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The Evaluation of Knowledge Based on Bayesian Network and Ranking of Students in an Intelligent Tutoring System

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Abstract: Intelligent tutoring system is a dynamic personalized environment which makes use of e-learning system's benefits. In this paper, a new approach using Bayesian network is proposed to evaluate and analyze the perception level, knowledge level and the skill level of students in an intelligent tutoring system. Further, the levels of perception, knowledge, and student’s skills are clustered into four groups of very low, low, average, and high utilizing k-means clustering algorithm. Hence, the system has the capacity to suggest applicable recommendations to each student. To evaluate the proposed approach, it has been applied on the recorded factual data which are provided by the students during an Artificial Intelligence (AI) course. The obtained results confirm that our approach is achieved a remarkable performance.

Keywords: Intelligent Tutoring System, E-learning, Bayesian Network, Clustering.

1. Introduction

Intelligent tutoring system is software that can present training similar to a human teacher. It includes four models: Student’s model, training model, expert model, and Learning Environment.

Student's model stores the data related to the student to distinguish student's weak and strong points. Training model manages the way of training and presentation of feedback. Expert model may also infer from knowledge to solve the problems on that scope rather than modeling of knowledge as subject matter. Model of Learning Environment is tasked with providing an environment similar to the real situation and context in the training domain [1, 2].

One challenge is how to evaluate student's knowledge and then based on it, present an applicable training procedure [3]. To be more specific, in this research we will evaluate and analyze student's perception, knowledge, and skills by interacting with intelligent tutoring systems.

Developing an intelligent tutoring system is an expensive and time- consuming task [1]. Hence, in this paper, data has been derived from Log-files of an artificial intelligence course that was simulated in MOODLE (Modular Object-Oriented Dynamic Learning Environment) by an expert. Learning management system is a software package which manages interaction between teacher and students. For example, when the student interacts with this system, student's physical behavior like time of problem solving, errors, and requests for help are recorded by the system, however students' perception, knowledge, and skills are ignored and remain unknown. As a result, training procedure and feedback of the system are the same for all students [1]. The appropriate evaluation and analysis of the data enables a system to investigate the behavior of students and identify their mistakes during the training procedure. Hence, it improves student's learning level by eliminating their errors. Incorporating the mentioned parameters in the learning procedure of the tutoring system is one of the main challenges of Artificial Intelligence Committee. This committee tries to link students' attitudes and learning to their actual behaviors [3-4]. For this purpose, some researchers have utilized aids and feedbacks to encourage students' proper behaviors to solve the problem [5]. In [6], an approach by using Bayesian network is introduced in which students' emotions and personality are involved in a mathematical game. In another effort, a Bayesian network has been employed to determine student satisfaction rate with a mathematical training system [7].

In this paper, due to uncertainty in learners' behavior (emotions, tiredness, effective reception of external information, and perception of data based on perception via five senses), Bayesian network is used to evaluate and analyze students' perception, knowledge, and skills levels. Based on perception, knowledge, and skills students are grouped into four levels: very low, low, average and high levels using k-means clustering algorithm. Then, based on the assigned cluster, some appropriate hints and reports are presented to students. The proposed approach can be used in intelligent tutoring systems and learning management systems.

The rest of the paper is structured as follows. In Section 2, Bayesian network is investigated. In Section 3, grouping of students is discussed. Section 4 shows the application of the proposed method in the training scenario. The obtained results are examined in section 5. Finally, conclusion remarks are provided in section 6.

2. Bayesian Network

A Bayesian network is a probabilistic graphical model which shows a set of random variables and their conditional dependencies via a graph. In general, when knowledge is incomplete and ambiguous, Bayesian network can be employed for inference [8]. A Bayesian network is defined using three following factors [9-10]:

a) Nodes which denote variables. Each variable has a finite state.

b) Edges show dependencies between nodes.

c) Conditional probability distribution is a marginal distribution which associated with each node.

The two first factors determine the network structure. Each edge indicates the probabilistic dependency between two nodes. Furthermore, direction of each edge indicates a causal relationship between the two variables. It should be pointed out that there is no cycle in the graph. In a Bayesian network, each node is linked to a conditional probability distribution which shows the probability of the variable of the node, considering the value of node's parent.

