

# Students' Self-Monitoring Skill Classification in Learning Activities

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**Abstract**—Intelligent Tutoring System (ITS) provides personalized instruction based on the level of knowledge and learning preferences of students. At ITS, student modeling has an important role; the role of student modeling in ITS includes student knowledge that is used to produce lessons, problems, feedback, and personalized learning guidance. ITS has the potential to develop into metacognitive tools. One of the metacognitive strategies is self-monitoring. Self-monitoring is a metacognitive strategy that students possibly control their learning activities. Developing an ITS with metacognitive needs rules for the treatment. The rules in ITS are from the classification method. This study focuses on self-monitoring skill as the metacognitive strategy to develop ITS. This paper will provide a method which can classify students' self-monitoring skill. Bayesian network is used as a method to classify students' self-monitoring in this research. The result shows that the Bayesian network can classify students' self-monitoring skill accurately. The accuracy result for the classification is 94%. The classification of self-monitoring skill can be used to develop metacognitive scaffolding in an ITS.

**Keywords:** *students' self-monitoring, skill classification, learning activities*

## I. INTRODUCTION

The development of computer technology and information participated in helping to develop and provide solutions to problems in other fields, one of which was in the field of education. In the field of education, one of the problems that are considered is in terms of learning. In the student learning process, the teacher prepares a strategy that can help students learn, understand, and memorize the material provided, such as quizzes and homework.

Intelligent tutoring systems (ITS) provide personalized education to its users. Unlike classroom learning, ITS does not teach students in the same way but adjusts instruction based on student performance. In this case, the system has a character similar to a personal tutor for students (one to one tutoring). Also, the performance of ITS is only limited to the algorithms in it, the limitations of this algorithm that make the opportunity to be re-improved the quality of ITS. Student modeling is essential for ITS because student modeling aims to improve student learning performance; besides, student modeling can also provide learning guidance that is appropriate to students' learning preferences. Student modeling has a role in maintaining the representation of students who are being taught well [1]. Student modeling

aims to model student learning. Student modeling that is widely developed is a prediction model that provides probabilistic predictions about whether a student will get the next learning item correctly and accordingly.

Over the past few decades, many researchers in the ITS field have developed various methods to determine ITS student modeling. Recent researches argue that ITS has the potential for improving learning, but they require skills including goal setting, monitoring, controlling cognition, and motivation. Computers have a lot of potential as metacognitive tools. For example, through their ability to record interactions with users, they can become powerful reflection tools. Having captured the actions of the student carrying out a task, these can be played back to her, properly abstracted and structured. This will help the student to become aware of her processes and help her improve performance on the task in question through reflection on the how's and why's of the chosen problem-solving paths [2].

Developing an ITS with metacognitive needs rules for the treatment. The rules in ITS are from the classification method. This study focuses on self-monitoring skill as the metacognitive strategy to develop ITS. Self-monitoring is a metacognitive strategy that students possibly control their learning activities. Individuals with high levels of self-monitoring are students who tend to monitor themselves [3]. Metacognitive is an awareness of someone's cognitive and how cognitive works and how to manage it.

This study is implemented Bayesian Network algorithm to classify student self-monitoring skill. Bayesian network algorithm is a probabilistic graphical model for reasoning under uncertainty. This method is good at classifying through the Graf and the nodes. Bayesian Network algorithm is classifying through Graf and nodes so that this algorithm will give the classification result more accurate. The connection networks between the nodes require storage of more probability parameters. The increasing exponentially require the number of probability parameters with the number of its parents. The result of this study can be implemented in ITS as metacognitive scaffolding or student modeling

## II. RELATED WORK

Many studies about overcoming student modeling, some studies focus on student performance and student skill. Kaeser et al. used the Dynamic Bayesian Network (DBN)

method to determine student modeling with skill hierarchy. This proposed method to improve the accuracy in predicting and to recognize more than one student's skills. The accuracy result of DBN will be compared with BKT (Bayesian Knowledge Tracing). The experimental result shows that DBN is worth to determine student modeling [4]. Hawkins et al. proposed the Empirical Probabilities (EP) method to improve BKT method. The result of the research shows that the computation using the combination method (BKT and EP) has been increased. An improvement to EP should be annotated knowledge more probable. EP makes only binary inferences of knowledge based on predictive performance, e.g. EP always considers incorrect responses on the first problem to be made in the unknown state, even though some of these are slips. Therefore, a more probabilistic approach should be able to produce a better parameter estimate [5].

