Integrating BDI and Bayesian Networks in Agent Reasoning

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Abstract. *This paper focuses on a Social Agent which has been modeled using probabilistic networks and acts in an educational application. Using the Social Agent as a testbed, we present a way to perform the deliberation process in BDI (Belief-Desire-Intention) and Bayesian networks. The assemblage of mental states and Bayesian Networks is done by viewing beliefs as networks, and desires and intentions as particular chance variable states that agents pursue. In this work, we are particularly concerned with the deliberation about which states of affairs the agent will intend. The focus of this paper is on how to build a real application by using the deliberation process developed in one of our previous work.*

1. Introduction

The research work presented in this paper is the result of the integration of two systems previously developed by our group (AMPLIA and PortEdu). AMPLIA system [Vicari 2003] is an ITS probabilistic multi-agent environment to support diagnostic reasoning and the modeling of diagnostic hypotheses in domains with complex and uncertain knowledge, such as the medical domain. PortEdu system is an educational portal that provides facilities in order to make possible those legacy systems, such as AMPLIA, to work on the Web. Once AMPLIA was available for collaborative activities, we need to improve our systems with social facilities to help students that are studying by distance learning.

The importance of social interactions in the learning process is already known by educational theoreticians, as in the socio-cultural approach of [Vygostky 1999], some works of [Piaget 1995], theories of collaborative learning [Dillenbourg 1995], and others. The principles of multi-agent systems have shown a very good potential in the development of teaching systems, due to the fact that the nature of teaching-learning problems is easily solved using a multi-agent system.

The design of Collaborative Learning Environments (CLE) may take into account social factors, such as the work presented in [Cao 2003]. They conclude that it is important to consider sociological aspects of collaboration in order to discover and describe existing relationships among people, existing organizational structures, and incentives for collaborative action. Hence, a learning environment may detect and solve conflicts. In a CLE the learner has to be active in order to manipulate objects, to integrate new concepts, to build models and to collaborate with each other. They also have to be reflective and critical.

The main difference between our educational application and the related environments is the fact that it considers cognitive, social, and affective states in the student model [Boff 2007]. Moreover, the strategies adopted in those systems consider user/system interaction, and not group interaction.

AMPLIA is composed by 4 different agents. The *Domain Agent* and the *Learner Agent* are modeled using Bayesian Networks (BNs) [Jensen 2001] as internal knowledge representation (beliefs), which have been widely employed to model uncertain domains, as in medicine. The *Mediator Agent* is modeled using Influence Diagrams (IDs), and the *ComServer Agent* coordinates the communication activities among other AMPLIA agents (see Figure 1).

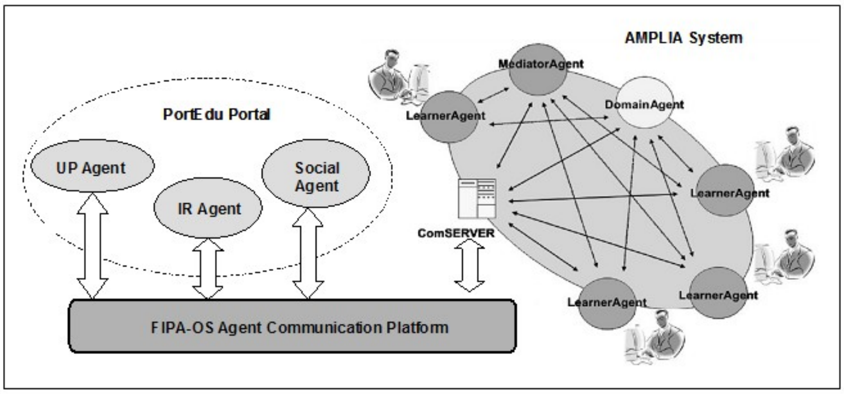

Figure 1. Integration between AMPLIA and PortEdu

The main idea that guides AMPLIA's design has been the need to offer an open environment in which a student can build a graphical model to represent his/her diagnostic hypothesis for a clinical case using Bayesian Networks. Students can build their diagnostic hypotheses by themselves or collaborating in a group of students. The student's or the group's network is then compared to that of an expert in the area, and the differences among the networks are monitored by the Mediator Agent, which uses pedagogic strategies based on the constructivist model in order to evaluate the BNs with a satisfactory solution.

