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# Didactic Decision-Making Process In a Surgery Learning Environment

Dima Mufti-Alchawafa<sup>1</sup>, Vanda Luengo<sup>1</sup>, Lucile Vadcard<sup>1</sup>

<sup>1</sup>Laboratoire CLIPS/ IMAG, 385 rue de la Bibliothèque,  
Domaine Universitaire, BP 53, 38041 Grenoble cedex 9, France  
{Dima.Mufti-alchawafa, Vanda.Luengo, Lucile.Vadcard}@imag.fr

**Abstract.** In this paper we present our model of the didactic decision-making process and our method to define the apprenticeship utility function. This model is embedded in a computer-based learning environment dedicated to orthopedic surgery. The decision model allows the production of feedback relevant to the user's knowledge during her/his activities with the learning environment.

The surgical knowledge in the learning environment is represented with Bayesian Networks and the decision-making process is modeled with Influence Diagrams. The decision model uses an apprenticeship utility function to infer the most relevant feedback from the diagnosis of the user's knowledge during his/her problem-solving activity. The diagnosis of user's knowledge in our learning environment is deduced within the Bayesian network.

**Keywords:** Decision analysis, Knowledge modeling, Bayesian networks, Influence Diagrams, Computer-based learning environment.

## 1. Introduction

The use of computers is seen by several authors as important to face issues in medical education (Eraut & du Boulay 2000), but on the condition that real underlying educational principles be integrated (Benyon & al. 1997, Lillehaug & al. 1998). In particular, they stress the importance of individual feedback (Rogers & al., 1998); from our point of view, it is effectively the backbone of the relevance of computer based systems for learning.

As pointed by Eraut and du Boulay (2000), we can consider Information Technology in medicine as divided into "tools" and "training systems". Tools support surgeons in their practice, while training systems are dedicated to the apprenticeship. Our personal aim is to use the same tools developed in the framework of computer assisted surgical techniques to create also training systems for conceptual notions. To illustrate our approach, we propose a computer based learning environment in the domain of surgical apprenticeship. The objective of this learning environment is to reduce the distance between the theoretical formation and the practical formation of the surgeons. The precise application field is orthopedic surgery (screwing of pelvic fractures).

We embed in the design of our learning environment a model of knowledge (Luengo & al., 2004), a model of knowledge diagnosis and a model of didactic decision-making process. These models in the environment allow the production of feedback linked to the user current knowledge, as diagnosed according to his/her actions.

In this paper we present the model of the didactic decision-making process. This work is related to three domains: education sciences, decision analysis and artificial intelligence. We have chosen to use Bayesian networks to model the domain knowledge and to infer the knowledge diagnosis. Thus, we use influence diagrams and the utility theory to calculate and choose the most relevant feedback from the apprenticeship point of view. Inference and calculation are based on didactic analysis of the surgical knowledge in problem-solving situations.

## 2. Research Framework

The aim of our learning environment is to allow the learning of empirical knowledge. Based on problem-solving, it takes declarative and empirical knowledge into account to interact with the user. The declarative knowledge represents the predicative part of surgeon's knowledge as described in courses, books, etc. The empirical knowledge represents the surgeon knowledge used during the resolution of a real problem.

Our environment consists of existing computer tools, and a model of declarative and empirical knowledge. It diagnoses the user's underlying knowledge according to his/her actions, and gives related feedback.

From these considerations, we based our work on the situation theory proposed by Brousseau(1997). In this theory, the "milieu" for the apprenticeship must be organized to favor learning. In particular, the system must produce relevant feedback to the learner's actions on the interface during the problem-solving situation. We consider that the system can produce relevant feedback for the apprenticeship if it reacts according to an internal validation of the learner's solution process. This means that we are basing the system feedback on local consistency checks of learner's actions rather than on a priori solutions (Ohlson 1994 and Luengo 1999). The architecture of our system is shown below.

