Towards Construction of Creative Collaborative Teams Using Multiagent Systems

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Abstract

Group creativity and innovation are of chief importance for both collaborative learning and collaborative working, as increasing the efficiency and effectiveness of groups of individuals performing together specific activities to achieve common goals, in given contexts, is of crucial importance nowadays. Nevertheless, construction of “the most” creative and innovative groups given a cohort of people and a set of common goals and tasks to perform is challenging. We present here our method for semi-automatic construction of “the most” creative and innovative teams given a group of persons and a particular goal, which is based on unsupervised learning and it is supported by a multiagent system. Individual creativity and motivation are both factors influencing group creativity used in the experiments performed with our Computer Science students. However, the method is general and can be used for building the most creative and innovative groups in any collaborative situation.

Keywords: Creative Collaborative Working or Learning Groups, Multiagent System, Unsupervised Learning.

1. Introduction

Group creativity and innovation are of chief importance for both collaborative learning and collaborative working, as increasing the efficiency and effectiveness of groups of individuals performing together specific activities to achieve common goals, in given contexts, is of crucial importance nowadays. Therefore, educational institutions and companies alike have become more and more interested in increasing group creativity in both learning and working situations. *Creative learning* refers to instructional processes that have an extra focus on the development of creative abilities of individuals. *Collaborative creative learning* approaches creative learning that results from interactions and collaborations that take place between learners, while working together to fulfill common goals, and that has potential to enhance creativity both at individual level and group level. Moreover, collaborative creativity may be improved by providing appropriate environments and contexts and by organizing the individuals in suitable groups, as related work shows. However, it is still quite challenging to determine in which way the interactions and collaborations that take place inside a group result in either increases or decreases in creative group performances.

In this paper, we present a method of grouping individuals in *creative collaborative groups* whose creativity is increased iteratively. This method is based on an adapted version of the unsupervised learning algorithm introduced in [40]. The method has been introduced in

[19] and has been developed and evaluated further in [39], being under implementation with support from a multiagent system. This method and the corresponding architecture have been developed from scratch to help us in our continuous work of improving educational processes in which we are involved. The main contributions of the current work are the new architecture of the multiagent system, the algorithm for constructing and storing execution plans, the detailed presentation of an educational experiment performed with our Computer Science students, based on the proposed method, along with an updated and much more comprehensive overview of the related work.

However, the method is general and can be used for obtaining the most creative and innovative groups in any collaborative working or learning situation.

The structure of the paper is as follows: the next section includes the related work, the third one presents our multi-agent system for building creative groups that are involved in collaborative working or learning and with which we have done some preliminary tests in CSCL situations that are presented in Section 4, and the last section include some conclusions and future work ideas.

2. Related Work

In this section we overview the related work that includes three research directions, i.e. creativity in groups, modeling group creativity, and approaches similar to ours with regard to building creative groups. Creativity is a concept highly debated in psychological literature. Sternberg et al. view *creativity as the ability to produce work that is novel (i.e., original, unexpected), high in quality, and appropriate* [34]. Understanding creativity is challenging and has lead to elaboration of many theories, e.g. the *investment theory of creativity* [35, 36]. According to that, creative people are the ones *who are willing and able to, metaphorically, buy low and sell high in the realm of ideas*. Buying low means working on ideas that are not well-known or not popular that, however, have an intrinsic potential for growth. When introduced for the very first time, such ideas may face resistance, but creative people will fight it, and, in the end, they have an important opportunity to "sell" high, an innovative, influential, or popular idea, achieving this way a *creativity habit* [36]. Some authors point out that creativity is multifaceted and can be assessed by measuring *fluency* (creative production of nonredundant ideas, insights, problem solutions, or products)*, originality* (uncommonness or rarity of these outcomes)*, and flexibility* (how creativity expresses itself when using comprehensive cognitive categories and perspectives) [27].

