GC-MAS - a Multiagent System for Building Creative Groups used in Computer Supported Collaborative Learning

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Abstract. Group creativity is a hot topic in the creativity literature, yet no method to obtain the most creative teams given a group of individuals is available. We introduce here a method for building creative teams, based on unsupervised learning and implemented with support from a multiagent system. Our first experiments with using this method for grouping learners involved in online brainstorming are presented as well.

Keywords: creativity, creative group, multi-agent system, unsupervised learning, computer supported collaborative learning

1 Introduction

The concept of group creativity has been lately in the attention of educational institutions and companies alike. However, it is quite challenging to determine in which way the interactions that take place inside a group result in either increases or decreases in creative group performances. *Creative learning* is concerned with instructional processes that focus on the development of creative abilities of individuals. *Collaborative creative learning* approaches learning that results from interactions and collaborations that take place between learners and that aspires to enhance creativity at both individual level and group level. Group creativity may be improved by providing appropriate contextual instructional environments and by organizing the individuals in suitable groups [1]. *Computer Supported Collaborative Learning (CSCL)* has appeared as a reaction to software used previously in learning, which have been forcing learners to study and learn as isolated individuals [2]. In CSCL, learning is obtained by computer-supported interactions both between learners and between learners and teachers. Thus CSCL is defined as *a field of study centrally concerned with meaning and the practices of meaning-making in the context of joint activity and the ways in which these practices are mediated through designed artifacts* [3].

In this paper, we introduce a method of grouping team members in creative groups whose creativity is increased iteratively during the process. Our method is based on an adapted version of the unsupervised learning algorithm introduced by Watkins in [4] and it is under implementation with support from a multiagent system. We have experimented with this method for grouping learners involved in a CSCL process by building up on the results obtained in our previous works [5, 6], which have approached the triggers that influence creativity in learning groups.

The structure of the paper is as follows: the next section presents the related work, the third one introduces our multi-agent system for building creative groups within CSCL processes, with which we have done some preliminary experiments 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, and point out some ideas that we have based our work on.

2.1 Creativity in Groups

Creativity is a concept highly debated in the psychological literature. Sternberg and his co-authors view *creativity as the ability to produce work that is novel (i.e., original, unexpected), high in quality, and appropriate* [7]. The challenge of understanding creativity has lead to the elaboration of many theories, for instance *the investment theory of creativity* proposed in [8, 9]. According to it, creative people are the ones *who are willing and able to, metaphorically, buy low and sell high in the realm of ideas*. Buying low refers to work on ideas that are unknown or unpopular, which have, however, built-in potential for growth. It is quite common that when such ideas are introduced for the first time they may encounter resistance. Nevertheless, a creative person would persist resisting to this opposition, and s/he will, eventually "sell" high, a new, powerful, or popular idea, achieving this way a *creativity habit* [9]. The creativity is multifaceted and it 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 manifests itself when using comprehensive cognitive categories and perspectives)* [10].

Nevertheless, group creativity is a recent topic in the literature, and it is seen as one of the expression of *the social nature of the creative act* [11]. However, 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 their backgrounds, abilities, and knowledge generate added value in creative processes. Baruah and Paulus approach the importance of interactions between the group members and their role in stimulating creative processes and point out that synergy refers to the added gain of collaboration within the group, which is obtained as a result of the stimulation, both cognitive and motivational, that results from these interactions. Further, based on the theoretical bases of synergy, 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. [12].

