Extending Cognitive Skill Classification of Common Verbs in the Domain of Computer Science for Algorithms Knowledge Units

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Abstract: To provide an adaptive guidance to the instructors through designing an effective curriculum and associated learning objective, an automatic system needs to have a solid idea of the prerequisite cognitive skills that students have before commencing a new knowledge before enhancing those skills which will enable students to steadily acquire new skills. Obtaining the learning objectives in knowledge units based on cognitive skills is a tedious and time-consuming task. This paper presents subtasks of an automatic meta-learning recommended model that enables the extraction of learning objectives from knowledge units, which are teaching materials. Knowing the cognitive skills will help mentors to connect the knowledge gaps between learning materials and their aims. The model applies Natural Language Processing (NLP) techniques to identify relevant knowledge units and their verbs, which assist in the identification of extracting the learning objectives and classifying the verbs based on cognitive skill levels. This work focuses on the computer science knowledge domain. We share the result that evaluates and validates the model using three textbooks. The performance analysis shows the importance and the strength of the automatic extraction and classification of the verbs among knowledge units based on cognitive skills.

1 INTRODUCTION

Bloom's Taxonomy is an important tool that is used as a guideline for educators to develop teaching materials, organize learning goals, and create assessments to match a learning activity with the learning objective (Thompson,2008) and (Lister,2000). Benjamin Bloom proposed Bloom's taxonomy; this divides learning objectives into three domains: cognitive, psychomotor, and affective (Bloom,1956). The cognitive domain is related to the knowledge and mental skills of a learner. It is the most widely used domain including six levels from moderate to high mental processing levels.

Bloom's taxonomy was modified by (Anderson, 2001), and a significant change was made by adding and ordering the levels' names. However, the number of levels was kept consistent. The revised cognitive domain's levels from simplest to most complex are: 1) remembering, 2) understanding, 3) applying, 4) analyzing, 5) evaluating, and 6) creating.

Bloom's Taxonomy is a cognitive skills classification that has been applied for different educational purposes in many fields of study. In the area of computer science, Bloom's taxonomy was used in course design, teaching methodology, preparing materials, and measuring student responses to learning (Doran,1995) and (Burgess,2005). The ACM Computer Science Curriculum specifies learning objectives based on the revised Bloom Taxonomy(Cassel,2008) and (Gluga, January 2013). There is a strong need to describe computer science knowledge units regarding learning goals and the level of mastery.

Using already acquired skills' will help nescience or lack of understanding to connect the knowledge gaps between learning objectives and learning materials as well as ensure the effectiveness of teaching and learning. Also, the learner should have a better understanding of learning objectives and learning materials, and teach students how to master all new concepts in each knowledge unit. Also, their mental skill levels should increase as they progress from one knowledge unit to the next.

Generally, the Bloom taxonomic relationships are extracted manually. Until now, extracting and describing learning objectives were derived using the verbs that connect concepts. In 1956, Bloom suggested a classification of verbs, which are now widely used as a "clue" to determine the relationship

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between concepts. In 2001, the verb list was extended and revised by Bloom. Bloom's measurable verbs are indicative of cognitive skills, (Nevid, 2013) but not all the verbs are included in Bloom's verb list. Unfortunately, for a fast-growing knowledge domain such as computer science, these tables do not contain many verbs used in the field. A question was raised as for how to determine the Bloom relationship that is implied by other verbs, not on Bloom's verbs list.

This paper presents a meta-learning recommended model foundation to extend the cognitive skill relations indicated by those new knowledge domain verbs figure 1 illustrates the model. A subtask of the model is used to classify verbs in the learning objectives into cognitive skill levels. For this task, not all verbs are equally important; we are primarily interested in a domain-specific verb, which is computer science. The classification of a domain-specific verb is defined as a relationship between the concepts that are used in sentences with the given verb.

We investigate three techniques to extend the current classification of the listed verbs, where Bloom's verb list is used as a baseline method. The first method includes WordNet (WordNet,2010) which was used to access the verb synonym. Then, we investigate the use of VerbNet to further extend the classification based on the class and the membership of the verbs in VerbNet database. Finally, The verbs that were not found in WordNet synonym, or VerbNet class another method is used, which is Singular Value Decomposition (SVD), to classify the rest of the verbs; the three methodologies will be explained in section 4.

The rest of the paper is organized as follows: the literature review is presented in Section 2; the problem definition is discussed in Section 3; Section 4 describes an overview of the meta-learning recommended model and the classification methodologies; Section 5 shows the experiment setup and an evaluation of the methods, and Section 6 presents the conclusion, discussion, and the direction for future work.

