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A Comparative Study on Part-of-Speech Taggers' Performance on Examination Questions Classification According to Bloom's Taxonomy

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Abstract. Examination questions classification according to Bloom's Taxonomy uses Natural Language Processing (NLP) approach, a series of text processing approach that generally can divided into the keywords identification stage and then the identified keywords classification to Bloom's Taxonomy levels stage. Since this NLP approach is a pipeline processes, the keywords identification stage's performance in term of accuracy is affecting the subsequent stage - the identified keywords classification and subsequently limits the final accuracy performance of the questions classification. The keywords identification stage's performance is mainly depending on the effectiveness of Part-Of-Speech (POS) tagging. Thus, this paper aims to identify the best performing POS tagger in keywords identification stage and enhance the tagger's performance with rule-based approach to achieve high accuracy performance and benefit the subsequent keyword classification and then the questions classification accuracy. The Perceptron tagger and the Stanford POS tagger are selected to be evaluated their performance in identifying the keywords of the randomly selected 200 examination questions from STEM subjects. This paper has observed the Stanford POS tagger is the best performing tagger in POS tagging with accuracy of 80.5%. Some rules are applied to the POS tagging to improve the accuracy further to 91.5%.

1. Introduction

The Bloom's Taxonomy has been also widely used in setting up learning outcomes of a learning subject or course. The examination questions are then a common tool used to access whether students meeting the pre-defined learning outcomes. To be effectively accessing the learning outcomes, the examination questions must be set up according to the Bloom's Taxonomy level of the learning outcomes [1]. "Compute the amplitude, frequency and wavelength for the amplifier circuit" is a simple example of an examination question. The "Compute" word is the keyword of this examination question and meets the third level of Bloom's Taxonomy, so the examination question is the Bloom's Taxonomy's third level examination question. This is the process of classifying an examination question according to the Bloom Taxonomy. Generally, the process can be divided into two main stages, which are the keyword identification stage and the identified keyword classification stage. The effectiveness of this examination questions classification depends on both stages.

The keyword identification from an examination question is a simple task for an educator. He or she as a human may identify the keyword in split of second. However, this task may not as simple in machine world because the task is a text processing that involves many Natural Language Processing (NLP) tasks such as word tokenization, stop-words removal, stemming, lemmatization, part-of-speech (POS) tagging and etc. The POS tagging is an important NLP stage of text processing as it assigns POS tags such as noun, verb, adjective, pronoun, etc to every word in the sentences. In examination questions classification, the POS tagger tags each word in the examination questions to noun, verb, adjective, pronoun and etc, and then the verbs are been identified and extracted for the subsequent Bloom's Taxonomy classification since the revised Bloom's Taxonomy revised from noun to verb form to indicate action because thinking implies active engagement [2]. In simple words, the keyword identification stage is to identify the key verb in the examination questions.

There are many POS tagging techniques available currently and they are trained and evaluated on a specific corpus [3]. However, it is an unknown whether they can be used to tag the POS of word correctly in examination questions and which of them can effectively tagged the verbs in the question perform best with highest accuracy. Be specific, which off-the-shelf POS tagger can perform the best with high accuracy in the examination questions of all Science, Technology, Engineering and Mathematics (STEM) subjects offered by the Technical and Vocational Education and Training (TVET) in Malaysia.

2. Related Works

The examination questions classification according to Bloom's Taxonomy is generally a process that identifies the verbs used in the question and then classifies the identified verbs according to Bloom's Taxonomy [4]. This process is a text processing process in machine that normally uses the Natural Language Processing (NLP) approach, a form of artificial intelligence that helps machine to read and understand text created by human. NLP is a pipeline processing because it consists of many processing stages in series and the subsequent stages are dependent on the output from previous stage. A well-known drawback of this pipeline processing is cascading error propagation caused by the residual error that is generated by each stage and affects overall performance of NLP [5]. Hence, each stage in the pipeline process must achieve high accuracy and less errors to get good overall performance. Without identifying the right verbs of the examination questions, the classification to the Bloom's Taxonomy is unable to classify correctly also.

Many researchers [6], [7] and [8] have attempted to classify examination questions based on Bloom's Taxonomy from 2010 to 2020. The research focuses mainly on questions classification. There is not much research done in analyzing the accurate verbs obtained from the examination questions. The verbs identification stage accuracy depends on each stage accuracy. The POS tagging is one of the sub-stages and determines the form of each word in a sentence of an examination question whether in noun, verb, adjective, pronoun etc [9]. Figure 1 is an POS tagging example that determines each word form of a sentence. The (PRP), (VBD), (VBG), (IN) and (NN) are known as POS name abbreviation which defined as the tagsets used by the POS tagger. The Penn Treebank tagset is widely used among the NLP community. It consists of 36 POS tags and 12 other tags for punctuation and currency symbols, shown in table 1. It is an important tagset for English [10]. Words often have more than one POS. For example, the "back" word may an adjective (JJ), noun (NN), adverb (RB) or verb (VB), as shown in figure 2. The POS tagger needs to determine the POS tag accurately for a particular instance of a word.

