A Proposed Framework for Learning Assessment Ontology Generator

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Abstract. Different institutions have shown interest in standardizing the learning result. It may be used in the same way to assess students' learning status. The teacher must quantify the learning outcomes for evaluation purposes. It often requires a great deal of time and effort to do paper tasks. Additionally, this activity prevents instructors from concentrating on the learning process. Teachers are continuously burdened with administrative responsibilities that should be alleviated using technology that adheres to the current framework. The Bloom Taxonomy, a widely used framework for defining learning outcomes, allows for the assessment of learning outcomes at several levels. The purpose of this research is to provide a framework that will assist the instructor in completing the evaluation more quickly and accurately. This study provided an algorithm for adapting ontology and text classification technologies to detect correlations between words and keywords to aid in evaluation. It is anticipated that the categorization findings will assist in shortening the time required to complete the evaluation.

Keywords: Learning outcome · Assessment · Ontology

1 Introduction

In recent years, the educational system has transformed because of new norms or principles [1]. One of the educational system's objectives is to perform learning outcome assessments. Assessment of learning outcomes is a critical component of every learning environment [2, 3]. The word "assessment" refers to the overall quality of all evaluation procedures, not just the quality of a particular assessment [4]. This term seems to be included into a growing number of higher education programs [5]. The outcomes aid students in discovering the course's intended objectives. Additionally, it helps instructors keep on track and ensures that students understand what they will accomplish at the end of the semester. Additionally, learning outcomes assist instructors and students in determining the optimal course of action [6].

The learning outcomes should describe the fundamental and significant components of the course or program. By defining learning outcomes, we may reflect on the major factors that contribute to learners acquiring these knowledge and abilities. Consideration

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of (1) the course's key terms, (2) the intended forms of learning, and (3) the environment in which the course's knowledge and skills will be employed, including projected applications, establishes the foundation for establishing learning outcomes [12]. According to a widely used framework, Bloom Taxonomy, a framework should relate to three distinct learning domains: cognitive, psychomotor, and emotional. Each domain comprises levels that are used to construct courses [7]. Formulate the learning outcomes to determine the breadth and depth of a course. A course with learning outcomes enables the technical quality of the outputs to be assessed [5]. Precision and effort may be used to the generation of learning outcomes by incorporating input from important stakeholders in a prescribed manner [8].

To guarantee good learning results, a guide is essential. The Bloom Taxonomy is a regularly used reference. The Bloom's Taxonomy of educational goals is particularly effective since it associates certain verbs with various stages of learning. While Bloom's Taxonomy is hierarchical, each level of aim may make a major contribution to a course's performance [12]. It is intended to explain the learning process and has therefore shown to be an effective tool for assisting in the development of learning outcomes [9]. Within each area of the bloom taxonomy, there are several tiers. This level describes the method through which students' skills are developed during the educational process.

According to Bloom Taxonomy, the following are some strategies for implementing learning outcome evaluations. To begin, we may evaluate learning outcomes by examining students' evaluation grades [2]. On the other hand, students' replies to tests, assignments, and examinations are evaluated. Additional evaluation may be based on instructor comments concerning students' emotional well-being. The current problem is that the technique for evaluating results is complicated. This issue arises because the lecturer is accountable for determining the specific results reached by each student. This consequence may influence students' test replies or the notes they take during the classroom learning process. Not infrequently, instructors make mistakes in assessing student achievement, jeopardizing the validity of the outcome evaluation. Another area of research involves evaluating student replies without regard for Bloom's taxonomy levels. However, no research has classified lecturer notes on student behavior in class into the emotional realms of Bloom's taxonomy. The challenge in tackling this problem is choosing the suitable algorithm to assure accurate classification results. Additionally, the algorithm must encompass the process of classification in the cognitive and affective dimensions that are the subject of this research.

While several techniques may be employed to categorize text, the phrases used in evaluation reports may vary. To resolve these issues, a word correction standard known as ontology is used. Ontology is a strategy for resolving this issue. Ontologies are clear and formal representations of prevalent conceptualizations of concepts and their connections [22]. The paper's objective is to demonstrate how to develop an ontology using Bloom's Taxonomy levels and keywords. Ontology may simplify the classification process for student responses and lecturer notes by detecting the relationship between words and keywords. Additionally, the ontology may regard levels and concepts in the cognitive and affective domains as children. This project will provide a framework for constructing an ontology capable of classifying student replies and lecturer comments according to Bloom's Taxonomy levels. This classification may aid in the process of assessing educational results. The ontology will be generated from the course learning outcomes that have Bloom's Taxonomy structure. From the data, we can collect the keywords of Bloom's Taxonomy level and generate into the ontology structure.