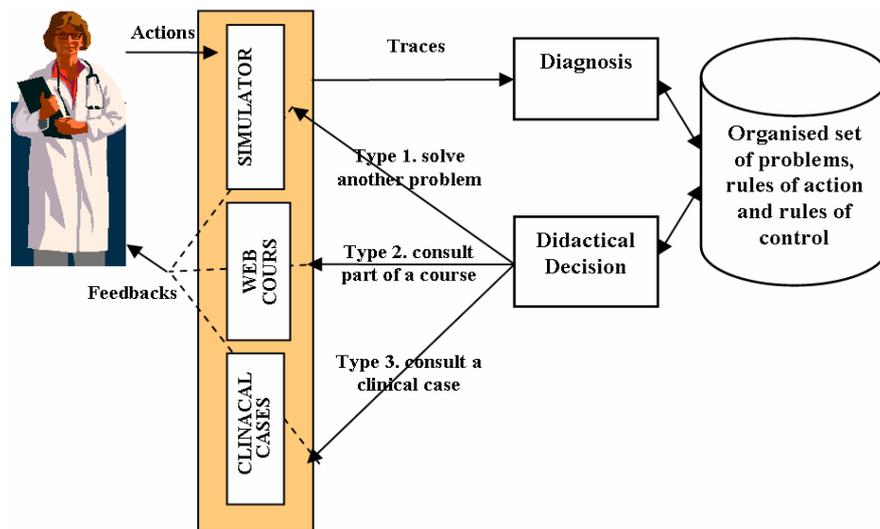


Figure1. Global architecture of our learning environment.

The user solves a problem using simulation software. In the diagnosis component, traces of the user's actions are analyzed in terms of their possible relation to identified surgical conceptions. A conception is an organized set of problems and pieces of knowledge. The user's knowledge diagnosis allows the didactical decision, which determines the most relevant feedback to send to the user. In our environment, there are three forms of feedback: presentation of another problem to solve with simulator, redirection to a specific part of the online associated course, or presentation of a clinical case to consult.

In the next paragraphs, we describe briefly the knowledge modeling and diagnosis aspects. Then, we describe in detail the didactical decision component.

## 3. Knowledge Modeling and the Diagnosis Consideration

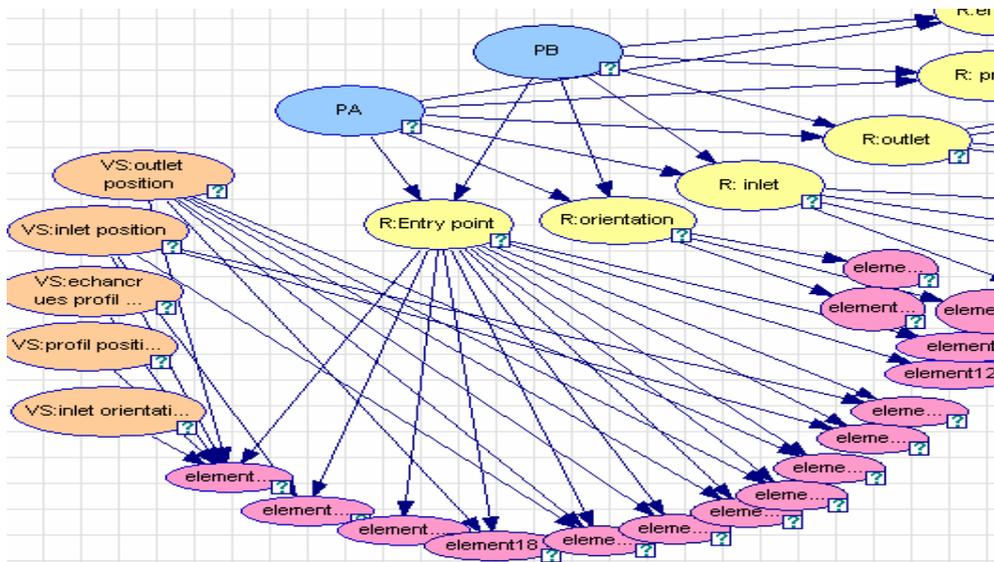
To formalize the surgical knowledge in our environment, we adopt the point of view described by Balacheff to define the notion of conception in the model cK $\zeta$  (Balacheff & al., 2002). This model has been developed to give readability to didactical research for computational modeling in artificial intelligence. In a previous work, we have described with this model the formalization of the surgical knowledge in problem-solving situations (Vadcard & al., 2005).

We use a Bayesian network to represent the formalized knowledge as a causality model. This computer representation allows to use the notion of uncertainty in the environment. Thus, it is becoming increasingly used in the artificial intelligence education domain, especially in the student model domain (Conati & al. 2002, Reye 2004, etc).

