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An Innovative Approach to Develop an Intelligent Virtual University

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Abstract: -Virtual University is widely used as a means of communication between teachers and students. However its educational impact has always been under an aura of ambiguity. In contrast, Intelligent Tutoring System increases education quality by providing feedback and hint to students, but its implementation cost is high. Assessment of student knowledge and choosing an appropriate hint are important components of an Intelligent Tutoring System which have a significant role in the educational impact of the system. This study presents a new approach to implement these two components of intelligence at low-cost in a virtual university with a desired knowledge domain. A Bayesian Network and an Artificial Neural Network based on training data, designed for knowledge assessment and choosing appropriate hints respectively. This approach implemented and evaluated at the Virtual University of Sistan and Baluchestan in domain of search techniques in Artificial Intelligence. Accuracy of the Bayesian Network is evaluated to be 98% on average and accuracy of the Artificial Neural Network is evaluated to be 92.5%. Using Rules for knowledge representation and designing networks based on training data has given a good expandability to the proposed approach.

Keywords: Intelligent Tutoring System, Virtual University, Bayesian Network, Artificial Neural Network.

1. Introduction

Nowadays using computer-based systems for education is prevalent. These systems have removed time and space limitations for learning. The most common computer education system is

Learning Management System (LMS), in which the teacher provides the student with tools such as text or multimedia and communicates with her/him. In other words, the objective of these systems is simulation of the class environment. Hence, virtual universities have widely employed Learning Management Systems [1].

On the other hands, private education has higher efficiency than conventional classes. Hence In contrast to the learning management system, Intelligent Tutoring System (ITS) tries to teach the subject by providing hint and support for students, similar to how a human teacher does it. Therefore, an Intelligent Tutoring System is a computer-based education system, however researchers use the term Intelligent Tutoring System for educational systems that have Expert Model, Student Model and Pedagogical Model [2], according to the definition and ideally, the Expert Model includes the representation of education domain knowledge and also problem-solving ability using human like reasoning, so that the system can compare students' solution with the correct solution. Student Model, models knowledge, skills and expertise level of the student and finally Pedagogical Model adapts teaching strategy based on the Student Model [3]. Among intelligence parameters of ITSs assessing student knowledge, tracking student actions and choosing the proper hint can be noted. Despite the tremendous educational impact, this type of system due to the high implementation cost has not had much commercial development [4]

In this research, an approach with low implementation cost is proposed for the components of intelligent education; including knowledge assessment and selection of appropriate hint. Then the proposed approach has been implemented on the Virtual University of Sistan and Baluchestan.

In the following, section 2 declares a general outline of the approach. Then section 3 investigates educational scenarios, representation of scenario knowledge and also the way it is placed on a virtual university. In section 4, a

Bayesian Network will be provided for implementing the first component of intelligence i.e. student knowledge assessment. In section 5 for the second component of intelligent i.e. selection of appropriate hints based on the student knowledge level, an Artificial Neural Network will be designed. Section 6 presents the study results. The content of paper will end with the conclusions in section 7.

2. General Outline of the Approach

The presented approach in this paper suggests some scenarios being designed with an emphasis on learning from errors strategy in the knowledge domain. Each scenario can include a few multi-step problems that the students solve. Then, the knowledge existing in the domain is represented by rules. These scenarios are placed on a working LMS utilized by the virtual university. During problem solving by the student, information such as the solving duration for each step, number of student attempts to solve each step, number of used helps and the result of each step are recorded using the LMS - which the virtual university is implemented on it - in log files. Then the Bayesian Network which is proposed in this study estimates the student's knowledge using this information. In the proposed approach, the designed system stores information related to every student such as solved problems and related information. The model of student knowledge based on understanding level of each rule is also recorded. Thus, the system can utilize this model and update it at any time. This approach also chooses appropriate hints in each step during problem solving through an Artificial Neural Network. A few hints are considered for each step of the scenario; which are provided to students when they make a mistake during problem solving. These hints are used to guide students to learn from their mistakes.