The semantics of the content of the messages exchanged between AMPLIA's and PortEdu's agents is given by an ontology that specifies the Bayesian networks knowledge representation. The ontology has been modeled using OWL (Web Ontology Language) [Dean 2004], forming the core of the interoperability between AMPLIA's agents and the Social Agent. For more details about this integration see [Santos 2007].

As depicted in Figure 1, AMPLIA's ITS is connected to PortEdu. The services provided by the PortEdu agents can be used by any agent-based educational application. In this paper we focus on the Social Agent, which is integrated to the PortEdu architecture to stimulate the interaction among students, tutors and professors. For more information about PortEdu system, see [Nakayama 2005].

The main goal of this paper is to present the Social Agent deliberation process, which is a BDI (*Belief-Desire-Intention*) [Bratman 1988] goal-oriented reasoning that takes into account the probabilistic information through the usage of Bayesian networks to abstract the mental states. Inside the deliberation process, uncertainty is dealt with in order to decide if an agent believes that a state can be achieved and if desires and intentions are compatible.

The next section presents the Bayesian Network Collaborative Editor from AMPLIA, which has been developed to support collaboration among students during learning activities. The Social Agent monitors the Collaborative Graphic Editor in order to obtain information about the students when they are working in a collaborative way. Section 3 focuses on the Social Agent's reasoning. Section 4 shows the results of our experiments. Finally, the last section of the paper presents conclusions and directions for future work.

2. Bayesian Network Editor

According to learning theories in medicine based on problem-based learning [Peterson 1997], we decided to extend the AMPLIA editor, that is part of the AMPLIA Learner Agent, to allow several students to operate it simultaneously in a collaborative fashion. Thus, besides the online editing support (see Figure 2), we designed the Social Agent whose main goal was to motivate collaboration and improve group activity. As depicted in Figure 2, BN editing is possible in the system through buttons available in the toolbars. There are menu options to insert nodes, arcs and probabilities.

In Figure 2 we can see part of the BN that is under development by a group of students. In the second window, on the right, we can see the Node's Properties Editor, where the CPT (Conditional Probability Table) associated with variables (nodes) can be updated. In the bottom of the screen we can find collaborative editing options, including online users' listing and a chat tool.

The Social Agent uses different strategies to suggest a particular student to a workgroup. Students can join different groups whereas each group can work with different study cases, knowing that within medicine the teaching approach relies mostly on problem-based leaning. The strategies are detailed in [Boff 2007].

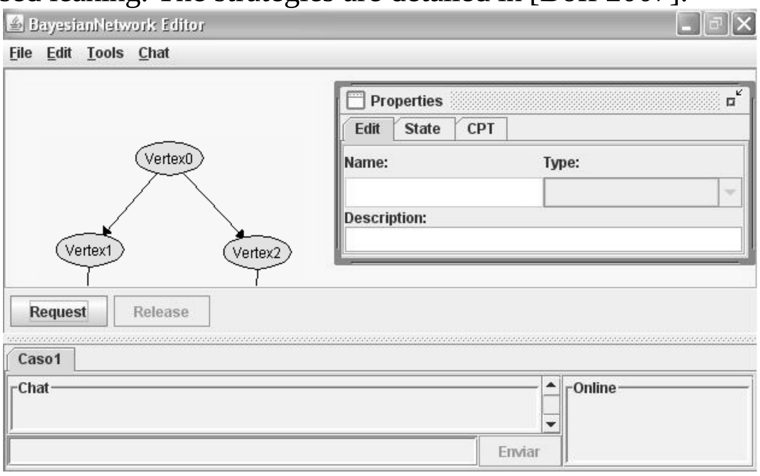

Figure 2. Collaborative Bayesian Net Editor

Since this paper's focus is on the Social Agent, the next section brings detailed information about its reasoning process.

3. The Social Agent

The main goal of the Social Agent is to stimulate student interaction. Each user builds their own Bayesian networks for a specific pathology using the AMPLIA collaborative graphic editor.