2.2 Modeling Group Creativity

The work of Amabile introduces the *componential theory of creativity*, along with the elements that influence creativity [13]. Three of them concern the individual level: *domain-relevant skills*, *creativity-relevant processes,* and *task motivation.* The fourth component is external to the individual: *the social environment* in which the work takes place. Domain-relevant skills refer to knowledge and expertise of the individual in a specific field. *Creativity-relevant processes* include individual characteristics that favor creativity: cognitive style, personality traits etc. Internal motivation of the individual is captured in the *task-motivation* component. Moreover, the author points out that *a central tenet of the componential theory is the intrinsic motivation principle of creativity*. In his model of group creativity, Sawyer sees creativity as a synergy between *synchronic interactions* and *diachronic exchanges* [14]. 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* [15]. In their theoretical multilevel model of group creativity, Pirolla-Merlo and Mann explain how creativity evolve over time within teams and how it is influenced by the "climate" of creativity [16]. The contextual factors that influence creativity presented in [17] are divided in three categories: (1) factors that facilitate team creativity *(supervisory and co-workers support, psychological safety, group process*), (2) factors that obstruct the generation of creative ideas (*conformity, insufficient resources, bureaucratic structure*), and uncertain factors (*team diversity, conflicts in teams, group cohesion*).

The interactionist model of creative behavior at the individual level of Woodman et al. provides an *interactionist perspective on organizational creativity*. 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, degree of cohesiveness), group processes (e.g., approaches to problem solving), and contextual influences (e.g. the larger organization, characteristics of group task).* Further, organizational creativity is considered to be *a function of the creative outputs of its component groups and contextual influences (organizational culture, reward systems, resource constraints, the larger environment and so on).* This multifaceted mix boosts *the gestalt of creative output (new products, services, ideas, procedures, and processes).* When building creative groups several features 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.)* [18, 19, 20].

2.3 Similar Approaches of Building Creative Groups

Limited experiments with grouping students in creative teams are available in the literature. In [21], the authors present their work on using learning styles for grouping students involved in collaborative learning. 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 is done in [22].

The authors see that as *the hallmark of collaborative learning, understood in an emphatic sense*. An experimental study that evaluated the assumption that *shared cognition influences the effectiveness of collaborative learning* and it is crucial for cognitive construction and reconstruction of meaning is presented in [23]. A model of collaborative learning that aimed to build an intelligent collaborative learning system able to identify and target group interaction problem areas is available in [24]. Intense social interaction and collaboration is proven to contribute to the creation of a community of learning that nurtures *a space for fostering higher order thinking through co-creation of knowledge processes* in a case study presented in [25]. In [26], groups are classified and guided toward the optimal class that is a *high performing cooperative group with positive interdependence*. The issue of identifying peers and checking their fittingness for collaboration, as an essential pre-collaboration task, is approached in [27], where is shown that a more personalized cooperation can take place provided that individual tastes and styles of the peers are taken into consideration. In [28], the authors are concerned with the *liberating role of conflict in group creativity*, as a possible approach for weaknesses of group creativity, such as 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.

3 GC-MAS - A Multiagent System for Building Creative Groups

In this section we introduce our multi-agent system for building creative groups that we have experimented with in CSCL processes. Our approach is similar to the ones presented in Subsection 2.3, being concerned with teaming up individuals in the most appropriate teams with respect to creativity, but it is innovative in the sense that grouping students in creative teams in an iterative, semi-automated process has not been performed in our country or worldwide, up to our knowledge. Moreover, our first experiments are focused on online brainstorming to address some of the shortcomings of the face-to-face one revealed in the literature. Within our current stage of our work we focus on individual components of creativity when building the learning groups likely to be creative. The architecture of the system is presented in Fig. 1 and it includes the following agents (except for CommGC, all the other are *task agents*):

- *The Communication Agent (CommGC)* that 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)* that is an agent that assists the instructor in the construction of the creative groups based on an unsupervised learning algorithm and various classification techniques;
- *The Creativity Evaluation Agent (EvalGC)* that has a support role in assessment of group creativity;
- *The Creativity Booster (EnvrGC)* that stimulates the development and the maintenance of creative contextual environments that provide for increasing group creativity;

- *The Glue Role Agent (GlueGC)* that supports the instructor in seeking out and taking on otherwise neglected tasks that have potential to facilitate creative group performances;
- *The Facilitator Agent (FCL-GC)* that supports the facilitator in helping groups to interact more efficiently;
- *The Team Relational Support Agent (TRS-GC)* that supports the team members in providing support for the other group members.

