Supporting Learner’s Needs with an Ontology-Based Bayesian Network

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Abstract

This paper presents a study of MENTOR, a Web Adaptive Educational Environment (WBES), where the learner’s needs and preferences are diagnosed using an Ontology-based Bayesian Network approach during the learning process. Firstly, the proposed method uses an OWL Ontology to store the Affective Knowledge regarding the learner. Then, this Ontology is extended appropriately to deal with uncertainty so that a Bayesian Network (BN) can be constructed from it. Finally, using the derived BN we can make inferences and reasoning on the learner’s individual needs. In this way we form a schema where the uncertain Affective Information (AfI) can be represented efficiently and exploited properly in order to maintain the efforts of a learner. Therefore, based on this model we can detect the learner’s affective model and to support his efforts during the learning process by suggesting the proper pedagogical guidance.

1. Introduction

Despite the importance of the affective aspect, in most educational systems, this crucial parameter seems to be ignored, since the significant process of learning is supported by methods which are mainly concentrating on the cognitive abilities of the learner. Indeed, these systems in their majority develop their educational dimension, based only on cognitive parameters such as learning styles, without taking into consideration the emotional factors that are related to the mood and the personality of the learner. According to this point of view, we developed the MENTOR which is an Affective Educational Environment capable of supporting learning in distance education [4]. MENTOR takes into account the personality and the emotional state of the learner, in order to decide which is the appropriate affective tactic for him. The architecture of the MENTOR is designed with equal respect to the cognitive and the emotional dimension of teaching as well. The method to achieve this is to model the learner’s needs and preferences in a structure which stores affective knowledge such as personality, mood and emotions. This model is called Learner’s Affective Model (LAM) and is supported by an Ontology. This Ontology is called Affective Ontology (AO).

The main reason for using Ontologies in Adaptive Educational Systems (AES) is that they allow an accurate representation of the domain knowledge in a machine-processible way. Thus, Ontologies enable the ability to represent the formal hierarchical structure of complex domains and to explicitly identify a shared conceptualization [8]. However most of the AES in many cases have to deal with incomplete or imprecise information such as the Learner’s Model. Therefore, they are inevitably confronted with uncertainty factors, the appropriate handling of them is crucial for the learning process.

To model this uncertainty information we propose a method that allows the probabilistic extension of the Ontology representation to comprise uncertain factors. This method, which motivated by similar attempts to deal with uncertainty in Ontologies ([1], [3]) supports also the reasoning, inference and mapping of an OWL-Ontology to a BN in order to capture uncertain AfI about concepts, properties and relations and to make as well inferences about the suitable affective tactic which a learner could be provided. Initially in MENTOR, this can be achieved by extending the OWL-based AO to assign concepts, relations and properties to probabilistic factors. Then, the corresponding BN is derived from the extended Ontology and its conditional probability table (CPT) is constructed. Finally, the BN inference mechanism suggests the appropriate affective tactic to the learner.

In this paper we first introduce the basic concepts of our framework which are related to Ontologies, OWL and BN’s. In the next section we present the AO which supports the representation of the AfI. The following two sections analyze the proposed method for encoding uncertainty into the AO and constructing the BN. Then the inference mechanism for the appropriate
affective tactic is presented. Finally, conclusions and future plan of our research are discussed.

2. Ontologies, OWL and BN’s

Ontology is a formal way to represent the specific knowledge of a domain, providing an explicit and extendable framework to describe it. It is a technique of describing formally and explicitly the vocabulary of a domain in terms of concepts, classes, instances, relations, axioms, constraints and inference rules. Ontologies represent knowledge in taxonomies, where more specific concepts inherit the properties of those concepts which they specialize [8]. Therefore, an Ontology expresses a common understanding of a specific domain that serves as a formal platform for efficiently exchange data between information systems. We exploit the advantages of ontological representation in our model to set the vocabulary, properties, and relationships for learning and pedagogical concepts under an affective perspective, the result of which can be a set of rich schemas.

Taking advantage of the above, we use an Ontology of emotions and affective tactics in order to achieve a formal and proper representation of the affective learner model and the system’s learning strategies. In this way we are capable of reasoning efficiently with the affective factors which occur during the learning process. The structure of the proposed Ontology is in compliance with the OCC emotions classification [6] as well as the OCEAN model of personality [5] and has been adjusted suitably in order to attain the requiring domain knowledge and pedagogical representation for our educational system. This AO, which is an application – domain Ontology, it contains the necessary AfI to model and support specifically MENTOR’s educational operations.

