A Team Formation Tool for Educational Environments

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Abstract. Teamwork is a critical competence in the higher education area, and it has become a critical task in educational and management environments. Unfortunately, looking for optimal or near optimal teams is a costly task for humans due to the exponential number of outcomes. In this paper, we present a web application that facilitates the task of automatic team generation of near optimal teams based on collective intelligence, coalition structure generation, and Bayesian learning. This tool has been used in real classroom scenario and the data collected from the experience has been used as input for synthetic simulations. The experiments show that the tool is able of converging towards the optimal solution (team formation) as long as students do not have great difficulties evaluating others.

Keywords: Team formation, Coalitions, Education

1 Introduction

Nowadays, it is widely accepted that teamwork skills are at the heart of organizations' success [20, 4, 22]. In fact, many complex projects are carried out by multidisciplinary teams whose individuals come from different academic backgrounds. In these situations, cooperation mechanisms and correct team dynamics are necessary to aggregate the wide expertise of team members, and to accomplish the team's goal. In fact, team dynamics have been reported to be of critical importance to teams' success [5, 13, 2]. Inadequate team dynamics can lead to opposite results, even if individuals who form the team are successful workers. For all of these reasons, there has been a wide interest in the application of teamwork skills at the classroom. Firstly, it allows students to improve their teamwork skills in a scenario that is similar to the organizational world. Secondly, teamwork is highly correlated with cooperative learning, an active learning methodology that has been documented to report more positive learning results than classic methodologies [9, 8]. Due to these reasons, the European Higher Education Area has described teamwork as a competence on the core of its new education policies [10, 12].

One of the main theories for forming successful teams is Belbin's role taxonomy [1]. In that work, Belbin identifies nine behavioral patterns (i.e., roles) that help teams to succeed in their task: *plant, resources investigator, co-ordinator, shaper, monitor evaluator, teamworker, implementer, and completer finisher*. One of the key concepts underlying this theory is that teams should be formed by individuals playing heterogeneous roles [1, 7]. Therefore, in order to guarantee proper cooperation in a team, including teams of students, teams should be formed attending to the characteristics of individuals. The impact of Belbin's taxonomy has given birth to a wide variety of studies that attempt to form optimal teams of students according to each individual's prominent Belbin role [3, 6, 15]. Many of these approaches usually rely on the completion of a self-assessment form by students that determines their prominent role. However, in many occasions, one's own perception may differ from the actual behavioral patterns shown at the classroom. This situation is also commented by different scholars [19, 21].

Since other students' observations may be a more accurate source of information for estimating the prominent Belbin role teammates, aggregating the opinion provided by students becomes a useful mechanism for determining Belbin's roles. Nevertheless, one should consider that unanimously agreeing on any matter is a very unlikely situation, and, therefore, uncertainty arises as student express different opinions. One of the many applications of Artificial Intelligence is tacking decisions in uncertain environments [17]. On top of that, the problem of forming optimal groups of individuals, known in the literature as coalition structure generation [18, 14], has an exponential cost that exceeds the cognitive capabilities of humans. One of the many applications of Artificial Intelligence is taking optimal, or near optimal solutions, for exponential problems that go beyond the calculation capabilities of humans. Summing up both arguments, Artificial Intelligence becomes a perfect candidate for the problem of forming optimal teams of students in the classroom.

In this paper we present a tool that allows to form teams of students according to Belbin's role taxonomy. It employs Bayesian learning [17] in order to tackle uncertainty regarding students' roles, and coalition structure generation mechanisms for finding optimal teams according to the information provided by students. The rest of this paper is organized as follows. First we present the theoretical an practical model underlying our tool in Section 2. Then we introduce a case of study based on an ongoing experiment carried out in a university course. Finally, we briefly explain the conclusions of this paper and we highlight some future lines of work.

