NEGOTIATION PROCESS IN AN INTELLIGENT LEARNING ENVIRONMENT

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Abstract. AMPLIA is an Intelligent Learning Multi-Agent Environment. It is designed to support training of diagnostic reasoning and modeling of domains with complex and uncertain knowledge. AMPLIA focuses on the medical area, where learner's modeling tasks will consist of creating a Bayesian network for a problem the system will present. The construction of a network involves qualitative and quantitative aspects. A negotiation process (managed by an intelligent *MediatorAgent*) will treat the differences of topology and probability distribution between the model the learner built and the one built-in in the system. That negotiation process occurs between the agents that represent the expert knowledge domain (*DomainAgent*) and the agent that represents the learner knowledge (*LearnerAgent*). The possibility of using Bayesian networks to create knowledge representation allows the learner to visualize his/her ideas organization, create and test hypothesis. These actions attain the constructivist pedagogical orientation, where the subject (learner) constructs knowledge through his/her interactions with the object (domain). This differs from existing reasoning systems based on Bayesian networks, which contain a built-in knowledge base that may be used but not created or modified by the learner.

Key-words: Multi-Agent System, Intelligent Learning Environment, Bayesian Networks, Negotiation.

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1 Introduction

The increasing interest on autonomous interacting software agents and their potential application has shown an increment in the importance of automatic negotiation related research [10]. However, the construction of autonomous agents capable of improving their own negotiation capabilities within a learning environment and on the basis of their interaction with other agents, whether human or virtual, is still in its very early stages.

We are interested in the development of autonomous agents that are capable of aiding learning based on experience, and that are also able to improve their behavior during the learning process. In the field of education, negotiation is closely related to the pedagogical way of modeling a negotiation process in a cooperative environment. Since we are motivated by several different research fields – negotiation procedure in a learning environment – we have adopted a specific *mediation-based cooperative negotiation* style.

The basic characteristics of this negotiation model in a learning environment include: (1) besides the two main negotiation protagonists, learner and specialist, one more character who is interested in aiding the learner in the construction of his/her knowledge; that is a mediating agent; (2) there is a sequence of decision taking phases (different stages) which are dependant on one another; and (3) the learner updates his/her knowledge after analyzing the argument received during the execution of one of the decision taking phases, thus improving during the following stage. Such observations support a constructivist pedagogical orientaton, in which learning is constructed by the subject as a result of his/her interaction with the object. Such knowledge is assimilated and then adapted through changes in the pre-existing mental structures. Pondering over these actions yields a new mental structure, which will, in turn, go through new adaptation processes and so on [9]. This sort of incremental learning behavior is highly desirable in an intelligent learning environment.

Reviews of some case studies in the medical field [1,2,3,4,5,6] support the idea that a physician implicitly carries out some kind of probabilistic reasoning when diagnosing. There is empirical evidence that the process involved in probabilistic reasoning, like the one executed by the Baysian networks, resembles that of human reasoning patterns [7]. Providing a physician with probabilistic reasoning based systems is, currently, a way of dealing with uncertainty. Such systems can be used in the teaching/learning processes, as suggested in this article, and in daily clinical practice.

In AMPLIA, learning takes place explicitly through modeling the learner's beliefs before a proposed case study by using a probabilistic framework that includes a Bayesian updating and representational mechanism called SEAMED [8]. Last, we aim at developing an adaptive negotiation model in which the mediating agent resorts to pedagogical strategies in order to aid the learner in constructing his/her own knowledge. In the following section, we outline the architecture of the AMPLIA environment. Next, we describe the negotiation process and a real illustration of this scenario.

2 The AMPLIA Environment

The architecture of AMPLIA, as shown in Fig. 1, is made up of three cognitive agents (*LearnerAgent*, *MediatorAgent* and *DomainAgent*)., two data basis and the interface module.