In our framework we use an ontological approach based on Web Ontology Language (OWL) [7] as the knowledge representation mechanism of MENTOR’s AfI in combination with a BN model in order to provide the learner with the suitable affective guidance. OWL is a semantic markup language for publishing and sharing ontologies on the World Wide Web. In our model OWL is extended appropriately to model uncertain information and to incorporate probabilities in the ontology representation. In this way probability values can be assigned to the concepts of our Ontology. Moreover, suitable rules are defined to transform the enhanced OWL Ontology into a BN. Thus, the proposed method provides us with a powerful structure for the formal representation of the uncertainly AfI as well an effective method to convert respectively an ontological structure into the BN’s. Also, we show how the fundamentally conditional probability table (CPT) can be constructed from this Ontology, so that the necessary inferences and the reasoning processes of the BN’s can be performed.

Bayesian Networks are graphs the nodes of which depict random values and the arcs the correlations between independent assumptions [2]. More specifically a BN is a Directed Acyclic Graph, or DAG, that is a structure that has no directed cycles. A set of random variables makes up the nodes of the network. Directed arcs connect pairs of nodes. The meaning of an arc from node X to node Y is that X has a direct influence on Y. The uncertainty of the relationship of each node is represented by the Conditional Probability Table (CPT). The CPT presents the probability that a child node is assigned to a certain value for each combination of possible values of its parent nodes. The parents of a node are all those nodes that have arcs pointing to it. In this manner the CPT quantifies the effects that the parents have on the node. We denote as \( P(X_i | \text{Parents}(X_i)) \) the probability that is associated with each node \( X_i \), where \( \text{Parents}(X_i) \) is the parent set of \( X_i \). Then we can calculate the joint probability distribution of \( X_i \) under the conditional independence assumption make use of the following formula:

\[
P(X) = \prod_{i=1}^{n} P(X_i | \text{Parents}(X_i))
\]

Because of the nature of BN’s we can define the concepts of our Ontology as the variable nodes of the BN and the arcs between them as the probabilities which influence their relation. Under this perspective we can reliably estimate how the initial probabilities affect uncertain cases such as the suitable selection of the affective tactic and the future behavior of the learner after the adoption of this tactic. Consequently, we exploit the advantages of the BN’s in order to make predictions in relation to the support of the pedagogical development of the learner during his learning process.

3. The Affective Ontology

The model which is proposed in this paper is based on the combination of two different technological approaches (Figure 1). The first adopts an ontological approach, so that the representation of the AfI can be achieved. The second uses the BN model in order to select the most appropriate affective tactic according to the affective style of a learner with the aim of fitting better to his particular needs. In this way a BN-based Ontology it is formed which stores the AfI of MENTOR, the Acyclic Graph, the data set of implicit evidence and the transitions between situations.
Taking advantage of the above method, we use this BN-based Ontology in order to achieve a formal and proper representation of the LAM and to reason and infer efficiently with the affective factors which occur during the learning process. This Ontology is called Affective Ontology because it stores and deals with AfI such as the Affective Tactics, LAM, and Emotional State. Consequently, to represent the AfI in the Ontology the creation of the relative classes is necessary. Thus, the Affective_Model Class, Affective_Tactic Class and Emotional_State Class for instance, are constructed.

The first class represents the attributes and preferences of the learner. The second represents the twenty AT's that have been already implemented in MENTOR. The third represents the current emotional state of the learner which can be positive, negative or neutral. For example, the Emotional_State Class is encoded as follows:

```xml
<owl:Class rdf:ID="#Emotional_State">
  <rdfs:subClassOf>
    <owl:Class rdf:resource="#Learner_Affective_Model"/>
  </rdfs:subClassOf>
</owl:Class>
```

