POSSIBILISTIC NETWORKS FOR UNCERTAINY KNOWLEDGE PROCESSING IN STUDENT DIAGNOSIS

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Abstract: In this paper, a possibilistic network implementation for uncertain knowledge modeling of the diagnostic process is proposed as a means to achieve student diagnosis in intelligent tutoring system. This approach is proposed in the object oriented programming domain for diagnosis of students learning errors and misconception. In this expertise domain dependencies between data exist that are encoded in the structure of network. Also, it is available qualitative information about these data which are represented and interpreted with qualitative approach of possibility theory. The aim of student diagnosis system is to ensure an adapted support for the student and to sustain the student in personalized learning process and errors explanation.

Keywords: qualitative uncertainty management, intelligent computer based learning system, possibilistic network, student diagnosis, student modeling.

1. INTRODUCTION

Through user module, the intelligent tutoring systems implement a mechanism for achieving personalized interaction between computer system and user. This module represents several user related issues, like knowledge, goals, learning levels and action plans. Because the model involves information about the student, the most challenging task is to interpret and represent gathered knowledge that, usually, is subject of uncertainty.

The principal aim of the intelligent tutoring systems is to adapt to the needs of the student, with help of personalized learning material. Other goals are to implement different pedagogical methods, to adjust the learning material to the student knowledge level or behavioral model, to personalize human computer interaction, to adapt assessments methods depending on student knowledge level, learning goals and erroneous responses diagnosis, to discover misconceptions and errors in learning process. One of the most difficult missions in this context is the process of student diagnosis that generates the hypotheses about missed or erroneous concept learned by the student. There are two types of diagnosis in educational system: cognitive-behavior diagnostic and knowledge/ misconceptions/errors diagnostic.

The process of diagnosis consists, in the case that the errors type and the associated symptoms are known, in determining some symptoms from student behavior in order to find out a specific error. This behavior is accessible only concerning some observations offered by system interface and it must be inferred from available observations using artificial intelligence techniques. In psycho-pedagogical research fields (that are related to the educational systems research) some aspects about imperfection in every day life and the type of the errors made by the humans have been investigated. In conclusion the student model must be capable to deal with imperfection and uncertainty associated with large amounts of data for process observations about persons.

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In order to deal with imperfection, the researchers in the field of computer-based instructional systems have developed different approaches of student diagnosis using techniques from artificial intelligence. They use production rules associated with certainty factors in model trace (Anderson 1985; Daubias, 2000) or in conditions induction model (Langley, Ohlsson, 1984). Fuzzy rules are used for prediction of student behavior or his actions (Chin, 1989; Herzog, 1994 in Jameson, 1995). One of the limitations of diagnosis systems that use rules it is impossibility to use for complex learning domains. Other approaches exploit the possibility to manage the uncertainty through Bayes networks. There are two types of applications: in plan recognition (Huber and all, 1994; Pynadath, Wellman, 1995) and in prediction of student behavior (Jameson, 1990; Martin, VanLehn, 1995; Mislevy, Gitomer, 1995; Desmarais and all, 1995; Conati, VanLehn, 1996). Fuzzy theory is used for deduction of an expert inferential process (Katz and all, 1992; Grigoriadou and all, 2002). Another application is to assess the candidates’ level using the possibility theory (Dubois and all, 2000). A student adaptive testing approach applied for prediction of user performances represents uncertainty using probability theory (Guzman, Conejo, 2004). Also, hybrid neuro-fuzzy techniques were developed to learn and process knowledge from student diagnosis (Stathacopoulou and all, 2004).

The intelligent tutoring systems must be able to represent student knowledge, to make inferential processes about student knowledge state and to generate helpful explanations to the student, based on his tests results.

This work focuses on an application of student diagnose modeling through representation of knowledge in a qualitative possibilistic network and on an explanatory module that reason about student errors and misconceptions. The network arcs represent dependencies between learning domain items. The qualitative possibilities measures associated with each node, model the power of dependencies between nodes. In the light of new evidence about student knowledge level the system is capable to explain the most possible mistakes or lack of knowledge.

2. REPRESENTATION OF LEARNING CONCEPTS

We propose a system that structures the learning concepts in the educational domain of classical programming languages using relations implemented into a possibilistic network. This learning domain is structured through the different levels modules and a study curriculum is made by modules combination. Each module contains a set of basic learning concepts. In order to learn the basic concepts a student must identify and classify these concepts in learning material (Jonassen H., Beissner K., Yacci M., 1993) and must be able to correctly apply them in applications of a programming language. Thus, in language programming learning domain must be established a closely link between items. These must be represented into relational knowledge representation structure.

In our work the programming language domain can be split into more granular learning resources (sub-modules) and represented into a graphical model. We represent the basic concepts from the learning domain with a directed acyclic graph. Each learning concept is placed into a node of graphical model. The concepts are linked between them with arcs. The orientations of the arcs suggest that a node parent must be learned before the node child. The parent node is situated on a basically level in the scale of domain complexity. This structure can be implemented in practice and can be saved like a file with a structure of tags. Each tag represents a node or a relation between nodes or the associated attributes (number of childs, number of parents, possibility measures).