The student feature set is based on the social and collaborative theories. The information collected to define a suitable student for recommendation are: Personality Traits, Affective State, Acceptance Degree, Sociability Degree, Net Credit and Leadership. Details about the Student Model can be obtained in [Boff 2007].

The Sociability Degree (SD) or Social Profile is built during the students' interaction through a synchronous mechanism (e.g. the chat tool and the collaborative editor).

Based on Maturana´s ideas [Maturana 1998] we defined the Acceptance Degree (AD), which measures the acceptance between students. This value may also be considered from a viewpoint of Social Networks. As the Acceptance Degree is informed by the students themselves based on their affective structures, the value can indicate different emotions, such as love, envy, hatred, etc.

In order to infer the students' personality traits we use the model proposed in [Zhou 2003], based on the OCC model [Ortony 1988]. The affective states can be considered as emotion manifestations in a specific time. The research presented in this paper uses the BN to infer emotions proposed in [Conati 1997] and [Zhou 2003] to give us states values to Personality Traits and Affective State.

The Net Credit (NC) represents a possible classification for the student's Bayesian Network model (created through the AMPLIA's Collaborative Editor), according to major problems. This student action outcome is received from AMPLIA's Mediator Agent, and it can have the following values: *Unfeasible* (network that does not satisfy the definition of a Bayesian Network, as an oriented acyclic graph and/or a disconnected network), *Incorrect* (network whose model is conceptually incorrect, with presence of an excluder node), *Incomplete* (network that lacks some nodes or relationships considered important), *Feasible* (it is a network different from the built-in model but it satisfies the case study proposed to the learner) or *Complete* (it is identical to the model built by the expert).

Finally, the Leadership represents evidence indicating the students' capacity to lead. For instance, a student that helps other fellow students frequently, or a student that gives his/her opinion during the execution of a task, or a student that makes several changes in the Bayesian Network model built by his/her group.

Next section presents the Social Agent as a testbed to perform the deliberation process through a Bayesian BDI approach.

3.1. Deliberation Process

While Bayesian Networks are a formalized model for representing knowledge, there is not a unique BDI model for agency. The probabilistic BDI model [Fagundes 2007] used to develop the Social Agent employs Bayesian Networks to represent the agent's beliefs. These networks are graphical models that represent causality between variables, allowing the performance of reasoning under uncertainty in a consistent, efficient, and mathematically sound way.

To keep beliefs up to date is a crucial task to agents, since in a dynamic world it is necessary to make decisions and execute actions taking into account the current state of the world. The belief updating corresponds to probabilistic inferences. It is triggered when an agent believes in new evidence.

