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Factors Influencing Group Creativity of Computer Science Students: A Fuzzy Cognitive Map

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Abstract

Educational paradigms transform constantly to stay tuned with the change in our society. Promoting collaboration and boosting creativity in learning are major trends today. Therefore, increasing creative and collaborative skills of both students and employees is currently of immense interest for stakeholders in education, industry, policy making etc. In this paper, we first overview the main factors shown in the literature as having an influence on group creativity. Then, we approach the construction of the most (optimally) creative groups given a cohort of students and a particular learning scenario, based on the influence of various factors on group creativity. Our method is based on using fuzzy cognitive maps to capture the influence of these factors on group creativity, which are built accordingly with the results in the literature, our experience, and empirical data obtained during the instructional activities of our Software Engineering class. However, the method is general and it can be adapted to any learning scenario in any domain. A procedure on using this method is available as well.

1 Introduction

Increasing creative and collaborative skills of both students and employees is currently of immense interest for stakeholders in education, industry, policy making etc. Despite the abundance of research on factors that influence creativity of individuals and groups or teams, only few works mention metrics that express dependency rates between these factors and creativity [1-5]. When it comes to creativity, we acknowledge the difference between *group* and *team*. While both terms represent multiple people working together towards a common objective, in the case of teams collaboration relationships between the members have been established over longer periods of time compared to groups [2]. Furthermore, as a consequence of the shared work past, the team members have developed similar interests and affinities towards certain subjects. Moreover, often they share the same values.

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. Creativity of learning groups can be approached within augmented collaborative learning environments in which student learning groups work creatively, both at individual and social level, to fulfill particular tasks, to complete specific projects, or to achieve some particular goals. The results of their work can be problem solutions, papers, overviews, (pieces of) software or hardware, documents, essays, etc. The degree of creativity of these results is evaluated by instructors 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 imagination, creativity, and innovation.

The focus of this paper is dual, first to overview the main factors shown in the literature to have an influence on group creativity and, second, to present our work on using fuzzy cognitive maps to capture the influence of these factors on group creativity. The fuzzy cognitive map that we have constructed is based on the results in the literature, our experience, and empirical data obtained while working with Computer Science students enrolled in our Software Engineering course. However, the method is general and it can be adapted to any learning scenario in any domain. A procedure on using this method for a given cohort of students and a particular learning scenario is available as well.

The structure of this paper is as follows: the next section includes the related work, the third one presents fuzzy cognitive maps, the fourth one introduces our work on using fuzzy cognitive maps to capture the influence of various factors on group creativity within learning scenarios, while the last section include the conclusions and some future work ideas.

2 Factors that Influence Creativity of Groups

In this section, we overview the related work on group/team creativity and on creativity during working and learning situations. In [6], the authors have analyzed the cause-effect relationships between 6 factors: team creativity, exploitation, exploration, organizational learning culture, knowledge sharing, and expertise heterogeneity. The main research issue addressed in this work was *how do the processes of creative revelation—exploitation and exploration—engaged in by team members contribute to building team creativity, and how do environmental factors—organizational learning culture, knowledge sharing, and expertise heterogeneity—affect team creativity*. A general Bayesian Network of the dependencies between these factors and team creativity have been used within scenario-based simulations to show that a direct relationship exists between team creativity and exploitation, exploration, organizational learning culture, knowledge sharing, and expertise heterogeneity. Also, exploration is correlated to organizational learning culture and exploitation is associated with expertise heterogeneity. Moreover, to sustain high levels of team creativity both organizational learning culture and knowledge sharing are ought to remain high [6]. Team creativity is influenced by a variety of team characteristics such as size, Skills, Knowledge and Abilities (SKAs), diversity (age, gender, ethnicity), psychological and participative safety, leadership, conflict or cohesion groups, and group confidence [2]. In [3], the authors raise an interesting issue related to group creativity, namely the tendency toward conformity, and propose inclusion of new members as a coping mechanism that further stimulates innovation.