For a better examination, the proposed approach is implemented for a scenario on the domain of search methods of Artificial Intelligence in Virtual University of Sistan and Baluchestan. It is worth to mentioning that the key components

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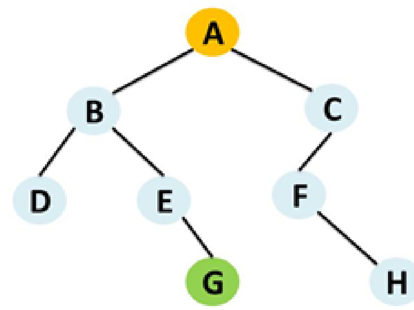
of the approach such as scenario, knowledge base, Bayesian Network and Artificial Neural Network are all designed and implemented and their accuracy will be examined. Synchronizing Artificial Neural Network and storing the knowledge model of each student with the virtual university is also easy to perform [5]. In the following, the proposed approach will be declared and examined more closely.

3. Educational Scenario

Similar to human private education, in Intelligent Tutoring Systems often some scenarios are considered for teaching. In this study too, a scenario has been used for teaching. This scenario is designed based on learning from errors strategy proposed by Olsen [6]. Olsen explains that learning from errors consists of two steps, the first is error detection and the second is error correction.

Step 2: Considering the following figure, Which is the next node surveyed by first-Breath search?



Answer	Feedback	Hint
C	Correct	-----------------
.F	Wrong	Priority is with small English letters in equal condition
D or E	Wrong	In search methods always the node is surveyed that is adjacent with one of the surveyed nodes.

Figure1. Second Step

Appropriate feedback after student action helps students to identify mistakes and the hints speed up error correction. So the scenario should include the key components including feedback and appropriate hint for every incorrect answer. The scenario of this study is on the knowledge domain of search methods which consist of a seven-step problem. In Figure 1 and Figure 2, the

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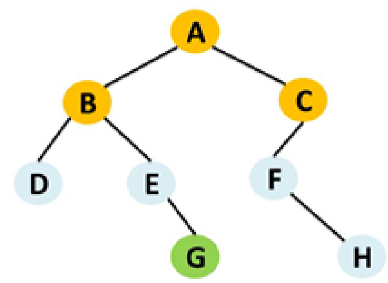
key components of some steps of the scenario are presented.

Step 4: Considering the following figure, Which is the next node surveyed by first-Breath search?



Answer	Feedback	Hint
D	Correct	-----------------
B	Wrong	In search methods always the node is surveyed that is adjacent with one of the surveyed nodes.
F or E	Wrong	Pay attention to deep and surface search difference.

Figure 2. Fourth Step

In this research, the scenario is placed on the virtual university of Sistan and Baluchestan. The virtual university is implemented by Moodle Learning Management System. In this system, each student is logged in with his/her username and benefits from features such as search, calendar and recent activities. Implementation is done in a way that the student receives an immediate hint as well as immediate feedback for an incorrect answer. Also, the student can try twice for each step to provide the correct answer. In order to make the learning system intelligent, it is necessary to represent the current scenario knowledge with knowledge representation methods. Knowledge Base (KB) is a place that expert knowledge is stored in an encoded and understandable form for the system [7]. Considering that the problem in the scenario is solved step by step, the procedural aspect of the knowledge dominates its descriptive aspect, so the network-based approach will be less efficient. Among the methods which represent the procedural knowledge, rule-based method is more efficient. Rule-based is one of knowledge representation methods used widely for representing knowledge in various systems. This method of knowledge representation has good extension capability, so developing the scope of knowledge does not need to change the rules extensively and often some rules are added simply. Also, the rule-based knowledge base is independent from the problem scenario, hence changing scenario steps or adding scenarios does not change the knowledge base. In this method, every piece of knowledge is presented by a conditional - functional rule as an If- Then [8]. Accordingly a rule-based knowledge base is designed to show the domain knowledge similar to Table 1.

From the perspective of an Intelligent Tutoring System, the Expert Model is in charge of knowledge engineering and solving problems in the knowledge domain. For this end, the Expert Model has two parts which include a "knowledge base" for representation of knowledge and an "inference engine" for solving problems. In this study, knowledge base consists of four rules; however the nature of the proposed approach to make the virtual university intelligent requires simulating scenarios in the virtual university, without implementing the inference engine. The decision also had a positive impact on lowering the implementation cost of the proposed method; moreover it caused the proposed method to be implemented independent from the inference engine.