Bayesian networks are the result of the convergence of statistical methodology and artificial intelligence. They allow the acquisition, representation and utilization of knowledge in a computer system (Naïm & al., 2002).

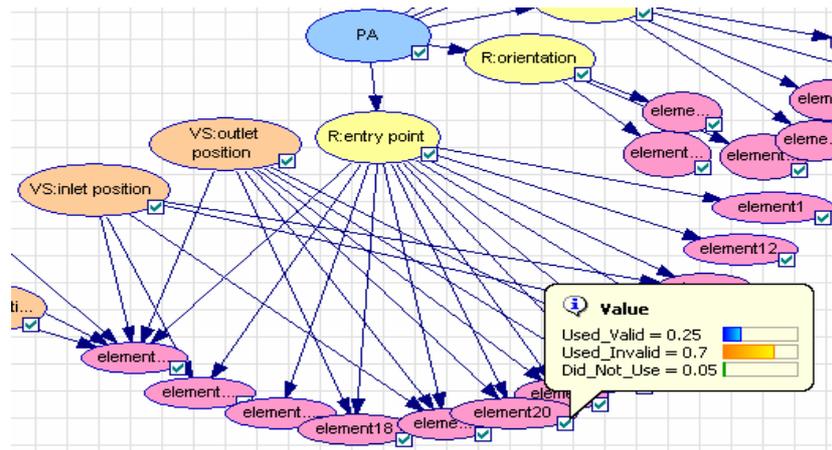
The figure (2) shows a first Bayesian network which is built from the data obtained from the didactic analysis and the knowledge formalization. From the cK $\phi$  model, we selected three variables: *P*, the problem to solve; *R*, the rules of solving this problem; and  $\Sigma$ , the control elements which allow the judgment of the relevance of the problem solution. Thus, we identify the situation variable *VS* which represents the state of resolution during the problem-solving process.

For example, in order to solve the problem *Pa* “insert a pin in the case of a pelvis fracture, normal bone”, it is necessary to apply several operators *R* (example: *r1* “choose entry point”) in a valid way. Several elements of controls  $\Sigma$  are identified to validate the operator *r1* (Entry point). For example  $\Sigma 1$  “if the skin landmarks are the sacrum projections, then the entry point is situated in the dorso-cranial quadrant”. The validation of the control element depends on the problem context and on the resolution situation *VS* (example: *vs1* “screw position in the inlet view”).



**Figure2.** A Bayesian network representing the surgical knowledge.

The diagnosis of the user’s knowledge in our environment is made according to the context of the problem and to the actions of the user in the simulator interface. This diagnosis allows to deduce the uncertain state of control elements in terms of probability. Each control element node in the diagnosis network has three states: *Used\_Invalid*, *Used\_Valid*, and *Didn’t\_Use*. These states correspond to the possible uses of this element by the learner. The diagnosis deduces a set of probability (for the three sates) indicating if a control element is used or not in the problem solving and if this use was valid or invalid according to the problem solving context. The figure (3) shows an example of calculated diagnosis.



**Figure3.** Example of calculated diagnosis.

The results of the knowledge diagnosis are used by the didactical decision component in order to produce a feedback relevant to the state of the user's knowledge. In the next paragraph we present the decision component. We base our decision model on the control elements because, from our consideration, these elements content the results of diagnostic. It should be noted that, in the next paragraphs, the notion of “knowledge element” corresponds to "control element".

#### 4. Didactical Decision Component

The objective of didactical decision making is the production of the best feedback which favours the learning, it is, thus, necessary to take into account the didactic analysis of the surgical knowledge. More precisely, the feedback must be the most relevant to the deduced state of user’s knowledge from the apprenticeship point of view.

We identify three stages in the decision-making procedure in this component:

1. Choice of the feedback subject: Which knowledge will be aimed in order to learn it with the feedback
2. Choice of the feedback form: decision about the relevant form of feedback to pass on the aimed knowledge (feedback subject)
3. Formulation of feedback: decision about the contents of the feedback in order to allow the learning of the aimed knowledge

For example, after solving the problem “*Pa*” the decision component determines successively: In the first stage, the subject of feedback as “taking into account the type of fracture in the determination of the screw length”; in the second stage, the feedback form as “asking the user to solve another problem with the simulator”; and finally in the third stage, the formulation of feedback as “showing *Pb* as the problem to solve in the simulator interface”, *Pb* being another problem in which the learner must take into account the type of fracture to determine the screw length. In the next paragraphs we describe these stages in detail.