Nevertheless, group creativity is a recent topic in the literature pointing to *the social nature of the creative act* [8]. Group creativity means more that summing up the individual creativities of the members, as the interactions that take place between them within the group, the diversity of members' backgrounds, abilities, and knowledge generate added value in creative processes. Thus, the importance of interactions between the group members and their role in stimulating creative processes contribute to increased group synergy. Several cognitive, social, and motivational factors influence the increase of group creativity such as: exchange of ideas, potential for competitiveness that allow individuals to compare their performances with the ones of their teammates, concept, product and perspective sharing, intrinsic motivation, openness to new experiences, etc. [3].

Amabile introduced the *componential theory of creativity*, along with the elements that influence creativity: at individual level (*domain-relevant skills, creativity-relevant processes, and task motivation*) and external (*the social environment in which the work takes place*). The domain-relevant skills refer to the knowledge and expertise of the individual in a specific field, while the creativity-relevant processes to individual characteristics that favor creativity: cognitive style, personality traits etc. Task-motivation is the internal individual motivation. Moreover, the author points out that *a central tenet of the componential theory is the intrinsic motivation principle of creativity* [2]. In his model of group creativity, Sawyer sees creativity as a synergy between *synchronic interactions* and *diachronic exchanges* [29]. While developing his *multilevel model of group creativity*, Taggar highlights that besides including creative members, team creativity is significantly influenced by *relevant processes that* *emerge as part of group interaction* [38]. Moreover, creativity evolves over time within teams and is influenced by the *climate of creativity*, an essential feature in the *multilevel model of group creativity* of Pirolla-Merlo and Mann [25].

Contextual factors that influence creativity are divided in three categories [45]: (1) *facilitators of team creativity* (supervisory and co-workers support, psychological safety, group process), *(2) obstructers of generation of creative ideas* (conformity, insufficient resources, bureaucratic structure)*, and uncertain factors* (team diversity, conflicts in teams, group cohesion). *An interactionist perspective on organizational creativity* is shown in the interactionist model of individual creative behavior of Woodman et al. Thus, group creativity is seen as *a function of individual creative behavior "inputs"*, *the interaction of the individuals involved* (e.g. group composition), *group characteristics* (e.g. norms, size, cohesiveness), *group processes* (e.g. approaches to problem solving), and *contextual influences* (e.g. the larger organization, the task). Moreover, organizational creativity is seen as *a function of the creative outputs of its constituent groups and contextual influences (organizational culture, reward systems, resource constraints, the larger environment, etc)*. This multifaceted mix boosts *the gestalt of creative output* (new products, services, ideas, procedures, processes, etc.). When building creative groups several characteristics may be considered, at various levels: *individual* (cognitive abilities/style, personality, intrinsic motivation, knowledge)*, group* (cohesiveness, size, diversity, role, task, problem-solving approaches)*, and organizational* (culture, structure, strategy, technology, resources, rewards etc.) [41], [43]. An outline for organization of group creative processes is proposed in [23]. A creative idea generation process was considered with respect to the social interactions inside the selected group, based on general principles from soft computing mathematical models.