Table 1. Rules of Knowledge Base

	Rules
1	**IF the problem's goal is to find key node with Breath-First Search THEN save starting node (push it in data structure) AND set the goal to continue traversing**
2	**IF there is a goal , to continue traversing AND data structure is empty THEN the key node doesn't exist ; end the problem**
3	**IF there is a goal to continue traversing AND data structure is not empty THEN get a node from the data structure AND set a goal to check the node**
4	**IF there is a goal to check the node AND the node is equal to key node THEN the key node is found; end problem ELSE add children of the node to the data structure upon with alphabet priority, respectively AND set the goal to continue traversing**

4.Assessment of Student Knowledge

Assessment of students' knowledge is decisive for choosing the appropriate hint during teaching. From the perspective of an Intelligent Tutoring system, assessment of student's knowledge is one of the most important tasks of the Student Model. In this research knowledge domain is represented by rules. Therefore assessing student's understanding of the rules evaluates his/her knowledge [9]. But, assessment of student knowledge faces a lot of uncertainties. In this research, Bayesian network was used to overcome the uncertainty of knowledge assessment.

In the following, first the uncertainty resources for assessment of student knowledge investigated, network variables are declared, educational data and structure of the proposed network will be reviewed; then, another Bayesian Network will be discussed and compared with the proposed network; and finally an example of the network utilization will follow.

4.1. Uncertainty Resources

Knowledge assessment in Student Model faces many uncertainty resources including multiple ways of achieving the answer, student's guessing, help of others, hidden reasoning process of the student in answers, unintentional mistakes, students do not write all the answer steps and different learning styles [9]. When expert knowledge is incomplete, vague and has uncertainty, Bayesian Networks can be used for overcoming the uncertainty. In the following, there will be a brief introduction to Bayesian Networks and methods to collect training data.

Bayesian Network is a probabilistic graphical model to represent the probabilistic relationships between variables and it is defined by three factors including nodes, edges and conditional probability distribution for each node [10]. Node is a variable with finite number of states and can indicate any variable like measured parameter, latent variables or hypotheses. Edge is utilized to connect variables [11]. There is a conditional probability distributions table for each variable, which is called the marginal distribution of that variable with respect to the condition of its parents [12].

In the present Intelligent Tutoring Systems, two types of Bayesian Networks are used for various purposes. First, a Bayesian Network whose structure is obtained from inference engine implementation method; Andes has used this type of network in Student Model to evaluate the student's knowledge and predict the actions he/she would take [13]. Second, a Bayesian Network whose structure is obtained by training data. Wayang system utilized this type of network for a complete implementation of the Student Model [14]. The first type of network does not require data training, however it is dependent on inference engine implementation method for Expert Model. In other words, this type of network is used in systems that their Expert Model forms a graph for each question. In these systems, structure of the Bayesian Network for student knowledge assessment has been formed by the structure of the graph. In contrast, the second type of network only needs training data, and does not have any restrictions on the system type; more training data increases accuracy of the network over time and finally it can be utilized on the Learning Management Systems.

Considering the advantages of the networks which utilize training data, these types of networks have been used in this research. So in the following, the process of network generation will be discussed. The proposed Bayesian Network is independent from inference engine implementation method in the Expert Model and assesses the student knowledge just by using the stored data obtained during problem solving. From the perspective of an Intelligent Tutoring System, this Bayesian network links the Expert Model and the Student Model in the context of knowledge assessment and can be utilized in any other rule-based system for knowledge assessment. In the subsequent parts of this section, the network structure will be outlined; first, network variables or its nodes will be declared in three layers, and then the network edges or the relationships between the variables will be expressed.

4.2. Input Variables

The data that at the end of each problem solving step stored in Moodle logs regarded as input variables. With these variables, the student understanding can be evaluated. The input variables are:

- Solution time for each step.
- Number of student's attempts for solving each step.
- Number of hints used by the student at each step.
- The result of each step.

These variables constitute the first layer nodes of the network.

4.3. Intermediate Variables

The scenario's question is designed based on multi-step ACT-R theory [4] in which it forces the student to engage in problem solving that result in deep learning and avoids stagnant knowledge. Considering the multi-step nature of the problem, intermediate variables for the first time are considered in this study to evaluate the extent of student's understanding of problem solving in each step. The numbers of intermediate variables are equal to the number of steps in the problem scenario which is seven. Intermediate variables constitute nodes of the second layer of the network.

To examine the impact of intermediate variables on the network, another network without intermediate variables that has a similar build process to the current network was considered, and it is used for comparison purposes. This network will be introduced in part G of this section.

4.4. Output Variables

The output variables are student's understanding of the rules. Knowledge base in the Expert Model has four rules, so there are four output variables. These variables constitute the nodes of the third layer.

