Research Article

International Journal of Advanced Computer Research, Vol 8(37)
ISSN (Print): 2249-7277 ISSN (Online): 2277-7970
http://dx.doi.org/10.19101/IJACR.2018.836020

A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems

Mouenis Anouar Tadlaoui[1*], Rommel Novaes Carvalho[2] and Mohamed Khaldi[3]
Research Scholar, Abdelmalek Essaâdi University, Faculty of Sciences, Lirosa, Tétouan, Morocco[1]
Professor, University of Brasília, Department of Computer Science, Brasília, Brazil[2]
Professor, Abdelmalek Essaâdi University, Faculty of Sciences, Lirosa, Tétouan, Morocco[3]

Received: 06-April-2018; Revised: 02-July-2018; Accepted: 05-July-2018

Abstract
The aim of this paper is to present a probabilistic and dynamic learner model in adaptive hypermedia educational systems based on multi-entity Bayesian networks (MEBN) and artificial intelligence. There are several methods and models for modelling the learner in adaptive hypermedia educational systems, but they're based on the initial profile of the learner created in his entry into the learning situation. They do not handle the uncertainty in the dynamic modelling of the learner based on the actions of the learner. The main hypothesis of this paper is the management of the learner model based on MEBN and artificial intelligence, taking into accounts the different action that the learner could take during his/her whole learning path. In this paper, the use of the notion of fragments and MEBN theory (MTheory) to lead to a Bayesian multi-entity network has been proposed. The use of this Bayesian method can handle the whole course of a learner as well as all of its shares in an adaptive educational hypermedia. The approach that we followed during this paper is marked initially by modelling the learner model in three levels: we started with the conceptual level of modelling with the unified modelling language, followed by the model based on Bayesian networks to be able to achieve probabilistic modelling in the three phases of learner modelling.

Keywords
E-learning, Adaptive hypermedia, Adaptive educational hypermedia, Bayesian networks, Multi entity Bayesian network (MEBN), Artificial intelligence learner model, MEBN theory (MTheory).

1.Introduction
The technological landscape of the modern e-learning is dominated by learning management systems. Learning management systems are powerful, integrated systems that support a number of activities carried out by teachers and students during the e-learning process. Teachers use e-learning systems to develop course notes and quizzes on the web, to communicate with students and to monitor and classify student progress. Students use it for learning, communication and collaboration [1−2].

There are various attempts to model the learner in different adaptive educational hypermedia; these are the static representations of this model, representations that are generally based on information given by the learner himself when he enters the system. This gives a static view of the learner model.

The learner model is characterized by a dynamic aspect, the knowledge of the learner evolves in the same module, and its characteristics change during a learning situation. This requires a dynamic vision for the management of this model [3].

We have shown in previous works [4], that the learner model in adaptive hypermedia is characterized by its complexity, large data size, dynamic evolution, and relativities. We have also presented a very precise approach to its management by using a combination of methods, models and techniques to try to treat dynamically and probabilistically its evolution [5]. We tried to specify in our work, a dynamic modelling of learning a formal model for adaptive educational hypermedia systems and also to ensure that management of the model developed that addresses both information domains and includes the three phases of the learner modelling process.

*Author for correspondence

We will focus in this paper on modeling the learner model in a dynamic and probabilistic way, we will propose in this work the use of the notion of fragments and MEBN theory (MTheory) to lead to a Bayesian multi-entity network. The use of this Bayesian method can handle the whole course of a learner as well as all of its shares in an adaptive educational hypermedia.

The main objective of this paper is the management of the learner model based on multi-entity Bayesian networks (MEBN) and artificial intelligence and to achieve a learner model that represents the different actions that the learner could take during his learning path. To achieve this goal, one must first ask the following questions: Why and how can one model the learner model with a probabilistic method? What is the approach to go from a conceptual model for this model to dynamic modeling? Is this taking into account experimentally justified?

First, the learner model modeled using the unified modeling language use case diagram, and then we will present the Bayesian network of the learner model that we have developed. Then, we will explain the approach followed in this paper for modeling the learner model with MEBN, beginning with the presentation of MEBN and their composition, then explaining the notions of fragments and theories. Finally, and in order to dismantle the validity of our hypothesis, we will present the fragments of each node of our network, its random variables, and then present our MEBN in a complete way.

2.Materials and methods

2.1Learner modelling in Adaptive hypermedia

In this section, we will come back to the steps to follow when modeling the learner in an adaptive education system using UML, from the user's meta model and in the use case diagram. Gathering all the learner's actions in the adaptive system.

2.1.1Learner model meta model

In this section, we will present a user-specific meta-model for e-learning presented by Souhaib [6]. This model includes a combination of models for e-Learning and adaptive hypermarkets. It takes into account elements such as the history of actions, which are missing in the formal models. The construction of this model allowed us to understand the user's creative process model for adaptive hypermedia, helping us build our hyperonym model. [7].

In our e-Learning user model is able to:

- Define characteristic attributes, essential and common to all users: name, username, password and age;
- Define the categories of attributes to separate the user's preferences, academic / professional characteristics and others. This distinction will make it easier to import data, maintain the system, and communicate with external systems; the attributes are differentiated according to their nature;
- Retain the documents covered by the user in two ways: first, by involving them in a complete course. On the other hand, specifically related to the notion they investigated. The purpose of this historical duplicate is to present the same documents to the user when he wished to return to a concept already brought to his attention during his first learning of this concept.

2.1.2The learner model's use case diagram

Based on the meta-model, we were able to map out the functionality of the learner using the use case diagram (*Figure 2)* to reflect a part of the student's actions in an adaptive system. We will explain in this part each of these actions beholding the relationships of these actions with each other and within the system operation process. Based upon the meta-model presented in the previous section, we have illustrated in the *Table 1*. It shows the learner's actions in a learning situation in an adaptive educational system:

Table 1 The main actions of a learner in learning situation in an adaptive system

Learner's actions
- Follow courses
- Take pretest
- Take evaluation

The UML class diagram representation of our user model is given in *Figure 1*.

In *Figure 2* a main actor is identified and named "the learner". The figure shows the generalization relationships between use cases and the learner, and the generalization relationships: inclusion and extension between use cases.