Limited experiments with grouping individuals in creative groups are available in the literature. In [17], students involved in collaborative learning are grouped based on their learning styles. A research project that *investigates empirically whether knowledge sharing in community contexts can result in group knowledge that exceeds the individual knowledge of the group's members and concludes that this is the hallmark of collaborative learning* is available in [33]. An experimental study that worked on the assumption that shared cognition influences the effectiveness of collaborative learning and is crucial for cognitive construction and reconstruction of meaning is available in [37]. The work towards an intelligent collaborative learning system able to identify and target group interaction problem areas is available in [31]. Intense social interaction and collaboration are proven to provide for creation of learning communities that *foster higher order thinking through co-creation of knowledge processes* [15]. In [10], the "optimal class" is seen as *a high performing cooperative group with positive interdependence*. The issue of identifying peers and checking their suitability for collaboration, as an essential pre-collaboration task, is approached in [13], which concludes that a more personalized cooperation can take place provided that individual tastes and styles are considered. In [22], the authors approach the *liberating role of conflict in group creativity*, as a possible solution for weaknesses of group creativity, namely social loafing, production blocking, and evaluation apprehension. They have carried out an experiment in two countries to prove that brainstorming may benefit significantly from dissent, debate, and competing views, stimulating this way divergent and creative thought. In [26], the authors build up on two main ideas, namely that creative groups fuel both innovation and organizational change and that collaborative systems can be used to team up individuals across the globe in creative groups. They are concerned with the relation between individual creative preference and group creative performance across different phases of creative problem solving, in a group supported system. After experimenting with 250 students, their results indicate that *group member creative styles play an important role in determining the groups' productivity as well as certain qualities of the solution they pick*.

3. GC-MAS - A Multiagent System for Building Creative Teams

This section includes a brief presentation of our multi-agent system for building creative and innovative teams. The goal is grouping individuals in "the best" teams possible and our approach is innovative in the sense that grouping individuals in creative and innovative teams in an iterative semi-automated process has not been performed yet, up to our knowledge. This work builds up on previous work [19], where the very first architecture of the system was introduced. However, after experimenting with it, we have refined it further and reduced the number of agents, some of them having more complex roles, such as the facilitator agent.
The current system architecture includes the following agents, in which all the agents are task agents, except for CommGC (Fig. 1):

- *The Communication Agent (CommGC)* has a dual role, being responsible with interfacing with the users (both students and instructors) and with the agents, along with managing the activities of the other agents;
- *The Creative Groups' Builder (BuildGC)* is an agent that assists the construction of creative groups based on an unsupervised learning algorithm;
- *The Creativity Evaluation Agent (EvalGC)* assesses each group creativity;
- *The Creativity Booster (EnvrGC)* boosts development and maintenance of contextual environments that provide for increasing group creativity;
- *The Facilitator Agent (FclGC)* facilitates a more efficient group interaction, e.g. by sustaining the team members who are shyer or less active. It also provides support for seeking out and taking on otherwise neglected tasks that have potential to facilitate creative group performances.

CommGC acts as a middle agent and has a horizontally stratified structure, in which each level is connected directly to both the input sensors and the output effectors (software entities that perform particular actions). Each level acts as an individual agent that provides the expected action. The two levels of CommGC are as follows: (1) *the social level* that ensures the communication with the other agents, the users, and with the external environment, as a true personal/interface agent, and (2) *the administrative level* that coordinates the actions of all the agents (see Fig. 2).

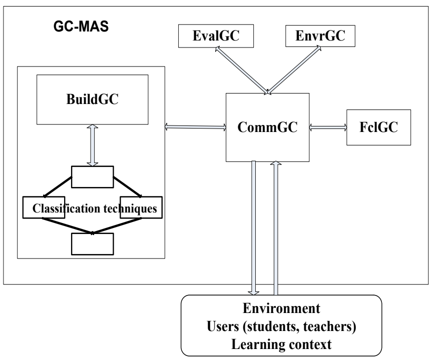

Fig. 1. GC-MAS - the bird's eye view architecture.

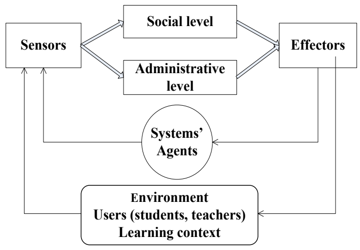

Fig. 2. The architecture of CommGC.