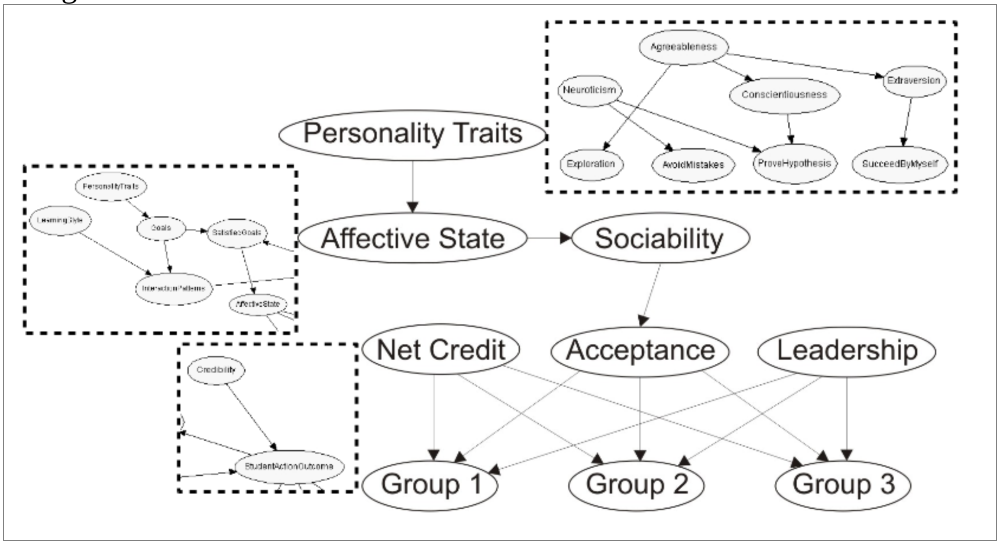

Figure 3. The Social Agent belief network

In Figure 3, we illustrate the Social Agent beliefs. The network was built according to the collected information, including Personality Traits, Affective State, Acceptance Degree, Sociability Degree, Net Credit and Leadership. The network depicted in Figure 3 relies on a Bayesian Network to assess the suitable group for a student and it includes only a subset of nodes that are necessary to completely specify the BN. The figure's details show the nodes that are assessed by other networks. The node Personality Traits is also a BN that shows the dependence between dominant personality traits, such as Neuroticism, Agreeableness, Conscientiousness and Extraversion [Costa 1992], and students' goals (Exploration, Avoid Mistakes, Prove Hypothesis, Succeed by myself). The BN that assesses the students' affective state (node Affective State) is composed by nodes such as Personality Traits, Goals, Learning Style, Interaction Patterns and Satisfied Goals. This network is based on Zhou´s model [Zhou 2003]. Finally, the node Net Credit includes the network where the students' network credibility (node Net Credit) has an influence on the student outcome (students' performance), node Student Action Outcome. The Social Agent represents the Intentional content of the desires through particular states of variables. Consequently, desires are a subset of beliefs. It makes possible to check when a state of affairs is achieved. The nodes Group 1, Group 2 and Group 3, illustrated in Figure 4, represent the beliefs (and desires in this case) of the Social Agent regarding the suggestion of those three different workgroups to the student. Therefore, the network represents how much the student fits on each group, and consequently, how much the agent desires to suggest each group to the student.

In Figure 4, Group 1 represents the group with high sociability profile. Group 2 is the one in which the dominant feature is positive affective state. Finally, Group 3 has dominant feature high performance.

The first requirement for a desire to become an intention is the belief support. In other words, the agent will not intend a state unless it believes it is possible to achieve that state. This is done by checking the computed marginal probability of the desired state. In Figure 4 the agent will desire the state True of the Group 1 when it believes the current conditions (given by Net Credit, Acceptance and Leadership) support this desire.

A proactive behavior is exhibited by the agent when it pursues states of the world where desires become feasible. More specifically, this behavior consists of achieving particular states of parent variables (conditions) based on the values of the conditional probability table of the desired state. They can be viewed as desires connected to a desire through causality.

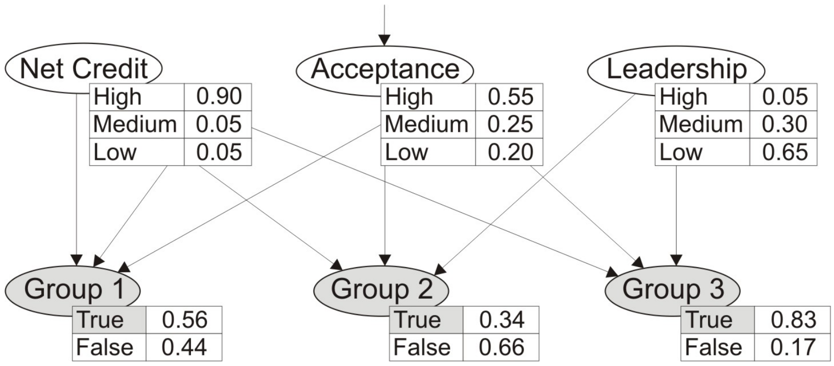

Figure 4. The desires of the Social Agent

Intentions correspond to states of affairs that BDI agents have committed to bring about. This commitment makes the agents to check intentions for incompatibility (mutually exclusive states of the world). In our approach, incompatibility between mental states is detected when some evidence indicating the achievement of an intention affects negatively other intention by decreasing its chances of success. This is explained by the fact that desires may share mutually exclusive conditions. For instance, consider the desire to suggest Group 1, whose profile is defined by students with high sociability. As the Social Agent aims to compose heterogeneous groups, it will desire to find students with negative affective state or students with low or medium performance.