If exist information about the concepts of the parent nodes then it is a big possibility to obtain information about the concepts of the child nodes.

In instructional learning systems the student knowledge about concepts in learning field is compared with the experts’ knowledge. The differences between student and experts’ knowledge can be viewed like errors or misconceptions.

In this work, the basic concepts are represented by the following language programming subjects: identifiers, pre-definite data types, operation of attribution (values attributed to a variable), and operators corresponding to specific pre-defined data type operands. We rely on facts of working with these concepts in order to model another set of concepts that consist of: variable declarations, repetitive structure – for – a statement that provides a compact way to iterate over a range of values, conditional statement – if – that enables a program to selectively execute other statements. The student must know the basic concepts that are a-priory knowledge of the concepts from the second set. All these concepts, enumerated before, if are learned, and then can influence the student capacity to work with vectors. With these intentions we created a relational structure that contains all the learning concepts explained previously. The concepts “for”, “if” and “vectors” are d-separated from the basic concepts, because are indirect links between them. A d-separation link is a connection among two nodes separated by a third node situated between the previous nodes. This special link will force the transmission of soft evidence into network which means any evidence that can be useful for recalculation of a-priori possibility values.

We consider that the possible student knowledge levels for the fundamental concepts are the values: “known” and “unknown”. In our application we note these values with “State-0” and “State-1”. For the other nodes (from the second set) the possible values are: “known very well”, “know something”, “unknown”, named in the following sections of this article with “State-0”, “State-1”, and “State-2”.

Student knowledge level about domain concepts (that must be learn), can be obtained using different evaluation methods. From our didactic experience we observed that, independent from used assessment methods, student knowledge level can not be obtained in a complete, clear mode without equivoque manner, because it is not possible to assess all basic theoretical concepts from learning program and all practical/applicative problems. In this situation too much theoretical questions and quantitatively bigger and complex applicative problems can be. Thus, we conclude that, as the results of the assessment process, the obtained information is subject of imperfection.

In our approach, the power of relation between nodes is represented through certainty grades modeled with conditional possibility measures. We decide to use a representation of certainty level because the power of link can not be provided, always, without equivoque, by the experts in the classical programming field. The aim of system is to compare the learning concepts with student knowledge level. In this work, we propose to use qualitative measure of possibility in modeling the power of relations between learning items.

For example, we consider a section that contains concepts in classical programming language (explained before) modeled in the figure 1.

One of the advantages of graphical representation model is that it can be easily modified to implement any structure of learning domain concepts. One major disadvantage is exponentially increasing of the computing complexity and computational time when we have a large amount of data (big number of nodes with large sets of possible associated values and many edges).

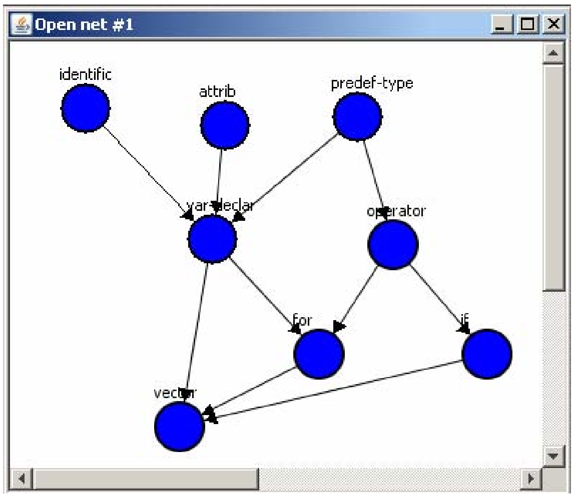

Fig.1 The relations between concepts about programming languages.

3. A POSSIBILISTIC NETWORK APPROACH IN STUDENT DIAGNOSIS

Each person learns in an individual manner, in concordance with his/her personality, learning domain type and difficulty level. The intelligent educational system, in order to be user adaptive, must discover through a reasoning process about student errors and misconceptions and explain the weak points in educational par-course of student. In order to do that, the system must have the real state of student knowledge at input. These inputs can be obtained through an assessment process or from the personal evaluation of student. Each item can be evaluated with one of the gradual values of attribute “known”. This information is provided to the system before the reasoning process. The system will explain if it is necessary to repeat some learning concepts or the learning process is satisfying and can be over.

In the explanatory reasoning process the system work with a-priori and conditional possibility measures modeled in each node. The nodes without parents must have explicitly specified a-priori possibilities. The nodes with parents must have modeled the conditional possibilities of all his possible values, depending on each possible combination values of the parents. One reason why we need conditional measures in our learning system is that the learning errors can be combined between them and a wrong answer may have multiple diagnoses. Another reason is the possibility to have multiple answers for an item.

Possibility logic has a qualitative nature and thus, the only needed property is one of the total orderly structures on a used scale. The arranged structure is introduced through pre-order “event p is more possible than event q” express in $\Pi(p) > \Pi(q)$, where Π is possibility measure. In our work, possibility measures are expressed in linguistic values situated on a perfect ordered scale (example, small, medium and big, or another scale very big, big, medium, and small). We choose this approach for the reason that is more appropriate by the human reasoning manner.