2 LITERATURE REVIEW

In the area of *linguistics*, verbs are central to the syntactic structure and semantics of a sentence. Some computational resources and classifications have been developed for verbs. These resources can be classified into these three types:

Syntactic Resources: Examples of these are multiple dictionaries (Grishman et al., 1994) and ANLT (Boguraev et al., 1987), which are manually developed. An entry here will have verb forms and subcategorization information.

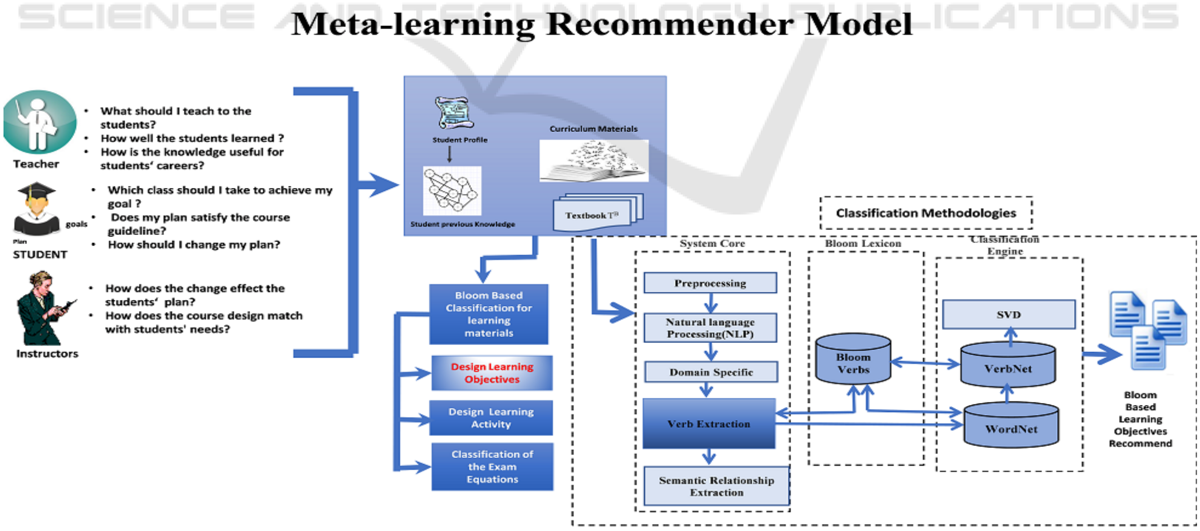

Figure 1: Meta-Learning Recommender Model.According to Palmer (2000), WordNet lacks generalization, and its level of sense distinction is too fine-grained for a computational lexicon. *Syntactic Semantic Resources*: Here verbs are grouped by properties such as shared meaning components and morpho-syntactic behaviour of words in Levin's 1993 verb classification. Since then, VerbNet expands this classification with new verbs and classes (Kipper-Schuler, 2005).

Semantic Resources: Examples of these include FrameNet (Baker et al., 1998) and WordNet (Miller, 1995). FrameNet groups word according to conceptual structures and their patterns of combinations. The second example, WordNet, groups words into synsets (synonym sets) and records semantic relations between synsets. There is little syntactic information present in these resources.

In the area of *cognitive domain*, to the best of our knowledge, there has been no previous work on Bloom's Taxonomy in the field of computer science for various purposes such as managing course design (Machanick, May), measuring the cognitive difficulty levels of computer science materials (Lister, 2003), and structuring assessments (Oliver,2004). Bloom's Taxonomy has also been used as an alternative to grading with a curve (Hearst, 1992). Additionally, from the perspective of mining information, there has been some interesting research about extracting relations among concepts. Relations could be replaced by the synonym relationships, or a hypernym, an association, etc. (Hearst, 1992), and (Ritter, 2009) these relationships are successfully used in different domains and applications (Fürst,2009).

Another related work comes under graphical representation; the graph being the representation of the relationship that was gathered by the extracted data. There has been some research on graphical text representation such as concept graphs (Rajaraman,2003) and ontology (Navigli,2003). The authors proposed Concept Graph Learning to present relations among concepts from prerequisite relations among courses.

Even though there exists an extensive collection of literature on verb classification, none of the presented techniques have been developed to classify the verbs based on Bloom's Taxonomy levels. Benjamin Bloom and his colleagues provided the verbs to help identify which action verbs align with each Bloom level to describe the learning objectives (Starr,2008). Benjamin Bloom provides a sub-list; to which not all the verbs are included. There is a need in the computer sciences to use the domain verbs to keep the description of the learning objectives measurable and clear.

3 PROBLEM DEFINITION

In this section, we introduce some terms used in this paper and define the problem.

Concept (C): Represent the most important words in a text that describe a particular domain.