Cultivation and promotion of creativity are highly sought after in Higher Education and personalized learning and game-based learning are seen as important ways of acquiring these goals in [7]. 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 [8]. 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. Learners' creativity can be triggered by several factors such as awareness of creativity's role within our society and in everyday life, development of social skills, using critical thinking models, encouraging brainstorming sessions followed by questions' and answers' sessions, involvement in multicultural or multidisciplinary tasks, etc. [9, 10].
Strong dependencies between learning styles and creativity results from a study presented in [11]. Identification of the relationship between learning styles and learners' creativity is researched

actively in educational psychology because it could help with identification of correct guidance and careful planning for motivating learners to develop and adopt appropriate pedagogical models [11]. A model for evaluation of activities that cultivate creative skills and attitudes, which can be used during planning of educational processes, is provided in [12]. Three main categories of indicators are taken into account, i.e. *cognitive category* (the student's abilities to reason on the content at hand, to make connections between existing elements, to create hypotheses and to construct new meanings while accomplishing the proposed task); *affective category* (that shows how much students like and value what they learn and how much they engage in the proposed activity and that also reflects their emotional status, behaviors, and attitudes they show while working on their task), and *meta-cognitive category*, which illustrates students' ability to take the overall process under control either during or at the end of the learning activity [12].

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 [13, 14]. Building on her previous work, she also proposed a componential theory of creativity which includes *three within-individual components* (*domain-relevant skills*, *creativity-relevant processes*, *task motivation*) and a component outside the individual, i.e. the *social environment* [15]. This theory emphasizes that creativity calls for a convergence of all these and that *creativity should be highest when an intrinsically motivated person with high domain expertise and high skill in creative thinking works in an environment highly supporting creativity*.

There is still a lot of controversy in the literature about the way in which some factors influence creativity, i.e. positively or negatively. For example, in [5], group cohesion is generally seen as positive, but it can also lead to rejection of criticism and less critical thinking, resulting in lower creativity and innovation. Moreover, for service oriented teams, task conflict has shown no effect on team creativity, while relationship conflict was *significantly and negatively related to team creativity* [5]. For other type of teams that focus on technology projects, no effects were determined for relationship conflict, while *task conflict was strongly associated with increased creativity* [5]. Other factors are considered as well in the literature, but so far the results are non conclusive – for example, with regard to group diversity, some studies show its positive effects, other show the opposite, while some find no effect whatsoever [2].

3 About Fuzzy Cognitive Maps

Our approach consists in using Fuzzy Cognitive Maps (FCMs) to analyze the influence of various factors on group creativity. *FCMs are fuzzy-graph structures for representing causal reasoning* [16]. FCMs derive from both cognitive maps and fuzzy logic and capture the dynamic of modifications within systems. Axelrod has introduced Cognitive Maps (CMs), as digraphs with the vertices representing *concept variables* and the arcs showing *the causal relations* between the concepts (with two possible values -1 or 1) [17]. The value +1 associated with an arc from the vertex A to the vertex B shows that A causally increases B, while -1 shows that A causally decreases B. CMs are represented with adjacency matrices having elements -1, 1 or 0. The value 0 signifies that there is no arc between the respective vertices, i.e. no causality between the respective concepts exist. Kosko has extended the cognitive maps allowing that values on the arcs belong to the interval [-1, 1] and iteratively computed the influence of a factor (vertex) on other factor (vertex) using neural networks-based methods [16]. The values associated with the arcs are causal values and can be defined by fuzzy values. Considering the following linguistic terms for causal values *{very low<=low<=none<=some<= high<=very high}* associated to links between nodes, a FCM with 4 concepts is represented in Fig. 1.