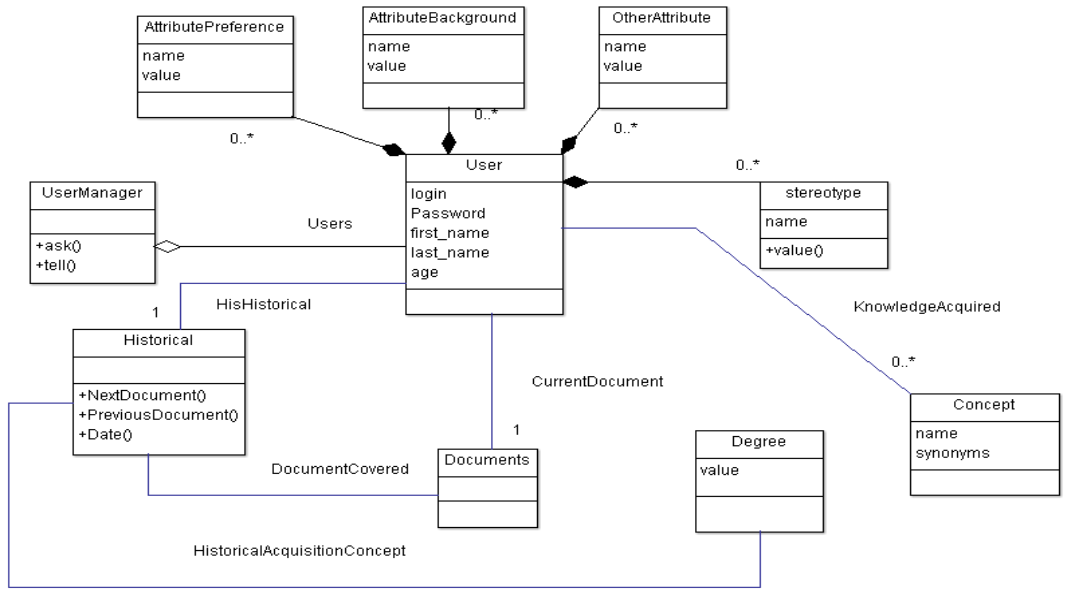

Figure 1 The class diagram of the user meta-model

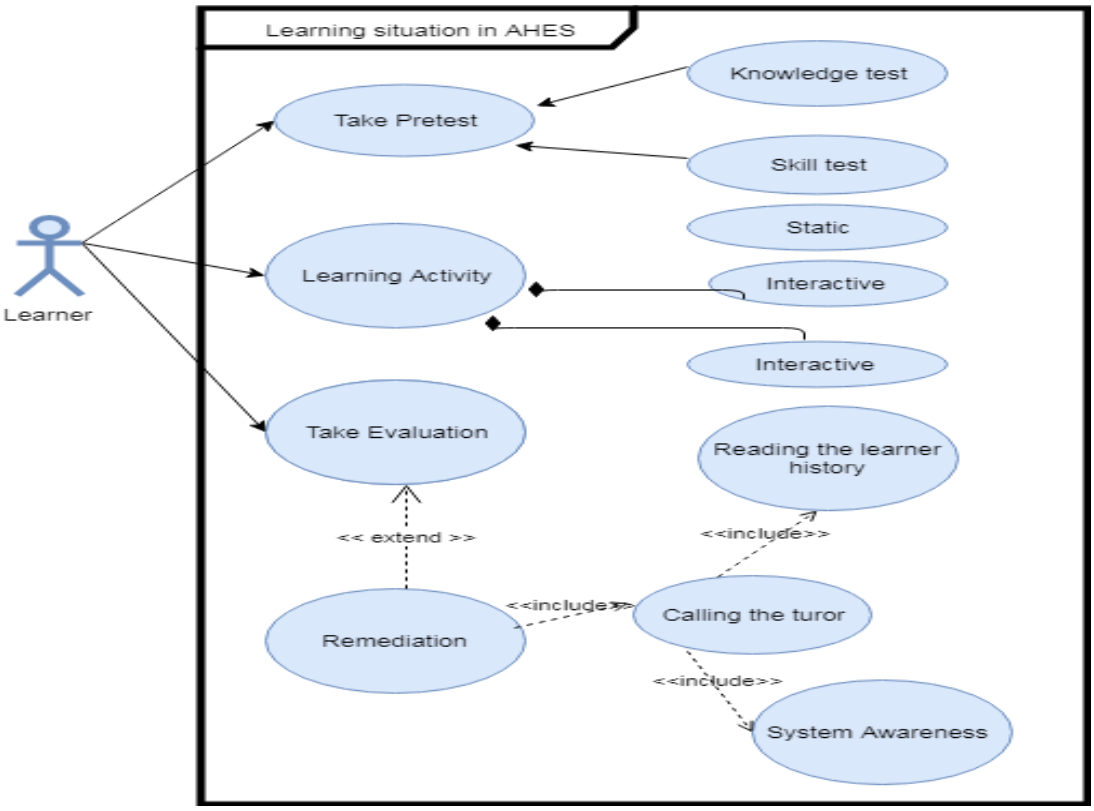

Figure 2 Use case diagram UML representing the learner actions

In particular, the functional requirement "learner" represents all information about the learner in the hypermedia system (his knowledge, his skills, personal information ...). This functional requirement is shown with a generalization relationship with three functional requirements:

- **"Pretest"** which represents the information about the pretest that the learner has to take before

entering the learning situation. The pretest is composed of two types of evaluation components: tests of knowledge, depicted with the functional requirement "knowledge" and a functional requirement "skills" which represents the test through which we will evaluate the learner's skills.

- **"Learning activity"** this functional requirement represents the information about the learning activities, each learning activity in adaptive educational hypermedia system is of two types, static activities represented by the functional requirement "static" and interactive activities represented by the functional requirement "interactive"
- **"Evaluation"**, which represents the information about the evaluation tests that the learner has to take over the completion of each learning activity. In case of failure of the learner in the evaluation, the learner must pass to remediation; which is represented through a functional requirement "remediation" which is connected with the functional requirement "evaluation" through an extension of the relationship.

In case of remediation, the functional requirement "remediation" involves the activation of the functional requirement "call tutor" through inclusion relation. This requirement represents the activation of the tutor to help the student to return to its shortcomings in the learning activity.