In the deliberation process the BDI agents examine which desires are possible, they choose between competing desires, and commit to achieving them. The process is divided in two stages: the first verifies which desires are possible to be achieved, and the second checks the compatibility among possible desires and intentions. We adopt the terms cautious and bold to describe the agents' behavior in the following three situations inside of the deliberation process: to decide if the agent believes in particular states, to decide if desires are incompatible with intentions and to decide if desires are incompatible among themselves. By adjusting a threshold value the Social Agent will exhibit a different degree of cautiousness or boldness in those decisions.

For more details about the Bayesian BDI architecture, including the deliberation algorithms and the different agent behaviors, see [Fagundes 2007].

Once an agent has committed with some states of affairs, it has to perform actions in order to achieve those intentions. In our testbed, the Social Agent has to interact with the students to suggest workgroups to them.

The three group nodes defined in the belief network do not represent group instances, but three different group profiles. The Social Agent will find a group instance that matches the intended group profile, and then it will suggest that group to the student. If at least one group is found, the intention is successful, otherwise it fails.

4. Results

Our learning environment has been tested in seminars involving medical professors and students at Porto Alegre's Clinic Hospital (Hospital de Clínicas de Porto Alegre, Brazil). Each seminar was divided in two phases: (1) discussion of pedagogic resources and of theoretical concepts about uncertain domains, probabilistic networks, and knowledge representation; (2) the medical specialists had to build expert's BN models on their domain areas, which were used by the AMPLIA Domain Agent. This work was carried out by the subjects using the collaborative BNs editor. Later, a group of students started using AMPLIA as a tutoring system. In this phase the collaborative editor supported the student's solutions that were proposed for a particular problem defined previously for the expert. More information about these tests may be found in [Flores 2005].

During the development of AMPLIA, we had to investigate whether the use of BNs as a pedagogical resource would be feasible, if they would enable the students to model their knowledge, if it would be possible to follow the students' actions during the learning process, to make inferences through a probabilistic agent, and to select pedagogical actions that would have the maximum utility for the students at each moment of their knowledge construction process. All these applications have been assumed to be probabilistic, as they involve the complexity and dynamics of a human learning process, but with the possibility of being followed by artificial agents.

Regarding the Social Agent, we have developed two experiments until this moment. The first of them was a case study to demonstrate the possibility to exchange Bayesian knowledge between the Social Agent and AMPLIA's Learner Agent. The results of this experiment were published in [Boff 2007] and [Santos 2007].

The second experiment had as a main goal to employ the Social Agent to form workgroups based on the features of twelve students and on the strategies detailed in section 3. According to these strategies, two scenarios had to be considered, as described in Tables 1 and 2.

Table 1. Scenario 1

ST	*DPT*	*S*	*A*	*NC*	*L*	*AS*	*DH*	*GS*
1	E	H	H	M	H	P	CE	1
2	E	M	H	M	H	J	CE	3
3	I	L	L	L	L	D	CE	2
4	A	M	L	M	L	J	CE	2
5	E	M	L	H	M	J	CE	1
6	I	M	M	H	L	J	CE	3
7	I	L	L	M	L	D	CE	1
8	I	L	L	L	L	D	CE	1
9	E	H	M	M	M	J	CE	3
10	E	H	H	H	H	J	CE	2
11	E	M	M	H	H	P	CE	3
12	E	M	M	M	M	J	CE	2

Table 1 and 2 present the following headers: ST (Student), DPT (Dominant Personality Trait), S (Sociability), A (Acceptance), NC (Net Credit), L (Leadership), AS (Affective State), DH (Diagnostic Hypotheses) and GS (Group Suggestion).

The AS (Affective State) column can assumes values such as: P (Pride), J (Joy) and D (Distress). In both tables the Dominant Personality Trait can be E (Extrovert), I (Introvert) and A (Agreeableness). The columns related to Sociability, Acceptance, Net Credit and Leadership can assume H (High), M (Medium) or L (Low) values. The Diagnostic Hypotheses in the first scenario 1 correspond to Cardiac Evaluation (CE), whereas in the scenario 2 correspond to Diabetic Neuropathy (DN).