There are two common methods to build a Bayesian network [9-10]:

1. Machine learning algorithms, which in this case, structure of a Bayesian network is learned automatically from data.
2. Using expert's knowledge

In the first method, we need to use training data while the second technique is based on expert's knowledge. In this study, the first method has been employed to build a Bayesian network. Training data is provided by using Moodle learning system. In this paper, to build a Bayesian network, the following steps are performed [9-10].

1. Determining variables or nodes
2. Identifying causal relations among variables of Bayesian network
3. Simplification and discreteness of Bayesian network
4. Calculation of prior probability
5. Determination of conditional probability tables for each variable
6. Evaluation of accuracy of a Bayesian network

Variables of the Bayesian network are divided into two categories: input and output. The input variables are derived from student's interaction with a system which is registered in Moodle log file. Also, output variables are student's perception, knowledge, and skill levels.

In the next step, Bayesian network edges, causative relations between variables should be identified. To do this, in our approach, Pearson's bi-vitiate correlation criterion is utilized to determine causative relations between input-input, input-output, and output-output variables. It should be noted that it may be an existing loop in the constructed graph. Hence, it is simplified and the existing loop is omitted. Also, to have an exact inference, variables are discretized by using mean discretization. The prior probability of each variable is computed using training data. To compute conditional probability tables for each variable maximum likelihood algorithm is used. In the next step, students based on their knowledge are grouped into four levels: very low, low, average, and high levels. To do so, k-means algorithm is employed. It causes the system to be able to give appropriate recommendations and reports to each student based on their performance. To evaluate our approach, it is applied to some real data which is achieved through students' interaction with Moodle system during learning the AI course. To make our approach robust to noise; K-Fold Cross Validation is used. One of the main advantages of our approach is that by adding a new training sample to the system, it can simply be updated. In the following, each step is explained in details.

2.1. Data Sources

As it mentioned before, machine learning algorithm is used to build the Bayesian network. Accordingly, we need training data.

In our approach, data has been obtained from artificial intelligence log-file course lessons in Moodle learning management system. In the artificial intelligence course, the following topics are considered: a breath first search, depth first search, A* search, greedy search, and problems of limitation satisfaction. The given system is a web-based system that is employed in a university, a school as well as a private educational institution. In these systems, problems are designed by an expert and then problems are presented to students in a specific order. Interaction between the system and the students such as: the number of problems which students solve, the time period that a student has spent to operate on the system, and the time that a student consumes to solve the problem. The data used in this study, is a sample of 17 fourth year of undergraduate computer science students aged 22-24 years at the University of Sistan and

Baluchestan. Sample obtained using Cochran's formula with 0.01 error [7]. At first, (before doing any action), a pretest is taken. Then, the students are trained using Moodle learning management system for an hour through solving multi-stage problems in which each step includes feedback. At the end, a post test is also given. After each problem in the pretest and posttest, the students should answer some questions as well; these questions have been designed such that they provide the ground truth data to evaluate and analyze the student's perception, knowledge, and skills levels in solving the problem. Some examples of questions are how much she/he has perceived the concept of the given problem and to what extent she/he knew the solution of that problem.

2.2. Observable Variables (Input):

The interactions between Moodle learning management system and students are recorded in a database that shows the students' physical behaviors (observable variable). These behaviors represent the actual perception and skills of the students. The artificial intelligence course in Moodle is designed such that it contains three steps: pretest, problem solving and posttest. Hence, observable variables are also divided into three groups:

1. Pretest variables include test period and mean score of the student
2. Posttest variables include the test period and mean score of the student
3. Training variables during solving multi-step problem include the number of trials at each step, mean time to solve each step, and mean number of requested helps at each step.

2.3. Output Variables:

As mentioned before, students should answer to some questions after each problem in the pretest and the posttest. These questions are designed such that encode the actual behavior of students. Some designed questions and their corresponding variables are presented in table 1. The answer of each question is between 0 and 1. For each student, mean value of each variable in the pretest and the posttest is calculated and assigned.

Due to uncertainty in the answers to the questions given by the students (i.e. guessing, unwilling to answer question and invalid answers) and uncertainty in learners' behavior (i.e. perception of the input data and different ways of data processing), a Bayesian network is employed to evaluate and analyze the perception, knowledge, and skill levels of students. In the following, the design of the Bayesian network structure is explained.