Yutao and Beck conducted research using the Bayesian Network method; the results of this study indicate that student modelers must consider additional resources to understand the students. Currently, researchers utilizing student and class information are considering using class parameters or student parameters. Thus, each model which the researcher compares is considered to use one resource for each parameter, but not both. Yutao and Beck said in their research that it is possible to use both sources of information simultaneously and even take into account the fact that a student is a member of the class, to construct a hierarchically structured model that combines the two sources of information (i.e. class information and student parameters). In this research, the researchers construct a model that classes can be the parents node of different students. The result of this research concludes that this model is easy to understand, but the researchers are not sure because Bayesian Network has a complex representation of this constructed model and re-learn the expected parameters. The limitation of this research is stated that the researcher did not discuss the performance parameters (guess and slip) must be grouped. In this paper, the researchers are grouping the performance parameters to simplify the experiments based on the assumption that the two parameters are related to performance and must have similar properties by considering the best grain size for modeling [6]. Yasuko and Ueno [7] used Bayesian network to evaluate learner's knowledge structure in e-learning. They use consistency index to identify repeated attempts of quizzes. The students classified into three groups using the index. The result shows that students who that need individual counseling can be detected by using this method.

Another research using the fuzzy inference system method with the Mamdani model conducted by Asopa et al. [8], this method is used to evaluate student performance. Student performance evaluation is based on two things, namely class records and exam performance. Fuzzy systems produce eight categories of student classification, namely remarkable, excellent, proficient, fair, less fair, poor, very poor and fail from the classification that has been done then tested to 100 students. From the results of the study, an evaluation of 100 students was re-evaluated manually. The evaluation of fuzzy ITS results in an accuracy of 72%. In the application of fuzzy inference system (FIS), a good method is used to determine student performance and student modeling, but the weakness of Mamdani FIS is that

knowledge systems in fuzzy must be updated regularly to maintain data accuracy [9].

Based on the studies above, various methods have been developed for determining the student modeling. In the previous studies, it was known that there are still gaps such as accuracy that is still relatively small, and the method used is complicated to implement on ITS. This paper, we propose a Bayesian Network to determine student modeling. From the studied above, the Bayesian network is one of the methods that commonly used to classify student performance.

This method is good at classifying through the Graf and the nodes. The Bayesian Network algorithm is classifying through Graf and nodes so that this algorithm will give the classification result more accurate. The connection networks between the nodes require storage of more probability parameters. The increasing exponentially require the number of probability parameters with the number of its parents. Therefore, the benefits in using network of low connectivity are the computational and possess conceptual advantage. The topology of the Bayesian Network is the information about the underlying causal and probabilistic relationship in the domain [10]. The simpler topology of the Bayesian Network, is the simpler to understand.

This research will classify student self-monitoring skill, and the result will be used to develop student modeling in Intelligent Tutoring System. Variables used to classify are planning, self-checking, and problem-solving ability.

### III. RESEARCH METHODOLOGY

#### A. Bayesian Network

One of the most effective classifiers, in the sense that its predictive performance is competitive with state-of-the-art classifiers, is the so-called naive Bayesian classifier [11]. A Bayesian network algorithm is a probabilistic graphical model for reasoning under uncertainty.

A Bayesian network processed the joint probability distribution of a set of variables,  $(X_1, X_2, \dots, X_n)$  which the set of variables is as a directed acyclic graph which expressing the conditional dependencies and a set of conditional probability models. Each node in Bayesian network corresponds to a variable which can be discrete or continuous. The model computes the probability of a state of the variable given the state of its parents [12].

Consider  $n$  random variables  $X_1, X_2, \dots, X_n$ , a directed acyclic graph with  $n$  numbered nodes, and suppose node  $j$  ( $1 \leq j \leq n$ ) of the graph is associated with the  $X_j$  variable. The formula is stated below:

$$P(X_1, X_2, \dots, X_n) = \prod_{j=1}^n P(X_j | \text{parents}(X_j))$$

where:  $\text{parents}(X_j)$  is the set of all variables,  $X_i$ , is an arc from node  $i$  to node  $j$  in the graph. In this study, the classifying process is using this equation below:

$$P(A = A_i | B = B_j) = \frac{P(B = B_j | A = A_i)}{P(B = B_j)}$$

where  $P(A=A_i | B=B_j)$  is the likelihood of occurrence of  $A$  with category  $B$ .  $A$  is for self-monitoring and  $B$  is for the category (e.g. low, medium, and high).

### B. Data

To measure the self-monitoring skill, this research data is collected through a questionnaire. The subject of the research is university students who are taking a basic computer programming course; the data consist of 53 data. The students are classified into two numerical intervals based on the result of the questionnaire: low-level: interval includes values from 0 to 36, medium-level: interval includes values from 37 to 74 high-level: interval includes values from 75 to 106. The variables to measure self-monitoring skill consist of problem-solving, planning, and self-checking.

