An automated cognitive analysis model for online asynchronous discussion

Andi Tenriawaru¹* and Abdul Rahman²

¹Department of Mathematics, Faculty of Mathematics and Natural Science, Halu Oleo University, Kendari 93231, Indonesia.
²Senior High School 1 Kendari, Indonesia.

atenriawaru36@gmail.com, andi.tenriawaru@uho.ac.id (corresponding author)

Abstract. Evaluation of students' cognitive abilities needs to be done as part of evaluating student learning outcomes. This evaluation must not only be done in conventional learning, but this must also be done in online learning. Evaluation of students' cognitive abilities can be done through cognitive evaluation of messages posted by students in online asynchronous discussion. There are several studies that have addressed the problem of evaluating students' cognitive abilities in online learning, but the process of identifying students' cognitive abilities in these studies has not been fully automated. There are parts of the identification process still carried out by humans. This study proposes a model that can produce classification automation of cognitive levels of messages posted by students in online asynchronous discussion. The messages used in this study are messages written in Indonesian. The proposed model consists of four main processes, namely the process of creating corpus, extraction and selection of features, classifier and training development, and testing. This model can help lecturers to identify cognitive levels of messages. The proposed model is expected to improve the performance of evaluation systems of e-learning learning.

1. Introduction

Learning evaluation is very important for all learning methods, both face-to-face and online learning [1-2]. The results of the evaluation can show the level of learning success. The success of a learning method can be measured from the level of student engagement or the level of student success in learning. One indicator of measuring student learning outcomes is measuring the level of student understanding of learning that has been obtained. The level of student understanding can be seen from the level of cognitive abilities of students.

The level of students' cognitive abilities in online learning can be measured through messages written by students in online asynchronous discussions [3]. In other words, measurement of the cognitive level of messages in asynchronous online discussions needs to be done. Several previous studies have discussed the evaluation of online learning outcomes based on students' cognitive engagement in online asynchronous discussion [4-5] and measuring students' cognitive levels [3,6]. The process of measuring students' cognitive levels in these studies involves measuring the cognitive level of messages written in online asynchronous discussions. The process of measuring the cognitive level of messages is still done manually. Therefore, the authors proposed a model to automatically analyze the cognitive level of messages in online asynchronous discussions.
2. Literature Review
As explained in the introduction, many studies have measured students' cognitive levels in online learning. Some of these studies have involved messages written in online asynchronous discussions.

Van der Meijden (2005) conducted a study on cognitive involvement of students. Determination of student cognitive involvement is done by evaluating student elaboration in online discussions, both synchronous and asynchronous discussions. Messages written by students are analyzed to determine their cognitive level based on cognitive dimensions. This study introduces three cognitive dimensions, namely Asking Questions, Giving Answers, and Giving Information. These three dimensions are described in 13 cognitive categories. Although this study has succeeded in determining the cognitive level of messages in online discussions, the determination process is still done manually.

Shukor et al. (2014) evaluated the quality of online learning through student cognitive involvement. This study divides the level of cognitive involvement of students into three categories, namely High-level cognitive engagement, High-low level cognitive engagement, and Low-level cognitive engagement. The data used are resource view actions, forum views, and forum posts. The process of determining the level of cognitive involvement of students is done by analyzing the cognitive level of messages written by students in the forum. The messages were analyzing based on Van der Meijden's (2005) cognitive categories. Although this research has measured the level of cognitive involvement of students, the message cognitive analysis process is still done manually.

3. The Proposed Conceptual Model
The framework is structured to determine the cognitive level of the message. The framework consists of four main processes, namely the process of creating corpus, extraction and selection of features, classifier and training development, and testing. The design of the framework is shown in Figure 1.

3.1. Creating corpus
In the classification process, corpus is needed as training data and test data. In this study, there are two corpus made from message data obtained from Moodle forum activities in courses that use
Indonesian. One corpus contains messages that are categorized as high cognitive and another corpus contains messages that are categorized as no-high cognitive by annotators. Annotators are provided with annotation guidance documents based on Van der Meijden’s cognitive categories. The annotators manually annotate each message submitted, which is categorized as high cognitive and which is not. Figure 2 illustrates the process of making a corpus. The data used in this study are messages obtained from forum activity on Moodle in courses that use Indonesian.