Table 1: Designed Questions For Evaluation Of Students' Perception, Knowledge, And Skills Levels

Title of variable	Question
Concept	Did you perceive the concept of the given question?
Skill	Do you have the required skills for solving the problem?
Solution	Do you know the solutions for the problem?
Problem solving	Could you solve the given problem?

2.4. Bayesian network structure

In this sub-section, the Bayesian network structure is determined and the way to compute the probability of output variables for a given input (observable) variables is explained. In other words, the system can predict students' answers to the final questions (output variables) for a given observable variable.

Up to now, graph nodes are illustrated. To obtain edges of the graph, the dependency between nodes should be reviewed. If there is an edge between two nodes, the correspondent variables are dependent, otherwise, they are independent [12].

2.5. Dependency Between Continuous Variables

Pearson' bivariate correlation criterion is employed to determine dependency between variable. Pearson' bivariate correlation criterion between any two variables is defined as [13]:

$$p = \frac{\text{cov}(x,y)}{\sqrt{\text{var}(x)\times\text{var}(y)}} = \frac{\sum(x_i-\bar{x})\sum(y_i-\bar{y})/N}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2/N^2}} \quad (1)$$

Where N denotes the number of training data, and x and y indicate to the input and output variables, respectively. If p is equal to or less than 0.01, it indicates a strong dependency between variables (bold lines in Fig. 1). Likewise, if there is $0.01<p<0.05$, then there is a moderate dependency between variables (dotted lines in Fig. 1) otherwise there is no dependency between the variables [3, 14]. The obtained graph for our training data is shown in Fig. 1in which input variables are indicated with circles, the pretest output variables with a hollow ellipse, and the posttest output variables with a grey ellipse.

2.6. Bayesian Network Simplification

It should be pointed out that the obtained graph may include loop. Hence, the probable loop should be removed. In our approach, the following steps are done to have a loop-less graph:

- Removing dependency between observable variables based on Naive Bays assumption.
- A Bayesian network is a generative model. Edges are directed from output variables to observable variables.
- Edges between output variable are directed through conceptual concepts. In other words, edges are directed from causal nodes to effect nodes.
- To remove loops, edges which include in the loop and have minimum rate of dependency are omitted [11].

2.7. Discretizing Of Variables

To have a precise inference, the variables should be discretized. To do this, at first, conditional probability is calculated for each node in a Bayesian network. Conditional probability can be computed in two ways: parametric or nonparametric [13]. In the former method, the distribution type of conditional probability is determined based on an assumption. If we have no prior knowledge of the conditional probability distribution, the assumption is not accurate and influences the final result. Hence, we use a nonparametric approach to estimate the conditional probability distribution. However, for continuous variables, a large number of training data are needed to estimate conditional probability distribution.