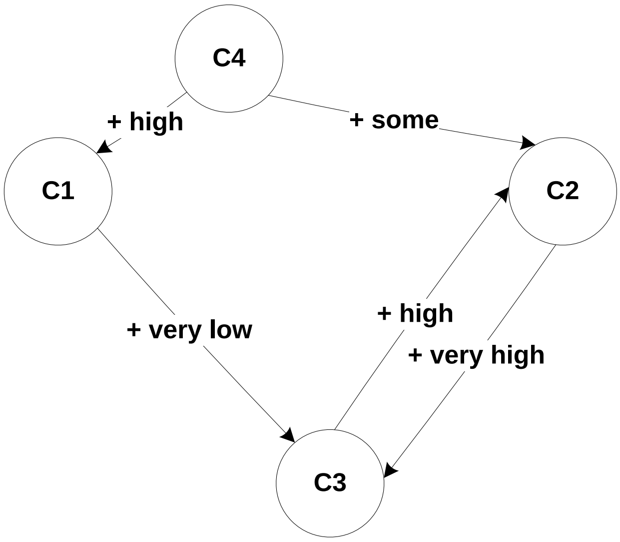

Figure 1: A Fuzzy Cognitive Map with 4 Concepts

To determine how the modification value of the concept C4 will affect the value associated to the concept C3, the technique presented in [16] can be used. Thus, there are two causal paths between concepts C4 and C3: (C4, C2, C3) and (C4, C1, C3).

The indirect effect through (C4, C2, C3) is:

$$min\{some, very\ high\} = some. \quad (1)$$

The indirect effect through (C4, C1, C3) is:

$$min\{high, very\ low\} = very\ low. \quad (2)$$

The total effect of C4 on C3 is:

$$max\{some, very\ low\} = some. \quad (3)$$

FCM can be also seen as a type of *Recurrent Artificial Neural Network (RANN)* with learning capacity [20, 21]. In this case, the values associated to arcs are called weights and take values in the interval [-1,1]. A FCM containing 4 concepts is presented in Fig. 2.

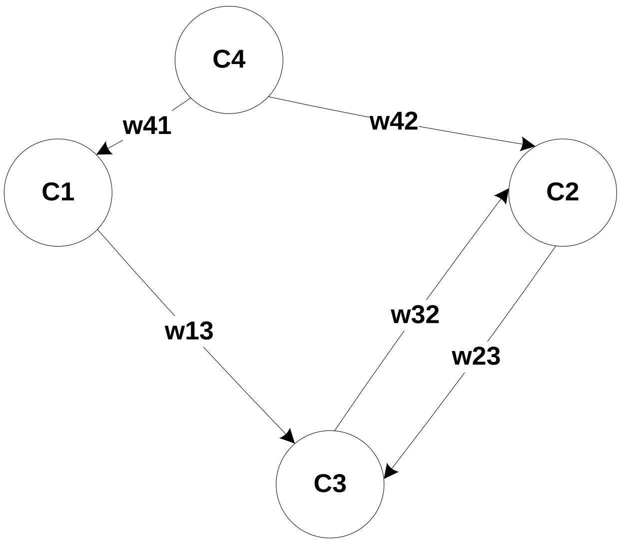

Figure 2: A Fuzzy Cognitive Map (as RANN) with 4 Concepts

The concepts are represented using vertices and the arcs between vertices show the dependencies between the respective concepts.

- A positive weight ($w_{ij}>0$) means that an increasing of the value of a concept C_i will determine an increasing of the value of the concept C_j;
- A negative weight ($w_{ij}<0$) means that an increasing of the value of a concept C_i will cause a decreasing of the value of the concept C_j;
- A null weight means that there are no dependencies between the concepts C_i and C_j.

The concepts' values are calculated using formula 4.

$$c_i(t) = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n} c_j(t-1)w_{ji}\right) \quad (4)$$

where n represent the number of concepts (in our case n=4), $c_j(t)$ is the value associated to the concept C_j, f is a transfer function, and w_{ji} is the weight of the link between C_j and C_i.