Properties for these classes are also defined. For instance, the following code specifies a data type property Valence for the previous class.

```xml
<owl:DatatypeProperty rdf:ID="Valence">
  <rdfs:range><owl:DataRange>
    <owl:oneOf rdf:parseType="Resource">
      <rdf:first rdf:datatype="xsd:string">positive</rdf:first>
      <rdf:rest rdf:parseType="Resource">
        <rdf:first rdf:datatype="xsd:string">neutral</rdf:first>
        <rdf:rest rdf:parseType="Resource">
          <rdf:first rdf:datatype="xsd:string">negative</rdf:first>
        </rdf:rest>
      </rdf:rest>
    </owl:oneOf>
  </rdfs:range>
</owl:DatatypeProperty>
```

4. Encoding Uncertainty into the Affective Ontology

According to the OWL’s semantics two concepts are represented by the classes A and B and we consider them as random variables. With the aim of corresponding the prior or conditional probabilities to the classes and relations of the AO we define the $P(A = a)$ as the prior probability that an arbitrary individual belongs to class $A$, and $P(a | b)$ as the conditional probability that an individual of class $B$ also belongs to class $A$. Regarding that the Ontology’s domain cannot be an empty collection of individuals we specify the following relations:

$P(CH)$, as the prior probability of a node $CH$

$P(CH | PA)$, as the conditional probability of a node $CH$ given $PA$, where $PA$ is a parent node of the $CH$, with $PA \subseteq \text{Parents}(X_i) \neq \emptyset$

To express the affectively uncertain information the OWL classes are defined: “Pri_Prob”, “Cnd_Prob” and “Jnt_Prob” which identify the prior probability, the conditional probability and the joint probability respectively. The first two classes have a datatype property “Value_Prob” which express a value between 0 and 1. The last one has two disjoint object properties the “has_Pri” or “has_Cnd, which are disjoint because any instance of the “Jnt_Prob” can only have either prior or conditional probability type. The “has_Pri” defines the relation between the “Pri_Prob” and “Jnt_Prob” classes and specifies that the instances of the “Pri_Prob” are elements of one instance of the “Jnt_Prob”. In the same way the “has_Cnd” defines the relation between the “Cnd_Prob” and “Jnt_Prob” classes and specifies that the instances of the “Cnd_Prob” are elements of one instance of the “Jnt_Prob”. Consequently, the encoding of the uncertainty relations in the Ontology is defined as follows:

**Definition 1.** Affective Ontology, $\text{AO} = \{C, I, P, \text{inst\_func}\}$, where $C \neq \emptyset$ is an affective concept which is represented as a class, $I$ is an instance set, $P$ is a property set which represent the various attributes and $\text{inst\_func}$ is the class instantiation function: $C \rightarrow 2^I$.

**Definition 2.** Uncertainty representation, Property Set $P = \{\text{caus\_rel}, \text{status}, \text{Value\_Prob}, \text{has\_Pri}, \text{has\_Cnd}\}$, where caus_rel is a property causal relation and indicates a directed arc: $I \rightarrow I$, status is a property relation with Boolean value that indicates if a property has activated. Value_Prob, has_Pri and has_Cnd are property relations: $I \rightarrow \text{Float}$.
Based on these definitions we define the prior probability of the suggested Affective Tactic as $P(\text{AT}) = 1/20$. The conditional probability distribution for the Affective Tactic AT given the Learner’s Emotional State ET is defined as $P(\text{AT} | \text{ET})$. Making use of the proposed OWL uncertainty model we can encode these probabilities. Some of them are encoded as follows:

```xml
<long.Prob rdf:ID="P(\text{AT})">
  <hasPri rdf:resource="#P(\text{AT}=1)"/>
  <hasPri rdf:resource="#P(\text{AT}=2)"/>
  <hasPri rdf:resource="#P(\text{AT}=3)"/>
  …………………………………………………
</long.Prob>
```

```xml
<short.Prob rdf:ID="P(\text{AT}=1)">
  <Value_Prob>0.1</Value_Prob>
  <status>true</status>
</short.Prob>
```

```xml
<cond.Prob rdf:ID="P(\text{AT}=1|\text{ET}=\text{positive})">
  <Value_Prob>0.5</Value_Prob>
  <status>true</status>
</cond.Prob>
```

5. Constructing the Bayesian Network and the Conditional Probability Table

The extended with OWL AO must be transformed into a BN. We establish a set of rules by first introducing a property element <owl:Dependent> to specify dependency information in an OWL ontology. According to the proposed schema all classes of the Ontology are converted into nodes in BN using the following rules:

- If two classes of the Ontology are related by the Dependent property then we draw an arc which connects two nodes of the BN to the direction from the superclass to the subclass. Every class of the Ontology is mapped as a two-valued (True or False) variable node. Thus an instance I which belongs to a class C is marked as True.
- If a class C is related to other superclasses A1,..,An with the identifier <owl:subClassOf> then an additional node S is used to denote the intersection property, so that C is mapped into a subnet in the derived BN with directed arcs from each Ci to C, each Ci to S and one arc from C to S, as shown in the example of Figure 4.
- If a class C is related to other classes C1,…,Cn with the identifier <owl:intersectionOf> then an additional node U is used to denote the intersection property, so that C is mapped into a subnet in the derived BN with directed arcs from each Ci to C, each Ci to U and one arc from C to U, as shown in the example of Figure 5.
- Finally, if a class C is related to a class B via the identifiers <owl:complementOf>, or <owl:equivalentWith>, or disjoint (owl:disjointWith) then an additional node P, or E, or D is used to denote the complement, equivalent, or disjoint property respectively, so that C and B are mapped into a subnet in the derived BN with directed arcs from these nodes to the new node. In Figure 6 is shown the disjoint relation.

After the encoding of the uncertainty information in the ontology and the completion of the network’s construction, the final step is the construction of the CPT for the BN. For this reason we propose the following algorithm:

```python
for each node N of the BN do
  
```
if N can be identified in a relation then
  set property status of C in AO True
end_if
if N cannot be identified in a relation then
  set property status of C in AO False
  set property has_Pri of C with value 0.5
end_if
end_for
if C₁,…Cₙ are connected to N and S value is True then
  set property status of C₁,…Cₙ, N in AO True
  set property has_Cond of N with value 1
end_if
if N is connected to C₁,…Cₙ and U value is True then
  set property status of C₁,…Cₙ, N in AO True
  set property has_Cond each C₁,…Cₙ with value 1/n
end_if

A node CH of the BN has a prior probability P(CH)
if any parent nodes are not connected to it and conditional probability P(CH | PA ) if there are a parent set PA≠∅. We set the values of the BN’s CPT according to the logical relation that is held between the parent nodes. Thus, when a node S, U, P, E or D held it in relations of intersection, union, complement, equivalent or disjoint as already described, then its value can be set in as True in the CPT. For example, when the value of a S node is set True, then is held the intersection relation of the nodes C1 and C2 that is connected to it.

6. The Inference of the Appropriate Affective Tactic

One of the most significant features of the BN’s is that enable us to reason and to make inferences in an efficient way. The probabilistic inference considers a set S of propositional variables Sᵢ, i=1,…,n and the evidence that the variables in a subset U of S have definite values, Uᵢ = u. (True or false). Then the conditional probability, that a variable Sᵢ has value s given the evidence is calculated by the type P(Sᵢ = s | Uᵢ = u).

In this paper we described a formal method using a BN-based Ontology approach to represent the AfI of MENTOR while dealing with uncertainty factors which occurred during the learning process such as the emotions and mood. All this information is stored in the Affective Model in order to provide the learner with the suitable affective tactic and engage him effectively into the learning process. We use the term affective tactic [4], so as to denote that the learning method which is suggested by the MENTOR is a two-dimensional combination of cognitive and emotional guidance and support. The main reason for using the

BN model in our method is that it allows us to easily infer the values of the nodes corresponding to the AfI of the learner’s model. This model supplies us with evidences, for selecting the appropriate affective tactic given the values of the affective model node. As a result, calculating the posterior probability that a certain affective tactic has a given value we infer that the suitable is the one having the greatest probability value.

7. Conclusions and Further Research

In this paper we presented a framework to support the learner’s actions during the learning process in an affective way. The proposed model makes use of an ontological approach in combination with Bayesian Network in order to provide the learner with the suitably affective guidance. Based on this model MENTOR provides the learner with the appropriate Affective Tactic in a WBES for distance learning.

At this time we have implemented twenty different affective tactics. The designation of these tactics has taken into account the professional opinion of teachers and psychologists. We hope in future versions that the accuracy of the suggested AT’s will be improved and the number of affective tactics will be further evolved in order to include more cases. When the integration of the MENTOR will have been completed, we plan to keep running an experimental study conducting a web evaluation in order to testify its reliability more precisely.

8. References