Cognitive domain verb (βi): According to Bloom theory, a learnable concept, can be learned at multiple cognitive skill level. The prerequisite concept which needs to learn the target concept at specific cognitive level depends on the verb connecting them. Thus, each verb can have multiple cognitive skill level labels (βi) where $\beta i = \{\beta 1, \beta 2, \beta 3, \beta 4\}$.

Cognitive graph (Gc): It is a directed Graph Gc = (C, CL) where Nodes represent a concept (c) and Edges represent CL (cognitive level).

Computer-Science based Cognitive Domain (CSCD): is a modification of the Bloom Taxonomy tool which is more useful to computer science learners than existing generic ones (Nafa and Khan, 2015).

Semantic domain knowledge graph (Gk): is an instruction of the domain knowledge content in a field text. Each text has a set of domain concepts(C), the sentences in the text describes the relationship between a pair of concepts. We label the concepts by their domain terminology, and we mark the edges (E) by the principal verb connecting two concepts in a sentence.

Problem Definition: Given 1) a semantic domain knowledge graph Gk = (C, E), where nodes represent concept(C) and edges(E)represent knowledge domain verbs (Vi) and 2) a subset of cognitive domain verbs $Vi \subset \beta i$. Find out a mapping function £: $Vi \rightarrow \beta i$ which maps domain knowledge verbs to their βi cognitive levels, where each edge $v \in V$ belongs to a particular relation type £ (v) $\in \beta i$.

For example, suppose we have a knowledge unit represented as a semantic graph Gs including ten nodes, which are concepts C = {Heap-Sort, heap-property, time, priority-Queue, max-heap, producer, sorting, array, Data Structure and elements} and edges E = {Analyse, Describe, Has, Implement, Maintain, and Update}. We need to map the domain knowledge verb Vi to its βi levels which are used to describe the learning objectives required for mastering this knowledge unit at different cognitive levels. Figure 2.a shows a given semantic graph Gs and figure 2.b illustrates the cognitive level required to master each group of concepts in the knowledge unit.

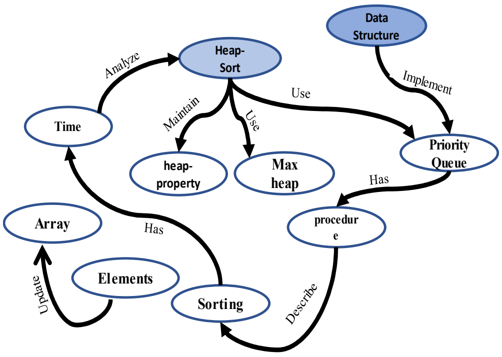

Figure 2.a: The example of our problem.

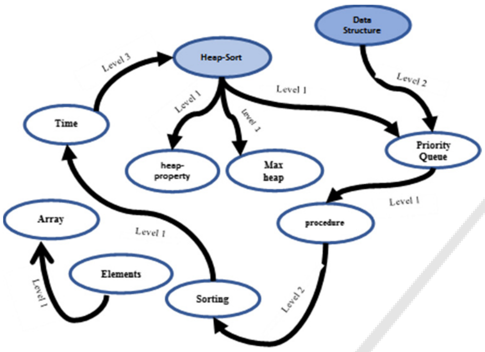

Figure 2.b: The example of our problem.

4 META-LEARNING RECOMMENDED MODEL (PHASE 2)

In this subtask of the model, which is extracting learning objectives based on cognitive skills, the verb level used to describe the obtained learning objectives. Bloom's Taxonomy provides a ready-made structure and list of action verbs. These verbs are vital to writing learning objectives. All the verbs are action verbs since the learning objectives are concerned with what the students can do at the end of mastering a specific knowledge unit. As an example, a list of the active verbs used to assess a remembering level is shown in Figure 3.

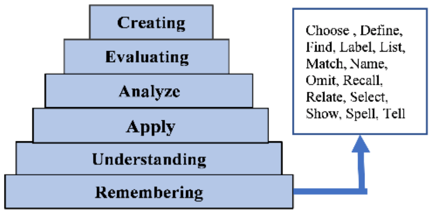

Figure 3: Example of Bloom Action Verb List Remembering Level.

To run the linguistic analysis for the knowledge unit in the textbook, Stanford University's Core NLP library is used. This step has been done in the first phase of our model, but more characteristics are added to analyze the verbs in the knowledge units. We analyzed the results of the sentence structures for the verbs. The most common modification to get a high accuracy of the results were incorrect POS tags; we noticed errors are stemming, sometimes a verb can be mistagged as a noun. These incorrect POS tags, causing incorrect parsing structures, are modified manually. Also for auxiliary verbs, we removed all of them by checking the verb with a list of all auxiliary verbs and their derivatives. For more accurate results, we introduce the proposed methodologies used (WordNet, VerbNet, and Value Decomposition (SVD)). The three methodologies will be explained in detail respectively.