The most used transfer functions in FCMs are the sign function, the trivalent function, or the sigmoid function [20, 21]. More information on FCMs can be found in [16-21].

FCMs can be built using human expertise or using training data sets and a learning algorithm. The FCM that captures the dependencies between various factors and group creativity in this work has been built based on the results in the literature, our experience, and empirical data obtained while working with Computer Science students enrolled in particular course.

4 A Fuzzy Cognitive Map on Group Creativity in Computer Science Higher Education

A general FCM that represents the dependencies between group creativity and some factors identified in the related work is shown in Fig. 3. The arc between group creativity and learning style is purposely left unlabelled because no established correlation is available yet and, moreover, tackling this issue is very difficult given the variety of learning styles (visual, auditory, kinesthetic, etc.). The group dimension has to be relatively small to have a positive influence on creativity, but not to small – for example, a group of five will generally be more creative than a group of two. Some factors may have a negative influence on group creativity, for example, too much or too little controversial communication or task conflict [5]. The biggest challenge of building a FCM for group creativity consists in determining each value associated to each arc between a specific factor and group creativity.

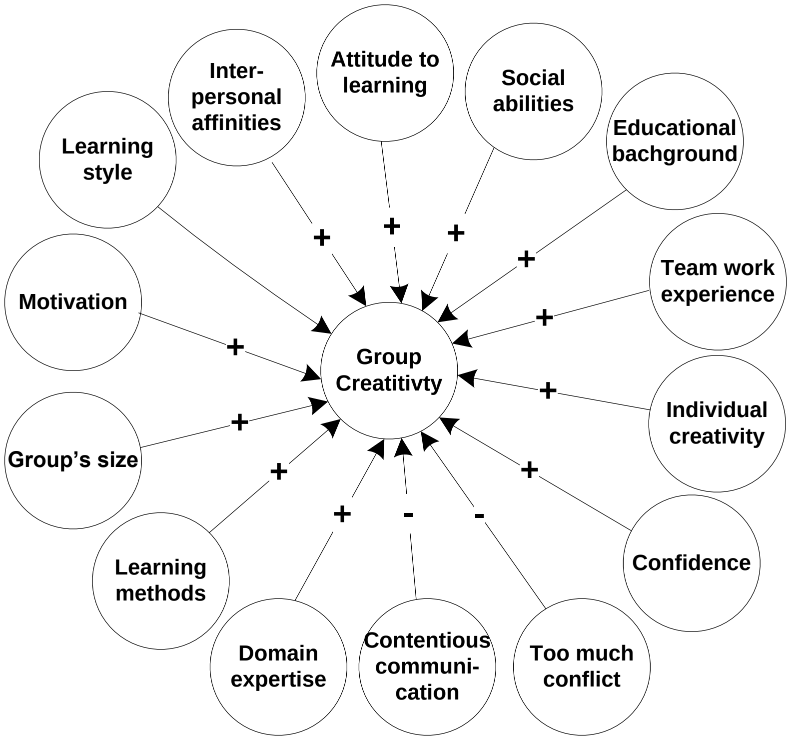

Figure 3: A FCM for Group Creativity

One of our real-world experiments aiming at building such a FCM was performed two years ago on 20 of our final-year Computer Science students enrolled in the Software Engineering course. The final grade measures both how well they have achieved the course requirements with respect to the domain knowledge and how well they work together in small developers' teams that need to complete a common software development project and to present properly their work. For our first Group Creativity – Fuzzy Cognitive Map (GC-FCM) we have considered only four factors: *individual creativity, motivation, domain expertise, and inter-personal affinities*. We aim to continue this work and to consider more and more factors, and to evaluate the degree in which each such factor influences group creativity.