4.5. Training Data

The Bayesian Network is trained by training data to learn its parameters. The training data used in this study, is derived from a sample of 17 undergraduate computer science students at the University of Sistan and Baluchestan. Sample obtained using Cochran formula with 0.01 errors [6, 11]. These students have worked with Virtual University of Sistan and Baluchestan that is implemented on Moodle. Training data include input, intermediate and output variables. Input variables are obtained from log files data that Moodle stores for each student. The value of intermediate variables is gathered and stored from students after each step of the problem and finally output variables are initialized by an expert.

After training the network and creating conditional probability tables for each variable, the network can be used to evaluate the values of intermediate and output variables with new input values. Next sub-section examines the structure of the Bayesian network including dependency between variables and conditional probability tables for each variable.

4.6. Bayesian Network Structure

To determine the network edges, the dependency between variables is examined using Spearman's correlation criteria. The dependency of the two variables is evaluated by correlation coefficient and significance level which is between 0 and 1, if this number is less than 0.05, it indicates there is a significant relationship between the two variables. In this study, the significance level is used as the criterion to determine dependency between the two variables. This dependency appears as an edge between the two variables in the network. The value of correlation and significance level between input/intermediate variables and output/intermediate variables are obtained using SPSS software.

In a Bayesian Network each variable (node) value should be discretized. In this study, two-value hierarchical discretization algorithm is used. This algorithm will take a threshold by considering the efficiency of values. Then all the values divided to two values like 0 and 1 considering this threshold.

The edges will be drawn based on significant relationship and the following criteria:

- The edge between an input and intermediate variable is drawn from the intermediate variable to the input variable.
- The edge between an intermediate and output variable is drawn from the output variable to the intermediate variable.

• The edge between two input variables is ignored (based on new Bayesian condition) [6].

• The edge between input and output variables is ignored.

• The direction of edges between intermediate variables together is from cause to effect, based on a cause and effect relationship.

• The direction of edges between outputs variables together is from effect to cause based on a cause and effect relationship.