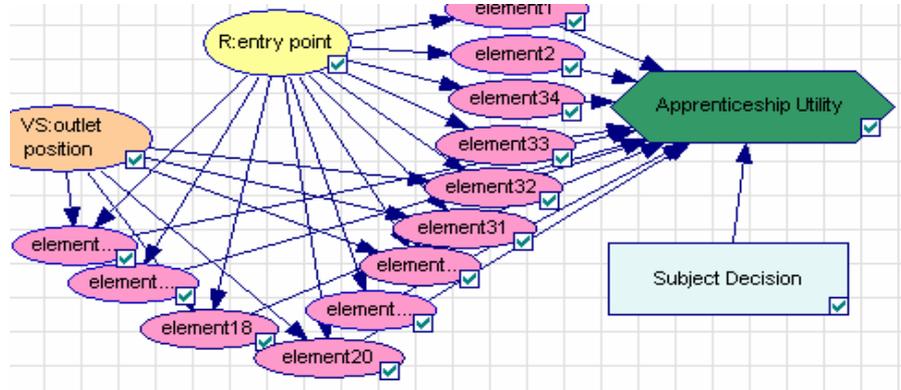
##### 4.1. Subject of feedback

This decision is based on the results of the knowledge diagnosis which are expressed with probabilities. The probabilities represent what the diagnosis has deduced about the use (by user) of each knowledge element in the problem solving process. The objective is to choose the element(s) on which it is better to focus the feedback. This decision identifies what are the most important knowledge element(s) that have to be learnt with the feedback.

We use influence diagrams to represent this decision. “An influence diagram allows the design of decision model and it is a graphical tool used to capture the essence of a problem and facilitate communication among multi-disciplined teams and the decision board” (Skinner, 1999). It is used to represent and to calculate the decision-making in several applications (for example: Horvitz & al. 1995, 2003, Charneau & al. 2005, etc.) Thus, influence diagrams are an extension of Bayesian

networks (Naïm & al., 2002). In influence diagrams there are decision nodes and utility nodes as well as chance nodes (in the Bayesian networks).

We model the subject decision with an influence diagram (figure 4), by adding the apprenticeship utility node (hexagonal node) and the subject decision node (rectangular node) to the Diagnosis Bayesian network shown in (figure 3).



**Figure4.** The influence diagram of feedback subject decision.

In our diagram shown in figure (4), the “subject decision” node contains all possible choices for subject feedback. It contains a list of all the elements of knowledge in the environment. Thus, the decision on the best choice is made according to the calculation in the “Apprenticeship Utility” node. The subject feedback decision must take into account the state of all the knowledge elements (resulting from diagnosis); we thus link all the knowledge elements to the “apprenticeship utility” node.

The inference in the diagram allows calculating the apprenticeship utility corresponding to each knowledge element listed in the decision node. The result is the utility value corresponding to the choice of this element as feedback subject from the apprenticeship point of view. For example, if after the inference the apprenticeship utility is "52" for an element  $e1$  and "63" for  $e2$ , it means that  $e2$  is more important to learn, so it should more probably be the subject of feedback. In the next paragraph we describe our method to calculate the utility function.

### ***Apprenticeship utility function:***

The inference in the subject decision diagram is based on a utility table included in the apprenticeship utility node. To initialize a prior utility of best feedback and to fill this table we define a utility function which in our research will be calculated with the apprenticeship point of view.

For example if we have just two elements of knowledge  $e1$  et  $e2$  and if the diagnosis has indicated that the state of  $e1$  is “Used\_invalid” (meaning: used in an invalid way in the problem solving) and the state of  $e2$  is “Used\_Valid”, then from the apprenticeship point of view the utility value of  $e1$  has to be higher than the utility value of  $e2$  in this case. That means we consider  $e1$  is more important to learn than  $e2$ .

Thus, the element states allow calculating apprenticeship utility values and we should also to take into account several factors related to the element characteristic.

In order to define the utility function, we have identified (from the results of the didactical analysis of surgical knowledge in problem solving activity and from knowledge formalization) four factors that influence the subject decision:

- Element State: it represents the result of knowledge diagnosis concerning this element (the three states: used\_valid; Used\_invalid; and Didn't\_Use).
- Element Type: it represents the type of this element. This type can be: “Declarative” (element related to declarative part of surgical knowledge), or “Empirical”.
- Element Order: it represents the stage(s) of problem-solving in which this element intervenes. An element can intervene in several stages in the solving process.