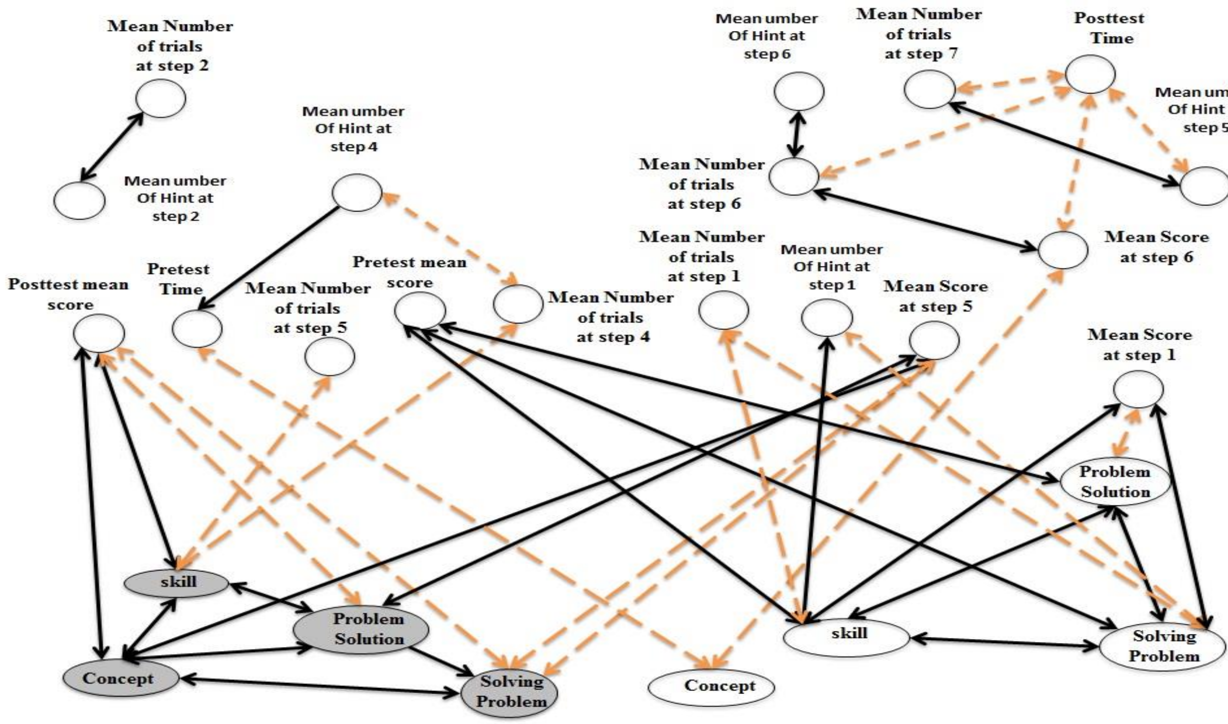

Figure 1: Primary dependency graph

Whereas in our approach, providing a large number of training samples is hard and time consuming. Hence, variables are discretized. In our approach, two steps are taken to discretize each continuous variable. In the first step, the mean value of the training variables is calculated. In the subsequent step, if value of the variable for each training data is greater than the mean value, the value of the variable is set to one (high) otherwise it is set to zero (low). After this step, the dependency between discrete variables is considered once again.

2.8. Determining Dependency Between Discrete Variables

To determine the dependency between discrete variables, Chi-square correlation test is used. Chi-square or chi-2 ($\chi 2$) is one of the well-known nonparametric statistical tests that is widely used in statistical analysis. The Chi-square test is computed between each of the two

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variables and dependency between them is decided based on the following rules [13]:

- In $\chi 2$ test, if P>0.05 is satisfied then there is significant dependency between variables.
- In $\chi 2$ test, if P< 0.05 is satisfied then there is no significant dependency between variables.

The final Bayesian network is illustrated in Fig. 2. In Fig. 2, input variables are indicated with circles, the pretest and the posttest are denoted with hollow ellipses and grey ellipses respectively. Similarly, high and average dependencies between variables are indicated with bold and dotted lines respectively. Now, conditional probability table is calculated for each variable in a Bayesian network. In the next step, how to generate conditional probability table is explained.

2.9. Conditional Probability Tables

To infer from the given Bayesian network, we need to train conditional probability tables for all observable variables (input) and output variables in the Bayesian network. Numerous algorithms have to train conditional probability tables. In our approach, the maximum likelihood is used. In other words, conditional probability tables are computed as follows:

$$P(W=w \mid S=s \wedge R=r)= \frac{N(W=w \wedge S=s \wedge R=r)}{N(S=s \wedge R=r)} \quad (2)$$

Where $P(W=w \mid (S=s \wedge R=r)$ denotes probability of W given S and R; $N(W=w \wedge S=s \wedge R=r)$ shows the number of training data that their W, S and R are equal to w, s and r, respectively. $N(S=s \wedge R=r)$ is defined in a similar way.

In Figure. 3, a sample of a Bayesian network is illustrated. Their prior and conditional probabilities are shown in table 2 and Table 3 respectively.

Now, using the prior probability and conditional probability tables, perception, knowledge and skills level of students are predicted. In the next section, students are clustered to groups.