Another inclusion relation is represented in our figure which represents the actions of the learner in an adaptive system, appearing in the relationship between the functional requirement "call tutor" and requirements "reading the history of the learner" that activates the return of the system to the profile and the course information of the learner and a requirement "system awareness", that enables the system to follow the course of the learner after remediation.

2.2The Bayesian network, developed from the learner model

The development of Bayesian network based on the use case diagram for modeling the learner in an adaptive educational system passes through two essential steps:

2.2.1Specification of the model structure

Taking the case of the node "Learner" to illustrate the stages of development of our Bayesian network representing the model of the learner, this node have three parent node name pretest, learning activity and evaluation, and each of these nodes is composed of child nodes. Links to these nodes are prerequisite relationships:

- **Learning activity:** In this node, all students following the course must go through activities, which are in the adaptive system of two types: static and interactive.
- **Pretest:** All learners, before taking the learning activities of each course must take a pretest, it consists of two types of evaluation:
  - **Knowledge:** The student must answer more than 10 questions to measure how his wealth of knowledge. This type of evaluation reflects the evaluation part of the knowledge of the learner.
  - **Skills:** This is a written proof if the student can apply the knowledge gained in the module. This type of evaluation reflects the part of the skills of the learner.
- **Evaluation:** After the student follows the learning activity, it is carried to conduct an evaluation to determine their level of knowledge and skill within the module. The evaluation is essential to guide the course of the learner.

The value that measures the relative importance of each condition varies from 0 to 1, the values of each evaluation element are defined by the teacher. In this case the teacher of the module is "Database".

The relationship between the target variable (T) and the evidence variable (E) is from T to E because the process that calculates the posterior probability of the target variable is the proof of knowledge of the diagnosis. So if variable evidence has no children, his parents must be the target variables. There are two types of relationships:

- Prerequisites relations between target variables.
- Diagnostic relations of target variables of evidence variables. The control of concepts (targets) effects on confidence of evidence. However, if the learner has failed a test, it is not sure of his lack of knowledge or ability because it can make an unexpected error.

2.2.2The specification of variable values

Once the use case diagrams were created, it is easy to create the structure of the Bayesian network using the rules described in the previous sections. *Figure 3* represents the Bayesian network built from the use case diagram shown in the previous section. Notice how the conditional independence was directly modeled by applying the rules as shown in the *Figure 3*.

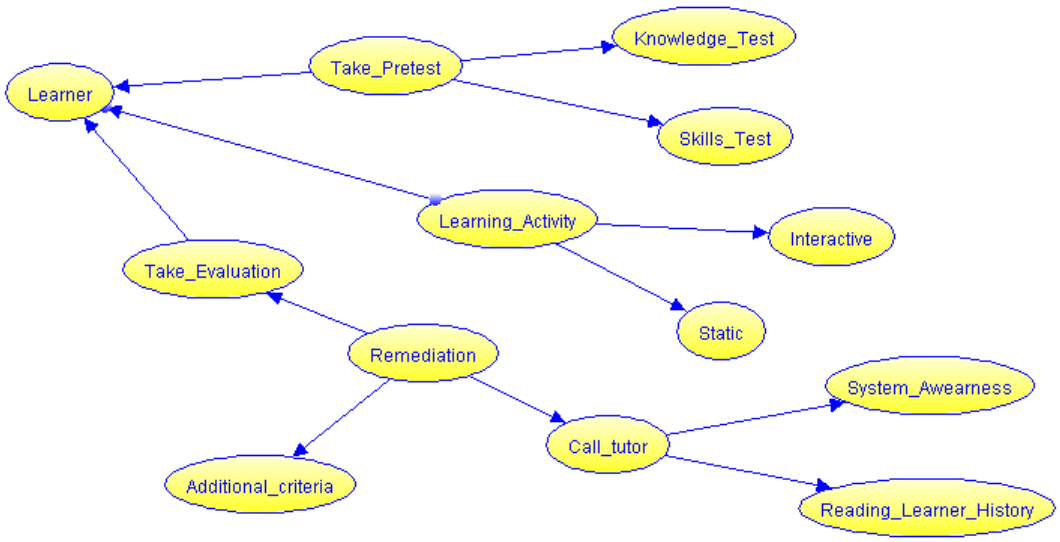

Figure 3 The Bayesian network developed of the learner model

In the Bayesian network developed, we observe that the node learner (L) has three parents: learning activity (A), evaluation (E) and pretest (T) which in turn are corresponding to three weights of prerequisite relationship: w1=0.1, w2=0.5 and w3=0.4. The conditional probability of (L) is computed as follows:

$$P(L|A,E,T) = w1 * h1 + w2 * h2 + w3 * h3$$

Where:

$$h1 = \begin{cases} 1 \text{ if } A = L \\ 0 \text{ otherwise} \end{cases}$$

$$h2 = \begin{cases} 1 \text{ if } E = L \\ 0 \text{ otherwise} \end{cases}$$

$$h3 = \begin{cases} 1 \text{ if } T = L \\ 0 \text{ otherwise} \end{cases}$$

We should state that {L, A, E, T} is a complete set of mutually exclusive variables, which each also a random and binary variable.
Generalizing about formula below, it is that:

$$P(X = 1|Y1, Y2 \ldots Yn) = \sum_{i=1}^{n} wi * hi$$

Where $h1 = \begin{cases} 1 \text{ if } Yi=X \\ 0 \text{ otherwise} \end{cases}$ with given random binary variables X, Yi. Obviously, $P(\text{not } X|Y1, Y2, \ldots, Yn) = 1 - P(X|Y1, Y2, \ldots, Yn)$.

(a)The conditional probability table (CPT) of the node "Learner"

Table 2 represents the CPT of each child node of the parent node Learner. Because concepts A, E, T have no prerequisite knowledge for understanding, their CPTs are specified as prior probabilities obeying uniform distribution as stated in *Table 3* (assigned a medium value 0.5 in most cases)

(b)The CPT of the node "Pretest"

Table 4 shows the CPT of each child node of the parent node Pretest:

(c)The CPT of the node "Learning activity"

Table 5 shows the CPT of each child node of the parent node learning activity:

2.3Multi-entity Bayesian networks

In this section, we will present the state of the art on Bayesian multi-entity networks, which are considered the new generation of probabilistic modeling, and on which we based our research for the management of the model of learning in adaptive hypermedia. We will first begin by presenting the first-order logic, which is considered the basis of Bayesian networks, and then we will present Bayesian multi-entity networks, their principles and their logic.