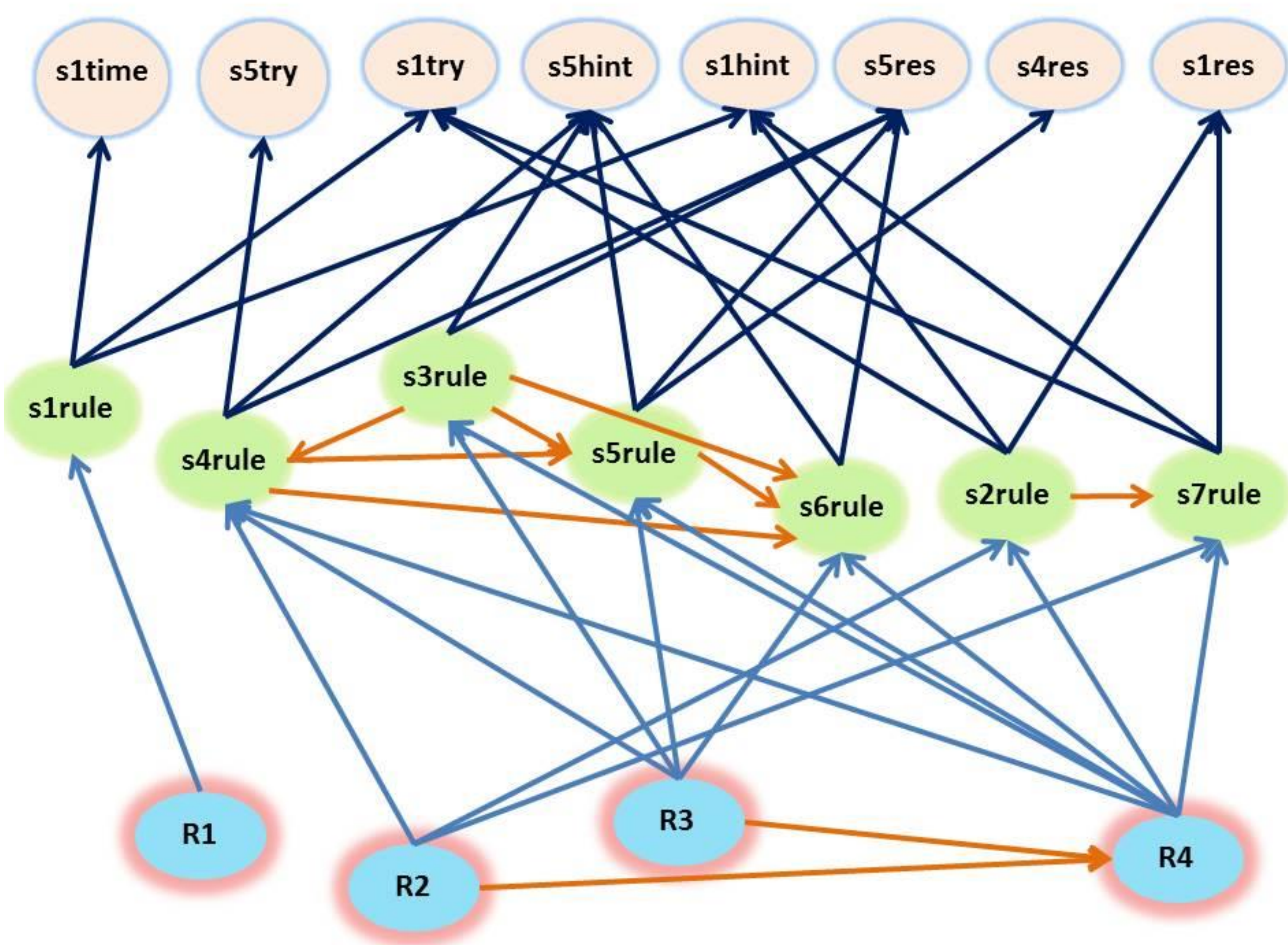


Figure 3 – Structure of the Proposed Bayesian Network

The structure of Bayesian Network resulted on this basis is shown in Figure 3. To form the Bayesian Network, the GeNIe software has been used. In the following figure, the variable names are summarized; for example **s1rule** means the level of student knowledge obtained from the rules that used to solve the problem in the first step and **s1try** means the number of student's attempts to solve the problem in the first step.

Then the prior probability table for each variable was obtained using the training data and to create evaluation probability tables for their parent's condition, Bayesian Search learning algorithm is used. Figure 4 shows an example of a Bayesian Network. Prior and conditional probability of its nodes is shown in Table 2 and Table 3.

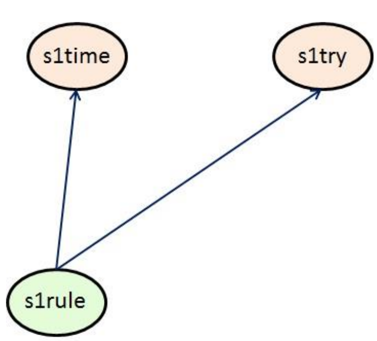


Figure 4 – A sample Bayesian Network with Three Variables

By using conditional probability tables which were generated for each variable, one can deduce the extent of student perceptions of each rule.

Table 2. Prior Probability of Variables

Probability	Step 6	Probability	Step5	Probability	Hint of step 5
0.008	Slight	0.25	Slight	0.92	Little
0.092	Full	0.75	Full	0.08	Much

Table 3. Conditional Probability Variable of Step5 hint

Probability	Hint of step5	Step 6	Step5
0.01	Much	Full	Fill
0.99	Little		
0.08	Much	Slight	
0.92	Little		
0.02	Much	Full	Slight
0.98	Little		
0.54	Much	Slight	
0.46	Little		

4.7. Bayesian Network Without Intermediate Variables

A Bayesian Network without intermediate variables will be designed to examine the impact of the proposed Bayesian Network. Therefore, this network has only two input and output variables layers. The Spearman correlation criterion is used to create the network edges.

Input variables that have no relationship with output variables are not included.

According to the rules that mentioned above and the following rules, the edges of the network will be determined.

• Direction for edges is from output variable to input variable.

• The relationships between input variables are ignored.

• Direction of edges between two output variables is from cause to effect, based on a cause and effect relationship.

Then the discretization and training will be done similar to the proposed Bayesian Network. This Bayesian Network is shown in Figure 5 and will be used in the next section to compare the accuracy of the proposed method.