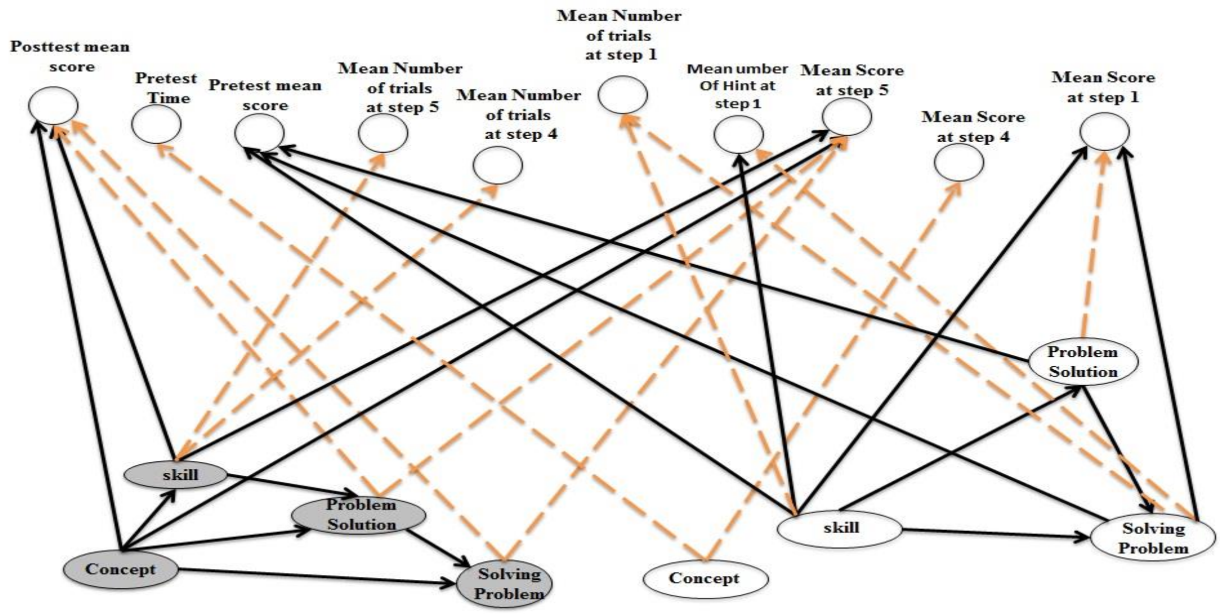

Figure 2: Loop-less Bayesian network- Values of continuous variables

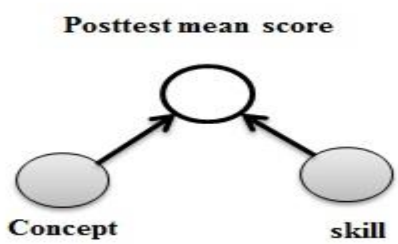

Figure 3: A Bayesian network with three discrete variables

Table 2: prior probability of concept and skill nodes

Skill	Probability	Concept	Probability
High	0.04	High	0.88
Low	0.96	Low	0.12

Table 3: Conditional probability of posttest score mean node

Concept	Skill	Mean score at posttest	Probability
Low	Low	Low	0.5
		High	0.5
	High	Low	0.5
		High	0.5
High	Low	Low	0.5
		High	0.5
	High	Low	0
		High	1

3. Grouping of students

Different level of knowledge and skill and other observable behaviors of learners cause the students to be clustered in diverge groups. In our proposed method, this information which is achieved with the student's model, are fed to the pedagogical model. And then, the pedagogical model groups students. Grouping students in several clusters, help an intelligent tutoring system to select an appropriate feedback for each student. In this paper, k-mean clustering algorithm is used to group students into different levels.

A cluster represents a group of data that are similar to each other. In clustering, data is divided into some clusters such that similarity between data which are placed in the same cluster is maximized and similarity between data from different clusters is decreased.

It should be pointed out that, in k-means, number of clusters (k) is needed as input. In our approach, k is set to 4.

According to k-means clustering algorithm in which k –value set to 4 in this essay, students are ranked. K-means clustering algorithm runs in the following steps:

1. Initialize cluster centers at random.

2. Each datum is assigned to a cluster which has a nearest distance to its center

3. For each cluster, the new centroid is computed by mean of data which are placed in the matching cluster.

4. Steps 2 and 3 are repeated until there is no change in the center of clusters.

The obtained results of k-means clustering algorithm on output variables are shown in Table 4. As it is presented, the obtained clusters are meaningful. The obtained groups of students and appropriate recommendations for each group are as follows:

1) Level I: Students who have relatively perceived the concept of the problem but they lacked the skills (students at very low level of perception, knowledge, and skills). In Table 4, rows 8 to 13 indicate these students, who have been placed at this level after the posttest.