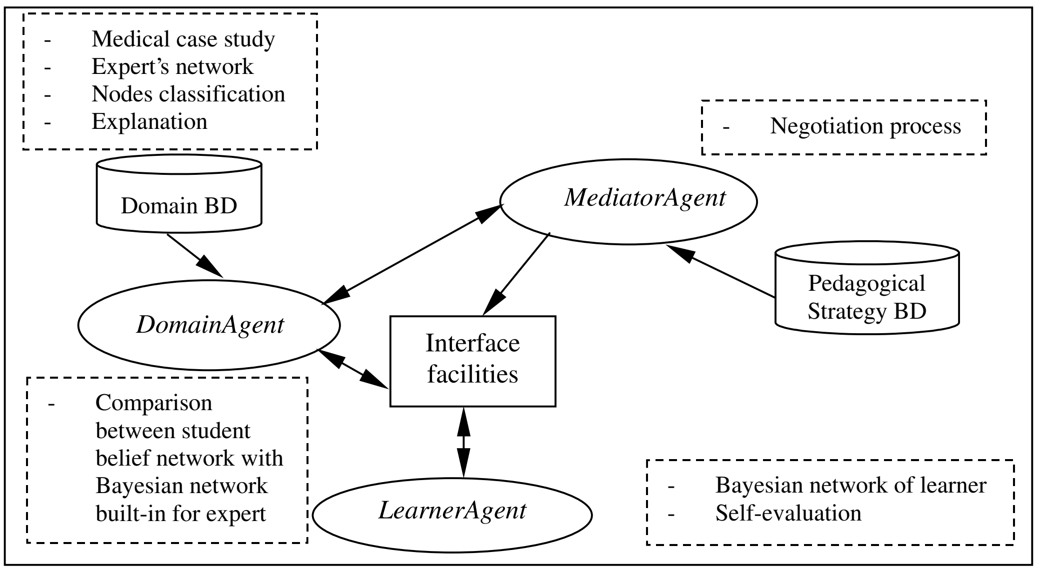

Fig. 1. The AMPLIA architecture

The *LearnerAgent* represents the learner's beliefs about the domain and his/her level of confidence on his/her model. The *MediatorAgent* coordinates the negotiation by deliberating on how and when to intervene in the learner's network model construction process.

The *DomainAgent* compares the specialist's network to the model constructed by the learner, identifying specific conflict points that will allow for the network classification as shown in Table 1. The result of this analysis is forwarded to the *MediatorAgent*.

Table 1. Learner's models classification

Category	Parameter
Impossible	The network does not fit into the description of a Bayesian network, that is to say that one or more of the following is true: the model is not an oriented acyclical graph, it bears a disconnected network, the distribution of the probabilities presented by the learner are not compatible with the probability axioms. This error identification process involves a number of algorithms that have not been described in this article.
Incorrect	The network has been wrongly conceived, as denoted, for example, by the existence of an excluding node which should make part of the model only as a diagnose rejecter.
Incomplete	This network lacks some important nodes or relations (trigger, essential, complementary). It is almost impossible to achieve the evaluation of a hypothesis regarded as correct in this case, even if the model constitutes a complete and well-formed Bayesian network.
Feasible	In spite of being different from the specialist's model, it meets the essential points present in the case study. The relations of probabilistic dependence and independence expressed in the feasible type model are equivalent to the specialist's model's ones. That is to say, the causal relations represented in both models are equivalent.
Complete	The network is identical to the model constructed by the specialist. The causal relations of the domain variables and the conditional probability distributions of all variables are identical to those of the model constructed by the specialist.

The data basis of the domain also store a classification of the nodes (as shown in table 2), the explanation resources supplied by the specialist (used by the *MediatorAgent* under the shape of arguments) and the text about the modeled problem (to be presented to the learner). A graphic interface tool, called SEAMED, aids the learner in constructing and consulting the probabilistic models.