The agents *BuildGC, EvalGC, EnvrGC* and *FclGC* are execution agents that perform precise actions in construction of creative groups. They have a very simple structure, are goal-oriented, and use plan libraries or classification techniques to perform their duties, as it can be seen in Fig. 3. At the core of execution agents is their plan library, as *planning is essentially automatic programming: the design of a detailed course of action which, when executed, will result in the achievement of some desired goal* [44]. *A plan library (PL)* is defined by a set of inputs (plans) $PL=\{P_1, P_2, \ldots, P_n\}$, which an agent uses to achieve its goals. Such an input includes the plan's pre-conditions, body, and its post-conditions. A plan P_i is defined as $P_i=<pre_i, body_i, post_i>$. *The pre-condi*tion is defined by a logical expression and each time the value of this expression is true the specified/associated plan is executed. *The post-*

condition specifies the goal that an agent is supposed to fulfill. *The body* of a plan is a computer program specified by a sequence of primitive actions that is executed when its pre-condition is true (1).

$$< actions\_sequence >=< primitive\_action >< actions\_sequence > |NULL \quad (1)$$

The plans are built using a constructor. One of the most well-known algorithms for this purpose is the STRIPS planning algorithm, in which a means-ends analysis is performed to find an action sequence that will lead to achieving the goal [6]. Planning is seen as a search of an action sequence in a state space based on the pre-conditions and on the outcomes of the actions. Another approach consists in adaptation of the existing plans to a specific situation (case based reasoning) [1]. The plan constructor is seen as a black box that returns a plan solution given a plan description. In GC-MAS, we use the algorithm for constructing and storing a plan in Fig. 4. First, we abstract the state of the system and its goal and we model them with a conjunction of primitive states (2), respectively of primitive goals (3) i.e. that cannot be decomposed any further. For example, primitive states could be *the learning style is visual or the motivation of the student is intrinsic*. A primitive rule is defined as follows: *if state then primitive_action*. A priority function is associated to each primitive rule P: R→N, where R is a set of rules and N is the set of natural numbers. The priority function helps solving the selection conflict when for the same pre-condition more than one action may be chosen. In such cases, the action with the highest value of priority function will be selected. The primitive actions and rules are stored in libraries available to each agent. The algorithm generates a plan that leads the system to achieve the goal **g** starting from a state **st**. Two situations are similar if their composing states and goals are similar. Two states *State1* and *State2*, respectively two goals *Goal1* and *Goal2* are similar if their similarity index is above a fixed threshold (4, 5).

$$State = st_1 \wedge st_2 \wedge \dots \wedge st_n \quad (2)$$

$$Goal = g_1 \wedge g_2 \wedge \dots \wedge g_m \quad (3)$$

$$State1 = st_{11} \wedge st_{12} \wedge \dots \wedge st_{1n} \; State2 = st_{21} \wedge st_{22} \wedge \dots \wedge st_{2m} \quad (4)$$
$$state\_index_{similarity} = |\{st_{11}, st_{12}, \dots, st_{1n}\} \cap \{st_{21}, st_{22}, \dots, st_{2m}\}|$$

$$Goal1 = g_{11} \wedge g_{12} \wedge \dots \wedge g_{1n} \; Goal2 = g_{21} \wedge g_{22} \wedge \dots \wedge g_{2m} \quad (5)$$
$$goal\_index_{similarity} = |\{g_{11}, g_{12}, \dots, g_{1n}\} \cap \{g_{21}, g_{22}, \dots, g_{2m}\}|$$

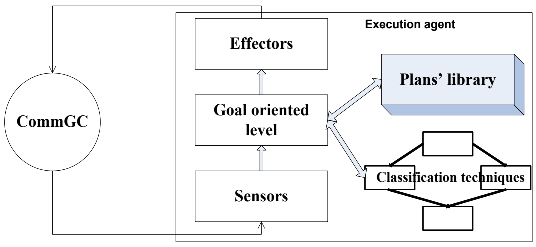

Fig. 3. The architecture of an execution agent.