2) Level II: Students who have perceived the concept of the problem but they do not know its solutions (students at low level of perception, knowledge, and skills).

3) Level III: Students, who know the solution to the problem but they could not solve the problem perfectly (students at an average level of perception, knowledge, and skills). In Table 4, rows 1, 7, 17 show characteristics of the students, who have been placed at the third level after the posttest.

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4) Level IV: Students, who can solve the problem and are ready for next problems (students at a high level of perception, knowledge, and skills). In Table 4, rows 3, 4, 5, 6, 9, 11, 12, 15, and 16 reflect features of the students, who have been ranked after posttest at fourth level.

Table 4: The Given Results From The Students Ranking By K-Mean Algorithm

	Posttest					Pretest				
Row	Concept	Skill	Problem solution	Solving problem	Level	Concept	Skill	Problem solution	Solving problem	Level
1	0.9	0.9	0.8	0.9	3	0.6	0.5	0.6	0.6	2
2	0.8	0.8	0.8	0.8	2	1	0.8	0.9	0.9	4
3	0.9	0.9	1	1	4	0.9	0.9	0.8	0.8	3
4	1	1	1	1	4	0.5	0.2	0.5	0	1
5	1	1	1	1	4	0.99	0.5	0.8	0.3	2
6	0.7	0.8	0.6	0.4	4	0.9	0.99	0.99	0.7	3
7	1	0.8	0.8	0.9	3	0.4	0.3	0.3	0.2	1
8	0.8	0.9	0.5	0.5	1	0.3	0.3	0.3	0.3	1
9	1	1	1	1	4	0.9	0.3	1	0.5	3
10	0.8	0.7	0.8	0.8	2	0.99	1	1	1	4
11	1	1	1	1	4	0.99	0.99	0.9	0.9	4
12	1	1	1	1	4	0.99	0.99	0.95	0.9	4
13	1	0.5	0.4	0.3	1	1	0.33	0.5	0.5	2
14	0.7	0.7	0.7	0.7	2	0.9	0.9	0.9	0.9	4
15	1	1	1	1	4	0.3	0.1	0	0	1
16	1	1	1	1	4	0.25	0.5	0.5	0.1	1
17	1	1	0.8	1	4	0.9	0.9	0.8	0.8	2

To provide a report about the student progress, cluster centers which have been derived from the posttest and the pretest steps, are arranged based on a specific criterion. In our approach, the average value of cluster centers elements has been chosen as the criteria. The obtained cluster centers of the posttest and the pretest are sorted based on the mentioned criteria which are shown in Tables 5 and 6 respectively. For a new student, after learning with the system, the output variables based on the learned Bayesian network are predicted. Then, using the predicted output variables, students assign to an appropriate cluster of pretest and posttest. Finally, difference in students' level in the pretest and the posttest determines whether the student had improvement or not. In this article, student improvement is evaluated based on the following cases:

1. If the difference in student level in the pretest and the posttest is positive, then student knowledge level has improved.

2. If student level is the same in both the pretest and the posttest, then the student has no achievement at this level.

3. If the difference in student's level in the pretest and the posttest is negative, then the student has not improved.

Table 5: The core of posttest clusters

	Problem solution	Solving problem	Skill	Concept
Level 1	0.8333	0.7333	0.5	0.4
Level 2	0.7667	0.7167	0.7667	0.7667
Level 3	0.9667	0.9	0.8	0.9333
Level 4	0.9625	0.9625	1	1

Table 6: The core of pretest clusters

	Problem solution	Solving problem	Skill	Concept
Level 1	0.35	0.28	0.32	0.12
Level 2	0.8725	0.4075	0.7250	0.4750
Level 3	0.92	0.8980	0.8760	0.82
Level 4	0.99	0.9933	0.95	0.9933

4. Application of the proposed method

In this section, the proposed method is investigated in a real application. To do so, a student has worked with the system in which she/he answers to pretest questions and then she/he has been trained with the system through step-by-step problems for an hour. Finally the student answers to the posttest questions. Input variables which are recorded by learning management system in Log files are presented in Table 7.