2.3.1First-order logic

First-order logic is by far the logical system most commonly used, studied and implemented. First-order logic is a formal system used to define theories in mathematics, computer science, and other scientific fields. It is a very important concept from both a theoretical and a practical point of view. First-order logic can also be used as a rigorous foundation for knowledge representation systems [8].

Table 2 The CPT of the "Learner" node.

A	T	E	P(J=1)	P(J=0) 1−P(J=1)
1	1	1	1.0 (0.1*1 + 0.5*1+ 0.4*1)	0.0
1	1	0	0.6 (0.1*1 + 0.5*1+ 0.4*0)	0.4
1	0	1	0.5 (0.1*1 + 0.5*0+ 0.4*0)	0.5
1	0	0	0.1 (0.1*1 + 0.5*0+ 0.4*0)	0.9
0	1	1	0.9 (0.1*0 + 0.5*1+ 0.4*1)	0.1
0	1	0	0.5 (0.1*0 + 0.5*1+ 0.4*0)	0.5
0	0	1	0.4 (0.1*0 + 0.5*0+ 0.4*1)	0.4
0	0	0	0.0 (0.1*0 + 0.5*0+ 0.4*0)	1.0

Table 3 The CPT of the "Learner" parents

P(A=1)	P(A=0)	P(T=1)	P(T=1)	P(E=1)	P(E=1)
0.5	0.5	0.5	0.5	0.5	0.5

Table 4 The CPT of the "Pretest" node

S	P(J=1)	P(J=0) 1−P(J=1)
1	0.8(0.8*1)	0.2
0	0.0(0.8*0)	1.0
D	**P(J=1)**	**P(J=0) 1−p(J=1)**
1	0.2(0.2*1)	0.8
0	0.0(0.8*0)	1.0

Table 5 The CPT of the "Learning activity" node.

S	P(J=1)	P(J=0) 1−P(J=1)
1	0.6(0.6*1)	0.4
0	0.0(0.6*0)	1.0
D	**P(J=1)**	**P(J=0) 1−p(J=1)**
1	0.4(0.4*1)	0.6
0	0.0(0.6*0)	1.0

A theory in first-order logic consists of axioms, expressed in sentences in the first-order language, in conjunction with sentences derived from axioms according to the rules of reasoning, that is, valid theorems or sentences. In practice, when a first order theory is implemented in a computer, the axioms are stored as data structures and the reasoning that evaluates the truth value of a sentence of the form of a computer program.

Theories are expressed using the first-order logical language. The main components of the first-order logical language are constants, variables, functions, and predicates. Variables are placeholders for constants. The functions return a relative constant of their input arguments. Predicates are an essential component of first-order logic (the reason why it is also called predicate logic), since they are used to define relationships between other components, such as variables and constants. For example, the preaching parents (John, Mary, George), can say that John and Mary are relatives of George. What also makes the first-order logic a strongly expressive language are the rules, such as "brothers (X, Y): -parents (X, X1, X2) AND (Y, X1, X2)". This rule states that two persons X, Y are siblings if they have the same parents.

An interpretation of a first-order logical theory gives a semantic meaning to each constant, predicate, and function (formulas). Specifically, an interpretation maps each formula to a specific nominal entity, to the constraints of each predicate to relate with other entities belonging to a specific set, and links a function to a domain function. A set containing all the instantiated formulas of a first-order logical theory is called an interpretation [9].

However, first-order logic does not provide expressivity for modeling uncertain knowledge, let alone a rigorous and rigorous reasoning mechanism. This is a consequence of the fact that each interpretation mentioned above shares an equal validity with the others. As we will see in the following sections, the key feature of MEBN is the assignment of a probability to each interpretation. This is achieved with Bayesian first order logic (FOBL) [10].

2.3.2Presentation of multi-entity Bayesian networks

Bayesian multi-entity networks are logical systems that integrate first-order logic (FOL) with Bayesian probability theory. Bayesian multi-entity networks extend ordinary Bayesian networks to allow representation of graphical models with repeated substructures. Knowledge is coded as a collection of Bayesian network fragments (MFrags) that can be instantiated and combined to form Bayesian networks specific to the complex situation. A theory of MEBN for MTheory implicitly represents a joint probability distribution on possibly unlimited numbers of hypotheses and uses Bayesian learning to refine a knowledge base as observations accumulate. The multi-entity Bayesian network provides a logical basis for the emergent collection of highly expressive, probability-based languages [11].

MEBN are the result of combining Bayesian networks with FOL. In other words, in a MEBN, Bayesian network capability to model uncertainty is combined with FOL expressivity. From the point of view of stochastic Bayesian modeling, the goal of using MEBN is to build a Bayesian situation-specific network (SSBN) that is customized based on the snapshot of the environment in that situation. In multi-entity Bayesian networks, the Bayesian network is extended to a first-order logical Bayesian network (FOBN), which is used to express and represent knowledge. This overcomes the gap in Bayesian networks by being very rigid and inflexible for modeling dynamic environments [11].

MEBN integrate first-order logic with Bayesian probability. The logic of Bayesian multi-entity networks expresses probabilistic knowledge as a collection of fragments of multi-entity Bayesian networks organized into MEBN Theories (MTheories). An MFrag represents a conditional probability distribution of the instances of its resident random variables taking into account the values of their parent instances in the fragment graphics and given context constraints [8].

A collection of MFrags represents a joint probability distribution over an unlimited number, possibly infinite, of its random variables. Joint distribution is specified using local distributions with conditional independence relationships implied by fragmented graphics. Contextual terms are used to specify the constraints under which local distributions apply.

A collection of MFrags that satisfies consistency constraints ensuring the existence of a single joint probability distribution on its random variables is called MTheories. MTheories can express probability distributions on the truth values of arbitrary first-order logic sequences and can be used to express domain-specific ontologies that capture statistical regularities in a particular application domain.

In addition, MTheories may represent particular facts relevant to a given reasoning problem. The conditioning of a prior distribution represented by an MTheorie on its results is the basis of the probabilistic inference with the logic of MEBN [12].