4.1 WordNet(WN) Methodology

WordNet is a lexical database for English words and was developed at the University of Princeton (WordNet,2010). It clusters words (Nouns, verbs, adjectives, and adverbs) into sets of synonyms called synsets to help identify the meaning of the words, and is interlinked with a variety of relations. There is a different type of relations available in WordNet. These relations relate to concepts as follows:
Nouns (Synonym ~ antonym, Hypernyms ~ hyponym, Coordinate, and Holonym ~ meronym);
Verbs (Synonym ~ antonym, Hypernym ~ troponym, Entailment, and Coordinate);
Adjectives/Adverbs in addition to above relations (Related nouns, Verb participles, and Derivational information).

In this research, we are interested in the Verbs relation, which is the Synonym relations only. The Synonymy relation is at the base of the structure of WordNet. WordNet-like taxonomies behave in some ways as a dictionary, in others as an ontology. To avoid confusion, we use WordNet in this research as a dictionary for verb synonym relations. Around 3,600 verb senses are included in WordNet.

As the first method to finding the level of domain-specific verbs based on Bloom Taxonomies, we mapped all domain-specific verbs to their verb synonym from the WordNet database. Due to the WordNet limitation of not having all the classes for all verbs, classifying some of the verbs nor the others. WordNet has certain restrictions. It does not cover particular domain words or includes the forms of irregular verbs.

Figure 4 presents an algorithm used in WordNet methodology Input for the algorithm include Bloom's verb list and a domain specific verb list. The algorithm starts by reading a domain-specific verb list and compares the verbs in both records. It then indicated the verbs that are in Bloom's list and those that are not. It then starts to maintain the unknown verb list by checking the verb synonym from the WordNet database; some new verbs have been added to known verbs in Bloom's list. In case the verb synonym does not return any Bloom level for the verb, the Algorithm returns a new verb list with Bloom's classification and another verb list, not in Bloom's taxonomy. Thus, new verbs synonym based have been added to known verbs as in Bloom list. The list will be saved in a text file as unknown verbs in Bloom's taxonomy. A limitation for WordNet suffers from gaps between verbs in the database for that reason; some of the verbs will not be found in the WordNet database. Finally, for those verbs in which a classification is not determined, the algorithm starts the classification process over for verbs and uses a different methodology using the VerbNet methodology. This will be explained in detail in the next section.

```
Verb-List=open('Verbs.txt','r')  //Reading verb-list
For Verb in Verb-List:
 Verb-Synonym = WordNet-Synonym(Verb)
// To check whose Synonym to who for the CS-VERB LIST
CS-Verb-Synonym=list(set(Verb-List).difference(Verb-Synonym))
// Check if each CS-Verb-Synonym in Bloom Verb-list
 Bloom-List, Level=Give-Bloom-Level(CS-Verb-Synonym)
Def Give-Bloom-Level(CS-Verb-Synonym):
  CS-Verb-Synonym ( )
  For Verb in CS-Verb-Synonym:
       CS-Verb-Synonym. Add(Verb)
       Bloom-Verb=open('Bloom-Verb.txt','r')
       Bloom-Verb-list( )
       Bloom-Verb-dic {}
       For Verb in Bloom-Verb:
         Bloom-Verb-list. Add(Verb)
         If Verb not in Bloom-Verb-dic. Keys ():
           Bloom-Verb-dic[Verb]=Level
         Else:
           Bloom-Verb-dic[Verb]. append(Level)
       Bloom-Found = GetmostFrequ (Bloom-Verb-list)
Return Bloom-Found
Def GetmostFrequ(Level):
 Return max(set(Level), key=Level.count)
Def WordNet-Synonym(Verb):
 WN_Verb = Verb.replace(' ', '_')
  For pos in poses:
    For synset in wn.synsets(WN_Verb, pos):
      For lemma in synset.lemmas():
         Name = lemma.name().replace('_', ' ')
      If Name != Verb and Name not in syns:
         Syns.append(Name)
 Return sync
```

Figure 4: WordNet Algorithm.

4.2 VerbNet (VN) Methodology

VerbNet is a vast online repository for the classification of English verbs, which includes syntactic and semantic information for classes of English verbs derived from Levin's classification as explained in related works, section 2. It is an updated version considered more detailed than that included in the original organization. VerbNet classification considers paramount properties, the lexical meaning of a verb and the kind of argument interchanges that can be observed in the sentences with a verb. The ranking of VerbNet is verb sense- based. It covers 5,200 verb senses. The classification is partially hierarchical, including 237 top-level classes with only three more levels of subdivision (Kipper Schuler 2005).