Because in the possibilistic network, the inferential process needs numerical values, the qualitative linguistic values are transformed into numerical ones.

The system offer the options to choose the number of possible values for each variable represented in one node or the number of samples for each qualitative scale. The transformations from linguistic into numerical values are made automate.

All the possibility measures modeled in the possibilistic network are specified thanks to pedagogical expertise of tutors in classical programming language domain. An example of setting possibilities measures table for the node of "variable declaration" situated on the second concepts set is illustrated in figure 2.

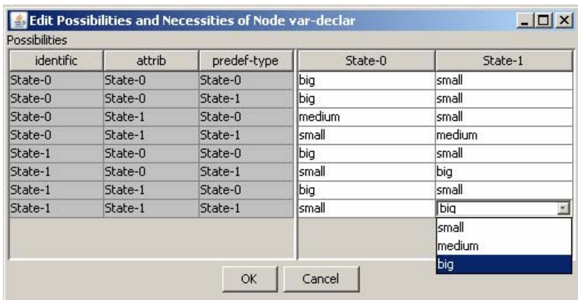

Fig. 2 The linguistic possibilities for "variable declaration" with two possible states node, depends by all the possible combination of parents states.

In the previous figure it can be observed that the more number of values has the parents, the much more conditional probabilities has the child.

In our system, inferential process consists on calculation of join possibility distribution for entire network when appear new events. The expression used for join possibility distribution computation is shown in equation (1):

$$\pi(x_1...x_n) = \prod_{i=1,n} \Pi(x_i \mid \omega_{x_i}) \quad (1)$$

where in node "i" we have number of i_m

possible values: $x_i = \{a_{i1,} a_{i2}, ..., a_{im}\}$

and ω_{x_i} are parents of variable x_i, $\omega_{x_i} \subseteq \{x_1, ..., x_n\}$

This computational expression is repeated by a number of times given in equation 2, where i_m is a number of possible values for node "i", for each possible combination of values for all the network nodes.

$$\prod_{i=1,n} i_m \quad (2)$$

For our network the number of join possibility measures to calculate is 864. This work can be considered difficult for the person who models these values, but here is the flexibility and power of representational model.

In order to diagnose explanatory purposes, we choose the first three biggest values of join possibility distribution.

We show that diagnose approach starts from some evidences about competences owned or not by the student and determine the basic knowledge that must be reviewed. The reasoning process must determine the causes which conduct to obtain unwanted effects.

We present an example in which is know that a student "don't know" work with concepts "vectors" and "for", but "know" something about "if". Following the inference results the data are presented in table 1.

Table 1. The results of inference

join poss	0.32804	0.32804	0.18224
identific	State-1= big	State-1= big	State-1= big
attrib.	State-1= big	State-1= big	State-1= big
predef - type	State-0= medium	State-1= medium	State-0= medium
var-declar	State-0= big	State-1= big	State-0= big
operator	State-0= big	State-1= big	State-1= medium
for	State-0= evidence	State-0= evidence	State-0= evidence
if	State-1= evidence	State-1= evidence	State-1= evidence
vector	State-0= evidence	State-0= evidence	State-0= evidence

We interpret these results in this way:

- From the second column we observe a big possibility that the student "don't know" the concepts for "variable declaration" and "operators" and "knows" "identifiers" and "attribution". These are the items that student must repeat in order to have better assessment results.

- The second and third columns have the same values for join possibility. This means that these scenarios are possible in the same manner.
- It is possible to know some basic concepts and yet do not know complex concepts.

Through this example we demonstrate some pertinent results, easy verifiable in practice.

4. CONCLUSIONS

We perform more experiments and we use the gathered information to evaluate the possibilistic network approach for explanatory diagnosis. All the results are confirmable by the domain experts and comparable with the assessment given by human tutor. The inferential process is made using the values (evidential or pre-defined) for nodes from the entirely network. Thus, it is easy to introduce any kind of evidence, simple, for one node, or complex, for more nodes (not necessarily linked through edges).

Our approach can be used for representation of complex learning domains. In real world, the errors can be combined and a diagnostic process must choose the more feasible diagnostic. The qualitative possibilistic network approach can achieve a complete diagnosis with diagnostic differences in term of join possibility values. The most approaches in student diagnosis provide one possible diagnostic, which, in our opinion, is a limitation. We can conclude that the possibilistic network method for uncertainty management is closed to the human qualitative expression of uncertainty.

The principal properties of a formal knowledge representation must be: expressivity and clarity. Our approach with qualitative measures follows these properties. Other graphical approaches (like Bayesian networks) need a large amount of numerical data, not easy to obtain in practice. Advantage of our approach is that it uses linguistic measures easy to obtain from human experts.

Another positive aspect is that the possibilistic networks are capable to perform both predictive (of final results in learning process) and interpretative (of incomplete or erroneous knowledge) reasoning.

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