2 Literature Review

2.1 Learning Outcome Assessment

Nowadays, many stakeholders in academic institutions put a priority on learning outcomes. Curriculum designers must understand the actual meaning and significance of the statements of Program Educational Objectives (PEOs), Program Outcomes (POs), and Course Outcomes (COs) while building the curriculum [8]. Course outcomes will be determined along with the definition of program goals. COs are acronyms for the criteria that a student must satisfy to pass the course [15]. Consequently, developing standards for learning outcomes becomes a popular issue [10]. Learning outcomes are a critical discussion topic, especially considering the expected skills of university graduates or new employees who will eventually support society [11]. Learning outcomes place a consideration on the context and potential applications of students' knowledge and skills, aid students in linking learning across settings, and facilitate assessment and evaluation [12]. The word "learning outcomes" refers to the characteristics, knowledge, and skill set acquired by a student following successful completion of a course [13]. The learning outcomes are more concerned with the growth of the learner than with the content of the course. Additionally, it supports instructors, teachers, and facilitators in establishing and planning beneficial student-centered learning activities [10]. Learning outcomes, in general, are statements that explain what each learner should know or be able to do after a learning experience [14].

The educational process is dependent on evaluation. Teachers and school administrations who embrace an assessment culture use data on students to generate new understandings about what works and why, share their discoveries with colleagues, and increase their ability to fulfill the diverse learning needs of their students [16]. Assessment is a systematic and ongoing process of collecting, assessing, and acting on data about the goals and outcomes established to support the institution's mission and purpose. The evaluation process begins with the establishment of objectives. Measurable results need the expression of the assessment cycle's first three components: outcome, assessment method, and success criteria [17]. Most evaluation tools analyze student achievements on a course-by-course basis. They must also be consistent with program learning objectives (PLOs) to give an overall assessment of students' achievement of these objectives [18]. Assessment supports the incorporation of learning objectives into the course design and delivery. Multiple choice or short answer questions may be used to evaluate an outcome that requires students to recollect crucial events leading up to a historical event. In comparison, an outcome that requires students to evaluate many policy models may be evaluated by a debate or written essay [12]. The similarities between grading with percentages and grading by learning goals in an assessment is that both methods offer an overall mark indicating proficiency [21].

2.2 Bloom Taxonomy Standard

Returning to Bloom's Taxonomy of educational goals is one strategy to align results with suitable means of evaluation. Bloom's Taxonomy was developed in 1956 and modified in 2001 by Bloom's associates Lorin Anderson and David Krathwohl. The educational process and often used framework for producing learning outcomes are shown by Bloom's Taxonomy. The framework categorizes learning objectives as cognitive, emotional, or sensorimotor/psychomotor. The authors of the new taxonomy underline this dynamic by using verbs to denote the taxonomy's divisions and subcategories. The cognitive domain is concerned with identifying facts, skills, and concepts to help pupils develop their knowledge and abilities. The affective area is where excitement and feeling occur. The psychomotor domain is involved with the physical development of the body [19]. The cognitive results of students were compared to the amount of knowledge and intellectual talents gained and mastered. External assessment tools such as user data, questionnaires, interviews, and observations were employed to analyze different aspects of participant learning [20].

2.3 Ontology Construction

Ontologies provide an ideal setting for the functioning of intelligent services. Ontologies, for instance, may enhance intelligent online search, information filtering, intelligent information integration, and knowledge management. Ontology alignment is crucial for developing information-based systems [23, 24]. The ontology has a lot of semantic information that may be used to effectively reduce conceptual ambiguity and help in the execution of a variety of text processing activities [25]. The ontology development approach is meant to assist developers in developing ontologies that follow to required specifications and essential procedures that have a direct impact on the ontology's knowledge representation and logical reasoning. When selecting ontology generation strategies, we should either pick the method that is most relevant for the current situation or combine the advantages of many ways to improve and optimize the existing methods [26]. Collaborative ontology is becoming more popular as a way for developing ontologies. The process of constructing ontologies from a variety of current data sources has emerged as a key topic of research and is crucial for ontology development [27]. Within this framework, programmers and domain specialists must collaborate with mutual understanding. By evaluating the validity of envisioned knowledge embeddings, domain experts contribute significantly throughout the ontology creation cycle [28].