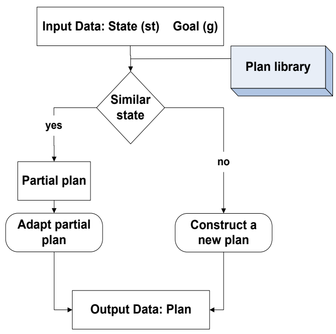

Fig. 4. The algorithm for plan construction.

Case I. A similar situation does exist, so there is a plan whose pre-condition is similar with the system state and the plan post-condition is similar with the desired goal (Fig. 5). This plan is selected, adapted if necessary for the similar situation, and then stored in the plan library. The procedure for plan adaptation is as follows:

- If the system state contains the plan pre-condition and the agent's goal is included in the plan post-condition then the plan remains unchanged;
- If a goal that is not included in the plan post-condition exists then a backward search is performed in the state space (built from the plan libraries and rules) to

determine a sequence of primitive actions that leads to that goal, given the system's state. This particular sequence of primitive actions is included in the selected plan to obtain its adaptation to a similar situation.

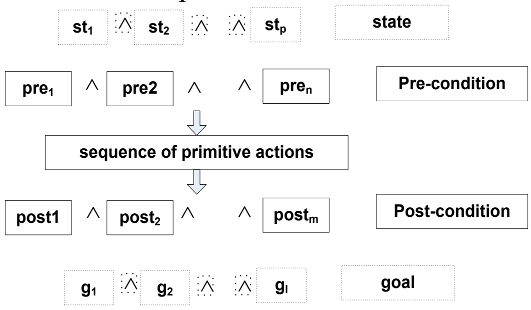

Fig. 5. A similar situation exists.

Case II. A similar situation does not exist

For each sub-goal g_i of the goal, a sequence of primitive actions is searched so that their execution leads to the desired goal starting from a particular state. The action sequences that are found this way are further combined to form the body of a plan.

BuildGC - The Creative Groups' Builder aims at construction and iterative refinement of creative groups taking into account factors that boost creativity, their interdependencies and the purpose of building of particular creative groups. *The input data* for BuildGC are *student data* (individual features that influence group creativity), *group data* (the purpose of constructing creative groups, i.e. the problem to be solved, the task to be completed, the research to be undertaken etc., the group size, the diversity of group members, etc., and support data generated by both users and other agents autonomously or as a result to the queries addressed by *BuildGC*. *The output data of BuildGC* consists of both the most creative learning groups buildable and the queries to other users and agents with respect to the process of group construction. In our experiments, BuildGC had the plan structure as follows: the pre-conditions consisted of each student's creativity features, the body consisted in a prediction reasoning tool based on an adapted version of the Q-learning algorithm [19], [40], while the post-condition included the best organization of a cohort of students in creative groups so that the value of Q is the largest possible for each group. In brief, this algorithm is a reward learning algorithm that starts with an initial estimate *Q(s, a)* for each pair <*state, action*>. When a certain action a is chosen in a state s, the intelligent system (the agent *BuildGC* in our case) gets a *reward* R(s, a) and the next state of the system is acknowledged. The function value-state-action is estimated as:

$$Q(s,a) \coloneqq Q(s,a) + \alpha\big(R(s,a) + \gamma max_{a'} Q(s',a') - Q(s,a)\big) \tag{6}$$

Where $\alpha \in (0,1)$ is the learning rate, $\gamma \in (0,1)$ is the discount factor, and s' is the state reached after executing the action a in the state s. The way in which the values for the learning rate and for the discount factor should be selected is discussed in [14]. Value 0 for the learning rate means that the value for Q is never updated and that the system never learns. Selection of a higher value means that learning is faster. In our first experiments, we used a 0.5 learning rate. The discount factor has values between 0 and 1. Closeness to 1 means that a future reward is more important to the system than an immediate reward, i.e. that the importance of a future reward is increased, as γ is still below 1. A balance between the immediate rewards and the past rewards is sought for in dynamic environments.