Sentence before POS tagging:
- *I liked watching that movies.*

Sentence after POS tagging:
- *I (**PRP**) liked (**VBD**) watching (**VBG**) that (**IN**) movies (**NN**) . (.)*

Figure 1. POS Tagging example.

1. The **back** door = **JJ**
2. On my **back** = **NN**
3. Win the voters **back** = **RB**
4. Promised to **back** the bill = **VB**

Figure 2. The "back" word and its POS tags.

In 2017, [11] have studied the tagging efficiency of POS taggers on Twitter. They have studied the TnT POS tagger, the Brill POS tagger, the ClassifiedBasedPOS tagger, the Perceptron POS tagger, and the Conditional Random Field (CRF) tagger. The Perceptron tagger has resulted the highest accuracy, 88.7%. This tagger is the default NLTK's POS tagger since NLTK version 3.1. The Perceptron tagger, also known as Averaged Perceptron Tagger is ported from TextBlob Perceptron Tagger into NLTK and is implemented originally by Matthew Honnibal. It is a pre-trained model on Penn Treebank Wall Street Journal (WSJ). This tagger is based on Hidden Markov Model (HMM) where next state is dependent only on the current state not on the previously occurred observation and which makes viterbi decoding possible. In simple words, it predicts the tag of the word on the basic of currently tag word on the previously tagged words [11].

Table 1. Penn Treebank Tagsets.

POS Tag	Description	POS Tag	Description
CC	coordinating conjunction	PRP$	possessive pronoun
CD	cardinal number	RB	adverb
DT	determiner	RBR	adverb, comparative
EX	existential there	RBS	adverb, superlative
FW	foreign word	RP	particle
IN	preposition/subordinating conjunction	SYM	Symbol (mathematical or scientific)
JJ	adjective	TO	to
JJR	adjective, comparative	UH	interjection
JJS	adjective, superlative	**VB**	**verb, base form**
LS	list marker	**VBD**	**verb, past tense**
MD	modal	**VBG**	**verb, gerund/present participle**
NN	noun, singular or mass	**VBN**	**verb, past participle**
NNS	noun plural	**VBP**	**verb, sing. present, non-3d**
NNP	proper noun, singular	**VBZ**	**verb, 3rd person sing. present**
NNPS	proper noun, plural	WDT	wh-determiner
PDT	predeterminer	WP	wh-pronoun
POS	possessive ending	WP$	possessive wh-pronoun
PRP	personal pronoun	WRB	wh-adverb

In 2015, [3] have studied on the effectiveness of seven (7) POS taggers on bug reports. The POS taggers are the Unigram POS tagger that uses Unigram method, the Trigrams'n'Tags POS (TnT) tagger and the Tree POS tagger that both use HMM method, the NLTK tagger and the Stanford POS tagger that both use maximum entropy (ME) method, and the Transformation based POS tagger (TBT) and the Annie POS tagger that both use transformation method. The Stanford POS tagger performs the best with 90.5% accuracy, followed by the Tree POS tagger with 90.4%. In other words, the Stanford POS tagger is found to be better than the NLTK tagger which is the Perceptron tagger by default. In 2013, [12] have studied four leading POS taggers with their off-the-shelf models trained from general English and biomedical abstracts, and how these POS taggers perform against clinical narratives. The POS taggers are the Stanford POS tagger that uses a ME method, the OpenNLP POS tagger that uses a different model of the ME method, the LBJ POS tagger that uses the two-layer neural network, and the LingPipe POS tagger that uses a HMM. The highest performing POS tagger is the Stanford POS tagger with the "english-left3words-distsim" model has achieved 87.2% accuracy, while the Stanford POS tagger with "english-bidirectional-distsim" model has reported 86.2%.

The Stanford POS tagger is one of the high performing POS taggers usable for multiple languages [13]. It uses the ME method with several models. The commonly used models are the "english-left3words-distsim" (left3words) and the "english-bidirectional-distsim" (bidirectional). The left3words model is trained on Penn Treebank WSJ sections 0-18 and extra parser training data using the left3words architecture and includes word shape and distributional similarity features. The bidirectional model is same as the left3words model but is using a bidirectional architecture. The left3words architecture is based on left-to-right third-order conditional Markov model considering the three left words (x-3, x-2, x-1) to the target word (x), while the bidirectional architecture is based on bidirectional dependency network considering preceding and following word (x-1, x+1) context to the target word (x) [12].

