Towards Building Creative Collaborative Learning Groups Using Reinforcement Learning

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Abstract

Increasing creative skills in collaborative groups is of huge interest for stakeholders in education, industry, policy making etc. However, construction of “the most” creative groups given a cohort of people and a set of common goals and tasks to perform is challenging. The complexity of this undertaking is amplified by the necessity to first understand and then measure what “the most” creative means in a particular situation. We present here our method of semi-automatic building of “the most” creative learning groups given a cohort of students and a particular learning context based on *reinforcement learning* (an adapted Q-learning algorithm). Various attributes that influence individual and group creativity may be considered. A case study on using this method with our Computer Science students is also included. However, the method is general and can be used for building collaborative groups in any situation, with the appropriate “the most” creative goal and attributes.

Keywords: Collaborative Groups, Optimally Creative Learning Groups, Reinforcement Learning, Computer Supported Collaborative Learning

1. Introduction

Educational paradigms adjust continuously to stay tuned with the continuous change in our society. Promoting collaboration and boosting creativity in learning are major trends nowadays. Hence, increasing creative and collaborative skills of both students and employees is currently of huge interest for stakeholders in education, industry, policy making, etc. However, creativity is a concept still highly debated in the psychological literature. Sternberg et al. see *creativity as the ability to produce work that is novel (i.e., original, unexpected), high in quality, and appropriate* [19]. *Group or collective creativity* is a much more recent topic in the literature, which takes into account *the social nature of the creative act* [7]. Nevertheless, group creativity means much more that summing up the individual creativities of group members, as the interactions that take place between them, the stimulation, both cognitive and motivational, that results from these interactions, the diversity of their backgrounds, their abilities and knowledge contribute further to adding value in creative processes, resulting in *a true synergy* [5]. *Collaborative learning groups* are working groups that evolve during common educational scenarios that unfold over long periods of time and, generally, become teams, based on the evolution of the relationships inside the group. Their creativity can be approached within augmented collaborative learning environments, in which group members work creatively, both individually and collaboratively, to fulfill particular tasks, to complete specific projects, or to achieve particular goals. The results of their work can be problem solutions, papers, overviews, (pieces of) software or hardware, documents, essays etc. These results are evaluated by instructors who assess the creativity of the resulted products and, this way, a measurement of group creativity can be obtained. An example of an augmented collaborative learning environment can be a classroom with instructional materials and/or equipments (e.g. drawings, robots, drones, maps etc.), along with a set of teaching and learning methods (problem-based learning, brainstorming, project-based learning, game-based learning, etc.) that stimulate innovation and imagination.

Various approaches may be taken to build optimally creative collaborative learning groups given a cohort of students and a learning context. During the eighties, Amabile has developed *The Componential Model of Creativity* for individual creativity, which she has further extended to team creativity and innovation in organizations [1], [4]. Further, in 2012, she proposed a componential theory of creativity, which includes three within-individual components (domain-relevant skills, creativity-relevant processes, task motivation) and a non-individual component, i.e. the social environment [2, 3]. Her theory points out that creativity calls for a convergence of all these components and that creativity should be at peak when a deeply motivated and very skillful in creative thinking person with high domain expertise works in an environment providing highly for creativity [2, 3]. Similarly, Taggar has shown that team creativity is significantly influenced by relevant processes that emerge as part of group interaction [18]. Further, based on the theoretical bases of synergy, in [5], the authors identify the cognitive, social, and motivational factors that influence the increase of group creativity: 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.

Contextual factors that influence group creativity are summarized in [21] as being factors that facilitate team creativity (supervisory and co-workers support, psychological safety, group process), factors that obstruct generation of creative ideas (conformity, insufficient resources, bureaucratic structure), and uncertain factors (team diversity, conflicts in teams, group cohesion). In [6], the authors analyzed the cause-effect relationships between 6 factors: team creativity, exploitation, exploration, organizational learning culture, knowledge sharing, and expertise heterogeneity. Several correlations have been found, for example, to sustain high levels of team creativity both organizational learning culture and knowledge sharing should be high. A model of collaborative creativity that takes into account four categories of variables and three categories of processes which influence creativity and innovation is provided in [13]. The four categories of variables are: group member variables, group structure, group climate, and external demands, while the three categories of processes are: cognitive, motivational, and social. The research in [15] shows that creativity is multifaceted and it can be assessed by measuring *fluency* (creative production of non-redundant ideas, insights, problem solutions, or products), *originality* (uncommonness or rarity of these outcomes), and *flexibility* (how creativity manifests itself when using comprehensive cognitive categories and perspectives).