From GC-MAS's point of view, the environment consists in the students, the instructor, and the learning context (as in [28]). For *BuildGC*, the agent that computes the best grouping of a cohort of students in creative teams, the environment is the structural organization in a set of groups. However, the groups' structure changes over time, as the agent learns from its interactions with its environment how to construct more and more creative groups. To fulfill its goal of building the most creative k groups, *BuildGC* uses the GC-Q-learning adapted algorithm [19]. In this case, the reward is the "value of group creativity" that ranges between

1 and 5. The goal here is to obtain a final state, *namely an optimal organization of students in groups*, each such group having a creativity value larger than a desired threshold. The GC-Q-learning algorithm is as follows:

1. Build a bi-dimensional matrix *Q* for all the possible pairs <*state, action*>. The columns of this matrix consist of *(c_1, c_2, ..., c_m, no_group, action_number, q)*. A value of the *action_number* of *i* means that if a particular type of student (given by his creativity vector c_1, c_2, ..., c_m) will be moved to the group having the value of *no_group i* then her contribution to group creativity is quantified by q (in this stage). All the elements in the q column may be initialized with 0 or with a randomly chosen low value. On each line of the matrix, the data that corresponds to each type of student involved in the grouping process is included, i.e. the values of his characteristics, the current group number, the action number, and the value computed for *q (that quantifies a potential for creativity)*. One particular type of student could have more related lines, one for each combination <*current group number, action*>;
2. Initialize the *optim_policy* with an initial policy. In our case, the optimal policy is the optimal grouping of students for boosting group creativity. The initial grouping is set by the instructor and the students together;
3. Group the students and have them carry on working sessions, in which each group's creativity is assessed and its score is assigned to the reward *R(s,a)*. The values of *R(s,a)* are obtained for now with help from human experts. We may say that R *materializes* that potential for creativity (q). Then, the matrix *Q* is re-calculated for each such working session. This procedure is shown below.

```
procedure working_session_computation
select action of (optimal_policy)  /* student grouping*/
compute R(s,a)
compute table Q /* using formula (6)*/
```

4. Analyze the group creativity for each group against the global objective (the optimal grouping policy), which is getting closer to the maximum value possible for R, for each group or for all the groups. Re-iterate from step 3, if necessary.

Once the optimal policy consisting in tuples *(c_1, c_2, ..., c_m, group number)* is obtained and *BuildGC* has learned enough, *predictions may be made for each new type of student, given his set of characteristics*. The predictions consist of a series of group numbers, which are presented sorted decreasingly according to the contribution made by that particular generic student to each group's creativity. Thus, the first number in the series is of the group in which that generic student would contribute the most to the group creativity, the second one of the group in which she would make the second best contribution, and so on. Other classification techniques may be used as well (neural network based classifiers, Bayes classifiers, decision trees, or support vector machines). A detailed description of the Bayesian networks-based classification techniques can be found in [7], [11]. We have already worked on this idea of building the most creative and innovative collaborative groups using Bayes classifiers with encouraging results [18].

EvalGC - The Creativity Evaluation Agent supports assessing of group creativity based on criteria for measuring ideation, namely novelty, variety, quantity, and quality [30]. It uses a plan library to achieve its goals of (1) recording the ideas generated by the group and classifying them, (2) calculating the frequency of good ideas' production (as the number of innovative and useful ideas per time unit), and (3) keeping the creativity score and ensuring the communication via *CommGC*.

EnvrGC - The Creativity Booster aims to enhance group creativity by providing for contextual environments that include consistent activators that contribute to creativity boosting. The agent works by "pushing on" the creativity triggers specific to the situation. In our case, this action can be performed using a fuzzy controller with which we have worked previously [20].