The POS taggers' accuracy is varying on text corpora. A POS tagger may perform well in a text corpus but may not perform good in another text corpus. For example, the Perceptron tagger performs the best in the in the Twitter text but not so good in the bug reports. As a result, this paper selects the Perceptron tagger because it is the default NLTK's POS tagger which currently used in the examination questions classification framework proposed by [14]. It will be considered a baseline. The Stanford POS tagger is then selected since both [3] and [12] has studied and observed it is the best performing POS tagger. Both the Perceptron tagger and the Stanford POS tagger will be evaluated in a same framework.

Ref [14] has proposed a framework of questions classification according to Bloom's Taxonomy using Universal Dependency and WordNet, shown in figure 3. This framework consists of two main stages as mentioned earlier – Verbs Identification stage and Verb Classification stage. The Verbs Identification stage in the framework starts from Questions Extraction, Segmentation to Sentences, and then Verb Extraction and Keywords Extraction. Next in framework is the Verb Classification stage that consists of Bloom Similarity and Question Classification to Bloom's Taxonomy. The framework adopts NLTK and uses the default NLTK's sentence and word tokenization and POS tagging. The default NLTK's sentence tokenization is PunktSentenceTokenizer, which is a pre-trained version and works well for many European language. It knows what punctuation and characters mark the end of a sentence and the beginning of a new sentence. Then the default NLTK's word tokenization is TreebankWordTokenizer, which uses regular expressions to tokenize text as in Penn Treebank. It splits standard contractions, treats most punctuation characters as separate tokens, splits off commas and single quotes when followed by whitespace, and separate periods that appear at the end of line.

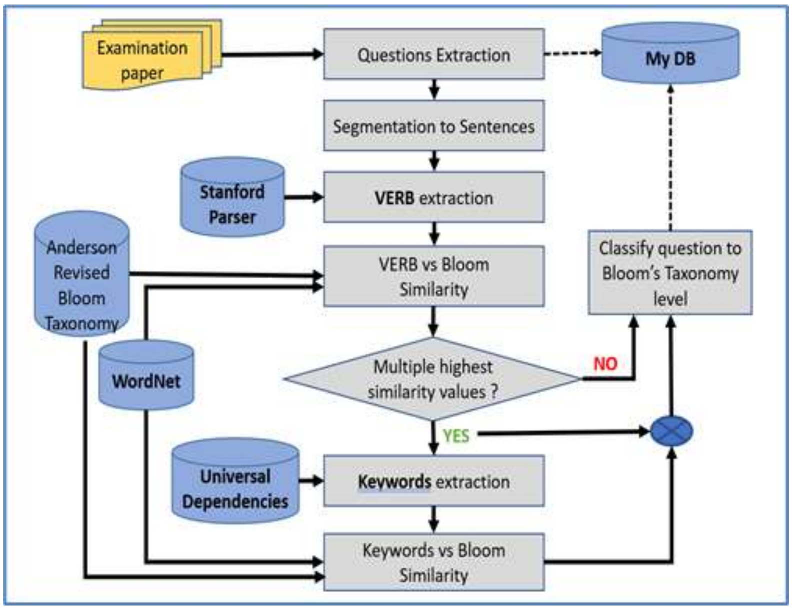

Figure 3. A framework of question classification according to Bloom's Taxonomy. [11]

3. Methodology

The Verb Identification stage of the proposed framework [14] is used in this paper to evaluate the POS tagging techniques effectiveness on the examination questions from the STEM subjects offered by the TVET in Malaysia. The POS tagging stage is the focus, measuring the effectiveness of the selected tagger – (1) the Perceptron tagger, (2) the Stanford POS tagger with the left3words model, and (3) the Stanford POS with the bidirectional model. The tagger tags each word tokens with a POS tag and the word with the POS tags associated to verbs are extracted and identified as the key verbs of the examination questions for next stage of processing. The Penn Treebank tagset has six POS tags are associated with verbs and they are VB, VBD, VBG, VBN, VBP and VBG with description shown in table 1. Firstly, the word tokens with these five POS tags - VB, VBD, VBG, VBP and VBG are extracted as the first round of tagging. Secondly, the word tokens with only VB POS are extracted as the second round of tagging. The reason of extracting the only VB POS tag result is that the VB is most likelihood indicating action because thinking implies active engagement in the revised Bloom's Taxonomy.