However, construction of creative groups is not straightforward and, up to our knowledge, research on this subject is rather scarce. An overview is available in our previous works [11, 12], though most of the (very loosely) related work do not use data mining techniques, machine learning, nor intelligent data analysis neither take into account individual creativity measures to support the construction of creative collaborative groups.

We introduce here *a method based on reinforcement learning* (an adapted Q-learning algorithm) *to semi-automatically build optimally ("the most") creative learning groups*, given a cohort of students and a particular learning context. Various attributes that influence individual and group creativity may be considered. However, the method is general and can be used for obtaining "the most" creative groups in any learning, working, or other collaborative situation. Reinforcement learning is an area of machine learning concerned with how software agents learn to take actions within an environment (as a result of their interaction with that environment) so that they maximize some cumulative reward. In the typical reinforcement learning model, an agent is connected to its environment via perception and action. On each step of its interaction with the environment, a particular agent receives as input some indication of the current state of this environment and it then chooses an action that changes the state of the environment. The value of this state transition is communicated to the agent through a scalar reinforcement signal. The agent is expected to behave by choosing actions that tend to increase the long-run sum of values of this reinforcement signal. It can learn to do this in time by prearranged trial and error iterations directed by a wide variety of algorithms [9]. The most well-known algorithms for solving problems using reinforcement learning are based on Q-learning [20] and SARSA-learning [16].

During this work, we used an adapted Q-learning algorithm to build "the most" (optimally) creative groups given a cohort of students and a particular learning context. *Individual creativity* and *motivation* are the attributes that influence group creativity, which have been taken into account in the case study included here. Individual creativity has been assessed using the Gough Creative Personality Scale [8], while students' motivation has been determined using our adapted questionnaire based on MSLQ [14]. This case study has been performed with our Computer Science students and it is based on the algorithm introduced briefly in [12]. Particularly, we have determined, for each student, to what group's creativity s/he would contribute the most, given the attributes considered.

The structure of the paper is as follows: the general Q-learning algorithm is shown briefly in Section 2, while the third one includes the adapted version used in our method for building creative groups. Section 4 presents the results obtained when using this method in a particular educational context, while the last section includes some conclusions and future work ideas.

2. The Q-Learning Algorithm

In brief, the Q-learning 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 gets a reward R(s, a) and the next state of the system is acknowledged. The Q-learning algorithm estimates the function value-state-action as follows:

$$Q(s,a) \coloneqq Q(s,a) + \alpha\big(R(s,a) + \gamma max_{a'} Q(s',a') - Q(s,a)\big) \qquad (1)$$

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". Values for the learning rate and for the discount factor are selected according to [10]. The higher the value of the learning rate the faster the learning is, while a value of 0 means that the value for Q is never updated, and therefore the system never learns. When the learning rate is 1 it means that the immediate reward is much more important than a past reward. A balance between the immediate rewards and the past rewards is sought for in dynamic environments. In our first experiments, we had used a 0.5 learning rate. The discount factor takes values between 0 and 1. Closeness to 1 means that a future reward is more important than an immediate reward, i.e. that the importance of a future reward is significant (as γ is still below 1). The pseudo-code of the Q-learning algorithm is presented below [20].

```
initialize random Q-values (Q(s, a)) for each pair <state, action>
      repeat (for each scenario)
            initialize s
            repeat (for each step of scenario)
                  choose a using a policy derived from Q
                  observe s, execute a, observe reward R, observe s'
                  update Q(s,a)
                  s:=s'
            until s is terminal
```

3. GC-Q-Learning Algorithm for Building Creative Groups

The GC-Q-Learning adapted algorithm used in our method is presented further on. It starts with *n* students. For each student, *a creativity vector c* that includes “m” individual characteristics that influence creativity is constructed, i.e. $c=(c_1, c_2, \ldots, c_m)$. In fact, for this algorithm, a student is not a particular person, but a particular *type of student* given by her set of characteristics. Therefore, all the students having the same creativity vector will be a generic student for our algorithm. *A state* consists of this creativity vector and the group number of each student, while *an action* consists in moving a student to another group in which *he would contribute the most to increasing group creativity*. *Q* expresses the quality of association between a state and an action. Our goal is to build “the most” creative *k* groups (*k* being given). The state space includes the set of tuples that can be built taking into account that each characteristic can have a finite number of values. The size of action space is given by the number of groups (*k*) to be constructed. More individual characteristics taken into consideration would lead to increasing the dimension of the state space, which can result in difficulties in implementing the algorithm. For the time being, the main characteristics taken into account in our case studies have been the following: *individual creativity, motivation, domain knowledge,* and *inter-personal affinities* [11, 12].