The VerbNet database contains information about the correspondence between the categories of verbs and lexical entries in other resources. Each verb class in VerbNet include a set of members, thematic roles for the predicate-argument structure of these members, local restrictions on the arguments, and frames consisting of a syntactic description and semantic predicates with a temporal function. New subclasses are added to the original Levin classes to achieve syntactic and semantic coherence among members.

VerbNet Includes over 5,000 verb senses. It is a rich database with verb classification and provides easy access to be used by the programming language. It is also not very helpful when it comes to processing texts in specific domains where verb senses only partly overlap with those in general language use. It has been used to help NLP applications such as semantic role labeling (Swier and Stevenson, 2004) and word sense disambiguation (Dang, 2004).

Figure 5 explains the algorithm used for VerbNet methodology. As an input for the algorithm, it starts by reading the output verb lists from the previous methodology, which is WordNet. It then checks unknown verbs in Bloom's list to return the verb class from the VerbNet database. After it returns the verb class from the VerbNet database, new verbs are added to the known verbs as Bloom's list. In case the verb class returns nothing for the verb, the algorithm uses the verb member to check the availability of having new verb members for the verb under study and checks if the new verb is in Bloom's list. If so, the verb level is returned.

If the verb is not found either in a class or members in the VerbNet database, the list will be saved in a text file as unknown verbs in Bloom's taxonomy. A limitation for VerbNet includes gaps between verbs in the database; for that reason, some of the verbs will not be found in the VerbNet database. Finally, for those verbs whose classification is not found, the algorithm starts the classification process over for verbs but uses a different methodology, the Singular Value Decomposition (SVD) method, which will be explained in detail in the next section.

```
Verb-List=open('Verbs.txt','r') //Reading verb-list
 For Verb in Verb-List:
  Verb-Class = VerbNet.classids(Verb.strip())
   If Verb-Class!= [ ]:
      For Each in Verb-Class:
         Verb-Class-list.append(Each)
// Check if each verb-class in Bloom Verb-list
         Bloom-List,Level=Give-Bloom-Level(Verb-Class-list)
Def Give-Bloom-Level(Verb-Class-list):
 Verb-Class-list( )
 For Verb in Verb-Class-list:
  Verb-Class-list.add(Verb)
   Bloom-Verb=open('Bloom-Verb.txt','r')
   Bloom-Verb-list( )
   Bloom-Verb-dic{}
  For Verb in Bloom-Verb:
    Bloom-Verb-list.add(Verb)
    If Verb not in Bloom-Verb-dic.keys():
      Bloom-Verb-dic[Verb]=Level
   Else:
      Bloom-Verb-dic[Verb].append(Level)
Bloom-Found=Verb-Class-list.intersection(Bloom-Verb-list)
 Return Bloom-Found
 Verb-List=open('Verbs.txt','r')
 For Verb in Verb-List:
 Verb-Class = VerbNet.classids(Verb.strip())
 Def GetmostFrequ(Level):
   Return max(set(Level), key=Level. Count)
```

Figure 5: VerbNet Algorithm.

4.3 Singular Value Decomposition (Svd) Methodology

In this part, verbs are classified based on Latent Semantic Analysis (LSA). LSA is a theory and method for extracting and representing the usage meaning of domain concepts by statistical computations (Landauer et al. 1998). The process is divided into two tasks, calculating SVD to split the matrix A into three matrixes, and finding verb level in Bloom Taxonomy applying SVD to the matrix (A) will break down each dimension in the matrix using equation 1. The details of this methodology were published in (Nafa, 2015).

$$Matrix(A) = USV^T \tag{1}$$

4.4 Example to Explain the Methodologies

Let the given knowledge unit include ten high-level concepts C = {Heap-Sort, heap-property, time, priority-Queue, max-heap, producer, sorting, array, Data Structure and elements}. The process of finding the cognitive level of the verb is to describe the learning objectives required for mastering this knowledge unit at different cognitive levels.

Figure 6 shows an example of a text graph where the concepts extracted as learning objectives are used to describe the knowledge unit with instances of the high-level concepts.

In figure 6 A, only four verbs are known their cognitive level from the Bloom original list appears as black lines in the graph. In figure 6 B, by using the first methodology for verb classification which is WordNet only, one verb is classified into its cognitive level. The verb appears with a double line in the graph. In figure 6 C, by using the second methodology for verb classification which is VerbNet only, two verbs are classified into their cognitive level. The verbs appear with a double line in the graph. In figure 6.D, by using the third methodology for verb classification which is SVD, the rest of the verbs are classified into their cognitive levels. The verbs appear with a double line in the graph.