Using similar concept to the confusion matrix, which is often used to describe the performance of classification model [15] like the framework, the two set of POS tagging result are measured on following categories:

- True Positive (TP) is that all verbs in the list of verbs identified by the POS tagger matches exactly all verbs in the list of verbs identified manually by experience educators.
- Error 1 (Err1) is that some verbs in the list of verbs identified by the POS tagger matches some verbs in the list of verbs identified manually by experience educators.
- Error 2 (Err2) is that the POS tagger does not identify any verbs, or the identified verbs are not in the list of verbs identified manually by experience educators.

Then, the POS tagger effectiveness is measured by obtaining the accuracy as following formula:

$$Accuracy = TP/(TP + Err1 + Err2)$$

200 examination questions have been prepared and extracted from a diploma programme offered by a TVET in Malaysia. The 200 questions are randomly picked from seven different subjects – automation, electronics, mechanical, power, physics, computer programming and management, with different Bloom's Taxonomy levels, as shown in table 2. These 200 examination questions' key verb or verbs for Bloom's level classification need to be extracted manually as the expected verbs to be compared against by the POS taggers' result. The experience educators are tasked to identify the key verbs of the examination questions manually. Some examination questions may have more than one key verb. There is maximum of three key verbs identified in these 200 examination questions set.

Table 2. Statistic of the 200 examination questions in subject domain and Bloom level.

Domain	**Automation**	**Electronics**	**Management**	**Mechanical**	**Physics**	**Power**	**Program**	Total
Bloom Lvl 1	0.5%	2.0%	2.0%	3.0%	1.0%	3.0%	4.5%	16.0%
Bloom Lvl 2		2.5%	2.0%	5.0%	0.5%	4.5%	5.0%	19.5%
Bloom Lvl 3		2.5%		7.0%	5.0%	7.5%	6.5%	28.5%
Bloom Lvl 4	2.5%	3.5%	2.5%	5.0%	0.5%	1.0%	4.5%	19.5%
Bloom Lvl 5	1.0%		1.5%	0.5%	0.5%	4.5%		8.0%
Bloom Lvl 6	2.5%	1.0%			0.5%		4.5%	8.5%
Total	6.5%	11.5%	8.0%	20.5%	8.0%	20.5%	25.0	100.0%

4. Result and Discussion

The 200 examination questions set is tested by using the framework proposed by [14]. The beginning stage of the framework – sentence and word tokenization using the PunktSentenceTokenizer and the TreebankWordTokenizer respectively, has achieved accuracy of 99%. The word tokens output from the tokenization stage are then feed into the POS tagging stage. Table 3 is the POS tagging result of the three selected POS taggers after measuring the True Positive (TP), Error 1 (Err1) and Error 2 (Err2) value of each tagger on both the first round of word tokens tagged with VB, VBD, VBG, VBN, VBP and VBG, and the second round of word tokens tagged with VB only on the 200 examination questions set. The Perceptron tagger achieves accuracy of 60.5% and 55.5% respectively. It generally performs worsen than the Stanford POS (SPOS) tagger either the bidirectional or left3words model. In addition, the Stanford (SPOS) tagger with the left3words model (SPOS-le) has shown higher accuracy than the bidirectional model (SPOS-bi). The left3words model has achieved 83.5% and 80.5% accuracy respectively on first (VB, VBD, VBG, VBN, VBP and VBG) and second (VB only) set of taggers result and has achieved significant gap over the bidirectional model on the second set of tagger result which is extracting VB POS tag only.

Table 3. POS tagging result.

POS tagging result[1]	1st round result of POS tagging with *VB, VBD, VBG, VBP and VBZ tags*			2nd round result of POS tagging with the *VB tag only*		
	PercT[2]	**SPOS-bi[3]**	**SPOS-le[4]**	**PercT[2]**	**SPOS-bi[3]**	**SPOS-le[4]**
TP	60.5%	82.0%	83.5%	55.5%	72.5%	80.5%
Err1	24.5%	11.5%	11.5%	18.5%	9.0%	8.0%
Err2	15.0%	6.5%	5.0%	26.0%	18.5%	11.5%

[1] 200 examination questions set
[2] Perceptron Tagger
[3] Stanford POS Tagger with bidirectional model
[4] Stanford POS Tagger with left3words model

Referring to table 3 result, the framework should adopt the SPOS with left3words model (SPOS-le) that yielded the highest accuracy in POS tagging stage instead of the default NLTK's Perceptron tagger. Since the framework is a pipeline process, the SPOS tagger with the highest 83.5% accuracy needs to be improved further to achieve high overall framework performance. By referring to SPOS tagger with the left3word model performance on the second set of tagger result, the Err2 bucket is the top errors bucket that has contributed 11.5% errors. The errors in Err2 bucket have been analysed and observed two errors trends: (1) 8% errors due to the examination question structure where the first word of the questions is tagged as noun instead of verb, and (2) 3% error due to non-word tokens tagged with VB tag in the examination questions which means no verb (VB) found in the questions. The err1 bucket that contributed 8%, has been analysed also but does not observe any specific error trends.