When using this algorithm, a large number of students to be grouped at once can be challenging as well. Thus, for *n* students and *k* groups, each group will contain the closest natural number larger or equal with *n/k* (when *n/k* is not a natural number, the rest of students (*m*) is distributed, randomly, one student per each of the already formed groups). The number of groups that can be obtained this way is $C_n^{n/k}$, which can be very large for particular values of *n* and *k*. Though, for reasonable group size, between 10-30 students, the algorithm can be applied easily, while significantly larger cohorts of students need to be divided in smaller groups, randomly, and only then perform the algorithm on these groups.

The GC-Q-Learning algorithm computes the best organization of a cohort of students in creative groups, while the environment consists mainly of this *structural organization* [17]. Of course, the structure of the groups generally changes over time, as the system learns from its interactions with its environment how to construct more and more creative groups. The reward is the value of group creativity and it ranges between 1 and 5. The global creativity objective 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. The GC-Q-learning adapted algorithm is as follows:

1. Build a bi-dimensional matrix *Q* for all the possible pairs <*state, action*>. The columns consist of $(c_1, c_2, \ldots, c_m,$ *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 $c_1, c_2, \ldots, c_m$) 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 corresponding lines, one for each combination <*current group number, action*>;

2. Initialize the *optimal_policy* with an initial policy. In our case, the optimal policy is an optimal grouping of students that maximizes group creativity. The initial grouping is set by the instructor and the students together and experience shows that they tend to group as cliques based on their inter-personal affinities;

3. Group the students and have them carry on working sessions (in the case study presented here those were several *online brainstorming* sessions, but any collaborative situation involving creativity can be used), 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 with help from human experts (in our tests, they have scored each idea in each session). 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 presented below.

```
procedure working_session_computation
select action of (optimal_policy)  /* student grouping*/
compute R(s,a)
compute table Q /* using formula (1)*/
```

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, an intelligent system (or an agent) based on this algorithm has learned to build the most creative groups given the circumstances. Consequently, it can make prediction for *each new type of student*, given his set of characteristics, using advanced classification techniques (Bayesian networks, neural networks etc.). 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. We have already worked on this idea of building the most creative and innovative collaborative groups using Bayes classifiers with encouraging results [11].

4. Experimenting with the GC-Q-Learning Algorithm

In this section, the data obtained during one of our testing of the GC-Q-Learning algorithm is presented. This particular one was performed on 36 undergraduates in Computer Science, who participated voluntarily in three working sessions. We have grouped and re-grouped these students during the three sessions, aiming at having each student being a member of the group to which creativity s/he contributes "the most" according to our assumptions. In this testing, *individual creativity* and *motivation* were the attributes included in the creativity vector. The Gough Creative Personality Scale [8] has been used to assess each individual's creativity. Generally, the Gough Score values range between -12 and 18. Students' motivation has been determined using our adapted questionnaire based on MSLQ (Motivated Strategies for Learning Questionnaire) [14] (both are presented in the apendices). It contains 31 statements with a possible value between 1 and 7 (1 means that the statement is totally untrue, 7 means that the statement is completely true, while scores between 2 and 6 are somewhere in between). In our trials, we considered low motivation between 31 and 93 (the associated motivation score being 0), medium motivation between 94 and 155 (motivation score 1), and high motivation between 156 and 217 (motivation score 2). After evaluation, we have obtained the following classification of students with respect with their creativity vector:

Table 1. Classification of students with respect with the creativity vector.