Table 2. Node Classification

Trigger	It brings a (causally related) diagnosis to "positive" status, independently of any other indication
Essential	It must be available to warrant the identification of the diagnosis
Complementary	It increases the probability of a diagnosis
Excluding	It indicates that the diagnosis is unfeasible (that is, it bears a low probability rate)

3 Negotiation Process

Cooperation is a feature of the multiagent learning environment, in which the learner takes part in the learning process. This cooperation needs to be planned beforehand and achieved through communication and negotiation. Negotiation frequently involves justification, which often takes the form of message exchange or dialogues. Arguments are statements aimed at causing some change in the learner's intentions and, as a consequence, the learner's actions. There are a number of arguments available to the *MediatorAgent*, which can be used to bring about this change. No matter what arguments the *MediatorAgent* resorts to, they all need be evaluated by the *LearnerAgent* before any decision is taken. Such arguments are used by the *MediatorAgent* as a resource of dynamical change on the part of the *LearnerAgent*, in regard to his/her actions and beliefs, who, in turn, finds in them the necessary motivation to increase learning.

The AMPLIA environment suggests the learner should carry out an evaluation of his own performance and indicate his level of confidence; this variable should then be taken into consideration by the *MediatorAgent*. From the pedagogical viewpoint, mistakes and uncertainties are of importance for self-evaluation and reflection, allowing the learner to set his/her own pace of study. Accordingly, the *MediatorAgent* should always intervene so as to question the learner's doubts and statements.

The *MediatorAgent* initiates the negotiation process only after the *DomainAgent* has reviewed the learner beliefs. Such review is carried out by means of algorithms that encourage both qualitative and quantitative evaluation of the learner's solution, having the model classified according to table 1. By qualitative evaluation it is meant the network topology, or, in other words, the causal relationships among the domain variables. In turn, quantitative evaluation refers to the pattern of conditional probability distribution of the domain variable.

The *DomainAgent* classifies the learner's model and sends the *MediatorAgent* a message containing the conflict points and a relation of the explanations to be regarded as arguments in the negotiation process. Then, the *MediatorAgent* suggests that the learner should carry out a self-evaluation and report his/her level of confidence on the model he/she constructed, which fits into one of the three categories; low, medium or high. Then, the *MediatorAgent* sends the *LearnerAgent* a message containing arguments based on the classification set by the *DomainAgent* and on the learner's level of confidence. This messages aims at encouraging the learner to review his/her beliefs, aiding him/her on the following steps to be taken.

Table 3 shows some strategies the *MediatorAgent* can resort to.

The *MediatorAgent* then waits for the next step to be taken by the *LearnerAgent*, which may be: (1) request further information about nodes in which the *LearnerAgent* reports to have a low confidence level; (2) request a review of the concept of Bayesian networks; (3) keep on making adjustments in the network and send it back to the *DomainAgent* later; (4) abandon the negotiation process; and (5) reveal the specialist's network model.

Table 3. Some of the MediatorAgent's negotiation strategies

	Strategies
1	"Your diagnostic model is complete; it is coherent with the specialist's network model."
2	"You should report all the nodes or the causal relationships in which your level of confidence is low."
3	"You should report all nodes or all the causal relationships in which your level of confidence is high."
4	"You should take the following information into account (.....) and decide on the nodes that will be necessary in order to include those findings."
5	"Your diagnostic model does not fit into a Bayesian network structure. You should re-consider your probabilistic concepts."

The negotiation process is na interactive method composed of a sequential decision-making steps dependant upon one another, in which the *MediatorAgent* keeps encouraging the *LearnerAgent* to achieve his/her goals. Such goals include the construction of a hypothetical model and the development of his/her diagnosis-oriented reasoning. After a number of encounters, the *MediatorAgent* is capable of analyzing the learner's behavioral patterns in order to determine an analogy with the teacher's role within a constructivist approach. Such analyses could influence on the argument evaluation in conflictive situations. One possible example of a conflictive situation occurs when the learner commits the same mistake again and again, in spite of all the arguments presented. A new strategy needs to be applied in such cases.