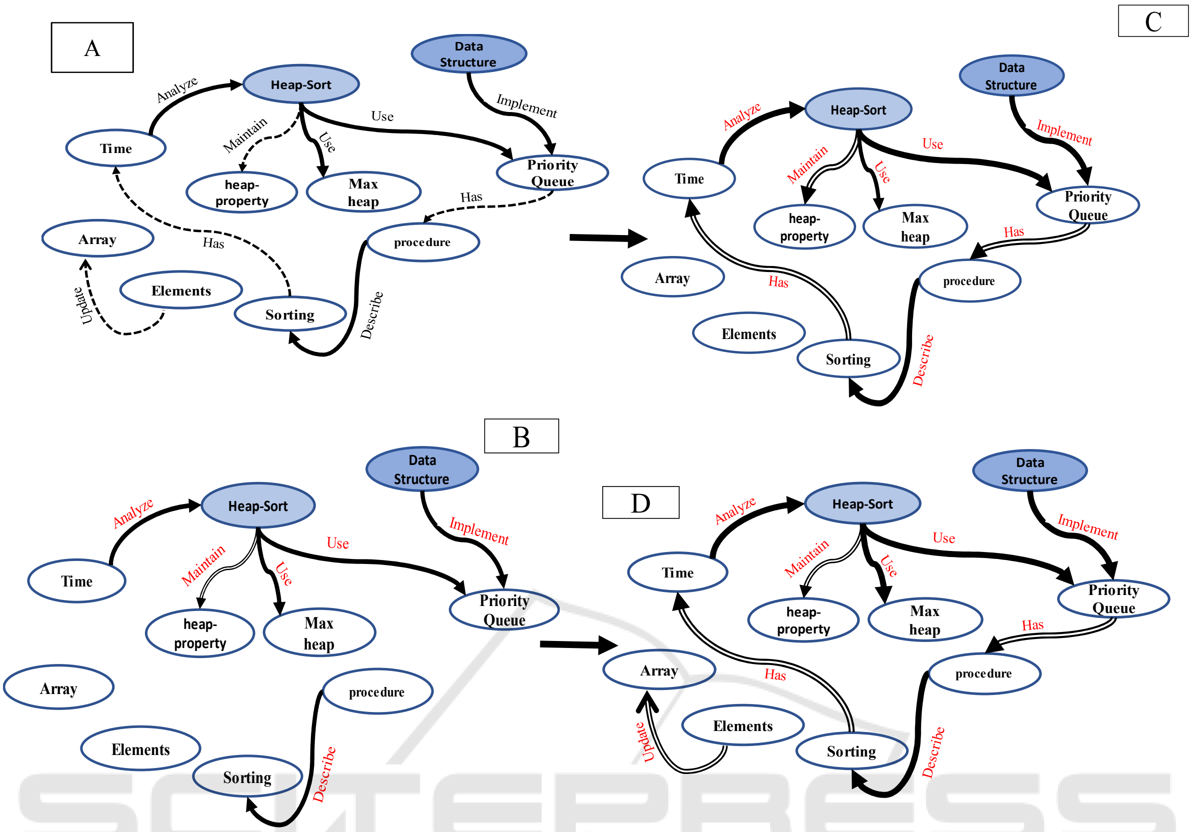

Figure 6: Example of verb Classification Methodologies.

After all, verbs are classified into their cognitive levels, and the high-level concepts candidate to be learning objectives for this knowledge unit, the teacher queries his\herself on what cognitive level are needed for my students to master this knowledge unit. Based on that, we query the graph to answer the question as a subgraph to describe the learning objectives for the knowledge unit.

The task of a learning objective extractor is to automatically identify a set of high-level concepts in the textbook that best describes it. Figure 6 illustrates three different levels of learning objectives for mastering a knowledge unit, which is Heapsort Algorithm. As it is evident in figure 6, to understand Heapsort Algorithm, students must learn the concepts in subgraph A, which represents the concepts that are in one of the lowest skill levels which is the understanding and remembering level because most of the concepts are common but important to understand the knowledge unit.

5 EXPERIMENT RESULT AND EVALUATION

5.1 Experiment Result

For this paper, we test the methodologies using three high-quality textbooks that are used in computer science classes as course materials. We obtain three text corpora, “Introduction to Algorithms,” “Data Structures and Algorithms,” and “Algorithms,” respectively. These written works are used at other universities. Experimental result and evaluation show that the proposed task of our model is effective in classifying verbs based on the cognitive level of learning. Table I. shows the statistical information for the three textbooks.

Table 1: Physical Characteristics of the Textbooks.

	Book1	Book2	Book3
Number of Knowledge unit	120	60	30
Number of extracted Relationships	8500	8200	3000
Number of concepts	1060	1020	950
Number of verbs	341	480	300

In this paper, our focus is only to classify the extracted computer science action verbs based on CSCD levels. As a subtask of the meta-learning model, the verbs are used to describe the learning objectives.