2 Team Formation Tool

During a course, the teacher carries out several team activities in the classroom. The main problem of teachers is how to create teams when there is a high number of students and there is no previous information about the profiles of the students. Considering a classroom of 60 students to be grouped in teams of 6, over than 50 millions of teams can be obtained. In order to support the teacher with a framework to create and manage teams, we propose a software application that prevents teachers from carrying out the costly task of dividing students into optimal or near optimal teams. The application relies on collective intelligence, coalition formation, and Bayesian learning to form proper distributions of students teams.

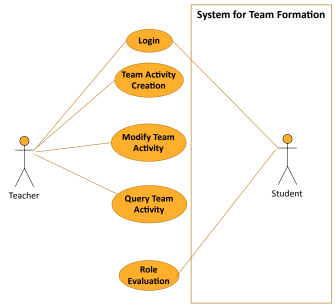


Fig. 1: Use case for the Team Formation Application

The proposed application uses a web platform where the actors, teachers and students, can interact with the system. The main functionalities of the system can be observed in the UML diagram in Figure 1. Both, teachers and students, must log in in the system in order to start to interact with the application. This login allows the system to show a personalized view of the possible actions available for each role.

The usual workflow of the application starts with the creation of a new team activity for an specific course. This action has as result a list of students teams for the team activity. If there is no previous information about the students in the system database, the system provides a random set of groups of students. Otherwise, the system provides a set of groups based on previous evaluations. In the case that the teacher does not agree with the data about the activity or the proposed teams, he/she can modify them through the action *Modify Team Activity*. When teacher considers appropriate, he/she can publish the teams that are notified to the students through an email.

Once the activity has been carried out, the students are allowed to provide their opinion about their teammates in the activity. Basically, each team member, gives an opinion about which is the most predominant role in each teammate. The result of this process is that the new information is stored in a database to be considered in future team formations. This set of actions is repeated during the team activities in the course. The idea behind this iterative sequence of actions is that as the system obtains more information, the system will have more evidences about the predominant roles in each student. This fact should allow the system to form more adequate teams in each iteration.

In the following sections, we describe with detail the two main actions of the web application: *Team Activity Creation* and *Role Evaluation*.

2.1 Team Activity Creation

At the start, the teacher should login in the system (see Figure 2), and then he can create a new activity. After that, the web shows a pull-down menu with the courses associated to the teacher. The teacher selects the activity where he/she is going to create the team activity. Optionally, he/she can fill out all the fields that describe the activity (activity description, start date, end date, on-line material for the activity). The next step consists on determining the maximum and minimum size for the students teams. With these parameters, the application is ready to generate an automatic proposal of teams. If there is no previous information about students, the first set of teams is generated randomly. Otherwise, the system based on the information from previous activities uses a coalition algorithm to generate the set of teams for the activity.

To calculate the teams for the next activity, the system is based on a process of structural coalition formation. The problem of coalition formation can be described as follows.

Let $A = \{a_i, ..., a_n\}$, be a set of students, and $R = \{r_1, r_2, ..., r_m\}$ be the set of roles that the student can play (in our case it is the set of Belbin's roles), and let $role_i$ denote the true predominant role of a_i.

A subset $T \in A$ is called a *team*, and a *team structure* $S = \{T_1, T_2, ..., T_k\}$ is a partition of disjoint teams such that $\bigcup\limits_{\forall T_j \in S} T_j = A$ and $S \in 2^A$. The goal of the application is determining an optimal team structure for the classroom $\underset{S \in 2^A}{argmax}\ \ v(S)$, where $v(S)$ is a evaluation function for the team structure. In this study, we will consider that the quality of each team is independent of other teams. Hence, we can calculate the value of the team structure as $v(S) = \sum\limits_{T_j \in S} v(T_j)$. The value of a team $v(T_j)$ can be calculated attending to the predominant role that each student $a_i \in T_j$ has ($role(a_i)$). Let $|T_j| = k$ denote the size of the team and $\pi_j = \{r'_1, ..., r'_k\}$ with $\forall r'_i \in R$ be a vector with the true predominant role of each team member. In that case, $v(T_j) = v(\pi_j)$. According to different studies [7], the team should benefit from having a balanced distributions of roles (i.e., one person per role). This score can be provided by an expert.