Scenario 1 presents three groups proposed by the Social Agent. The first group shows a balanced profile distribution. The second group put together four students with different profiles. The strategy used has been to compose heterogeneous groups, i.e. to mix students with different personality traits and social roles (leadership). The third group assembled three extrovert students with only one introverted student. But, in this particular case, the likelihood that the introverted student feels intimidated is very small, as he/she has a high value on the Net Credit and his/her Affective State has the value "Joy", which is a positive social feature. In this scenario, all students were working in the same diagnostic hypothesis, which was "Cardiac Evaluation". The Social Agent suggested heterogeneous groups, but with small differences among members. For example: an introverted and distressed student should work better with an agreeable or extroverted student that is happy. It is possible that proud students, in this case, could intimidate the participation of an extremely introverted student.

Table 2. Scenario 2

ST	*DPT*	*S*	*A*	*NC*	*L*	*AS*	*DH*	*GS*
1	E	H	M	H	H	P	DN	1
2	E	H	H	L	M	J	DN	2
3	I	L	H	H	M	J	DN	1
4	A	M	L	M	L	J	DN	1
5	A	H	M	H	M	P	DN	2
6	I	L	L	L	L	D	DN	2
7	E	H	H	M	H	J	DN	3
8	I	L	L	L	L	D	DN	1
9	I	L	L	L	L	D	DN	2
10	I	L	L	L	L	D	DN	3
11	I	M	M	M	L	J	DN	3
12	I	M	M	H	L	J	DN	3

Scenario 2 shows three balanced groups proposed by the Social Agent. Table 2 presents the organization of these groups.

In this scenario, all students were working in the same diagnostic hypothesis, which was "Diabetic Neuropathy". The groups created by the Social Agent were composed by three students with different profiles. Each group had as a member a student with a different personality trait and a balanced (but diverse) degree of Sociability, Social Acceptance, Net Credit (or level of performance in the learning subject), Leadership and Affective State. In this example, we had some students with exactly the same profile (students 8, 9 and 10). In order to keep the group balanced, these students have been distributed in different groups by the Social Agent.

The ideas described in this paper show our perspective on how to analyze, interpret and model the complex phenomena that occurs in the teaching-learning process, through the modeling of the student. The validation of these ideas and their generalization can only happen over time and within real world application and testing.

5. Conclusion

We have built a Social Agent which interacts with the users in order to motivate group formation among students and to promote collaborative learning. The Social Agent identifies suitable students that can play the role of a tutor, and to recommend them to other students needing assistance. The tutor recommendation mechanism explores the social dimension through the analysis of emotional states and social behavior of the users. In this direction, we aim to contribute to the design of learning environments centered in students' features and collaborative learning.

In a real classroom, students form workgroups considering mainly the affinity between them. Sometimes, workgroups are composed taking into account geographic proximity (especially for Distance Learning), but not always these groups present a good performance in learning activities.

The AMPLIA editor can be considered a collaborative tool which allows the creation of virtual workgroups to solve tasks in a collaborative way. In addition, the AMPLIA environment contributes to CLEs research as it considers in the students' models, some cognitive, affective and social states.

When students are involved in the same task and with the same goal, they are compromised to each other. Suggesting students to help others we can motivate collaboration and initiate students' interaction in the AMPLIA environment. We aim to reduce the professors' involvement and give more autonomy to students.

The strategies adopted by the Social Agent are based on established theories presented in Section 3. All knowledge has been used to infer the student's social skills, and then place them in groups in order to obtain the best individual and collaborative performance.

We focused on the Social Agent's deliberation (selection of intentions), leaving outside the paper scope issues such as performance measurements of the agent's architecture, methodology of development, uncertainty on perceptions, and advanced planning techniques. The adopted model has an implicit representation of incompatibility among mental states through causal relations and conditional probabilities. By this we mean that the Social Agent infers incompatible desires by checking mutually exclusive conditions.

The results presented in section 4 are based on a method which aims at more effective group composition. An effective group is a group with cohesion, good performance in learning activities and minimum conflicts. That experiment is a starting point to indicate that Social Agent reasoning can be used to make up groups according to group dynamics literature.

Future work is twofold. The first research direction is concerned with the improvement of the approach here presented to cover the reconsideration of intentions and commitment strategies. Still on the deliberation process, we intend to experiment AI techniques to develop a dynamic threshold function that adjusts its value according to the circumstance. The second research direction, concerning the Social Agent design, consists of exploring other intentions in order to improve the workgroup formation.