2.3.3Fragments of multi-entity Bayesian networks

The logic of Bayesian multi-entity networks represents the world composed of entities with attributes and related to other entities. Random variables represent features of entities and relationships between entities. The knowledge of attributes and relationships is expressed as a collection of fragments organized in MTheory. A fragment represents a conditional probability distribution for the cases of its resident random variables given their parents in the fragment graph and the context nodes [13].

Like a Bayesian network, an MFrag contains nodes, which represent random variables, arranged in a directed graph whose edges represent direct dependency relationships. An isolated MFrag can be compared to a standard Bayesian network with known values for its root nodes and known local distributions for its child nodes.

For example, the MFrag shown in *Figure 4* was taken from a model of a Bayesian multi-entity network in the Star Trek domain and represents knowledge of the degree of danger to which the spacecraft is exposed. The fragment graph has seven nodes. The four nodes at the top of the figure are contextual nodes; the two rectangular nodes shaded under the context nodes are the input nodes; and the lower node is a resident node.

A node in an MFrag can have a parentheses list of arguments. These arguments are placeholders for domain entities. For example, the *st* argument of the *HarmPotential* node (*st*, *t*) is a placeholder for an entity that may be harmful, while the t argument is a placeholder for the time step that this instance represents. To refer to an actual entity in the domain, the argument is replaced by a unique identifier. By convention, unique identifiers begin with an exclamation point and no separate entity can have the same unique identifier. The result of the substitution

of unique identifiers for the arguments of a random variable is one or more instances of this variable. For example, *HarmPotential(!ST1,!T1)* and *HarmPotential* (*!ST2,!T1*) are two instances of *HarmPotential* (*st, t*) that both occur in the time step *!T1*.

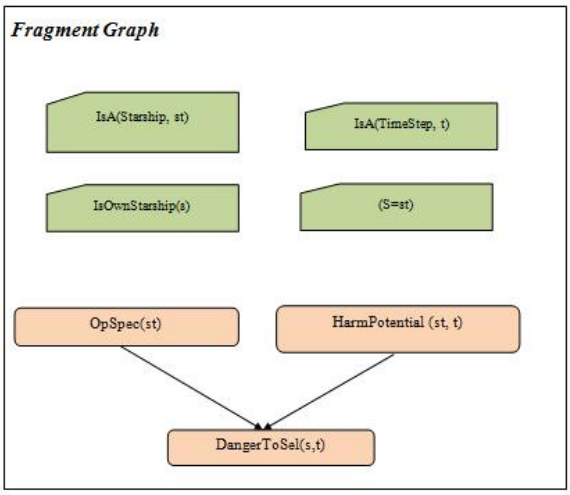

Figure 4 Example of a fragment of Bayesian multi-entity networks

The resident nodes of an MFrag have local distributions that define how their probabilities depend on their parent's values in the fragment graph. In a complete MTheory, each random variable has exactly one domestic MFrag, where its local distribution is defined. The input and context nodes (for example, *OpSpec* (st) or *IsOwnStarship* (s)) influence the distribution of resident nodes, but their distributions are defined in their own home MFrags [14].

Contextual nodes represent conditions that must be satisfied for local influences and distributions of the fragment graph to be applied. Contextual nodes can have a true, false, or absurd value. Context nodes with a true value are considered satisfied. For example, if the unique identifier for Enterprise (*! ST0*) is replaced by the variable s in *IsOwnStarship* (*s*), the resulting assumption will be true. If, instead, a unique star identifier (*ST1*) is used, then this assumption will be false. Finally, if the unique identifier of a non-spacecraft (*! Z1*) replaces s, this statement is absurd (i.e. it is absurd to wonder if an area in space is its own ship spatial).

To avoid cluttering the graph of fragments, the states of the context nodes are not represented, unlike what happens with the input and resident nodes. This is mainly because they are Boolean nodes whose values are relevant only to decide whether to use the local distribution of a residential random variable or its default distribution [15].

2.4Managing the learner model with MEBN

In this section, we will first present the fragments that we have developed from the Bayesian Learner Model Network. Then, we will present the complete MEBN of the learner model based on first-order logic.

2.4.1Fragments of the learner model

In the previous sections of this paper, we presented the Bayesian network of the learner model that we developed from a use case diagram. To arrive at a MEBN of the learner model, it is essential to start by first developing the fragments of this network based on the predominant nodes of this network.

The main nodes of our Bayesian network, which will be transformed into fragments of the Bayesian multi-entity network of the learner model, are:

- The pretest fragment
- The learning situation fragment
- The evaluation fragment

In order to develop the Bayesian multi-entity network of the learner model, it is first necessary to define the context nodes, the input nodes, and the distribution within each resident node of these fragments.

a) Fragment of the node pretest

For the pretest node fragment that represents information about the pretest that the learner must first pass before entering a learning situation. This fragment is composed as we have already shown in the previous sections of two types of pretests, the first concerns the knowledge of the learner, and the second is a pretest concerning the skills of the learner. The green flowcharts in our fragment represent the random variables of the context that express the validation conditions of our fragment within the multi-entity Bayesian network. The rounded rectangles in our fragment represent the input random variables, the distribution of its variables will be used in other fragments of the multi-entity Bayesian network.

Figure 5 shows the fragment of the Pre-test node of our MEBN. There are two random variables in our fragment, is (Knowledge, Abilities) which concerns the determination of the type of pretest that the learner must take represented by the input random variable type *pretest (obj).* The variable *isP (Passed, Failed)* which concerns the validation of the pretest

by the learner represented by the input random variable *Validation pretest (Pre-test) (obj).*

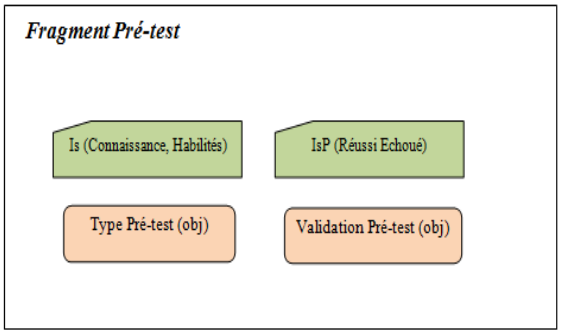

Figure 5 The fragment of the node pretest of the MEBN

b) Fragment of the node learning activity

For the node learning activity fragment, that represents information about the learning activity that the learner must follow during his or her learning path. This fragment is composed as we have already shown in the preceding sections of two types of activities.