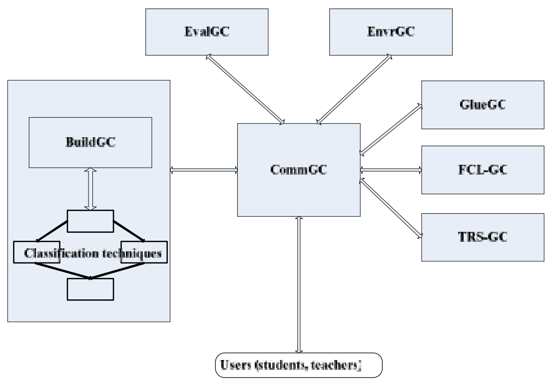

Fig. 1. GC-MAS - the bird's eye view architecture of the system

CommGC has a horizontally stratified structure, in which each level is connected directly to both the input sensors and the output actors (software entities that perform particular actions). Each level acts as an individual agent that provides the expected action. CommGC has two levels 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, so CommGC acts as a *middle agent* as well (see Fig. 2).

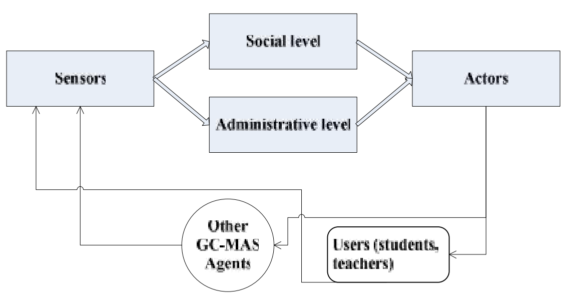

Fig. 2. CommGC– the agent's architecture

The agents **BuildGC, EvalGC, EnvrGC, GlueGC, TRS-GC** are execution agents that perform precise actions in the process of construction of the creative groups. They have a very simple structure, are goal-oriented, and they use plans libraries or classification techniques to perform their duties, as it can be seen in Fig. 3.

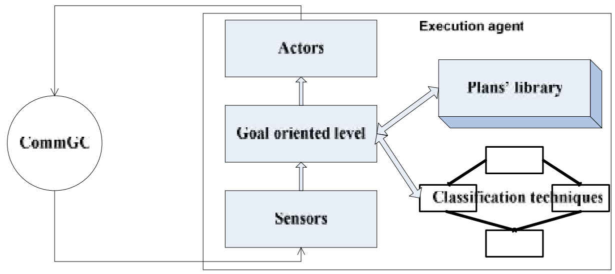

Fig. 3. The architecture of an execution agent

BuildGC - The Creative Groups' Builder aims at construction and iterative refinement of creative groups taking into account the components that generate creativity, their interdependencies that have effect on creativity and the purpose of building of creative groups (because, generally, the creativity of the group is sought for a specific goal - to solve a problem, to complete a task etc.). The data inputs for BuildCG are:

- *Student data* that include the individual characteristics that influence (both positively and negatively) the group creativity;
- *Group data* that contain the purpose of constructing creative groups (the problem to be solved, the task to be completed, the research to be undertaken etc.), the group size, the diversity of group members and so on;
- *Support data* that is 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 the group construction. BuildGC works using a module that includes various classification techniques (naïve Bayes and neural network based classifiers, decision trees, and support vector machines) to group learners. In our first experiment we had used a Naïve Bayes classifier, which is a probabilistic classifier based on Bayes theorem [29]. A detailed description of the Bayesian networks-based classification techniques can be found in [30]. The current reasoning process of the BuildCG agent is based on a combined approach between an adapted version of the Q-learning algorithm [4] and a classification technique based on Bayesian networks. 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 system (BuildCG) 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:

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

Where $\alpha \in (0,1)$ is the instruction 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 instruction rate and for the discount factor are selected is presented in [31]. Value 0 for the instruction rate means that the value for

Q is never updated, and that the system never learns. Selection of a high value for this rate means that learning is faster. When the instruction rate equals 1 it means that the immediate reward is much more important than a past reward. For dynamic environments a balance between the immediate rewards and the past rewards is sought for. In our first experiments we had used a 0.5 instruction 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.