Table 7: The values of student's new input variables

Posttest mean score	Pretest mean time	Pretest mean score	Mean number of trials at step 1	Mean number of trials at step 4
66.6	350	33.3	2	1
Mean number of trials at step 5	Mean number of aids	Mean sore at step 1	Mean sore at step 4	Mean sore at step 5
2	2	1	1	1

Discretizing the input variables are shown in Table 8. Each variable is quantized into high (1) or low (0) level.

Bayesian network infers probability of output variables which are given in Table 9.

According to Table 9, the probability of understanding the concept of problems in the posttest is 0.882, the probability of finding solutions for the problems in the posttest is

0.882, the probability of knowing the required skills to solve the problems in the posttest is 0.882 and the probability of solving the problem is 0.764. Then, the distance of the student states to the cluster centers in the pretest and the posttest is calculated which are given in Table 10 and Table 11 respectively. Hence, students belong to the cluster (level) 1 in the pretest and belong to the cluster (level) 3 in the posttest. It shows that the students have improved.

Table 8: Discrete Values Of Student's New Input Variables

Posttest mean score	Pretest mean time	Pretest mean score	Mean number of trials at step 1	Mean number of trials at step 4
High	High	Low	High	Low
Mean number of trials at step 5	Mean number of aids	Mean sore at step 1	Mean sore at step 4	Mean sore at step 5
High	Low	High	High	High

Table 9: The Inferred Probability Values In Bayesian Network

	Pretest				Posttest			
Discrete values	Solving problem	Problem solution	Skill	Concept	Solving problem	Problem solution	Skill	Concept
Low	0.304	0.531	0.729	0.943	0.236	0.118	0.118	0.118
High	0.696	0.469	0.269	0.057	0.764	0.882	0.882	0.882

Table 10: Pretest Minimum Distance

	Problem solution	Solving problem	skill	concept	Sum of difference
Level 1	0.346	0.189	0.051	0.063	0.649
Level 2	0.1765	0.0615	0.465	0.418	1.121
Level 3	0.224	0.429	0.607	0.763	2.023
Level 4	0.294	0.5243	0.681	0.9363	2.4356

Table 11: Posttest Minimum Distance

	Problem solution	Solving problem	skill	concept	Sum of difference
Level 1	0.0963	0.1478	0.382	0.482	1.0271
Level 2	0.0027	0.1653	0.1153	0.1153	0.3986
Level 3	0.2027	0.018	0.018	0.0513	0.29
Level 4	0.1585	0.0805	0.178	0.178	0.595

5. Results

In this section, the performance of the proposed method is evaluated to estimate perception, knowledge, and skill levels of students and to group the students in clusters. To do so, we employ k-fold cross validation technique. In this case, data is divided into k subsets. In each iteration, one subset is used as the test data and the other k-1 subsets are utilized as the training data. This process is repeated k times. It means that each datum is used k-1 times as training data and one time for validation. In our approach, in all of the experiments, k is set to 5. It should be noted that in the proposed approach, a probability value is assigned to each of the output variables. Therefore, if the probability of the output variable of a specific value is greater than 0.7, then it is regarded as 1 and if it is lower than 0.3, then it is regarded as zero. To calculate accuracy, if the actual value and the predicted value are identical, then a "hit" is occurred otherwise a "miss" is occurred. As a result, the accuracy is calculated based on the following formula:

$$accuracy = \frac{\#hit}{\#hir + \#miss} \qquad (3)$$

The obtained accuracy using 5-fold cross validation for output variables of the pretest and the posttest is shown in Fig. 4 and Fig. 5 respectively. The average accuracy for all output variables of the posttest and the pretest is 97% and 74% respectively. As it is indicated, our approach achieves a remarkable accuracy.