The first type of activity is interactive, and the second type is static.

Figure 6 shows the fragment of the learning activity node of our MEBN. There are two random variables in our fragment, is (Interactive, Static) which relates to the determination of the type of learning activity that the learner must follow represented by the input random variable type *Learning Activity (obj)*. The variable *isAP (Passed, Failed)* which concerns the validation of the learning activity by the learner represented by the input random variable *Validation Learning Activity (obj).*

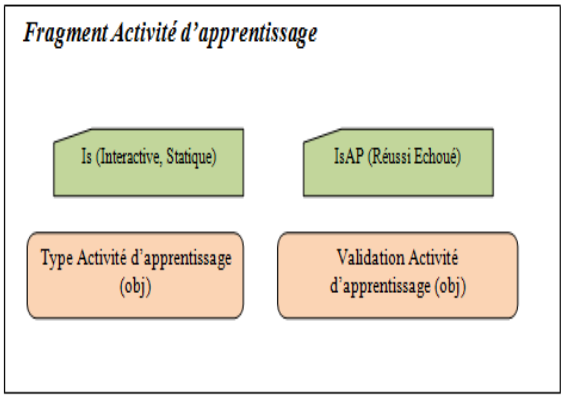

Figure 6 The fragment of the node Learning Activity of the MEBN

c) Fragment of the node evaluation

For the node evaluation fragment, that represents the assessment information that the learner must take at the end of each learning activity during their learning journey. This fragment is composed as we have already shown a primordial relation concerning the call of a tutor to help the learner in case of remediation.

Figure 7 shows the fragment of the node evaluation of our MEBN. There are two random variables in our tutor call (History, System Awareness) fragment that pertains to a tutor's call to help the learner based on his or her browsing history and to sensitize the system to the remediation case that is represented by the random input variable *Remediation (Tutor call).* The variable *isE (Passed, Failed)* which concerns the validation of the evaluation of the learner represented by the input random variable *Validation Evaluation (obj).*

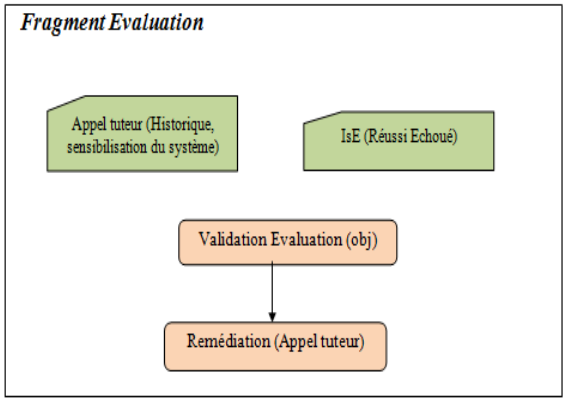

Figure 7 The fragment of node the Learning Activity of the MEBN

The random input variable *Remediation (Tutor call)* is related to the conditioning of the input random variable *Validation Evaluation (obj),* which means that remediation is enabled only in the case of failure of the evaluation; this condition requires the tutor's call to help the learner in difficulty.

2.4.2The MEBN of the learner model

After the development of the three main fragments of Bayesian network, we will present the MEBN for the learner model. As we defined in the previous sections of this paper, the knowledge of attributes and relationships is expressed as a collection of fragments organized in MTheory.

We will begin with a presentation of the learner fragment of our learner model, which concerns the main node of our learner model, its random variables,

its output variables, and the probabilistic relationships between the father node and its children. Then we will treat the multi-entity Bayesian network of the learner model that represents all the fragments of the model and the relationships between them.

a) Learner's node fragment

For the learning node, there are three child nodes of this main node: the pretest, the learning activity, and the evaluation, which in turn represents a conditional child node called remediation.

The green flowcharts in our fragment represent the random variables of the context that express the validation conditions of our fragment within the MEBN. The rounded rectangles in our fragment represent the input random variables, the distribution of its variables will be used in other fragments of the MEBN.

Figure 8 shows the fragment of the learner node of our MEBN. There are four random variables in our *call tutor (History, System Awareness)* fragment which concerns a tutor's call to help the learner based on his / her browsing history and to sensitize the system to the case of remediation that is represented by the random input variable *Remediation (Tutor call).* The variable *isE (Passed, Failed)* which concerns the validation of the evaluation of the learner represented by the input random variable *Validation Evaluation (obj).*

The variable isAP (Passed, Failed) which concerns the validation of the learning activity by the learner represented by the input random variable *Validation Learning Activity (obj).* The *variable isP (Passed, Failed)* which the validation of the pre-test performed by the learner represented thanks to the input random variable *Validation pretest (obj).*

The learner in this fragment begins by passing the pretest of the entry through a random variable input *validation pre-test (obj).* After the validation of this condition, the learner is directed to a learning activity, and will be led to validate it by reaching the conditions for success of the random variable *Validation Learning Activity (obj).*

Finally, the learner will be led to pass an evaluation in the random variable *Validation Evaluation (obj).* In case of failure of this assessment, a remediation will be activated in the Random Remediation variable which requires a call to the tutor who will help the learners in difficulty based on their browsing history.

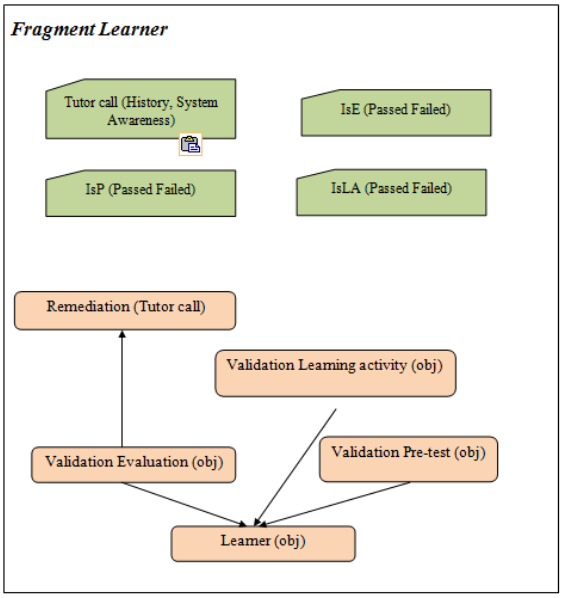

Figure 8 The learner fragment of the learner model

b) The MTheory of the learner model

Figure 9 shows the MTheory of the learner model, a set of coherent fragments defining a joint distribution on situations involving cases of random variables. There are 3 fragments in our Mtheory of the learner model such as the pretest, the learning activity as well as the evaluation, and finally the learner reference fragment. Each of the MFrags consists of context, input and resident nodes.