First, we performed a Gough-based evaluation of creativity of our students [25]. In general, the range of individual creativity on the Gough scale is [-12, +18]. The creativity score mean in our case is 2.55 (Table 1). The values obtained for the two other attributes considered in the classification are shown in Table 1 (the students are distinguished by their unique identifier). The domain expertise is the grade obtained at the Data Structures and Algorithms class, while they were sophomores. We have chosen this grade because the programming part of the Software Engineering project consists of developing Java computer applications with fundamental data structures and algorithms. The motivation attribute has been determined using a questionnaire based on MSLQ that we have adapted for Computer Science students. MSLQ is a multi-item, self-report Likert-scaled instrument designed to assess motivation and use of learning strategies by college students [22]. A value of 2 for motivation means a highly motivated student, a value of 1 means a motivated student, while a value of 0 means a less motivated student.

Table 1: Individual creativity factors of final-year students

	Gough score	Domain Expertise	Motivation
Learner 1	5	8	2
Learner 2	4	8	1
Learner 3	7	8	2
Learner 4	7	10	2
Learner 5	8	8	1
Learner 6	3	8	2
Learner 7	2	7	0
Learner 8	2	6	0
Learner 9	2	6	1
Learner 10	-2	5	0
Learner 11	8	10	1
Learner 12	-2	7	1
Learner 13	-1	6	2
Learner 14	7	7	1
Learner 15	4	8	1
Learner 16	0	5	2
Learner 17	5	5	2
Learner 18	3	5	0
Learner 19	-5	6	0
Learner 20	-6	6	0

During this real-world scenario, the students have grouped themselves in small teams based on their inter-personal affinities (the members of each teams were buddies). Four cliques resulted this way (the numbers between parentheses are student identifiers), namely Group 1 (1, 2, 3, 4, 5, 6), Group 2 (7, 8, 9, 10), Group 3 (11, 12, 13, 14, 15, 16, 17), and Group 4 (18, 19, 20).

When the group creativity was measured (by evaluating their projects with respect to meeting the requirements, including creativity), we obtained the following results:

- no group was in the high creativity class (H);
- two groups (groups 1 and 3) pertained to the medium creativity class (M);
- two groups (groups 2 and 4) belonged to the low creativity class L.

To determine the values associated to relationships between group creativity and the influencing factors two methods are available, i.e. an expert-based method and a data-based method [23]. In the expert-based method, each expert determines the influence of the factors on group creativity using linguistic values (such as low, very high, strong, very strong etc.) and all these linguistic values are combined using an aggregation function. The data-based method is more elaborated - it uses a FCM learning algorithm and training data. The process of obtaining the training data takes time and well formulated procedures to measure the factors using numerical values are necessary. More information about learning algorithms can be found in [24].

Based on the empirical data resulted from our first experiments with Computer Science students enrolled in our Software Engineering course, our experience (using human expertise being a method to construct FCMs), and some results in the related work [15], we have got an estimation, based on mathematical mean, for the influence of domain expertise, individual creativity, motivation, and inter-personal affinities on group creativity. Thus, all these factors have a positive influence on creativity. However, the relation below may be true only for the cohorts of students that we have experimented with (we repeated the experiment two years in a row). Nevertheless, we believe that it can be a starting point for further experiments with Computer Science students.

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grade of influence of *domain expertise*>= grade of influence of *individual creativity*>= grade of *influence of motivation*>= grade of influence of *inter-personal affinities*

Given the large number of factors affecting group creativity, we propose using the linguistic values in [23] to assess the influence degree, namely *negatively very strong*, *negatively strong*, *negatively medium*, *negatively weak*, *negatively very weak*, *zero*, *positively very weak*, *positively weak*, *positively medium*, *positively strong*, *positively very strong*, and *positively very very strong*. Based on the relation above and using these possible values for the influence degree, we have constructed a particular group creativity FCM for Computer Science students (Fig. 4).