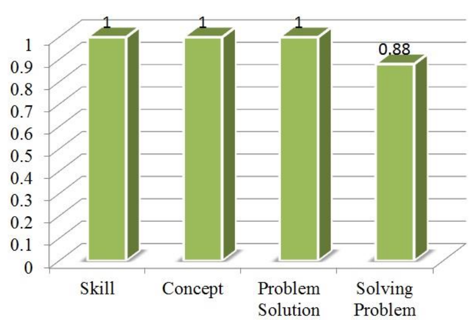

Figure 4: Posttest output variables by 5-Fold Cross Validation

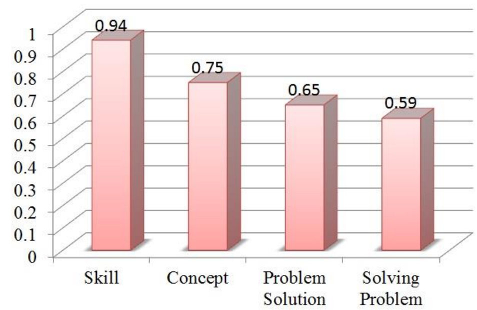

Figure 5: Pretest Output Variables By 5-Fold Cross Validation

6. Conclusion

In this paper, the prediction of perception level, knowledge level, and skill level of students in an intelligent tutoring system was addressed. To do so, a Bayesian network is utilized. After predicting the perception, knowledge, and skill level of students, they are clustered into four groups (very low, low, average, and high levels) using k-means algorithm. It is utilized in order to produce appropriate feedbacks and identify the students weak and strong points.

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Appendix I: Values of Input Variables

	Pretest		Posttest		Mean number of trials						
No	**Score in 9 questions**	**Time (s)**	**Score in 6 questions**	**Time (s)**	**Step 1**	**Step 2**	**Step 3**	**Step 4**	**Step 5**	**Step 6**	**Step 7**
1	44.44	170	83.4	358	1	1	1	2	2	1	1
2	55.55	306	33.3	310	2	1	1	1	1	1	2
3	88.88	256	50	309	1	1	1	2	1	1	1
4	88.88	248	0	294	1	1	1	1	1	2	1
5	66.66	217	66.7	284	1	1	1	1	2	1	1
6	55.55	136	33.7	258	2	2	1	1	1	1	1
7	100	151	50	262	1	2	1	2	1	1	1
8	100	151	66.7	274	1	3	1	2	1	1	1
9	44.44	157	16.7	257	1	2	1	1	1	1	1
10	77.77	211	50	201	2	1	3	1	1	2	1
11	33.33	90	66.7	213	2	1	3	2	2	1	1
12	66.66	308	50	225	2	2	1	2	2	3	1
13	77.77	189	66.7	220	1	2	2	1	1	1	1
14	55.55	106	50	259	2	1	1	1	1	1	1
15	44.44	190	50	215	2	2	1	2	2	2	1
16	77.77	172	66.7	241	1	2	1	2	1	2	1
17	77.77	157	66.7	190	1	2	1	1	1	1	1

Appendix II: Values of Output Variables

	Mean number of aids							Mean score						
No	**Step7**	**Step6**	**Step5**	**Step4**	**Step3**	**Step2**	**Step1**	**Step7**	**Step6**	**Step5**	**Step4**	**Step3**	**Step2**	**Step1**
1	0	0	1	1	0	0	0	1	1	1	1	1	1	1
2	1	0	0	0	0	0	2	1	1	1	1	1	1	0
3	0	0	0	1	0	0	0	1	1	1	1	1	1	1
4	0	2	0	0	0	0	0	1	0	1	1	1	1	1
5	0	0	2	0	0	0	0	1	1	0	1	1	1	1
6	0	0	0	0	0	1	2	1	1	1	1	1	1	0
7	0	0	0	1	0	1	0	1	1	1	1	1	1	1
8	0	0	0	1	0	2	0	1	1	1	1	1	1	1
9	0	0	0	0	0	2	0	1	1	1	1	1	0	1
10	0	2	0	0	2	0	2	1	0	1	1	1	1	0
11	0	0	1	1	2	0	2	1	1	1	1	1	1	0
12	0	2	1	2	1	2	2	1	1	1	0	0	0	0
13	0	0	0	0	2	1	0	1	1	1	1	0	1	1
14	0	0	0	0	0	0	1	1	1	1	1	1	1	1
15	0	1	1	1	0	1	1	1	1	1	1	1	1	1
16	0	1	0	1	0	1	0	1	1	1	1	1	1	1
17	0	0	0	0	0	1	0	1	1	1	1	1	1	1

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