References

Boff, E., Vicari, R. M., Flores, C. D., Reategui, E. B. (2007) "A Probabilistic Agent to support Collaboration in a Medical Learning Environment". In: 13th Portuguese Conference in Artificial Intelligence, 2007, Guimarães. New Trends in Artificial Intelligence. Braga: APPIA - Associação Portuguesa para a Inteligência Artificial, 2007. LNAI, p. 704-715.

Bratman, M.E., Israel, D.J., Pollack, M.E. (1988) "Plans and resource-bounded practical reasoning", In: Computational Intelligence, 4 349-355.

Cao, Y., Sharifi, G., Upadrashta, Y. and Vassileva, J. (2003) "Interpersonal Relationships in Group Interaction in CSCW Environments", In: Proceedings of the User Modelling UM03 Workshop on Assessing and Adapting to User Attitudes and

Affect, Johnstown, June 22.

Conati, C. et al. (1997) “On-line student modeling for coached problem solving using Bayesian networks”, In: Proceedings User Modeling: Sixth International Conference - UM97, Springer, Vienna, 1997, p. 231-42.

Costa, P. T. and McCrae, R. R. (1992) “Four ways five factors are basic”, Personality and Individual Differences, 13, 653-665.

Dean M. and Schreiber, G. (2004) “OWL Web Ontology Language Reference”, Technical Report, W3C, February.

Dillenbourg, P., Baker, M., Blaye, A. and O’Malley, C. (1995) “The evolution of research on collaborative learning”, In: P. Reimann & H. Spada (Eds). Learning in humans and machines. Towards an interdisciplinary learning science, 189-211. London: Pergamon.

Fagundes, M. S, Vicari, R. M. and Coelho, H. (2007) “Deliberation Process in a BDI Model with Bayesian Networks”, In: 10th Pacific RIM International Workshop on Multi-Agents (PRIMA 2007). Lecture Notes in Artificial Intelligence.

Flores, C. D., Seixas, L., Gluz, J. C. and Vicari, R. M. (2005) “A Model of Pedagogical Negotiation”, In: Multi-Agent Systems: Theory and Applications Workshop - MASTA, 2005, Covilhã. 12th Encontro Portugues de Inteligencia Artificial - EPIA 2005 (EPIA 2005, LNAI 3808). Berlin: Springer Verlag, 2005. v. 1. p. 488-499.

Jensen, F.V. (2001) “Bayesian Networks and Decision Graphs”. Springer.

Maturana, H. and Varela, F. (1998) “Tree of Knowledge: The Biological Roots of Human Understanding”, Shambhala Publications, Boston, MA.

Nakayama, L., Vicari, R. M. and Coelho H. (2005) “An Information Retrieving Service for Distance Learning”, In: The IPSI BgDTransactions on Internet Research, v. 1, n. 1, Jan.

Ortony, A., Clore, G. and Collins, A. (1988) “The Cognitive Structure of Emotions”, Cambridge University Press.

Peterson, M. (1997) “Skills to Enhance Problem-based Learning”, In: Med Educ Online [serial online] 1997; 2,3. Available from: URL http://www.med-ed-online/

Piaget, J. (1995) “Explanation in sociology”, In: Sociological studies, New York: Routledge (1995).

Santos, E. R., Fagundes M. and Vicari, R. M. (2007) “An Ontology-Based Approach to Interoperability for Bayesian Agents”, In: AAMAS.

Vicari, R. M., Flores, C. D., Silvestre, A. M., Seixas, L., Ladeira, M. and Coelho, H. (2003) “A Multi-Agent Intelligent Environment for Medical Knowledge”, In: Artificial Intelligence in Medicine, Elsevier Science B. V., v. 27, p. 335-366.

Vygotsky, L.S. (1999) “The collected works of L. S. Vygotsky”, New York: Plenum Press, c1987-c1999 v. 1-6.

Zhou X. and Conati, C. (2003) “Inferring User Goals from Personality and Behavior in a Causal Model of User Affect”, In: Proceedings of IUI 2003, International Conference on Intelligent User Interfaces, Miami, FL, U.S.A. p. 211-218.