Unfortunately, it is not possible to accurately know the predominant role of each team member π_j and therefore $v(\pi_j)$ cannot be calculated with precision. However, it is possible for us to calculate an estimation of the value of the coalition given the history of evaluations H that is gathered from the students during the course. Let $\pi' = \{role_1 = r'_1, ..., role_k = r'_k\}$ be a vector containing a set of hypotheses for the predominant roles of each team member, and $\mathit{\Pi}$ be the set of all possible vectors of hypotheses for predominant roles of T_j. In that case, we can calculate the expected value of a team given the history of evaluations as:

$$\hat{v}(T_j|H) = \sum_{\pi' \in \mathit{\Pi}} p(\pi'|H) \times v(\pi') = \sum_{\pi' \in \mathit{\Pi}} v(\pi') \times \prod_{a_i \in T_j} p(role_i = r'_i|H) \tag{1}$$

where and $p(\pi'|H)$ represents the probability for π' to be the real role distribution in T_j given the history of evaluations H. Each $p(\pi'|H)$ can be divided into its $p(role_i = r'_i|H)$ since we assume that the role of each student is conditionally independent given the history of evaluations. Therefore, our team formation problem at each iteration is casted out to one problem that follows the next expression:

$$\underset{S \in 2^A}{argmax} \sum_{T \in S} \hat{v}(T|H) \tag{2}$$

It turns out that partitioning a set students into disjoint teams while optimizing a social welfare function corresponds to the formalization of coalition structure generation

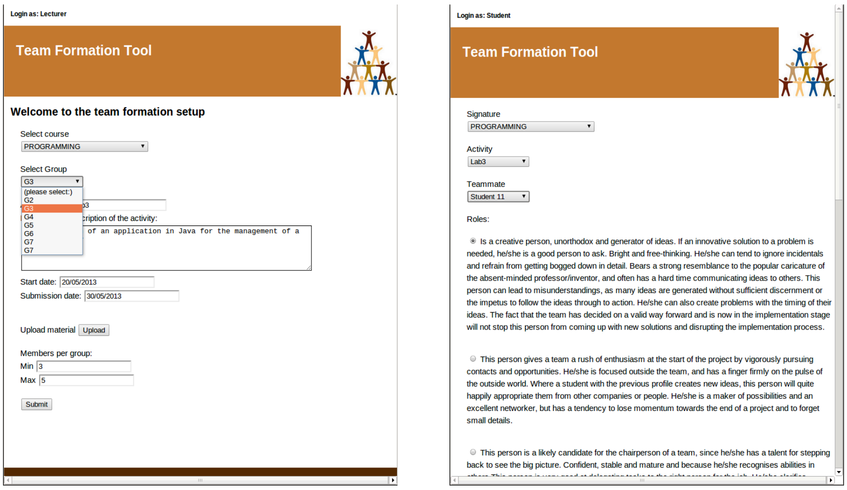


Fig. 2: (Left) Form to introduce the information about the team activity. (Right) Form to evaluate teammates.

problems. For our simulation experiments, we formalize the coalition structure generation problem as a linear programming problem [11] and solve it with the commercial software *ILOG CPLEX 12.5* [1].

2.2 Role Evaluation

Once the activity is finished, each student receives a notification from the system to evaluate his teammates according to Belbin's roles. Each student should login the software application. Then, he/she selects the course, the activity inside the course, and finally the teammate to evaluate 2. Then, the application shows a full description of Belbin's roles. The application does not show the name of the roles, only the description of the main features with the aim of avoiding skewed opinions in the students. At that point, the student should classify each teammate into a role. The information is then gathered by the application and stored in a database.