- ***State*** *three importance in implementing recycling campaign for waste material*
- ***Design*** *a DC motor control circuit with one push button*

Figure 4. Err2 bucket - 8% due to the First word of the examination Question.

- *By showing all necessary steps,* ***convert*** *the decimal number 49 to binary.*
- *If the mechanical efficiency of the turbine generator unit is 95% and the heat loss in the turbine casing is 10kW,* ***estimate*** *the power generated by the plant.*

Figure 5. Err2 bucket - 3% due to "VBP" POS tag.

Figure 4 shows two examples of examination questions that the first word of the questions is a verb. The first word such as “state” and “design” have more than one possible POS tag which may be tagged as a noun or a verb, depending on the word context. The SPOS tagger has been trained to tags these first words as nouns, but they are verbs. A simple rule can be applied to this type of error result to rectify the POS tag from nouns to verbs with a condition if the first word of the examination questions is in the possible error word list which is a list of commonly used words as the first words in examination question such as “state”, “design”, “name”, “estimate”, “select”, etc. Figure 5 shows two examples of examination questions that non-word tokens tagged as VB POS tag in the examination questions. The “convert” and “estimate” words in the examples are verbs that tagged with “VBP” POS tag – non-3rd person singular present verb, a type of verb also. The “VBZ” POS tag on the other hand is the 3rd person singular present verb. Both “VBP” and “VBZ” POS tags are same as “VB” POS tag that fulfils indicating action engagement that reflects the thinking level in the revised Bloom’s Taxonomy. A simple rule is applied also to rectify this error type – non word tokens are tagged as “VB” but there are word tokens with “VBP” or “VBZ” POS tags. The rule is to take the word token with “VBP” or “VBZ” POS tag into the consideration as a key verb to be extracted for questions classification, with a condition if non word tokens in the examination questions are tagged “VB” POS tag. As a result, two simple rules are applied to the POS tagging stage that uses the SPOS tagger with the left3words model and extracts the VB POS tag only, to improve the accuracy from 80.5% to 91.5%. The two rules are:

RULE 1: If the first word of the examination questions is in the possible error word list, the first word will be identified as verb to be extracted for subsequent question classification stage.

RULE 2: If there are no word tokens with “VB” tag but there are “VBP” or “VBZ” tags in the examination questions, the word tokens with “VBP” of “VBZ” tags will be identified as verb to be extracted for subsequent question classification stage.

This study has improved the accuracy of POS tagging on examination questions done by [14] which has obtained 55.5% accuracy using Perceptron tagger. By implementing left3words model of the Stanford POS tagger, the accuracy has improved to 80.5% and improved further to 91.5% by applying rules on top of the Stanford POS tagger as shown in table 4.

Table 4. POS Tagging Improvement after applying rules.

POS Tagging Improvement	Accuracy
(a) Stanford POS Tagger with the left3words model + “VB” POS tag only	80.5%
(b) Rule 1: First word are verbs	8.0%
(c) Rule 2: “VBP” and “VBZ”	3.0%
Total Accuracy =	91.5%

5. Conclusion

This paper is continuous study on the framework proposed by [14] for the examination questions classification according to Bloom’s Taxonomy. It aims to study the framework’s POS tagging accuracy since the questions classification is a pipeline processing and the POS tagging accuracy affects overall questions classification accuracy. The default NLTK tagger – the Perceptron tagger used by the framework, are evaluated against the 200 examination questions set from the STEM subjects and compared with another popular POS tagger – the Stanford POS tagger. The SPOS tagger generally performs much better than the Perceptron tagger, while the left3words model of the SPOS tagger shows better performance than the bidirectional model. The result has suggested the framework to adopt the SPOS tagger with the left3words model. In addition, the POS tagging accuracy can be improved to 91.5% by applying two simple rules to the POS tagging process. First rule is to mitigate the POS tagging error caused by the examination questions structure which the first word of the questions is a verb. Second rule is to mitigate the POS tagging error due to the verbs’ POS tags – VBP or VBZ instead of VB. After improving the framework’s POS tagging accuracy, the study continues to study the performance of the subsequent stage which is the identified keywords classification according to Bloom’s Taxonomy, especially the WordNet similarity approach.

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