The MEBN of the learner model developed can be used to estimate and predict a learning situation in adaptive hypermedia systems, dynamically tracking in real time all learners' actions during their course. Learning pathways and during their presence in adaptive hypermedia.

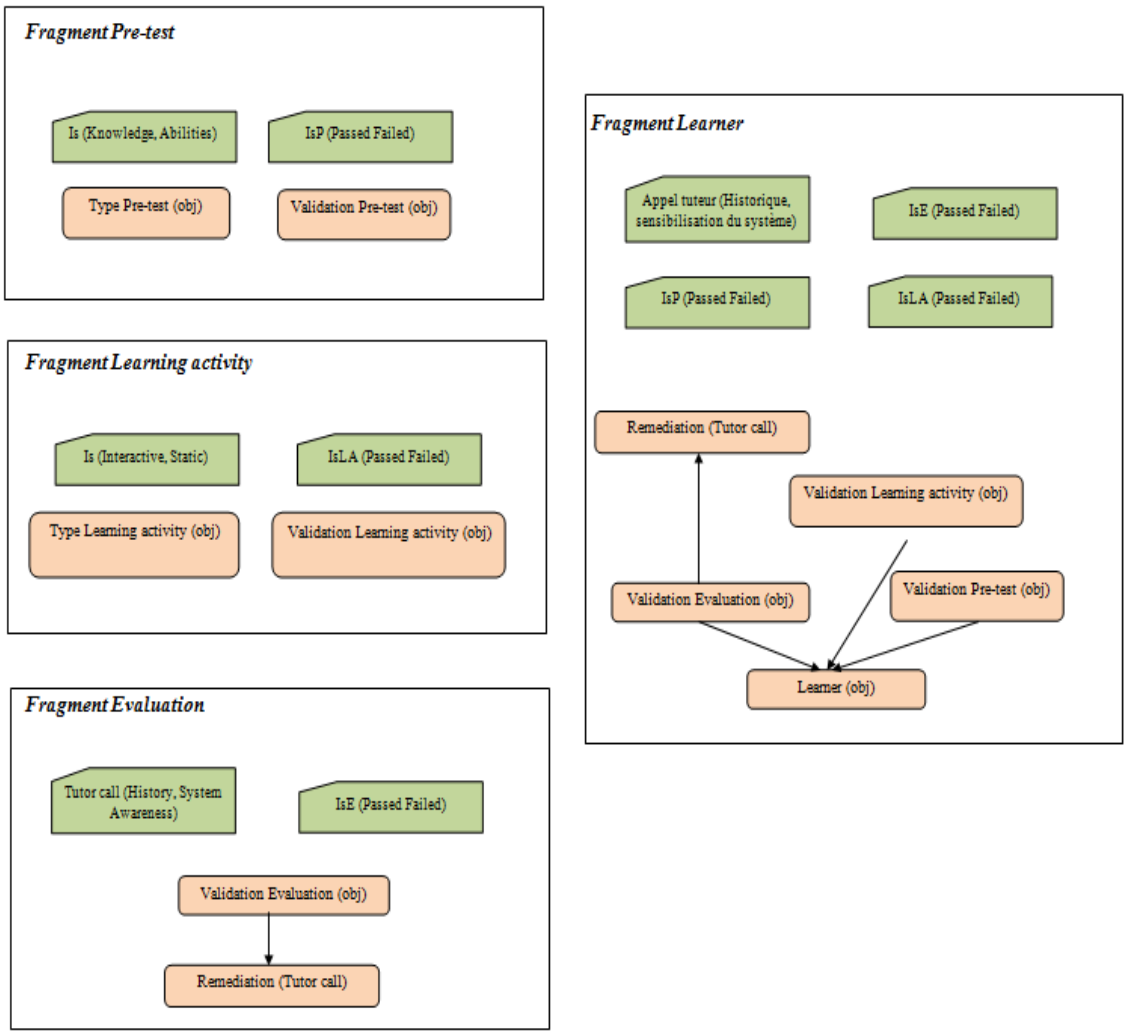

Figure 9 The MTheory of the learner model in an adaptive hypermedia

3.Discussion

The fact that MEBN incorporate the ontological concept into their modeling part allows the systematic collection and formal representation of multiple concepts of learner knowledge. Thus, with Bayesian multi-entity networks, we also aim to exploit the useful functionality of ontologies to facilitate a practical and non-error-prone development of the part of the representation of learner knowledge within adaptive educational hypermedia. Thus, Bayesian multi-entity networks combine, for this specific problem, the advantages of the two worlds, that is, the expression and representation of knowledge in the framework of ontologies and the uncertainty of modeling using probabilistic models in the framework of Bayesian networks.

The approach that we followed during this paper is marked initially by modeling the learner model in three levels: we started with the conceptual level of modeling with the unified modeling language, followed by the modeling model based on Bayesian networks to be able to achieve probabilistic modeling in the three phases of learner modeling. Finally, we have proposed in this paper a dynamic and probabilistic modeling of this model using MEBN.

All of the elements discussed above represent the essence of this work. The transformation of Bayesian networks developed for the management of the learner model to machine-readable language, such as ontologies, or as we have already proposed, using probabilistic ontologies as a formalism that gives us

the possibility of combine Bayesian networks with ontologies [16−18].

The elaborate learner model could be reused and adapted to other environments in various domains while using an engineering approach, which provides a better framework for design. The choice of Bayesian multi-entity networks as a formalism to manage the uncertainty of this model becomes more beneficial especially for environments with many examples. The model could also help the teacher to better adapt his teaching to the learner. Nevertheless, learner participation largely influences the effect of using our model.

4.Conclusion and future work

We have already introduced our learner model using Bayesian networks as formalization for learner management. Also, we have covered all phases of initialization and updating of this model to the combination of networks with other methods and models to ensure a complete management of all areas of the learner model. We wanted to take our work to the next level, to machine-readable modeling. This is why the main hypothesis of this paper was the management of the learner model based on MEBN, for a dynamic and probabilistic management of the learner model in adaptive hypermedia.