After the peer evaluation, the application updates the information for each student. Then, new information becomes available regarding the most predominant role of each student and the history of evaluations H grows. Hence, at each iteration we can update information regarding the probability for an agent a_i to have r'_i as his/her most predominant role given the evaluation history $p(role_i = r'_i|H)$. We employ Bayesian learning for this matter :

$$p(role_i = r'_i|H) = \frac{p(H|role_i = r'_i) \times p(role_i = r'_i)}{\sum_{r \in R} p(H|role_i = r) \times p(role_i = r)} \quad (3)$$

[1] http://www.ibm.com/software/commerce/optimization/cplex-optimizer/

where $p(H|role_i = r'_i)$ is the likelihood function and $p(role_i = r'_i)$ is the prior probability for the hypothesis. For the likelihood function, we can calculate it as $p(H|role_i = r'_i) = \frac{\#\{r'_i \in H_i\}}{|H_i|}$, where H_i denotes the peer evaluations about agent a_i, and $\#\{r'_i \in H_i\}$ indicates the number of times that r'_i appears as evaluation in H_i. As for the prior probability, we calculate it as $p(role_i = r'_i) = \frac{\#\{r'_i \in H\}}{|H|}$. Laplace smoothing [16] is employed to ensure that the likelihood for each role hypothesis can be calculated in the first iterations.

3 Case Study

In order to validate the team formation model provided by the tool, in this section we present a case study tested in the 2013-2014 course of Tourism Management at the Universitat Politècnica de València. This course is composed by 60 students that were distributed into teams.

At the beginning of the course, we did not have any information regarding the roles of the students. Therefore, the whole 60 students were firstly grouped into teams of 6 members according to a random criteria, in order to delevop a project. After finishing this project, all the students entered the information regarding their partners. It is important to remark that the evaluation of each individual after this project, would provide a general opinion due to the evaluation of those who worked which him. This general opinion determines the main role associated to this individual. Instead, if relying only on the own self-perception, individuals main role would be determined by considering the self-opinion, which may cause a biased view.

In addition, students were asked about their own self-perception by a test which comprised several parameters associated to the roles. The differences between the self-perception of individuals and the general opinion is around 70%. This means that the self-perception of each student was different from the general opinion of his partners in 7 out of every 10 students. This is a significant, because one individual may be affected by his self-awareness or aspirations to a *co-ordinator* role, but exhibits the behavior of a *plant* role. Therefore, his creative abilities are more appreciated by the others rather than his abilities as *co-ordinator*.

According to these evaluations, Figure 3 shows the number of students which were evaluated by their partners according to these main roles. As it can be observed, the distribution of roles seems to be heterogenous. As an example, it can be appreciated that the number of *co-ordinators* in the whole team is much lower than the number of *plants*. This is remarkable, since the number of students who correspond to a *co-ordinator* role according to their own self-perception is around the 20% of students. In contrast, this percentage is slightly higher than the 3% according to the opinion of the partners.

We must point that some students were not matched to any main role (e.g. an student who was evaluated as four different roles by four partners). However, considering that this is the first project, it is assumed that when performing more projects, the number of evaluations will increase and the roles could be defined more accurately.

Although the number of evaluations for each member is higher than only considering the self-perception of each individual, increasing the number of evaluations through

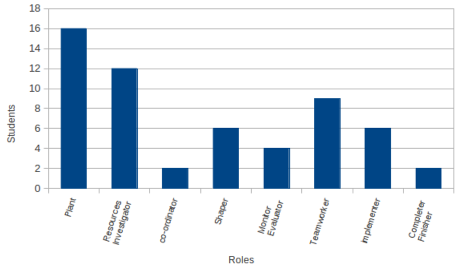


Fig. 3: Roles distribution

several projects would also increase the significance of the roles associated. According to Belbin, a team composed by heterogenous roles would provide higher effectiveness than a team composed by homogeneous roles. Therefore, we can measure this heterogeneity depending on the roles distribution. As a result, a team composed by heterogenous roles has associated a heterogeneity of 1, while a team composed by homogeneous role has a minimum heterogeneity of 0.125. This heterogeneity is related to the satisfaction of the students when working together.