In our case, we tackle *n* students. For each student, a characteristic vector that includes *m* individual features is constructed, namely (c_1, c_2, …, c_m). *A state* consists of this vector and the group number, while *an action* refers to moving a student to another group. 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). To fulfill this goal we use the *GC-Q-learning adapted algorithm*, which is presented below:

1. `Build` a bi-dimensional matrix Q for all the possible pairs <*state, action*>. The columns of this matrix consists of *(c_1, c_2, …, c_m, no_group, action_number, q).* The action 1 corresponds to the selection for a particular student (given by the tuple of his individual characteristics) of the group number 1 to which he pertains. The action number 2 corresponds to the selection of group 2, and so on. All the elements in the *q* column are initialized with the value 0 or with a random low value;
2. `Initialize` the optim_policy (in our case is the optimal grouping) with a guided policy, and *Q_optimal* with *Q*;
3. `Group` the students and undertake working sessions (in our first experiments, brainstorming), in which the group creativity is assessed and its score is assigned to *R(s,a)*. For each such working session, the matrix Q is calculated.

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

4. `Analyze` matrix Q. The optimal policy is given by the action for which Q_optimal gets the maximum value.

Once the optimal policy consisting in tuples *(c_1, c_2, …, c_m, group number)* is obtained, predictions for each set of data can be made based on advanced classification techniques (Bayesian networks, neural networks etc.). The Q values are the same for all the members of a group.

EvalGC, The Creativity Evaluation Agent supports the instructor in assessing the group creativity. This agent evaluates the group creativity based on the criteria for measuring ideation, namely novelty, variety, quantity, and quality introduced in [32]. 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 ideas' production (as the number of ideas per time unit), and (3) keeping the creativity score and ensuring the conversation with the instructor via CommGC. **EnvrGC**, The Creativity Booster aims to enhance group creativity by providing for contextual environments that provide for creativeness. The agent works by "pushing on" the creativity triggers identified in our previous works to obtain a better creativity score for each group [5, 6]. This action is performed using a fuzzy controller with which we have worked previously. More details can be found in [6]. **GlueGC**, The Glue Role Agent is concerned with the coordination of group members' contributions and the management of group conflict. It 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, as it is shown in [33].

4 Experimenting with GC-MAS

In this section we present briefly our first experiments with our system. After clarifying the conceptual aspects of GC-MAS, we have been concerned with investigating the viability of our approach and therefore we have undertaken a pedagogical experiment with our undergraduates and graduate students in Computer Science. The core of the experiment consists of brainstorming sessions concerned with the issues that regard the improvement of the curricula and of the syllabuses of the courses for our Computer Science programs, both at undergraduate and graduate level. In order to avoid some of the shortcomings of the face-to-face brainstorming sessions, we have undertaken these sessions online. This experiment consists in several stages:

- Assessing the individual student creativity with several evaluation tools. For the time being we have worked with the Gough Creative Personality Scale [34] and an extended version of Creative Achievement Questionnaire [35] that we have adapted for Computer Science students. We have chosen to start with Gough because is simple to use it and interpret it. Within our 27 students, the maximum score is 10 and the minimum one is -3. The average score is 2.9. In the Gough Scale the values are between -12 and 18. The student motivation can be low (having value 0), middle (1), or high (2);
- Activating BuildCG for the pool of 27 students based on the next procedure:
  0. Build matrix Q;
  1. Group them, let them have a brainstorming session, and obtain a reward R;
  2. Update column q of matrix Q;
  3. Iterate step 1,2 for the initial pool of students;
  4. Consider (randomly for now) other student pools to undertake step 1,2, 3;
  5. Analyze table Q. The optimal policy is given by the action for which Q_optimal gets the maximum value;
- Analyzing the preliminary results and improving of the multi-agent system.

Following this simple procedure, BuildCG undergoes a process of unsupervised learning based on the CG-Q-Algorithm, which associates an action to a state aiming at increasing the reward. The data from our first experiments are available at http://www.unde.ro/GC-MAS.zip. We will continue to update this archive.