4 An Actual Medical Case Example: Dengue

After the learner has identified him/herself, the *LearnerAgent* picks up a case study from the Domain Agent's data base (see table 4). After the text has been read, the learner initiates the process of model construction with the aid of a graphic editor. The *DomainAgent* then shows a list of all the nodes, whether related or not to the learner's study case. The learner is then encouraged to develop a Bayesian network by choosing from the list of nodes all those he/she considers adequate to the case. The learner can elaborate the qualitative and quantitative model parts, identifying all the variables that make up the findings and those that are actually diagnoses presented. He/she, then, starts estimating the initial conditional probability distribution concerning the group of selected variables.

Table 4. An Actual Medical Case Example: Dengue

Identification: P.H.S. 33 years old, female, Caucasian, resident in the city of Porto Alegre, Rio Grande do Sul state.
Main Complaint: "Fever for 5 days"
Present Medical History: Patient suffering from abrupt fever onset reaching up to 39 Celsius, pain in the upper and lower limb joints and diffuse muscular pain. Fever started about 6 days ago and has not responded to ASA and anti-inflammatory therapies. Three days after the fever onset, the patient began to suffer from acute frontal headache and retro-ocular pain. Extreme tiredness. No cough or shortness of breath. The patient is married to a truck driver and mentions having traveled to the state of Alagoas, 12 days ago. She claims to have suffered from nausea, vomits and hematemesis since then.
Vital signs:
- HR (Heart Rate): 116 bpm
- BR (Breath Rate): 28 ipm
- BP (Blood Pressure) 80/50 Hg mm
- Temperature: 38.2 Celsius

Physical examination:
- Hypo-colored mucosae, pale-looking face
- Ectoscopy: presence of petechiae on the abdominal region
- Limbs – Cold and sweaty hands. Filiform pulse
- Pulmonary auscultation: uniformly distributed vesicular sounds heard
- Cardiac auscultation: Sinus tachycardia, muffled heart sounds
- Oral Examination: signs of gum bleeding
- Ear examination: no alterations
- Abdomen: Tender to palpation liver, felt 4 cm below the right rib border. No signs of ascitis or percussion.
- 10 petechiae per square cm, following arm compression with sphygmomanometer for 5 minutes

Fig. 2 shows a specialist developed model por the above example. This model will be available to the learner at his/her request.