This approach is considered very useful for the learner model, especially in the case of a large number of data stored in the system. The transformation of the nodes for fragments gives us the possibility of a separate management of the data of each fragment, keeping at the same time all types of relations of each fragment with the other fragments by using the random variables which exist in several fragments within an MTheory of the learner model.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

References

[1] Yudelson M, Brusilovsky P, Zadorozhny V. A user modeling server for contemporary adaptive hypermedia: an evaluation of the push approach to evidence propagation. In international conference on user modeling 2007 (pp. 27-36). Springer, Berlin, Heidelberg.

[2] Brusilovsky P, Sosnovsky S, Shcherbinina O. User modeling in a distributed e-learning architecture. In international conference on user modeling 2005 (pp. 387-91). Springer, Berlin, Heidelberg.

[3] Zaitseva L, Boule C. Student models in computer-based education. In international conference on advanced learning technologies (p. 451). IEEE.

[4] Tadlaoui MA, Carvalho RN, Khaldi M. The initialization of the learner model combining the Bayesian networks and the stereotypes methods. International Journal of Advanced Computer Research. 2017; 7(33):200-12.

[5] Tadlaoui MA, Aammou S, Khaldi M, Carvalho RN. Learner modeling in adaptive educational systems: a comparative study. International Journal of Modern Education and Computer Science. 2016; 8(3):1-10.

[6] Souhaib A. Design of semantic interoperability of adaptive hypermedia educational systems, based on ontologies 2013.

[7] Mouenis AT, Souhaib A, Mohamed K. Learner modeling based on Bayesian networks. In E-Learning-Instructional Design, Organizational Strategy and Management 2015:165-87. Intech Publication.

[8] Laskey KB. MEBN: a language for first-order Bayesian knowledge bases. Artificial Intelligence. 2008; 172(2-3):140-78.

[9] Self JA. Formal approaches to student modelling. In student modelling: the key to individualized knowledge-based instruction 1994 (pp. 295-352). Springer, Berlin, Heidelberg.

[10] Laskey KB, D'ambrosio B, Levitt TS, Mahoney S. Limited rationality in action: decision support for military situation assessment. Minds and Machines. 2000; 10(1):53-77.

[11] Costa PC. Bayesian semantics for the semantic web. George Mason University; 2005.

[12] Da Costa PC, Laskey KB, Chang KC. PROGNOS: applying probabilistic ontologies to distributed predictive situation assessment in naval operations. 2009.

[13] Carvalho RN, Costa PC, Laskey KB, Chang KC. PROGNOS: predictive situational awareness with probabilistic ontologies. In conference on information fusion 2010 (pp. 1-8). IEEE.

[14] Carvalho RN. Probabilistic ontology: representation and modeling methodology. George Mason University; 2011.

[15] Wright E, Mahoney S, Laskey K, Takikawa M, Levitt T. Multi-entity Bayesian networks for situation assessment. In fifth international conference on information fusion, 2002 (pp. 804-11). IEEE.

[16] Mouenis AT, Mohamed K, Souhaib A. Towards probabilistic ontology based on Bayesian networks. International Journal of Software and Web Sciences. 2014; 10(1): 102-6.

[17] Tadlaoui MA, Khaldi M, Aammou S. Towards a Learning model based on Bayesian networks. In EDULEARN proceedings 2014 (pp. 3185-93). IATED.

[18] Mouenis AT. Managing a learner model in an adaptive education system based on Bayesian networks. 2016.

Mouenis Anouar Tadlaoui is a PhD Research Scholar in Computer Science, at the Laboratory of Informatics, Research Operational and Statistic Applied (LIROSA) at Faculty of Sciences, Abdelmalek Essaadi University. His dissertation research, focus on managing the learner model in Adaptive Hypermedia Systems based on Bayesian methods and Artificial Intelligence. Mouenis have a Master's degree in Instructional design Multimedia Engineering, and a BSC in Web Development from Abdelmalek Essaadi University in 2013 and 2011. He has produced several technical outputs, including papers, book chapters, technical presentations, processes, among others in the field of adaptive systems management. His research areas are E-Learning, Adaptive Hypermedia Systems, Artificial Intelligence, and Bayesian Networks.
Email: tadlaouimouenis@gmail.com

Rommel Novaes Carvalho completed his Postdoctoral at George Mason University (GMU) in the area of Artificial Intelligence, Data Mining, Uncertainty, and Knowledge Discovery in May 2012. During the 3 years of his PhD, he was a Graduate Research Assistant in the Department of Systems Engineering and Operations Research at GMU, Virginia, USA. He received his Master in Computer Science and his Bachelor of Computer Science from University of Brasília (UnB), DF, Brazil, in 2008 and 2003, respectively. He has been working in the Brazilian Office of the Comptroller General (CGU) as an IT expert since 2005 and at UnB as a Professor on the Applied Computer Science Master's program since 2012. From 2011 to 2012 he participated in the Transparency Portal team, where his key role was to be the main expert in Open Government Data (OGD). At the end of 2012 he started working as the leader of the Data Science team at the Department of Research and Strategic Information (DIE). One of the projects developed at DIE, the Reference Price Database, won the first place on the CONIP 2013 Excellence Award in the category Management and Geographical Information Systems. He has done research on fraud detection and prevention for the Brazilian Government and situation awareness for the US Navy. With almost 11 years of experience in the area, he has produced more than 80 different technical outputs, including papers, book chapters, technical presentations, processes, among others. He is an Artificial Intelligence researcher with focus on Data Mining, Uncertainty in the Semantic Web using Bayesian Inference, Software Engineering, and both R and Java programming. Awarded programmer with experience in implementation of Bayesian Network Systems (UnBBayes), Multi-Entity Bayesian Network (MEBN) and Probabilistic Web Ontology Language (PR-OWL), R Packages, and various Web-Based Applications.
Email: rommel.carvalho@gmail.com

Mohamed Khaldi is a Professor at the The École Normale Supérieure at Abdelmalek Essaadi University, and he is with the Laboratory of Informatics, Research Operational and Statistic Applied (LIROSA) at Faculty of Sciences, Abdelmalek Essaadi University, Tétouan, Morocco.
Email: medkhaldi@yahoo.fr