5 Conclusions and Future Work

We introduced here our semi-automated method of grouping team members in increasingly creative groups, which is put to practice by a multiagent system prototype. Moreover, we had performed some experiments for grouping learners involved in online brainstorming, the results being encouraging. Future work ideas regard the improvement of both the method and the working prototype in several directions: corroborating the results obtained with several creativity evaluation scales, assessment of creativity before and after activities assumed to help trigger creativity, inclusion of contextual and organizational factors, testing the method in other activities, improving of the algorithm, offering the method as an online open service etc.

References

1. Mannix, E. A., Goncalo, J. A., Neale M. A. (eds.): Creativity in Groups, Research on Managing Groups and Teams Series. 12, Emerald Group Publishing Ltd. (2009)
2. Stahl, G., Koschmann, T., Suthers, D.: Computer-Supported Collaborative learning: An historical perspective. In Sawyer R. K. (ed.), Cambridge handbook of the learning sciences, pp. 409-426, Cambridge University Press, Cambridge, UK, (2006)
3. Koschmann, T.: Dewey's Contribution to the Foundations of CSCL Research, in Conference on Computer Support for Collaborative Learning: Foundations for a CSCL Community, pp. 17-22 International Society of the Learning Sciences (2002)
4. Watkins,C. : Learning from Delayed Rewards, PhD Thesis,University of Cambridge, England (1989), http://www.cs.rhul.ac.uk/home/chrisw/thesis.html
5. Moise, G.: Triggers for Creativity in CSCL. In 9th International Scientific Conference eLearning and Software for Education, pp 326-331, Bucharest (2013)
6. Moise, G.: Fuzzy Enhancement of Creativity in Collaborative Online Learning, LNCS 7697, Chiu D. K.W. et al. (eds.), in press (2014)
7. Sternberg, R.J., Lubart, T.I. , Kaufman, J.C., Pretz, J. E.: Creativity. In Holyoak K. J., Morrison, R. G., The Cambridge Handbook of Thinking and Reasoning, pp 351-369, Cambridge University Press, New York (2005)
8. Sternberg, R. J., Lubart, T. I.: An Investment Theory of Creativity and its Development, Human Development. 34(1), pp. 1–31 (1991)
9. Sternberg, R. J.: The Assessment of Creativity: An Investment-Based Approach, Creativity Research Journal. 24(1), pp. 3–12 (2012)
10. Rietzschel, E. F., De Dreu, C. K. W. and Nijstad, B. A.: What are we talking about, when we talk about creativity? Group creativity as a multifaceted, multistage phenomenon. In Mannix, E. A., Goncalo, J. A., Neale M. A. (eds.): Creativity in Groups, Research on Managing Groups and Teams Series. 12, Emerald Group Publishing Ltd. (2009)
11. Gorny, E. (ed.): Group creativity. Dictionary of Creativity: Terms, Concepts, Theories & Findings in Creativity Research (2007) http://creativity.netslova.ru/Group_creativity.html
12. Baruah, J., Paulus, P. B.: Enhancing Group Creativity: The Search for Synergy. In Mannix, E. A., Goncalo, J. A., Neale M. A. (eds.): Creativity in Groups, Research on Managing Groups and Teams Series. 12, Emerald Group Publishing Ltd. (2009)
13. Amabile, T. M.: Componential Theory of Creativity. In Kessler, E. H. (ed.), Encyclopedia of Management Theory, SAGE Publications Inc. (2013)
14. Sawyer, R. K.: Group Creativity. Mahwah, NJ, Lawrence Erlbaum (2003)
15. Taggar, S.: Individual Creativity and Group Ability to Utilize Individual Creative Resources, The Academy of Management Journal, 45(2), pp. 315-330 (2002)