Currently, ontology is widely used in a variety of text processing activities, including information retrieval, information extraction, information integration, data management, information recommendation, text classification and clustering, and question and answer systems [25]. Some study in education makes use of ontology to address problems. In teaching and learning processes, ontology is employed to construct a cognitive conversational agent. Numerous studies in education use the ontology as question-and-answer generators [9, 29–31]. The research serves as the foundation for a question-answering system for measuring students' domain understanding, providing natural-language explanations for students' errors, and designing adaptive quizzes [29]. Other study indicates that ontology may provide a variety of various sorts of feedback in response to an inquiry [32]. Not only can ontology be used to produce questions and answers, but it may also be utilized to assist in the development of a curriculum [33].

The ontology's story is described by the fact that it establishes the relationship between reusable competences categorized according to Bloom's taxonomy and Knowledge Topics in the field of Computer Sciences [34]. According to the other studies, ontology represents notions that aid pupils' thinking processes. It offers a mechanism for resolving often reported issues that learners have while using a web-based learning system [35]. In 2021, the study included the learning result into a relevant course by quantitative assessment and cluster analysis [21].

The growth of ontology research has resulted in the presentation of numerous semi-automatic and automated construction strategies, some of which have been utilized to produce ontologies from textual data [22, 36]. To begin, ontology learning takes concepts from a variety of textual sources and establishes taxonomic and non-taxonomic relationships between them [22]. Now, automatic ontology building from plain text captures most hierarchical relationships. After harmonizing the concepts from these diverse ontological frameworks, these phrase ontologies are integrated to create an ontology for the whole text [37].

3 Proposed Framework

This section will discuss how to create an ontology schema and how to categorize student responses according to Bloom's taxonomy levels. The procedure is shown in Fig. 1.

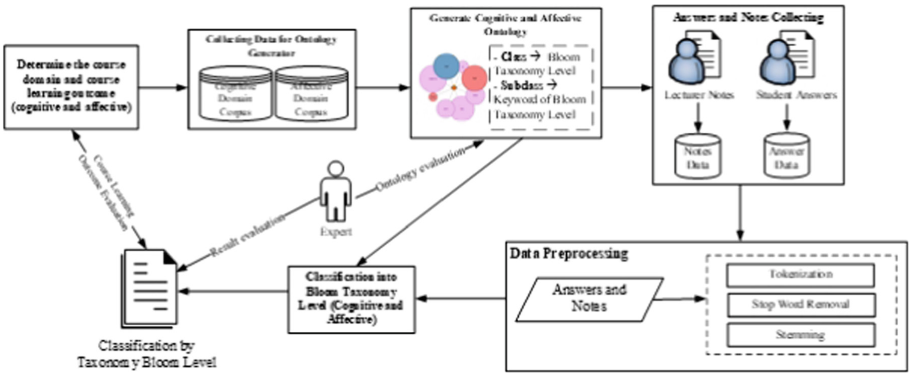

Fig. 1. Proposed framework for learning assessment ontology generator

3.1 Data Collection

The first step determines the scope of the research. The data for this research will be gathered from a sample of chosen courses. Additionally, we analyze the learning outcomes of cognitive and affective domains. Following that, we will collect data through a series of procedures. We gather questions and answers from various courses for the cognitive domain. We use lecturer notes to describe each student's emotive recall. These data will provide a corpus from which the ontology will be constructed.

3.2 Ontology Construction

The ontology is separated into parent and child classes. Bloom's taxonomy level is defined by its parent classes. Keywords linked with each bloom taxonomy category are included in the child classes. At this step, we will create the ontology using Lexical Semantic Analysis (LSA). We may use LSA to find phrases that are synonyms with bloom taxonomy keywords. As is the case with a bachelor's degree, this research concentrates only on four taxonomy flowering levels in the cognitive domain: remember, understand, apply, and analyze. On the other hand, this research will include all Bloom taxonomy levels for the emotional domain: attention, response, value, organization, and generalization. On Fig. 2, we can see the example of Bloom Taxonomy cognitive ontology scheme.