### C. Participants and Instrument

The subject of this research is an undergraduate student at the Department of Electrical and Information Engineering, Universitas Gadjah Mada who has been taking a basic programming course. The sample consisted of 53 undergraduate students who have been taking a basic programming course. All the participants are from 2014 to 2017 for the academic year. The academic year 2014 to 2017 were selected because all the students had been taking the course before so that they knew their capability when solving problems and monitor themselves in a basic programming course.

This research adopted a questionnaire from Hong et al. for self-monitoring skill and Bruce et al. for problem-solving ability [13][14]. This questionnaire consists of 26 items of questions and using a Likert scale (1 to 4). Participants responded to each item by rating themselves on the following scale: (1) Strongly disagree, (2) disagree, (3) agree, and (4) Strongly agree.

To measure self-monitoring skill in academic performance, a modified version was used. The current version consisted of 14 items that assisted participants' self-monitoring skill and 12 items that assisted participants' problem-solving ability. These two questionnaires were combined, because of the subject of the course that was chosen to be implemented in ITS. Basic programming course is one of the courses that require problem-solving abilities.

Self-monitoring questionnaires consisted two indicators (e.g., planning and self-checking) and for the problem-solving consisted identifying goals, self-assessing, self-explaining, self-questioning, reflecting and making concepts personally relevant [14][15][16][17]. The example of the item for problem-solving is: "I think of several ways to solve problems and choose the best one." The example of the items for self-monitoring (planning and self-checking) are: "I carefully planned my actions to solve the problem"; "I checked my work while I am working on it."

## IV. RESULTS AND DISCUSSION

This section will present the result of the classification of students' self-monitoring skill using Bayesian network algorithm. The classification used WEKA as tools. The students' self-monitoring skill classification was computed using 10-fold cross-validation. In 10 fold cross-validation, the data were divided into 10 folds of approximately the same size, so we had 10 subsets of data to evaluate the performance of the model or algorithm. For each of the 10 subsets of data, cross-validation used 9 fold for training and 1 fold for testing.

The data classified into three classes (i.e., low-level, medium-level, and high-level). Based on the formula (1) and (2), the classification is based on the defined score above in section III. From the data description above, the computation of the classification is defined by the score, the probability of self-monitoring skill with category Bi if the score is more than equal 75, then the class is high-level. The probability of self-monitoring skill with category Bi if the score is less than 75 then the student self-monitoring skill is medium-level and for the probability of self-monitoring skill with category Bi if the score is less than equal 36, then student's self-monitoring skill is low-level. All the data will be computed the probability of the occurrence based on each category classifying. Table 1 show the classification result for the computational and Table 2 show the accuracy result. The total column score means the sum of the score from the questionnaire, and the amount of total score appears the amount of the score appears in the table. This summary data makes easier to understand.

**Table 1.** Classification Result Summary

Total score	The amount of total score	
	appears	Class
96	1	high
95	2	high
94	2	high
92	1	high
90	2	high
88	2	high
86	1	high
85	3	high
84	1	high
83	2	high
82	3	high
81	2	high
80	2	high
79	6	high
78	1	high
77	3	high
76	2	high
75	1	high
74	4	medium
73	2	medium
72	2	medium
71	4	medium
70	2	medium
68	1	medium
67	1	medium
Total respondents	53	

**Table 2.** Accuracy Result

Correctly Classified	94%
Incorrectly Classified	5.6604%

The classification result in Table 1, the class is divided into three classes, i.e., low-level, medium-level, and high-level. The result shows that 28 instances are classified into high-level, and 25 instances are classified into medium-level and 0 into low-level. From 53 participants, all the participants are only classified into two classes (i.e., high-level and medium-level). From Table 1, the result is only classified into two classes, i.e., medium and high. This is caused by the respondents of this study who answer the questionnaire. The respondents are the students who have been taking the basic programming course so that they have high confidence in their self-monitoring skill. The result shows that the accuracy of the classification is 94%, this accuracy means the Bayesian Network algorithm is pretty good at classifying students' self-monitoring skill. Student's self-monitoring is classified into three classes, i.e., low-level, medium-level, and high-level. But from the answer of the questionnaire, the result of the self-monitoring skill classification is only two classes, i.e., medium and high. This is caused by the respondents of this study who answer the questionnaire. The respondents are the students who have been taking the basic programming course so that they have high confidence in their self-monitoring skill.