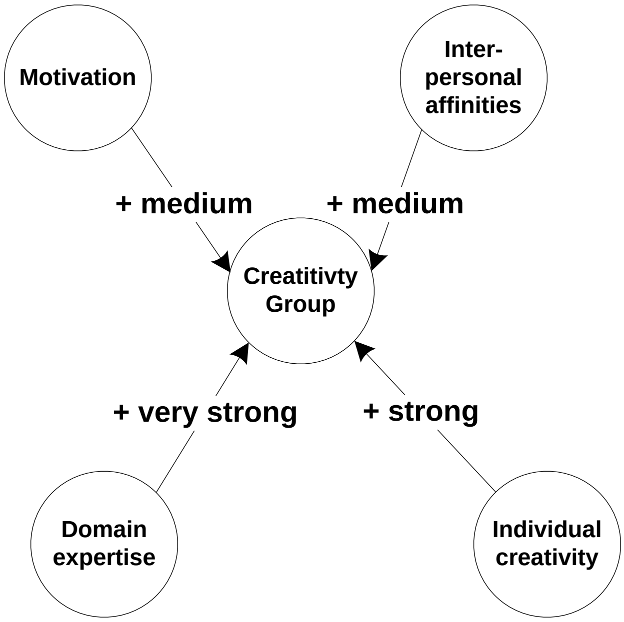

Figure 4: The resulted FCM of Group Creativity

This FCM can be further used to experiment with building groups of students and making predictions about their creativity. In addition, comparative estimations of the influence that various factors have on creativity can be performed because group creativity depends on both individual factors (and their influences) and interactions that take place between group members.

To use this method, one needs follow the procedure beneath that starts by establishing the factors that influence group creativity to be taken into account, followed by building a FCM with help from experts in the educational domain of interest (in our case, Computer Science education). The obtained FCM can be further improved using machine learning algorithms. The refined FCM can be used for making predictions about group creativity given a cohort of students and a particular learning scenario. A software tool that implements the machine learning part can be integrated as well. For example, a FCM tool for Matlab already exists and can be used to develop models and to obtain predictions on group creativity [26].

Procedure for construction of a particular FCM for a cohort of students and a learning scenario

1. Establish the factors that influence group creativity to be considered
2. Build a FCM based on human expertise in the field of interest
3. Refine the FCM obtained in step 2 using machine learning algorithms and specific tools
4. Use the refined FCM to make predictions on group creativity given a cohort of students and a particular learning scenario

5 Conclusions

Educational paradigms change constantly to stay tuned with evolution of our society and, consequently, promoting collaboration and boosting creativity in learning are major trends today. This paper approached the construction of “the most” (optimally) creative groups, given a cohort of students and a particular learning scenario, and taking into account various factors that influence creativity, both at individual and group level. This is not an easy task, as the related work shows. Some factors positively influence group creativity (such as domain expertise), some others may have a positive influence given that they are in an appropriate amount (such as controversial communication or task conflict) and are correlated with the type of activities that groups perform (for example, service-oriented or technology development), while the influence or others is non-conclusive (e.g. group diversity). The approach taken here consists in using fuzzy cognitive maps to illustrate the influence that various factors have on creativity within various learning scenarios. We have built such a map based on the empirical data resulted from our first experiments with Computer Science students enrolled in our Software Engineering course, our experience (using human expertise being a method to construct FCMs), and some results in the related work. Nevertheless, the method is general and it can be adapted to any learning scenario in any domain. A procedure on using this method for a certain cohort of students and a particular learning scenario has been included in this paper as well.

This is work in progress and many future work directions unfold. One would be to determinate the particular values for the arc weights in our FCM that correspond to particular learning scenarios. To accomplish that, more learning scenarios need to be considered in Computer Science education, as well as in other domains. A software tool that provide for construction of FCMs given a set of influence factors would be useful to facilitate the use of this method. Despite the promising results so far, our approach here is not to be used exclusively, but in combination with others that allow using numeric values for some factors that influence creativity in order to obtain the most appropriate organization of students in creative groups, in any given learning scenario.

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