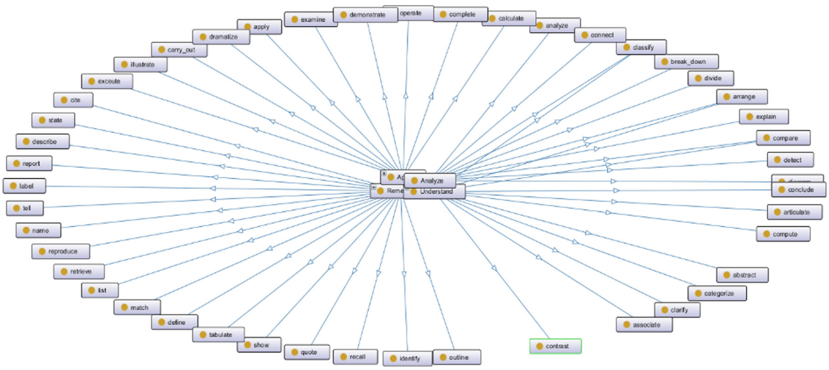

Fig. 2. Example of bloom taxonomy cognitive ontology scheme

3.3 Data Preprocessing

The next stage is to gather answers in accordance with the cognitive and emotional domains as part of the data collection process. We collect course-specific questions and answers, as well as lecturer notes for the emotional domain. Following then, the system is made up of several steps for pre-processing the questions and replies. This phase generates a dataset of questions and responses that has been classified in the succeeding stage. Three executable processes are included in this Sect. (1) Tokenization is a process that divides a corpus of text into smaller units called tokens. In this scenario, tokens may be words, characters, or subwords. Thus, tokenization may be classified in broad terms as follows: word tokenization, character tokenization, and subword tokenization (n-gram characters). (2) A stop word is a series of words that are often used in a language. Stop words in English include "a", "the", "is", and "are." Stop words are often used in Text Mining and Natural Language Processing (NLP) to remove keywords that are overused and contain little useful information. (3) Stemming is the process of reducing a word to its word stem, which is connected to suffixes and prefixes or to the root of words known as a lemma. Natural language understanding (NLU) and natural language processing rely heavily on stemming (NLP).

3.4 Classification

This classification process takes use of the ontology we developed to facilitate categorization and deep learning model. We compare the pre-processed data set to the ontology. For this research, we use word2vec embedding approach with neural network to do the classification tasks. The classification process, we can use Recurrent Neural Network (RNN) model. RNNs have been effectively used in machine translation and natural language processing applications. They are divided into three layers: an input layer, a hidden layer, and an output layer. The input and output layers perform the same function [38]. A RNN is a sort of architecture in which individual neurons have recurrent connections. Like feedback loops in biology, such designs facilitate memory storage to a certain degree. For sequence classification, the most often employed recurrent architectures are Long-Short Term Memory (LSTM) cells (see Fig. 3) and Gated Recurrent Units (GRUs) [39]. A single LSTM cell is composed of three primary gates: input, output, and forget. Individual LSTM cell activations are defined as sigmoid functions:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

Together, the three gates form a feedback loop that preserves gradients throughout training. The primary advantage of LSTMs for sequence learning is that they partially address the vanishing gradient issue, which means that long term signals persist in memory, while a basic feedforward architecture is prone to disappearing gradients [39].

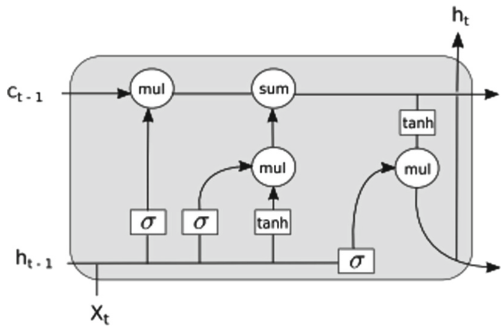

Fig. 3. The LSTM cell [39]

Additionally, this work seeks to connect a term in the ontology with a word in the dataset. Following that, we get Taxonomy Bloom-categorized data for the questions and replies. Following publication, the result must be independently verified by specialists. Education professionals will check the classification to ensure it is correct. After the verification operation is complete, the percentage of classification is shown. Based on this percentage, we may adapt the ontology scheme to get a high rate. The analysis of course results is predicated on previously gathered data. We may determine the subject's success in learning based on the result. Is the learning result of the courses we've created adequate, or are the prerequisites set too high?

4 Conclusions

The educational institutions could benefit from standardizing learning outcomes. They may use learning outcomes to determine a student's degree of accomplishment throughout the learning process. This process takes a lot of time. A helpful tool could save lots of time for lecturers. This paper proposed text mining techniques with ontology to shorten the assessment process. Utilizing Bloom's taxonomy simplifies the process of evaluating learning results. This study should facilitate educational institutions to measure the extent of defined learning outcomes. By using the proposed framework, the learning outcomes should alter the students' skills to produce high-quality graduates.

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