Facilitator Agent-FclGC provides for a more efficient group interaction, e.g., by sustaining the team members who are shyer or less active, and by supporting seeking out and taking on otherwise neglected tasks that have potential to increase creative group performances. The execution plans of this agent are presented below:

FclGC - Execution plan 1
Pre-condition: whenever the number of ideas generated per minute is more than 10;
Body: the agent asks the online group members to focus on the task to do, following their common goal; specific creativity triggers: advising; motivation;
Post-condition: group refocuses on the task at hand, draws some conclusions.

FclGC - Execution plan 2
Pre-condition: whenever a group member has not been active, generating ideas or contributing to the discussions for 5 minutes;
Body: the agent asks that member to say a new idea or to make a comment on what it has been said so far; specific creativity triggers: advising; motivation;
Post-condition: a new idea/comment made by the less active member is generated.

FclGC pro-actively prevents situations in which group members focus entirely on coming up with their own ideas and ignore completely (to build on) the ideas of others, which is an essential added value of working together in a group [4]. For this situation, the execution plan of FclGC is as follows:

FclGC - Execution plan 3
Pre-condition: every 15 minutes or every 25 ideas generated;
Body: the agent asks the online group members what they think about the ideas generated so far and if they could build up on them for a while instead of generating new ideas; specific creativity triggers: reviewing and replaying session histories;
Post-condition: students overview previous ideas and build up on them for 5 minutes.

4. A Real World Educational Experiment

To use this method, one needs to initially group the students randomly or based on their interpersonal affinities, then have them work as groups in a particular (educational or working) scenario, after which their group creativity can be assessed. Based on their creativity characteristics and using the adapted Q-learning algorithm, the composition of the groups may change in order to reach the global creativity objective. The goal here is to obtain a final state, *namely an organization of students in groups*, in which either each group will have a creativity value larger than a desired threshold or the average creativity on all the groups will be higher than such a threshold). Further on, the obtained data (group creativity is the reward of the algorithm) is fed back to the algorithm and, this way, *it learns over time what is the best option of moving a (particular type of) student in the group in which s/he has the maximum contribution to the group's creativity*. Globally, for a pool of students, the objective is to group the students so that the global creativity objective is reached [39].

After clarifying the conceptual aspects of GC-MAS, we have been concerned with investigating the viability of our approach and therefore we have tested it in some educational scenarios with our Computer Science students (both undergraduate and graduate). In this section, we present briefly an educational experiment performed using the proposed approach. More details about a similar larger experiment may be found in [39]. The main stages of the experiment have been as follows:

1. *The evaluation of each student's individual creativity and motivation using several evaluation tools*. To assess individual creativity, we have used both the Gough Creative Personality Scale [9] [39] and an extended version of the Creative Achievement Questionnaire [4] that we have adapted for Computer Science students. We present here the data obtained using Gough Scale, which is simpler and easier to understand. Generally, the Gough Score values range between -12 and 18. The

student motivation can be low (having value 0), middle (1), or high (2) and it has been determined using our adapted questionnaire based on MSLQ (Motivated Strategies for Learning Questionnaire) [24] [39].

2. *Initial organization of students in groups based on their inter-personal affinities.* Have them carry the first online brainstorming session. Evaluation of the group creativity for each group. If the global objective has been reached then stop.
3. *Activation of the BuildGC agent for the students' cohort to group them in the most creative groups possible.* First, this agent will indicate for each student to which group will contribute the most to group creativity. Based on that, a student may be moved to a group for which his q value is among first 30% in decreasing order (*to raise the potential for increasing group creativity*). Then the collaborative creative activity takes place, in our case a second online brainstorming session.
4. *Evaluation of group creativity for each group involved in the experiment*. If the global objective has not been reached, re-iterate from stage 3.

The experiment included three online brainstorming sessions on subjects of interest for them: (1) the improvement of both the curricula and the syllabuses for our Computer Science programs (undergraduate and graduate), (2) the preferred teaching and learning methods, and (3) the enhancement of their student life within university and campus. Each session had to end with a final conclusion on the issues discussed. We used brainstorming here just for measuring group creativity, but any kind of appropriate evaluation can be used.