Creativity vector ***(Individual Creativity, Motivation)***	**Number of students**
(2,1)	6
(2,2)	3
(3,1)	9
(3,2)	12
(4,1)	6

The students regrouped repeatedly in groups of four by permutation. Three online brainstorming sessions took place 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 alike. Each session had to end with a final conclusion on the issues discussed. We used brainstorming here just for measuring group creativity, but any other way of appropriate evaluation can be used. These sessions have taken place online to avoid some of the shortcomings of the face-to-face brainstorming sessions emphasized in the literature.

In total, the creativity for the 27 groups (three sessions, each session involved nine groups) has been measured using the scores below (human expert evaluated):

- A score R1 has been given after evaluation of the quality of ideas generated by each group of students;
- A score R2 has been given for the frequency of ideas generated by each group of students;
- A score R3 has been obtained for the quality of the final conclusion of each session; this evaluation was performed by human experts.
- A final score, R, has been computed as the mathematical mean of the three scores above. It will be the reward used by the algorithm (Table 2).

For this working session, the Q matrix had 135 lines (because there are 5 types of students having the characteristics (3,1), (3,2), (2,1), (2,2) and (4,1) and 27 groups) and 4 columns. Each column consists in, respectively, the Gough score, the motivation value, the action number (that means to move her in the group in which she would contribute the most to that group's creativity, if included in it, given her characteristics), and the q value. On each line of the matrix the data that correspond to each type of student involved in the grouping process is available, i. e. the values for: the Gough score, the motivation, the current group number, the action number, and the value computed for q. We present below some data sample consisting of 9 groups of 4 (type of) students given by their creativity vector (Table 2: Label C = individual creativity, Label M = motivation score).

Table 2. Creativity Vector (Individual Creativity, Motivation) of each student of each group.

	Student i		**Student j**		**Student k**		**Student l**		
No. of group	**C**	**M**	**C**	**M**	**C**	**M**	**C**	**M**	**R (Reward)**
1	3	1	3	2	3	1	3	1	3
2	2	1	2	2	2	1	3	2	4
3	4	1	4	1	3	2	3	2	4,33
4	3	2	2	1	3	2	3	2	3
5	3	1	2	1	3	2	4	1	3,66
6	3	1	3	1	2	2	4	1	2,66
7	3	1	3	1	2	1	4	1	3,33
8	3	2	2	1	3	2	3	2	3,33
9	3	1	2	2	4	1	3	2	3,33

We present below some testing results obtained while trying to group, in increasingly creative teams, several pools of students having various values for *the creativity vector (Gough score, motivation value)*. In the case study presented further on, we had 5 types of students characteristic-wise, with the above mentioned pairs as follows: (3,1), (3,2), (2,1), (2,2), and (4,1), and we studied 27 possible groups, each formed with 4 students. The value of both the learning rate α and the discount factor γ were 0.5. In Table 3 and Fig. 1, some of the sample data for the students having the creativity vector (3,1) are shown. The action to be performed is moving such a student in a particular group, the computed q value being shown as well. The interpretation of this data snapshot is that a student with the pair (3,1) would contribute the most to the group creativity if s/he would be a part of group 7, and decreasingly - of group 1, 6, 5, or 9. Group number 7 is composed of 4 students with the characteristics pairs as follows: (3,1), (3,1), (2,1), and (4,1) (according to Table 2).

To use this method, one needs to group the students randomly or based on their interpersonal affinities, then have them work as groups in a learning scenario. Based on the values of their creativity vector and using the adapted Q-learning algorithm, the composition of the groups may change. Thus, 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. 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*. The goal here is to obtain a final state, namely *an organization of students in groups*, in which either *each such group has a creativity value larger than a desired threshold or the average creativity on all the groups is higher than such a threshold*.

Table 3. Sample Data for Students with Creativity Vector (3,1).

Gough score	Student motivation	Action: *move to group no*	Q value
3	1	1	3.46875
3	1	2	0
3	1	3	0
3	1	4	0
3	1	5	2.697188
3	1	6	3.295781
3	1	7	**3.798281**
3	1	8	0
3	1	9	2.532188

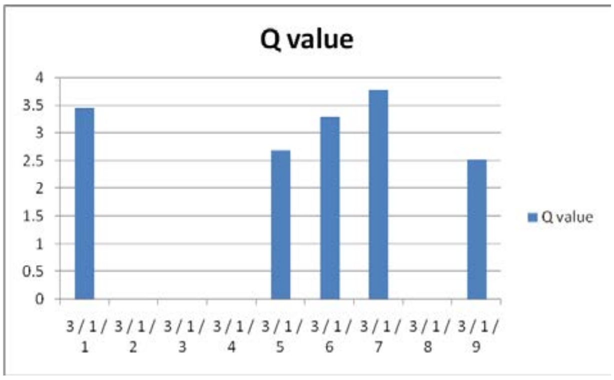

Fig. 1. Q value – students with (Gough, motivation): (3,1).