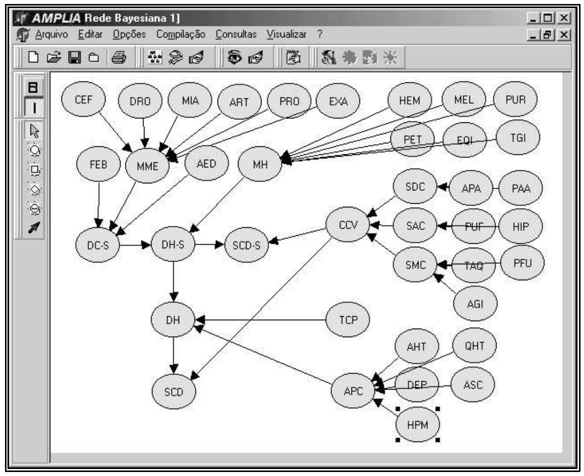

Fig. 2. Domain Specialist Modeled Network

Table 5. Lettering of the network nodes

Symbol Table	
AED	Contact (within the last 15 days) in an area where there have been notified cases of dengue transmission, and/or proved evidence of the presence of the mosquito Aedes aegypti.
AGI	Psychomotor agitation
AHT	Rise in hematocrit, 20% or more above first measure on admission
APA	Absent blood pressure
APC	Increased capillary permeability
ART	Arthralgia: tender joints
ASC	Ascites
CCV	Shock
CEF	Headache
DC-S	Classic Dengue (Not confirmed - Suspicion)
DEP	Pleural effusion
DH	Dengue hemorrhagic fever (Confirmed)
DH-S	Dengue hemorrhagic fever (Not Confirmed)
DRO	Pain in retroorbital area (behind the ocular globe)
EQI	Ecchymosis: red spots in skin (hemorrhage in skin)
EXA	Exanthem: an acute generalized eruption
FEB	Fever: acute febrile illness with maximum duration of 7 days
FEB-S15	More than 15 days long febrile illness
HEM	Hematemesis: vomiting of blood
HIP	Hypotension: low blood pressure
HPM	Hypoproteinemia
MEL	Melena: passage of stools rendered black and tarry by the presence of altered blood
MH	Hemorrhagic manifestations
MIA	Myalgia: muscular pain
MME	Minor Manifestations
PAA	Absent arterial pulse
PET	Petechiae: less than 2 mm wide red dots in skin
PFU	Cool, mottled extremities: indicative of reduced blood flow to the skin
PRO	Prostration: tiredness, fatigue
PUF	Weakness or disappearance of the arterial pulse
PUR	Purpura: more than 3mm wide hemorrhagic dots in skin: an extravasation of red blood cells into the dermis
QHT	20%, or more, drop in hematocrit, after therapy
SAC	Alert signs of shock
SCD	Dengue shock syndrome (Confirmed)
SCD-S	Dengue shock syndrome (Not Confirmed)
SDC	Diagnostic signs of shock
SMC	Minor signs of shock
TAQ	Tachycardia: increased heart rate
TCP	Thrombocytopenia: platelet count below 100,000 per microliter

It should be noted that that the nodes that follow: 'DC-S", 'DH-S", 'SCD-S", 'DH", and 'SCD" stand for the definite diagnoses of this case. The medicine student s challenged not only to come to a final diagnoses (Dengue), but also to classify this disease among its several levels of pathological seriousness. As stated from the beginning, the nodes may be classified as diagnosed, found, or both. The "APA" entity in figure 3 is na example of the 'trigger" node. A positive evidence of this node is enough to indicate a posterior positive probability distribution of 'SDC" (a diagnostic and evidence node)

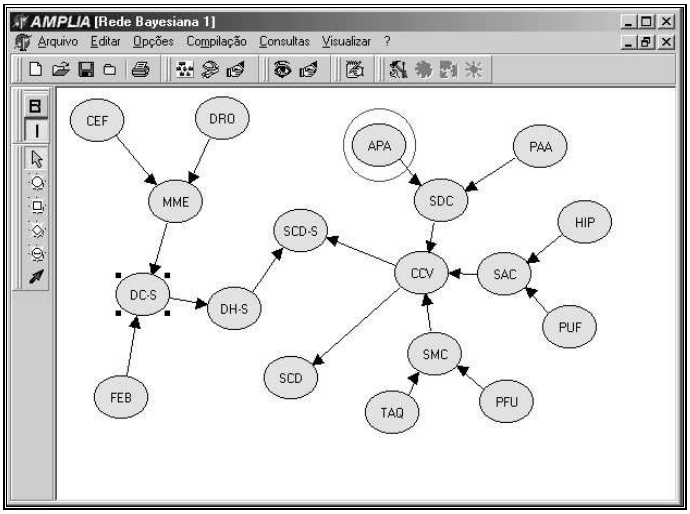

Fig. 3. A network containing a 'trigger" node

'FEB", 'MME", and "AED" (figure 4) represent the 'essential" nodes of this network.

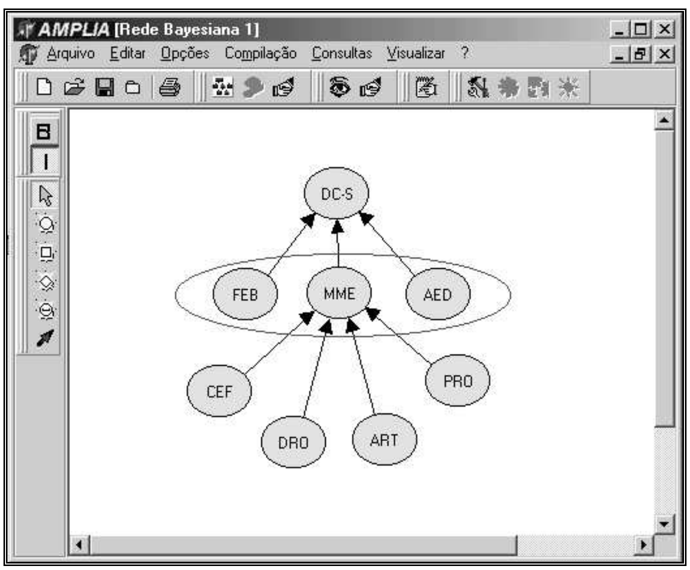

Fig. 4. A network with 'essential" nodes.