## V. CONCLUSION

This research conduct student performance classification based on student's self-monitoring skill. This classification used Bayesian network classifiers. The result shows that the accuracy of the classification is 94%, this accuracy means the Bayesian Network algorithm is pretty good at classifying students' self-monitoring skill. Student's self-monitoring is classified into three classes, i.e., low-level, medium-level, and high-level. For the future work, this questionnaire will be given to the students' who are taking the basic programming skill which has been applied in ITS to make the adaptive treatment based on students' self-monitoring skill and analyze the impact of self-monitoring skill to the learning outcomes. The result of this pilot research will be used as a reference to make rules for the adaptive treatments in ITS. The limitation of this study is only using one algorithm, i.e. Bayesian network, for the future work, to classify student's self-monitoring skill can use another algorithm and compare with Bayesian network. The challenge to develop ITS with metacognitive base is complexity and Adaptivity. This research conduct student performance classification based on student's self-monitoring skill. This classification used Bayesian network classifiers. The result shows that the accuracy of the classification is 94%, this accuracy means the Bayesian Network algorithm is pretty good at classifying students' self-monitoring skill. Student's self-monitoring is classified into three classes, i.e., low-level, medium-level, and high-level. For the future work, this questionnaire will be given to the students' who are taking the basic programming skill

which has been applied in ITS to make the adaptive treatment based on students' self-monitoring skill and analyze the impact of self-monitoring skill to the learning outcomes. The result of this pilot research will be used as a reference to make rules for the adaptive treatments in ITS. The limitation of this study is only using one algorithm, i.e. Bayesian network, for the future work, to classify student's self-monitoring skill can use another algorithm and compare with Bayesian network. The challenge to develop ITS with metacognitive base is complexity and Adaptivity

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## REFERENCES

- [1] Rollinson J and Brunskill E 2015 From Predictive Models to Instructional Policies Proc. 8th Int. Conf. Educ. Data Mining 179–86
- [2] Gama C A 2004 Integrating Metacognition Instruction in Interactive Learning Environments Univ. Sussex 232
- [3] Arslantas S and Kurnaz A 2017 The Effect of Using Self-Monitoring Strategies in Social Studies Course on Self-Monitoring, Self-Regulation and Academic Achievement Int. J. Res. Educ. Sci. 452–452
- [4] Kaeser T, Klingler S, Schwing A G and Gross M 2017 Dynamic Bayesian Networks for Student Modeling IEEE Trans. Learn. Technol. 1382 1–1
- [5] Hawkins W J, Heffernan N T and Baker R S J 2011 Learning Bayesian Knowledge Tracing Parameters with a Knowledge Heuristic and Empirical Probabilities
- [6] Yutao and Beck J 2013 Class vs. student in a bayesian network student model Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) 7926 LNAI 151–60
- [7] Namatame Y and Ueno M 2006 A Method to Evaluate Learner's Knowledge Structure in e-Learning 43–5
- [8] Asopa P, Asopa S, Joshi N and Mathur I 2016 Evaluating student performance using fuzzy inference system in fuzzy ITS 2016 Int. Conf. Adv. Comput. Commun. Informatics, ICACCI 2016 1847–51
- [9] Yulmaini 2015 Penggunaan Metode Fuzzy Inference System (Fis) Mamdani Dalam Pemilihan Peminatan Mahasiswa Untuk Tugas Akhir J. Inform. 15
- [10] Lam, W., & Bacchus F 1994 Learning Bayesian Networks from Distributed Data : An Approach Based on the MDL Principle Comput. Intell. 10 1–14
- [11] Division C S, Park M, Langley P and Smyth P 1997 Bayesian Network Classifiers \* 163 131–63
- [12] Prinzie A and Van Den Poel D 2011 Modeling complex longitudinal consumer behavior with Dynamic Bayesian networks: An Acquisition Pattern Analysis application J. Intell. Inf. Syst. 36 283–304
- [13] Hong E and O'Neil H F 2001 Construct validation of a trait self-regulation Howard B C, Mcgee S, Shia R and Hong N S 2000 Metacognitive Self-Regulation and Problem-Solving: Expanding model Int. J. Psychol. 36 186–94
- [14] Howard B C, Mcgee S, Shia R and Hong N S 2000 Metacognitive Self-Regulation and Problem-Solving: Expanding
- [15] Linn M C 1995 Designing computer learning environments for engineering and computer science: The scaffolded knowledge integration framework J. Sci. Educ. Technol. 4 103–26
- [16] Chi M T H, Bassok M, Lewis M W, Reimann P and Glaser R 1989 Self-explanations: How students study and use examples in learning to solve problems Cogn. Sci. 13 145–82
- [17] King A 2005 Verbal Interaction and Problem-Solving within Computer-Assisted Cooperative Learning Groups J. Educ. Comput. Res. 5 1–15