- Element Nature: it indicates when this element intervenes. The element is “simple” if it intervenes in the main problem; else it intervenes in a sub-problem and it is “contextual”.

From all of these factors we define  $U_{app}(ei, E)$  (the utility to choose an element  $ei$  as feedback subject in taking into account  $E$  the set of the knowledge elements) as the sum of all the utilities related to each factor in the equation (1) :

$$U_{app}(e_i, E) = \alpha \cdot U_{state}(e_i, E) + \beta \cdot U_{Type}(e_i) + \sigma \cdot U_{order}(e_i) + \delta \cdot U_{nature}(e_i) \quad (1)$$

In our didactical hypothesis these factors don't have the same weight for influencing the subject choice. We thus attribute to each factor a basic variable ( $\alpha$ ,  $\beta$ ,  $\sigma$ , et  $\delta$ ) which represents its weight in the utility calculation. In future work, for the validation of the didactical hypothesis we will attribute values to these variables to examine the order of importance of these factors in the subject decision. For example if  $\alpha = 100$  and  $\beta = 10$ , then that means the element state is more important than its type for the subject feedback decision.

The state utility  $U_{state}(ei, E)$  depends on the states of the other environment elements. We define it as the sum of the state utilities for each element in the environment. See equation (2), where  $n$  is the number of the knowledge elements:

$$U_{state}(e_i, E) = \sum_{j=1}^n U_{State}(e_i, e_j) \quad (2)$$

Thus, we identify a state utility table to calculate  $U_{state}(ei, ej)$  based on didactical hypothesis. This table defines the utility (from state point of view) of choosing an element  $ei$  as subject of feedback in taking into account its state and the state of another element in the environment  $ej$ .

**Table1.** The state utility table.

$U_{state}(ei, ej)$		ej		
		Used Invalid	Used Valid	Didn't Use
ei	Used Invalid	0	-2	-1
	Used Valid	2	1	0
	Didn't Use	1	-1	0

In the definition of the type utility  $U_{type}(ei)$ , we consider that from the apprenticeship point of view the declarative elements are more important than the empirical one. We express this by equation (3):

$$U_{Type}(e_i) = \begin{cases} 1; & \text{if } ei \text{ is declarative} \\ 0; & \text{if } ei \text{ is empirical} \end{cases} \quad (3)$$

For the order utility  $U_{order}(ei)$  we consider that if the element appears in a primary step of the problem solving it is more important than an element which appears in later steps. Thus, it is possible that an element appears in several steps of problem solving. We define the order utility in equation (4), where  $m$  is the number of the steps where this element appears and  $O(ei)$  is its order.

$$U_{order}(e_i) = \sum_{j=1}^m \frac{1}{O_j(e_i)} \quad (4)$$

In the definition of the nature utility  $U_{nature}(ei)$  we consider that learning a simple element is more important than learning a contextual one. We express that by equation (5):

$$U_{nature}(e_i) = \begin{cases} 1; & \text{if } e_i \text{ is simple} \\ 0; & \text{if } e_i \text{ is contextual} \end{cases} \quad (5)$$

According to these considerations, we have defined an algorithm which calculates the apprenticeship utility function and allows the initialization of the utility table in the utility node.

The inference in the diagram takes into account the probabilities resulting from the knowledge diagnosis and it is based on the “utility theory” from the decision analysis domain to calculate the estimated utility for each decision. In the equation (6) the estimated utility to choose an element  $e_i$  as a feedback subject is the sum over the apprenticeship utilities, weighted by the likelihood of each state of the diagnosis results.  $E$  is the set of knowledge element and in our model,  $j=3$  according to the states “used\_valide”, “Used\_Invalide”, and “Didn’t\_use” for each element of knowledge.

$$EU(e_i) = \sum_j P(E_j) \cdot U_{app}(e_i, E_j) \quad (6)$$

Finally, the feedback subject is the element(s) that have the higher estimated utility values calculated according to equation (6).

#### 4.2. Form of feedback

In the second stage of the didactical decision making the system chooses the most relevant form of feedback which allows the apprenticeship of the aimed knowledge element(s) (chosen as feedback subject in the first stage).