3.1 Simulation

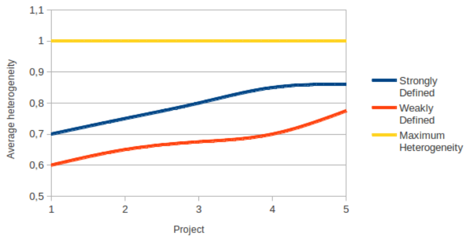
Assuming that the distribution of roles follows the distribution shown in Figure 3, we can simulate the performance of the teams, according to the algorithm provided by the team formation tool (Section 2.1. To do this, we start from the initial distribution of teams and perform 5 iterations of the algorithm (with would correspond with the forthcoming projects). We must note that the distribution of roles is not known by the students, who are only responsible of providing evaluations after each project.

Figure 4 shows the heterogeneity of the teams for each project. We test two different scenarios, one in which the roles of the students are strongly defined and thus, the students are able to determine the main role easier, and other scenario in which the roles of the students are weakly defined and thus, it is more difficult to determine the main role.

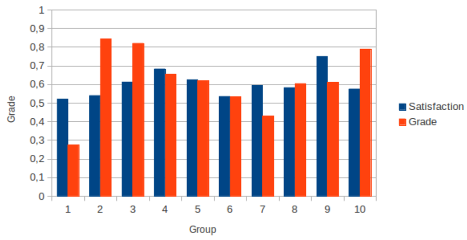
Although the distribution of roles in a real scenario is not homogeneous (there are more students whose main role is role 1 than role 3), it can be observed that as the number of projects increase (and therefore, the evaluations of students), the more heterogenous teams are found after each project. It can be observed that in case that roles are strongly defined (e.g. a student who clearly corresponds to an specific role), the heterogeneity increases earlier.

Figure 4b shows the average satisfaction of each team according to the evaluation of their members, with the real grade obtained with this project. Apparently, there is some relationship with both parameters. It can be observed that teams with high satisfaction (e.g. teams 4 and 9) obtained also a good grade in the project, while teams with lower satisfaction (e.g. team 1) obtained a low grade.

As the feedback provided by the students, we should point out that although the students initially did not like the grouping methodology (since they preferred to work



(a) Execution.



(b) Notes.

Fig. 4: Execution and Notes results

with their friends), they were still able to work together as a team. As a future work, we expect to perform several projects in order to improve the accuracy of the estimation and therefore, the teams performance.

4 Conclusions

In this paper we have presented a tool that facilitates the task of generating teams of students in an educational context. The tool is a web application based on Belbin's role taxonomy [1], collective intelligence, coalition structure generation algorithms, and Bayesian learning. The application facilitates the interaction of the teacher and students with the system. Basically, there are two main stages in the workflow of the application. In a first stage, the teacher generates an activity and the tool recommends a set of teams based on an algorithm of coalition formation. There is a second stage where the students provide their opinion about which is the most predominant role in each teammate. This information is used to improve the team formation process for next activities through bayesian learning. We have tested this tool in a real context and we have used the data collected as input for synthetic simulations. The results show that as long as students do not have great difficulties classifying others, the policy is capable of improving the quality of team structures in a few iterations and gradually converging towards the optimal solution.

We simulated different scenarios in order to test different environmental conditions. The results are encouraging enough to continue this research. As a future work, we plan to extend the experiments in order to consider large populations of students and environmental conditions, such as scenarios where some roles are more important than others. In addition, we also intend to study whether or not the inclusion of more attributes in the classification problem can improve the performance of the policy.

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