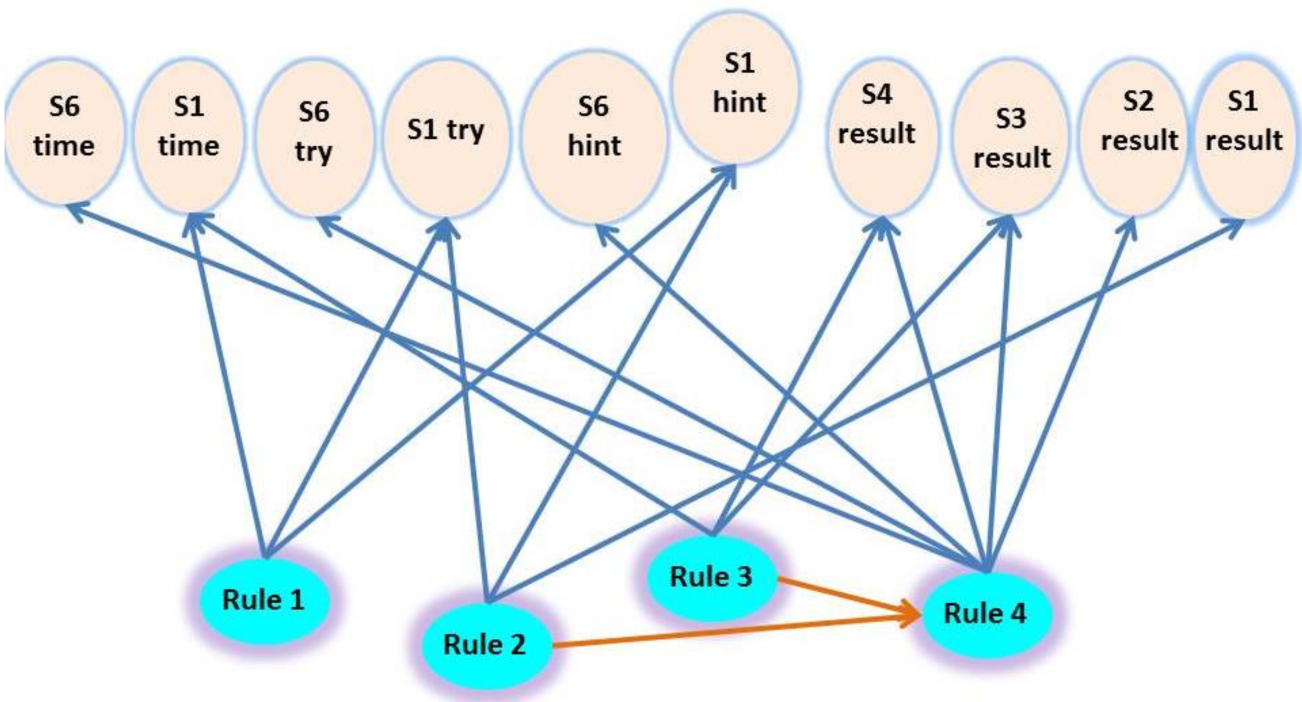


Figure 5. A Bayesian Network withouth Intermediate Variables

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4.8. Assessment Knowledge with the Proposed Bayesian Network

Now we use the proposed Bayesian Network (with intermediate variables) to evaluate a new student's knowledge. The new student data are shown in Table 4, recorded by Moodle.

Table 4. New Student Data

Hint for step 5	Result for step5	Result for step4	Result for step1
2	0	0	0
Duration of step1	Number of step 5 efforts	Number of step 1 efforts	Hint for step 1
106	2	2	2

Using the hierarchical discretization algorithm, the discrete values of each variable were calculated and are shown in Table 5.

Table 5. Discretized Data

Hint for step 5	Result for step5	Result for step4	Result of step1
Much	Bad	Bad	Bad
Duration of step1	Number of step 5 efforts	Number of step 1 efforts	Hint for step 11
Little	Much	Much	Much

Input variables are initialized with the table 5 values, and then the network evaluates the probability of other network variables. The network inference results for the output variables are given in Table 6.

Table 6. Output Variable Values Inferred from Bayesian Network

Rule 4	Rule 3	Rule 2	Rule 1	Discretized values
0.696	0.789	0.268	0.513	Slight
0.304	0.211	0.732	0.487	Full

For example, the probability of partial learning of rule 3 by a new student is estimated to be as 0.789. Often the probability of learning completely called as the percentage of learning the rule [15].

5. Choosing the Appropriate Hint

In learning from errors strategy, hint has a significant role in the learning process. From the perspective of an Intelligent Tutoring Systems, Pedagogical Model chooses the next action based on the Student Model for optimal tutoring. In this section, an approach is proposed to choose a hint based on the Bayesian Network assessment of student's knowledge of each rule.