To determine the feedback form, we take into account the type of the aimed knowledge element(s). In our environment there are three possible kinds of feedbacks shown in figure (1). In relating the feedback form to the type of aimed knowledge element(s), we determine:

- Consult part of a course: If the feedback subject is related to declarative knowledge, the feedback will ask the user to consult a specific part of a course where the explanation of the aimed knowledge is.
- Solve another problem: If the feedback subject is related to empirical knowledge, the feedback will ask the user to solve another problem with the environment’s simulator. The aimed knowledge element(s) must intervene in the solving of the other problem and it will be chosen by the didactical decision’s component. We explain the choice of another problem in formulation of feedback paragraph.
- Consult a clinical case: If the feedback subject is related to both types of knowledge the declarative and the empirical, the feedback will ask the user to consult a specific clinical case chosen in the base of clinical cases in the environment. The clinical case will show a use of the aimed knowledge element(s) in its solution and the results of using this knowledge in the context of this case.

#### 4.3. Formulation of feedback

The formulation of feedback depends on its form and its subject, chosen in the previous stages in the didactical decision process. For the first form of feedback “consult part of a course” the decision component sends to the user the links to pages in the course where the subject of feedback is explained. The production of links set of the relevant pages is made by a model of semantic WEB which consists of a set of connected ontology (formalized with OWL), a set of HTML pages, and a search engine (Luengo & al., 2005).

For the other two feedback forms the subject is related to empirical knowledge. Empirical knowledge by its nature has to be learned in problem solving situations. Thus, the decision component should formulate a problem context similar to the initial problem and allow the learning of this knowledge.

Before describing how to choose a similar problem, we first explain how the problems are identified. The formalized problems embedded in our environment are identified by didactical variables. These variables represent the context (characteristic) of the main class of problem. The instantiation of these variables identifies a class of problem. The didactical variables can be for example the bone fracture type, the bone quality, etc. the figure (5) shows an example of a formalized problem.

P	VD	fracture type		Quality of Bone			Exercise		P state : Screw position in			
		fracture	disjon	dense	norm	little d	determ	valid	as inlet	aut inlet	as outlet	hcr
PA			X		X		X					
	e1PA		X		X		X		X			
	e2PA		X		X		X			X		
	e3PA		X		X		X				X	
	...											
PB		X			X		X					
	e1PB	X			X		X		X			
	e2PB	X			X		X			X		
	e3PB	X			X		X				X	
	...											
PC		X			X		X					
PD			X		X		X					

Figure5. A formalized problems P with the didactical variables VD.

We identify the similarity between two problems as the number of didactical variables which have the same value in the two problems.

The formulation of the last two kinds of feedback (another problem or a clinical case) is made by choosing which problem or case it is better to send to the user. This choice is based on the similarity notion and on the subject of feedback.

Currently we work to identify an algorithm to infer the most similar problem which has a higher probability of using the feedback subject in its solving. This inference will be applied to the belief networks representing the surgical knowledge (shown in figure 2).

## 5. Conclusion and Future Work

We have presented in this paper a didactical decision component integrated in a computer-based learning environment in the orthopedic surgery field. From an architecture point of view, we separate in this environment the diagnosis component from the didactical decision component. We represent the surgical knowledge with Bayesian networks as a set of elements of knowledge linked with causality relations. The diagnosis of user's knowledge deduced the probabilities (in belief network) of using these elements in the problem-solving.

In the decision component the procedures of decision-making include three related stages. In the first stage, we extend the diagnosis belief networks by adding "apprenticeship utility" node and "subject decision" node in order to identify subject decision influence diagram. This diagram allows to infer the subject of feedback (the knowledge element(s) to be learnt through the feedback). Then the second stage allows the choice of the feedback form according to the type of the aimed knowledge element(s) as "feedback subject". Finally, taking into account "feedback subject" and "feedback form", the last stage allows formulating the feedback according to the similarity notion.

We have defined an apprenticeship utility function which allows the initialization of the utility table in the subject decision influence diagram. We defined basic variables related to the utility function factors; it allows weighting the influence of these factors in the subject decision.

We want to evaluate our model and our methods of calculation in the learning environment. The evaluation will be in two stages. In the first stage, we will evaluate, with educational scientists, the relevance of feedback with the results of diagnosis. In the second stage we will evaluate, with domain experts, the model of didactical decision.

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