For this experiment, the *Q* matrix had 45 lines and 5 columns. Each column consists in, respectively, the Gough score, the motivation value, the current group number, the action number (that means to move her in the group in which she would contribute the most to group creativity, given her characteristics), and the *q* value. On each line of the matrix we have the data that correspond to each type of student involved in the grouping process, i. e. the values for: the Gough score, the motivation, the current group number, the action number, and the value of *q*. We present below some experimental results obtained while trying to group in increasingly creative teams several pools of students having various values for *the creativity pair* (Gough score, motivation value). In this experiment, we had 5 types of students characteristic-wise with these pairs as follows: (3,1), (3,2), (2,1), (2,2), and (4,1), and we have studied 9 possible groups. In Table 1 the sample data for the students having the pairs (2,1) and (4,1) are shown. The interpretation of this data is that a student with the pair (2,1) would contribute the most to the group creativity if s/he would be in group 2, and decreasingly - in group 5, 7, 8 or 4. A student with (4,1) would contribute the most to the group creativity if s/he would be in group 3, and decreasingly - in group 5, 7, 9, or 6.

Table 1. Sample Data for Students with Creativity Pair (2,1) – left and (4,1) – right.

Gough score	Student motivation	Action – move to group no	Q value	Gough score	Student motivation	Action – move to group no	Q value
2	1	1	0	4	1	1	0
2	1	2	**3,5**	4	1	2	0
2	1	3	0	4	1	3	**3,78875**
2	1	4	1,9	4	1	4	0
2	1	5	2,705	4	1	5	2,777188
2	1	6	0	4	1	6	2,277188
2	1	7	2,54	4	1	7	2,612188
2	1	8	2,54	4	1	8	0
2	1	9	0	4	1	9	2,612188

However, the individuals are not grouped and re-grouped indefinitely, as the algorithm learns during time in which group a person should be to contribute the most to group's creativity. So, it can make a recommendation in this sense. In our particular case, during our work with the students involved, throughout their university years, both as undergraduate and graduate, we have evaluated the creativity of the teams obtained in this way and the results show that they are, indeed, more creative than ad-hoc or buddy teams, as they consistently obtain better evaluations of teamwork results [18, 19], [39]. But the method is general and can be used in any collaborative working situation where increasing group creativity is required.

5. Conclusions and Future Work

We introduced here our semi-automated method of grouping team members in increasingly creative groups, which has been tested using a multiagent system prototype. Moreover, we have performed some experiments for grouping individuals involved in online brainstorming, the results being encouraging so far. Thus, our first results show that students can be more creative provided that they are included in appropriate groups for activities that involve teamwork [18, 19], [39]. The importance of taking into account how the teams are made for such activities is pointed out once again in accordance with the results of other similar research [10], [12], [13], [15], [17], [22], [31], [33], [37]. It seems to make more sense to apply this semi-automatic grouping method for groups of people aiming at becoming teams, over long periods of time, such as university or working years. Though, the method can be used also for groups formed for shorter periods of time because it is based on characteristics that quite often have the same values for different people (for instance, the creativity pair <individual creativity, motivation>), so the process does not need to start from scratch each time, but just build up on previous results. More tests on various scenarios need to be performed, in various learning or working activities, with diverse pools of individuals, using control groups, and so on. More factors that influence group creativity need to be taken into account too, for example, group interactions and the way they develop over time, and also evaluation of group creativity using appropriate metrics.

Development of a software tool that implements the method presented here would be very useful to assist in construction of the most creative and innovative groups in particular learning or working scenarios and contexts and in other collaborative scenarios as well. Other future work ideas include corroborating the results obtained with several creativity evaluation scales, assessment of creativity before and after activities assumed to help trigger creativity and innovation, inclusion of contextual and organizational factors, using various classifiers, improving the algorithm, and, finally, offering the method as an online open service.

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