Solving each step in the educational scenario utilizes special rules of the knowledge base. As a result, hints will be different for each step. In the case of this study, rule 1 is used only in solving step 1 and rule 2 is utilized only in solving the latter step. Hence these two steps each have a hint that does not need to be selected! Although rule 3 and rule 4 are used to solve all other steps, their importance in the odd rules is different from the even rules; the importance is determined by the expert. Therefore even steps should be examined separately. In the following of this section, choosing hints for odd steps including step 3 and 5 are discussed.

For the two mentioned rules, three hints are provided by the expert as stated in the following.

Hint 1: Whenever a node is removed from the queue, all the children of that node will enter the queue (related to rule 3 and rule 4).

Hint 2: In a queue, always the head element will exit. In other words, the first element that enters is the first element that exits from the queue (related to rule 3).

Hint 3: Nodes that have already appeared once in the queue will not be added to the queue (related to rule 4).

The proposed Bayesian Network in section 4 evaluates the amount of student knowledge of each rule. An artificial intelligence expert was asked to choose an appropriate hint with respect to different values of understanding of each rule. We should find the pattern from this data to choose the appropriate hint for any new values of understanding, but there is no special algorithm for this aim. Artificial Neural Networks (ANNs) are computational model that are capable of machine learning and pattern recognition and can be used to find the appropriate pattern for matching each input to its output, when there are some data as input-output couples [13]. On the other hand the values of student understanding of rules 3 and 4 are continuous while the number of hints is limited. So we need a method that produces the same hint for those who have similar understanding values. The ANNs also are robust to noise so that the network outputs have not large change with small changes in inputs [15]. Therefore we decided to use ANNs, among the types of Artificial Neural Networks, Feed Forward Multilayer networks have high power to estimate the existing pattern between data [15], so this type of ANN is used.

In the following of this section, first Artificial Neural Network variables are declared, then the training data and test data are stated and finally the process of an Artificial Neural Network formation will be discussed.

5.1. Input Variables

Student's level of understanding the rules that are used in steps 3 and 5 (R3, R4). These variables are the output of the proposed Bayesian Network in section 6.

5.2. Output Variable

The objective is choosing a hint among the existing hints. For rules 3 and 4 three hints have been considered by an expert. So, we have one output variable that can take discrete values of 1, 2 and 3. These values correspond to the provided hints at the beginning of this section.

5.3. Training and Test Data

As previously mentioned, the training data is generated by an expert. Each row of the data determines a hint based on the values of learning of rules 3 and 4. The number of training data has significant impact on the accuracy of the ANN. It is better that the training data cover possible interval for a variable. A part of the training data is used for network testing. In this study 70 training data and 10 test data are considered.

5.4. Artificial Neural Network Formation

Implementation of Feed Forward Multilayer Artificial Neural Network was done in MATLAB software. First, the initial network is created by the **newff** function. The network parameters are: the number of network layers, the number of neurons in each layer, transition functions for each layer and the network learning function. Efficiency of the network learning is directly related to the values of these parameters. In most practical applications, three-layer networks are able to learn successfully. So in this study, a three-layer network is used. The initial network should be trained with train function; such that training data including input and output vectors are being sent to training function. This function performs learning process based on structural parameters of the network. If the error of learning time is more than an acceptable level, network parameters will be changed until the error is acceptable. When the training finished, the network performance is tested by feeding the network the test data and comparing the outputs with actual outputs; so that its authenticity is verified. Then the final network with a determined structure is used for practical applications. The final structural parameters for the network in this study were as follows:

•The first layer has three neurons; the second layer has seven neurons and the third layer has one neuron.

•The transfer function of the first layer is **logsig**; the second layer is **tansig** and for the third layer is **purelin**.

•**Trainlm** learning function was used to learn the network.

•Acceptable error of learning time is 10^{-4}.

•Learning rate is 0.1.

•The number of iterations is 500.

6. Findings

The findings of the proposed approach are declared in this section. So, in sub-section 6.1 the results of scenario simulation are evaluated. The proposed Bayesian Network using intermediate variables is compared with another Bayesian Network without using the intermediate variables in sub-section 6.2 and finally, the Feed Forward Multilayer Artificial Neural Network is investigated in sub-section 6.3.