Corpus documents are saved in ASCII text file format. Corpus can contain several messages that are not equipped with a period to mark the end of a sentence, have more than one period, contain a question mark, or contain an exclamation mark. Therefore, the corpus is normalized by adding a period to a sentence that does not have it, replacing the question mark with a period, replacing the exclamation mark with a period, and replacing all periods with a semicolon except the period in the last sentence in the message.

3.2. Extraction and selection of features
At this stage, the design of tools is made in the form of programs written in the Java programming language for feature extraction from documents that have high and no-high cognitive categories. Feature extraction in this study uses a quality statement of needs model introduced by Hussain et al., (2007). Specifically for surface understanding factors section of sentence-level features is shown in Figure 3.

Surface understanding at the message level in relation to high cognitive detection is seen from key words and syntactic features. Syntactic features included in the message level are the frequency of verbs, nouns, adjectives, modals, and words other than the three types of words mentioned.
The syntactic features extraction process is performed using message data in the corpus. As a first step, the changing process each letter to lowercase, the tokenization process, the stemming process, and the POS tagging process is carried out on every message data in the corpus. Then, candidate features that are considered to be able to distinguish between high and no-high cognitive messages are identified. In this extraction process, a dictionary containing dynamically keywords from the high cognitive corpus and a list of valid features will be generated. The process of making a keyword dictionary is done by calculating the frequency of occurrence of each word in the high cognitive corpus. Then the Likelihood Ratio (LR) of each word is calculated based on the idea of Wiebe et al. [7]. If corpus\(_1\) is a corpus contains messages that are categorized as high cognitive and corpus\(_2\) is a corpus contains messages that are categorized as no-high cognitive then the LR formula is shown in Equation 1.

\[
LR_{\text{of word } X} = \frac{\text{frequency } X \text{ in corpus}_1}{\text{frequency } X \text{ in corpus}_1 + \text{frequency } X \text{ in corpus}_2}
\] (1)

Furthermore, if the LR of the keyword is greater than the LR baseline then the keyword is selected or considered valid. The LR baseline is calculated by Equation 2.

\[
\text{Baseline LR} = \frac{\text{Number of words in corpus}_1}{\text{Number of words in corpus}_1 + \text{Number of words in corpus}_2}
\] (2)

The process of determining valid features is done in the same way as determining keywords. The frequency and LR of each feature in corpus\(_1\) and corpus\(_2\) are calculated using Equation 3. The process of feature extraction, feature selection, and keyword generation shown in Figure 4.

\[
LR_{\text{of feature } Y} = \frac{\text{frequency } Y \text{ in corpus}_1}{\text{frequency } Y \text{ in corpus}_1 + \text{frequency } Y \text{ in corpus}_2}
\] (3)

Figure 3 Feature extraction model
3.3. Classifier and training development
The next stage is the stage of constructing the message classifier using the C4.5 classification algorithm. The classifier has a training module that will generate dynamic decision tree models based on data from the corpus that has been created. The decision tree will classify a message into high or not high cognitive categories. The classification steps are shown in Figure 5. The classifier is built by using Weka software [6] which provides C4.5 implementation in Java, namely J48.

3.4. Testing
At this stage Cohen's Kappa will be used to assess the results of the classifier that has been created. Kappa value will be a benchmark whether the proposed framework can be reliable on to detect the cognitive level of the message or not. If \( P(A) \) is the proportion of total times that the annotators are observed to agree, and \( P(E) \) is the proportion of the total times that the annotators are expected to agree, then the Kappa value \( \kappa \) is calculated by Equation 4 [9].

\[
\kappa = \frac{P(A) - P(E)}{1 - P(E)}
\]
Stages of testing are carried out with two scenarios. The first scenario of testing is done using the default baseline LR (calculation). The second scenario, testing is done by changing the LR baseline value as a threshold parameter. The scenario to determine the threshold value is to observe the classifier results and then to test with several different threshold values until a high Kappa value is obtained.

4. Conclusion
An automated tool for determining the cognitive level of messages posted by learners to forums is essential for determining the cognitive engagement level of students. This tool can assist teachers in detecting messages that have a high cognitive level or messages that have a no-high cognitive level. This paper proposed a model to automatically analyze the cognitive level of messages in online asynchronous discussions. The proposed model consists of four main processes, namely the process of creating corpus, extraction and selection of features, classifier and training development, and testing.

5. References
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