These nodes are classified this way because all of them are necessary (all of them need to be present) so that the final 'DC-S" diagnosis can be carried out.

I should be noted that the 'MME" node represents an 'abstract" logical node, which bears a 'positive" probability only if at least two of its parent nodes are also positive. According to the definition issued by the Brazilian Health Bureau, a suspicion of infection by dengue can only be notified if the patient claimed to be suffering from high fever for 7 days at the longest along with at least two of the following symptoms: 'CEF", 'DRO", 'MIA", "ART", 'PRO", and 'EXA". Besides that, the patient needs to have been in a dengue-transmitting region (AED). It should be noted that the 'CEF", 'MIA", 'DRO", "ART", 'PRO", and 'EXA" nodes are considered to be 'complementary", for they induce us to assume other nodes as true (MME node in this case). Finally, as an example of the excluding node (Fig. 5), the entity 'FEB-S15" should be noted.

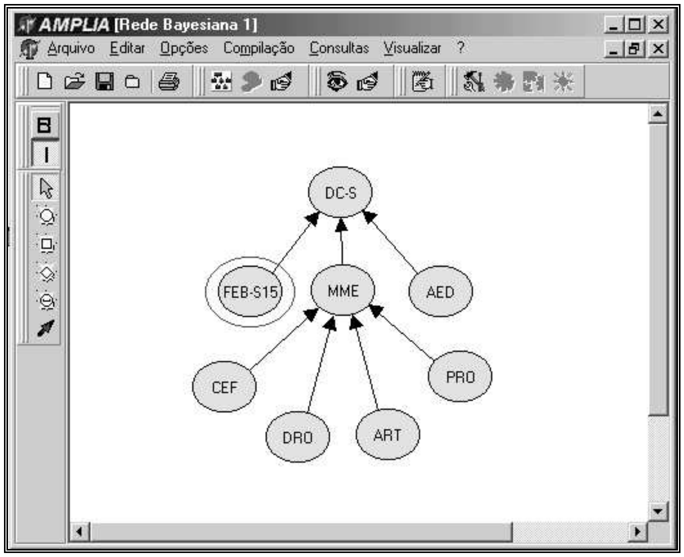

Fig. 5. A network of excluding nodes

The *DomainAgent* includes this variable in the list of nodes as a means of testing the learner's level of confidence. One patient who claims to have had fever for over 15 days is hardly considered to be suffering from the disease. In this case, even if the complementary MME and AED nodes are positive, the *DomainAgent* is still hopeful that "DC-S" shows a negative *a posteriori* probability distribution. After the learner has finished modeling the network, he/she starts to bring in evidence from the textual diagnostic investigation based upon his/her own interpretation.

The *LearnerAgent* sends the qualitative part of the learner's network along with the *a priori* and *a posteriori* probability distribution determined to the *DomainAgent*. It is then that the *DomainAgent* sets out to compare both the causal relationships and these probabilities to the model constructed by the Domain specialist. See figure 6 for a hypothetical network developed by the learner.

It should be noted that the network developed by the learner is a feasible one. All the signs and symptoms present in the clinical case are also present in the network. After inference testing has been carried out, the *DomainAgent* checks if all diagnostic node probabilities are correct *a posteriori*. The problem shown in this example is quite frequently found when the learner's and the specialist's models are compared. It has to do with the "abstract" nodes, which may or may not appear. Note that the "CPI" (Increase in Capillary Permeability) is actually missing. This is a logical node created by the specialist so as to synthesize the existence or absence of its parent nodes (in figure 6, the learner only includes one of such parent nodes – ART, since this is the only one mentioned in the clinical case). Logical nodes are frequently devised by specialists in order to decrease the number of probabilities to be estimated in the quantitative development phase of the network.