However, the students are not grouped and re-grouped indefinitely, as the algorithm learns during time in which group a student should be to contribute the most to group's creativity. So, it can make a recommendation in this sense (which, of course, can be followed or not by the instructors and students based on their learning objectives at that time).

We present here some evaluation data obtained during the educational activities related to the Software Engineering class. The performance of the groups is measured by two grades, which are granted based on several criteria that measure both the performance of each group as a whole and each individual contribution. These criteria assess the developed software, the related documentation, the difficulty of the problem, the creative and innovative solutions used during development and for the presentation of the final product, the complexity of the algorithms, the cost-effectiveness of the solution, the degree of being a close-knit team, and so on. The two grades are midterm and final, they being obtained for the initial, respectively, optimally created groups. As it can be seen below in Table 4, the performance of the majority of students is higher after this collaborative learning experience (the average grade of each group is presented). And this is not just an isolated situation, as we have already performed this kind of grouping, in similar circumstances, for 4 years now, and the results are consistent and show increased learning with respect to both domain expertise and soft skills achieved. Thus, 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 [11, 12].

Table 4. Sample data obtained while evaluating the method.

Year	Team	Midterm average group grade	Final average group grade
2018	1 (8 members)	6.87	7.50
	2 (8 members)	7.00	7.25
	3 (6 members)	9.00	9.33
	4 (7 members)	7.00	7.28
2017	1 (7 members)	6.14	6.85
	2 (5 members)	7.20	7.60
	3 (5 members)	5.00	5.00
	4 (6 members)	8.00	8.33
2016	1 (6 members)	7.16	9.16
	2 (6 members)	6.16	8.16
	3 (4 members)	6.50	7.50
	4 (5 members)	6.40	7.40
2015	1 (6 members)	7.66	9.16
	2 (4 members)	5.00	6.00
	3 (7 members)	8.42	10.00
	4 (3 members)	6.00	7.00

5. Conclusions and Future Work

One of the invariants of nowadays life is, paradoxically, continuous change that takes place in more and more aspects of our life. To keep pace, existent paradigms have to perpetually shift to better adapt to our constantly changing world. In this sense, education and collaboration among people have had an astonishing entwined evolution that allows better accomplishment of important common goals. For example, creativity and innovation are very much valued and sought after both in 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. Consequently, promoting collaboration and boosting creativity in learning and working are major trends nowadays, so group creativity has become an active topic of creativity research. However, despite the consensus that both individual creativity characteristics and inner interactions inside groups influence collaborative creativity, the construction of "the most" (optimally) creative groups given a cohort of people and a collaborative context is challenging. Various approaches may be taken based on various factors that influence creativity, both at individual and group level. Our approach in this work has been based on two important such factors, namely individual creativity and motivation. Well-known scales have been used as such or adapted to evaluate these factors in case of a cohort of Computer Science undergraduates, who volunteered to participate in this experiment that aimed at increasing group creativity in a collaborative learning context.

During successive online brainstorming sessions we have grouped and re-grouped the participants according with the results provided by the reinforcement algorithm aiming at obtaining "the most" creative groups possible given that particular cohort of students, their evaluated creativity scores, and the particular learning context. The algorithm has learnt, in time, in which particular group each (type of) student should be, so that s/he can contribute the most to a particular collaborative creativity.

This is work in progress and many future work directions unfold. More experiments on various learning scenarios need to be considered in Computer Science education, as well as in other domains, with diverse cohorts of students, evaluating group creativity using various metrics, maybe using control groups if this can be done respecting the principle of pedagogical fairness, etc. More factors need to be taken into account too, for example, group interactions and the way they develop over time. Testing the method in other collaborative contexts would be valuable as well. Development of a software tool that implements the method would be very useful to assist the construction of the most creative groups in particular collaborative scenarios.