Figure 8 illustrates the percentage of verbs found in the textbook which equates to 341 words. The first scan in the original Bloom list consisted of 100 verbs found in Bloom levels where 241 classified as unknown verbs in Bloom's list. Then, out of 241, a total of 120 verbs were classified using WordNet synonym methodology, and 121 of those were unknown verbs. Then by using VerbNet, out of 121, a total of 37 verbs found in Bloom levels and 84 verbs were classified as unknown verbs. Finally, a total of 84 verbs were classified as Bloom's verbs using SVD methodology.

As more details of the classification resulted in figure 9, a prominent feature is that significantly equal percentages of the verbs fell in Bloom level2, Bloom level3, and Bloom level4, while the proportion of the verbs in the Bloom level1 are the most heights. We can say that the textbook used to describe a small Bloom cognitive level is the undergrad level. So the learning objectives for this book will be a prerequisite for the advanced courses of the algorithm. On the other hand, there are equal opportunities for high Bloom cognitive levels in the textbook.

5.2 Evaluation Measures

As an evaluation step, the gold standard for any linguistic analysis is human judgment. In this paper, we used statistical measures to estimate the agreement between the human classification of the verbs as well as the agreement between the results of verb classification and the "gold standard." There are different measures of the agreement; we applied Cronbach's alpha measure from the fields of inter-rater agreement.

Cronbach's alpha α is one of the most common measures of internal consistency. The calculation of α uses equation 2. Cronbach's alpha is a value between 0 and 1; the closer a value is to 1, the higher the reliability. The acceptable ranges of alpha are from 0.70 to 0.95 (Mohsen and Reg, 2011). The result of Cronbach's alpha for our data was 0.70.

$$\propto = \frac{N}{N-1}\left(1 - \frac{\sum \mu_i^2}{\pi_t^2}\right) \quad (2)$$

where N is the number of cases, μ_i^2 refers to the variance associated with item $_i$, and π_t^2 refers to the variance associated with the observed total scores.

In this result, humans share intuitions about the analysis. For the methodologies output, the classified verbs were given to native English speakers, who are Master's students in English. This is typically done by checking to see if they agree or disagree with the automatic classification of the verbs. Apart from the cognitive validation of our analysis, the majority agreed that the verb classification could be used as a baseline classification for computer sciences to describe the learning objective.

6 CONCLUSIONS AND DISCUSSION

In this paper, we described and discussed the concept of using Bloom Taxonomy in the field of computer science. Automatic methodologies that are used to classify the verbs according to CSCD levels has been presented. The methodologies are a sub-task of our previous work (Nafa,2015) and (Nafa,2016). Classifying verbs based on CSCD levels is a novel and challenging problem.

The classification methodologies make use of the cognitive domain in computer sciences. Not all the verbs found in the corps are equally important in the process of extracting the learning objectives; the most informative are the action verbs. These verbs are automatically classified using proposed methodologies; Bloom suggested a short verb list be used as a baseline. The methodologies are also able to recover verbs that are relatively infrequent or specialized and thus unlikely to be captured manually by an expert.

In the three textbooks analysis, we started with the first textbook which is "Introduction to Algorithm," and we used it as a knowledge base for the other textbook that included four levels of CSCD. Also, we involved the intersection between verbs in the four levels; one verb could have more than one level based on the semantic meaning and the semantic function

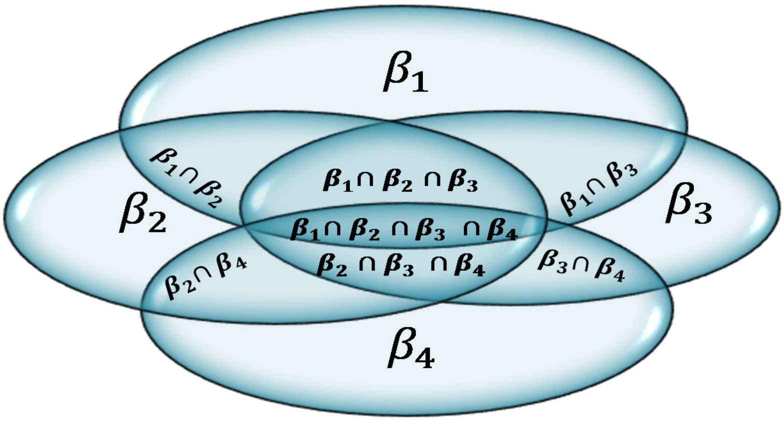

Figure 7: Verbs Intersection between Cognitive Classes.

that verb used for. The intersection set could be presented as:

$$|\beta_1 \cup \beta_2 \cup \beta_3 \cup \beta_4| = |\beta_1| + |\beta_2| + |\beta_3| + |\beta_4| - |\beta_1 \cap \beta_2| - |\beta_1 \cap \beta_3||\beta_1 \cap \beta_4| - |\beta_2 \cap \beta_3| - |\beta_2 \cap \beta_4| - |\beta_3 \cap \beta_4| + |\beta_1 \cap \beta_2 \cap \beta_3 \cap \beta_4|$$

Figure 7 shows the verbs intersection between cognitive classes.

