefore, a more appropriate estimation of students' predominant roles should be present. In order to tackle uncertainty in information provided by students, the strategy employs Bayesian learning, and a probability distribution over roles is calculated for each student. A more detailed description of this strategy can be found in [1].

Strategy based on MBTI The MBTI [8] model focuses on measuring the world's perception and the decision-making process of an individual, from a psychological point of view. The questionnaire defines four different dichotomies of human preferences, each divided in two opposite dimensions: Extroversion (E) -Introversion (I); Sensing (S) - Intuition (N); Thinking (T) - Feeling (F); and Judging (J) - Perceiving (P). This indicator has also been widely used for team formation in educational environment [2, 18, 10]. The basis for team formation in this approach is focused on balancing the personality types. In the current implementation, we calculate the team diversity by using the formula proposed by Pieterse et al. [12], which measures the degree of diversity for each preference dimension within a team. The algorithm associated to this team formation strategy obtains teams in which the number of students with preference dimensions are balanced in as many as the four dichotomies as possible.

2.3 Feedback and analysis

After the completion of an activity, the framework provides some tools to provide feedback from the participants, and to analyze the results.

On the one hand, some questionnaires are prepared to evaluate the teamwork performance in terms of several aspects such as the individual’s satisfaction with the team, the individual’s satisfaction with each partner, the individual’s satisfaction with the work, team dynamics, and the lecturer’s opinion.

This information is processed and delivered to the teacher in order to analyze team performance, and to compare the activity results with previous activities with different/similar team formation strategies.

3 Case Study

We applied this framework in a real in a real education environment, in order to test different team formation strategies. We carried out this in a first semester (2015/2016) module pertaining to the *Tourism Degree Program of at Universitat Politècnica de València*. Specifically, following we show the results of the Belbin self perception strategy, and using the MBTI strategy. It should be highlighted that these experiments were solely carried out for testing purposes and check the behavior of students in the classroom. More specifically, we were interested in studying whether or not well-balanced teams could be formed in terms of the different heuristics. In no case the experiments aimed to compare the performance of the different strategies. A total of 46 students participated in the test. We employed two student cohorts: Group A with 30 students, and Group B with 16 students. According to this, we created teams of 5 members in Group A and teams of 4 members in Group B.

	CW	CH	SH	PL	RI	ME	TW	CF
Significant scores	2	11	15	16	4	5	10	21

Table 1. Number of students with significant scores in the different Belbin roles

We conducted a first test by forming teams according to the Belbin self perception strategy. As mentioned, the performance of a team is measured on the premise that each role should have at least one significant score among team members’ scores. Thus, the highest expected value for a team is the maximum number of roles that can be played by the whole team, i.e. $v(S) = 8$. The role distribution is shown in Table 1. It can be observed, that there were roles such as *CW* that were played by only a few students, while other roles such as *CF* were played by a larger number of students. Despite this, the average expected value of the teams formed by the framework were 6.17 of a maximum of 8 in Group A and 5 of a maximum of 8 in Group B. Therefore, in both cases it was possible to form heterogeneous teams that maximize the team formation strategy.

The second test focused on forming teams according to the MBTI strategy. Table 2 shows the number of students distributed according to their preference for the eight personality dimensions defined by the MBTI model. We must note

	E	I	N	S	F	T	P	J
Group A	19	4	15	11	14	9	4	20
Group B	10	2	10	5	11	4	6	7
Total	29	6	25	16	25	13	10	27

Table 2. Students distributed according to their preference personality dimension

that those students who had not shown a clear preference in some dichotomy, were counted as having preference in both dimensions of this dichotomy. According to this strategy, the highest expected value for a team is the number of personality dimensions that are defined, i.e. $v(S) = 8$. Similar to the previous test, the distribution of personalities among the students was not balanced. As an example, only 6 students had preference in the *I* dimension while 29 students had preference in the *E* dimension. Despite this, the average expected value of the teams was very good compared to the optimal, being 5.65 of a maximum of 8 in Group A and in and 6 of a maximum of 8 in Group B. Again, in both cases it was possible to form heterogeneous teams that maximize the team formation strategy.

These experiments allowed us to test the applicability of these strategies in a real class environment. It was important to assess whether balanced teams would come from a real student population, and the results support this. We are currently running an additional experiment with these strategies that will allow us to compare both in terms of team performance.

4 Conclusions

In this article, we have presented a framework for team formation in educational environments. The framework provides different functionalities to lecturers and students that support the process of team formation. Specially, the framework includes different strategies for team formation, allowing the lecturer to select the most suitable approach depending on the group of students. On top of that, the tool also allows lecturers to compare the results of different team formation strategies after the completion of team activities. We carried out experiments in the classroom to assess the applicability of some of these strategies in a real scenario. The results show that despite the fact that the distribution of roles/personalities is not homogeneous, resulting teams are well-balanced in terms of the maximum value achievable by the heuristics. As for future lines of research, we plan to compare the performance of teams formed by different strategies, in terms of the activities that they carry out.

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