6.1. Scenario Simulation Results

Selection of the rule-based Knowledge Base gives development capability to the system to enhance the educational domain. Also, the scenario simulation using Moodle Learning Management System has dramatically reduced the cost of implementation. Cost of system simulation with Moodle is 10 times less costly compared to implementation of Expert Model. Ninety percent of students stated their relative satisfaction with the system and 65 percent expressed full satisfaction with the system. Also, the system was effective to improve learning of search for 80 percent of students.

6.2. Results of Bayesian Networks

In this study, for evaluating Bayesian Network accuracy the Leave One out Algorithm is utilized. In this algorithm, each time one data is put out for validation and network is trained by other data. Then the output value of validation data is compared with the inferential Bayesian Network value. This process will be repeated equal to the number of training data times. Proportion of correct inferences of outputs for each variable indicates the accuracy of network.

The results of the algorithm running on the proposed network with intermediate variables are shown in Figure 6. It shows that the network has an average accuracy of 98 percent.

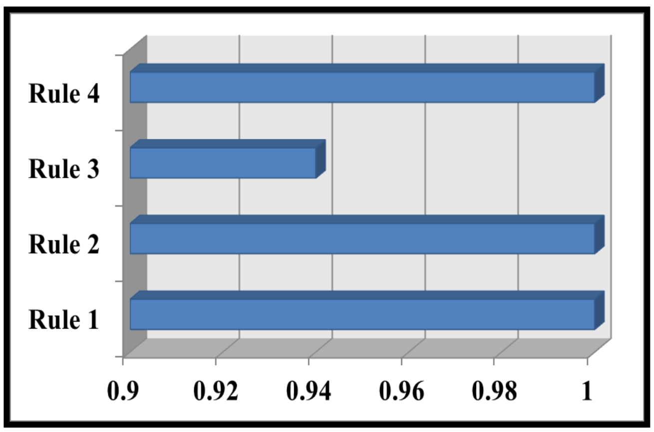

Figure 6 - Accuracy of the Proposed Bayesian Network

Also, the results of running the algorithm on the network without intermediate variables in section VI-G are presented in Figure 7. The network has an average accuracy of 80 percent.

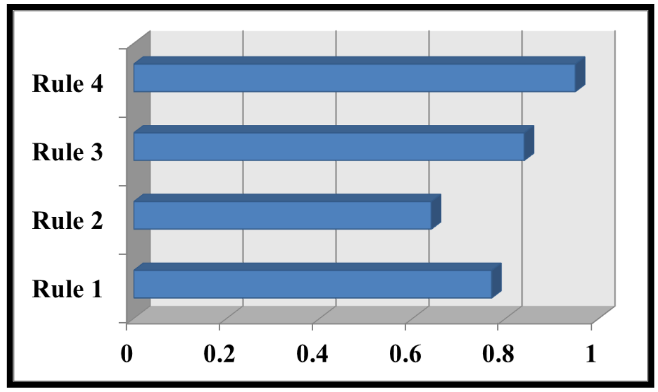

Figure 7 - Accuracy of the Bayesian Network Without Intermediate Variable

It is observed that the suggestion to use intermediate variables has increased average accuracy of the network by 18 percent.

6.3. Results of the Artificial Neural Network

Feed Forward Multilayer Artificial Neural Network is considered to have an acceptable error during learning time. Whenever the network is not converging for a given error, other parameters like the learning rate and number of repetitions will be changed so that the network converge to the desired accuracy. But Artificial Neural Networks like biological neural networks always don't have the same output over time with the same given data. Accordingly, for assessment of the final network, k-fold cross validation method was used. By K=20, the data are divided into 20 parts and each time one of them is considered as the test and other data are used for training the network. After performing every 20 times, by comparing the L value of the network with actual values for data, accuracy will be evaluated. Average accuracy for networks with a single output variable by this method is 92.5 percent.

7.Conclusion

The present research proposed an approach based on two successive Artificial Neural Network and Bayesian Network to build an intelligent virtual university. Due to the low implementation cost, the proposed approach is apt to promote the development of the idea of intelligent Learning Management Systems. In other words, this approach can be applied to other types of learning management systems on the desired knowledge domain. On the other hand, the approach is based on knowledge representation with rules. Therefore this method is more appropriate for making intelligent systems with procedural knowledge domain. Finally, it is suggested for it to be implemented on different systems to examine its general accuracy.

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