It is interesting to note that the *MediatorAgent* bears a complex heuristics for solving problems of this type. Firstly, the agent searches all the absent nodes. If the parent nodes of this absent nodes are found in the learner's model, which is the case shown in fig. 6, the *MediatorAgent* resources to sensitivity analysis in order to verify if any probabilistic impacts coherent with the model developed by the specialist can still be found in the learner's network. Since all diagnostic nodes are present and all bear acceptable probability levels, the *MediatorAgent* assumes that the learner fits into the "highly confident" category. In order to confirm this hypothesis, the learner is questioned on his/her level of confidence on the model, and then, only then, is he questioned about the absent nodes.

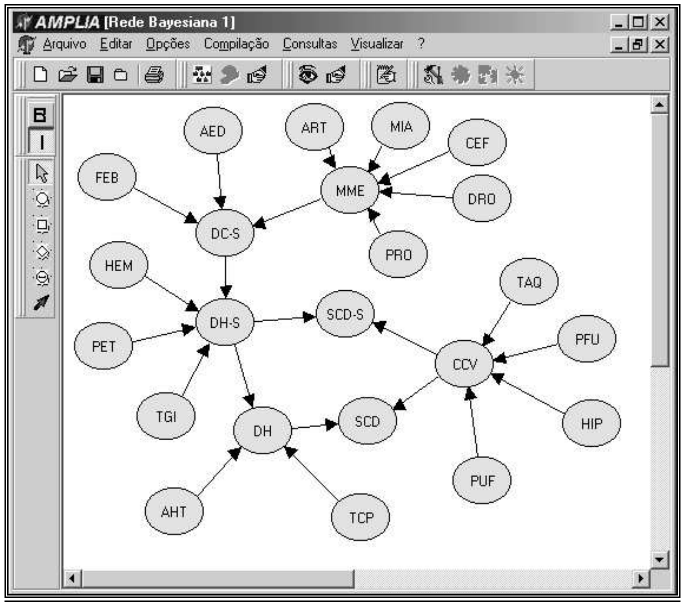

Fig. 6. a hypothetical learner network

5 Conclusions and future works

AMPLIA, the learning intelligent probabilistic environment was developed to aid in the construction of explanation models in complex and uncertain domains, supporting diagnostic reasoning. We have chosen the domain of medicine for the purpose of illustration. Differently from the existing Bayesian network based systems, AMPLIA, is devised as a medical diagnosis learning environment. The learner can construct diagnostic models and evaluate its consequences qualitatively and quantitatively. Currently, probabilistic reasoning is widely accepted all over the world, for it is regarded as a correct and efficient way of dealing with uncertainty.

The negotiation process used is referred to as *mediation based cooperative negotiation*, in which the intelligent *MediatorAgent* resorts to pedagogical strategies all along the learning process. A constructivist orientation is followed, according to which knowledge is built up by the learner by means of uncountable situations of interaction with the environment.

Concerning applications of AMPLIA, one of our co-operations is aimed at generating realistic models with the help of case data. These models will serve for health consulting as well as for diagnostic training.

MAS have been successfully employed in the development of applications in a large number of domains [11]. In this context, Multi-Agents approach is an interesting alternative because it makes it easier integration of several components of the AMPLIA environment (some were agentified, e.g. the SEAMED facilities [8]). This approach enables a better distance support to the learner, customized guiding, besides setting a real partnership among the several agents of the system, both human and artificial. The use of MAS helped also the development of systems with user' s participation (learner and physician). The result is a flexible system, both in what concerns evolution of knowledge and teaching practices, and in terms of inclusion of new features whose necessity is realized while using the environment.

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