16. Pirola-Merlo A., Mann, L.: The Relationship Between Individual Creativity and Team Creativity: Aggregating Across People and Time, Journal of Organizational Behavior. 25, pp. 235–257 (2004)
17. Yeh Y. C., The Effects of Contextual Characteristics on Team Creativity: Positive, Negative, or still Undecided, working paper, Lund University, Sweden (2012)
18. Woodman, R.W., Schoenfeldt, L. F., Individual Differences in Creativity: An Interactionist Perspective. In Glover, J.A., Ronning, R. R., Reynolds, C. R. (eds.), Handbook of creativity, pp. 77-92, Plenum Press, New York, (1989)
19. Woodman, R.W., Schoenfeldt, L. F.: An Interactionist Model of Creative Behaviour. Journal of Creative Behavior. 24, pp. 279-290 (1990)
20. Woodman, R.W., Sawyer, J. E., Griffin, R. W.: Toward a Theory of Organizational Creativity, Academy of Management Review. 18, No. 2, pp. 293-321 (1993)
21. Martin E., Paredes P.: Using Learning Styles for Dynamic Group Formation in Adaptive Collaborative Hypermedia Systems. In 1st International Workshop on Adaptive Hypermedia and Collaborative Web-based Systems AHCW 2004, pp. 188-198 (2004)
22. Stahl, G: Cognition in Computer Assisted Collaborative Learning, Journal of Computer Assisted Learning. 21, pp. 79-90, Blackwell Publishing Ltd. (2005)
23. Stoyanova N., Kommers P.: Concept Mapping as a medium of shared cognition in Computer-Supported Collaborative Learning. Journal of Interactive Learning Research. 13(1), pp. 111-133, AACE, Norfolk, VA (2012)
24. Soller, A.: Supporting Social Interaction in an Intelligent Collaborative Learning System. International Journal Artificial Intelligence in Education. 12, pp. 40-62 (2001)
25. Ma A. W. W.: Computer Supported Collaborative Learning and Higher Order Thinking Skills: A Case Study of Textile Studies. The Interdisciplinary Journal of E-Learning and Learning Objects. 5, 145-167 (2009)
26. Israel J., Aiken R.: Supporting Collaborative Learning with an Intelligent Web-based System. International Journal of Artificial Intelligence and Education. 17(1), 3-40 (2007)
27. Kumar, V.: Computer Supported Collaborative Learning - Issues for Research. University of Saskatchewan (1996), www.cos.ufrj.br/~jano/CSCW2008/Papers/Kumar_.pdf
28. Nemeth, C. J. et al.: The Liberating Role of Conflict in Group Creativity: A Study in Two Countries. European Journal of Social Psychology 34, pp. 365–374 (2004)
29. Joyce, J.: Bayes' Theorem. The Stanford Encyclopedia of Philosophy, Zalta E. N. (ed.), http://plato.stanford.edu/archives/fall2008/entries/bayes-theorem/ 2008
30. Friedman, N., Geiger, D. Goldszmidt, M.: Bayesian Network Classifiers. Machine Learning. 29, pp. 131–163 (1997)
31. Leon, F., Şova, I., Gâlea, D.: Reinforcement Learning Strategies for Intelligent Agents in Knowledge-Based Information Systems. In 8th International Symposium on Automatic Control and Computer Science, Iaşi, Romania (2004)
32. Shah, J. J.,Vargas-Hernandez, N.: Metrics for measuring ideation effectiveness. Design Studies, 24(2), pp. 111-134 (2003)
33. Bolinger, A.R., Bonner B. L. and Okhuysen, G. A.: Sticking together: the glue role and group creativity. In Mannix, E. A., Goncalo, J. A., Neale M. A. (eds.): Creativity in Groups, Research on Managing Groups and Teams Series. 12, pp. 267-291, Emerald Group Publishing Ltd. (2009)
34. Gough, H. G.: A Creative Personality Scale for the Adjective Check List. Journal of Personality and Social Psychology. 37, pp. 1398-1405 (1979)
35. Carson, S., Peterson, J. B., Higgins, D. M.: Reliability, Validity, and Factor Structure of the Creative Achievement Questionnaire. Creativity Research Journal. 17(1), pp. 37–50 (2005)