The results show that the classification of verbs is overlapping between CSCD levels; one verb can be in more than one level based on its function as a cognitive verb level. This adds a different flavor of describing the learning objectives. Based on our analytical result, it is possible to conclude that by using CSCD levels we can decide which verbs to use at which level to match with the learner's skills and help in writing the learning objectives.

Through our experiments, we identified several promising lines for future research. First, we planned to present our model as a complete online tool and included a feedback section for the expertise based on their background in the learning materials. Second, we plan to carry out larger-scale experiments to generalized across different domains such as physics and math.

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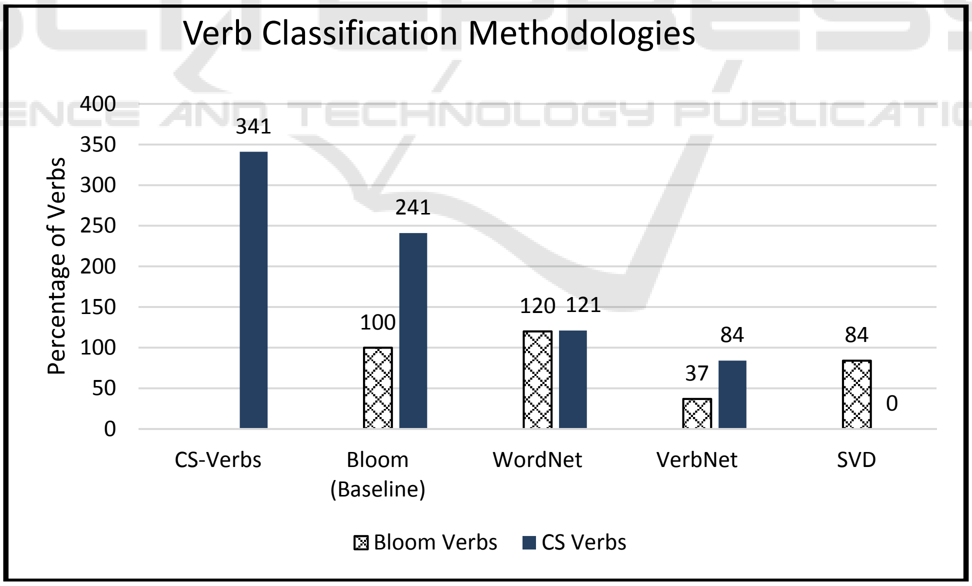

Figure 8: Verb Classification Methodologies for a txt-book (Introduction to Algorithms).

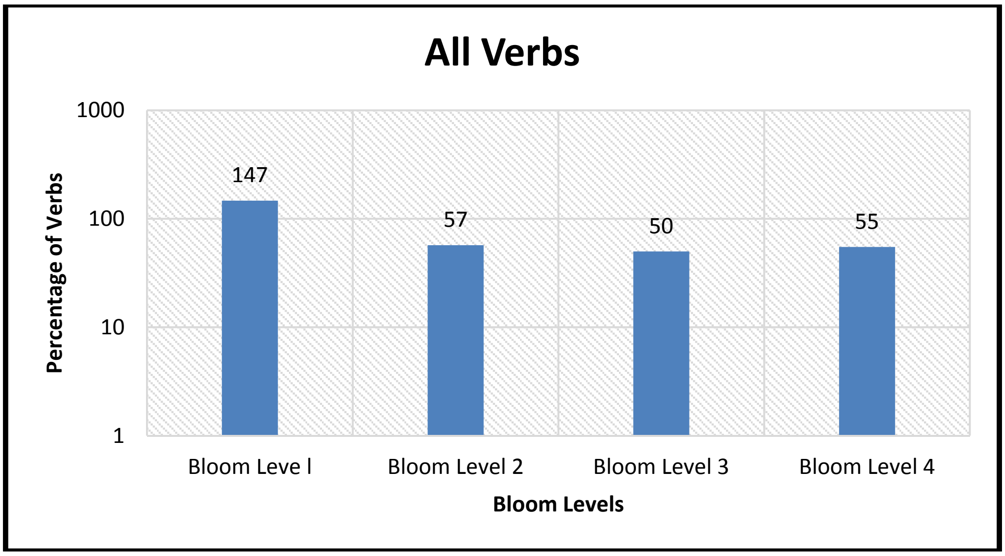

Figure 9: All verbs classified Based on Bloom levels for the textbook (Introduction to Algorithms).