Despite the promising results so far, the method is not to be used exclusively because it has an important limitation, i.e. the fact that all the factors that influence creativity need to be evaluated by numbers, while it is well known that same cannot be assessed that way whatsoever (for example, interpersonal affinities). Combining this method with others that allow using linguistic values, such as weak, strong, etc., seems to provide for a viable solution of semi-automatic grouping people in the most creative groups possible in a given collaborative context, this being the most important future work direction.

Of course, it makes more sense to apply this semi-automatic grouping method for groups of people aiming at becoming teams, during long periods of time, such as university or working years. However, 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 example, the creativity vector <individual creativity, motivation>), so the process does not need to start from scratch each time, but just build up on previous results.

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Appendix A: *Gough Personality Scale*

Please indicate which of the following adjectives describe yourself the best. Check all that apply. The scoring key is between the brackets and it is not known by the people being evaluated.

______ Capable (+)	______ Honest (-)
______ Artificial (-)	______ Intelligent (+)
______ Clever (+)	______ Well-mannered (-)
______ Cautious (-)	______ Wide interests (+)
______ Confident (+)	______ Inventive (+)
______ Egotistical (+)	______ Original (+)
______ Commonplace (-)	______ Narrow interests (-)
______ Humorous (+)	______ Reflective (+)
______ Conservative (-)	______ Sincere (-)
______ Individualistic (+)	______ Resourceful (+)
______ Conventional (-)	______ Self-confident (+)
______ Informal (+)	______ Sexy (+)
______ Dissatisfied (-)	______ Submissive (-)
______ Insightful (+)	______ Snobbish (+)
______ Suspicious (-)	______ Unconventional (+)

Appendix B: *MSLQ (Motivated Strategies for Learning Questionnaire) adapted for Computer Science students*

Please rate the following items based on your beliefs on a 7 point scale where *1=not at all true for me* and *7= very true for me*. For anything in between choose a number between 2 and 6. Please rate each item choosing the scoring that suits you the best.

1.	Being enrolled in a Computer Science study program, I prefer classes that are challenging and trying to put me to test, so that I can learn new things.	
2.	Provided that I will study properly, then I will be capable of acquire the knowledge in the curricula.	
3.	When taking a test, I kepp thinking how low my results will be compared with other students.	
4.	I think that I will be capable to use what I have learned during university years to other training or study programs and jobs.	
5.	I think I will graduate with a good GPA.	
6.	I amm sure I can understand the most difficult materials or ideas thought or found in the obligatory readings.	
7.	Obtaining a good GPA at graduation is the most satisfying thing for me at this point.	
8.	When I am taking a test, I can not stop thinking about the parts that I cannot solve adequately.	

9.	It is my doing wrong if I will not be able to acquire the knowledge required as a Computer Science graduate.	
10.	It is important to me to acquire the knowledge required as a Computer Science graduate.	
11.	Improving my GPA is the most important for me now, therefore my main concern is to get good grades.	
12.	I am confident that I can acquire the knowledge, abilities and skills required as a Computer Science graduate.	
13.	If I am able, I want to get better grades than most of my colleagues.	
14.	When taking tests or exams, I think of what may happen if I do not pass.	
15.	I am confident that I can understand the most comple material thought at this study program.	
16.	Being enrolled in a Computer Science study program, I prefer classes that make me curious even though they are difficult to understand.	
17.	I am very interested in the content of the courses thought at this study program.	
18.	If I try enough, I can understand the content of the courses thought at this study program.	
19.	I worry great deal about tests.	
20.	I believe that I can do an excellent job with regard to the given assignments, tests, and exams.	
21.	I expect I will be able to do well as a student of this study program.	
22.	The most satisfying thing for me as a student of this study program is to try understand the content of the courses as completely and as deeply possible.	
23.	I think that the instructional materials used for each course are useful and help me learn.	
24.	When given the opportunity during a class, I choose taks from which I can learn something new, even though that does not guarantee a good grade.	
25.	My not understanding of the content of the curricula thought is due to not working hard enough.	
26.	I like the subjects of the courses thought during this study program.	
27.	To understand the content thought is important to me.	
28.	I am very nervous when taking a test.	
29.	I am sure I can excell at the competencies achieved during this study program.	
30.	I want to do well during university years and at graduation because I want to show my capabilities to my family, friends, employeers or to others.	
31.	Taking into account the difficulty of this study program, the faculty and my abilities, I think I will do well as a student here.	