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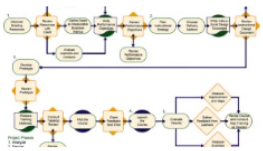

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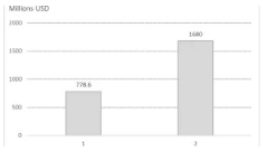

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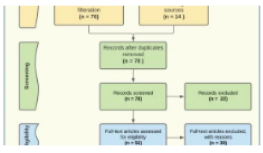

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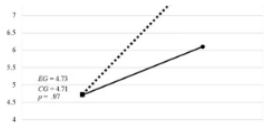

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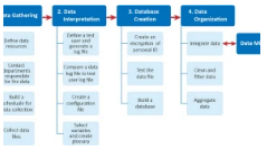

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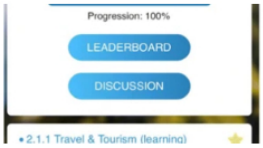

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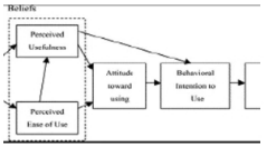

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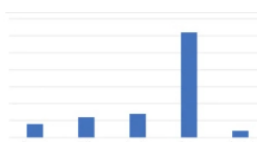

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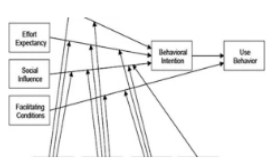

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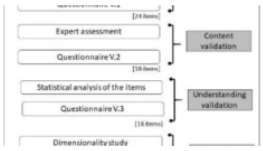

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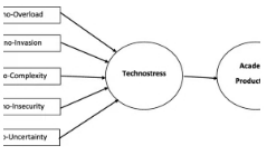

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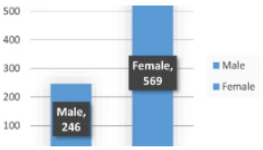

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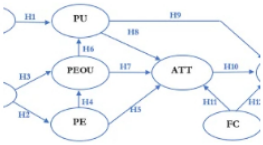

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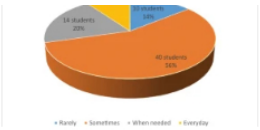

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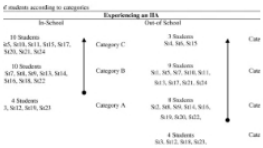

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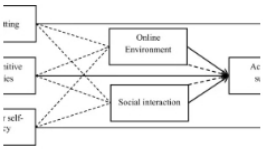

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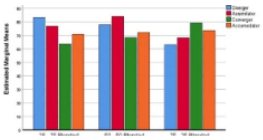

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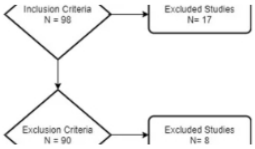

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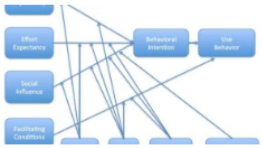

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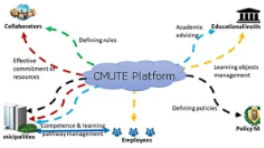

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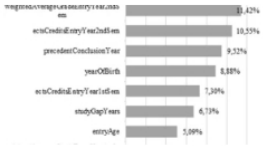

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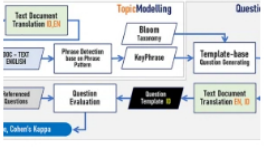

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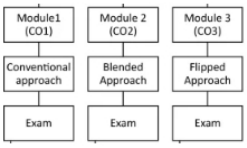

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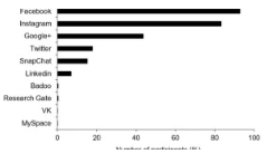

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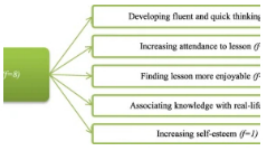

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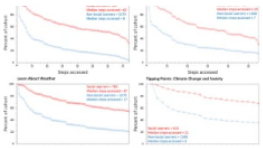

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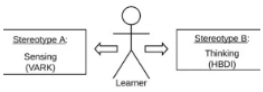

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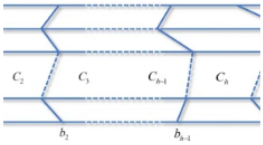

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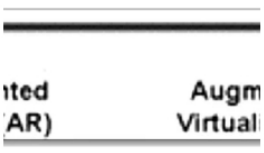

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Question generation model based on key-phrase, context-free grammar, and Bloom's taxonomy

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Abstract

Automated question generation is a task to generate questions from structured or unstructured data. The increasing popularity of online learning in recent years has given momentum to automated question generation in education field for facilitating learning process, learning material retrieval, and computer-based testing. This paper report on the development of question generation framework based on key-phrase method for online learning with a constraint that the generated questions should comply with the learning outcomes and skills from Bloom's Taxonomy. The proposed method was tested using learning materials of Software Engineering course for undergraduate level written in Bahasa Indonesia obtained from Bina Nusantara's (Binus's) Online Learning repository. Using one-semester lecture material, this study generated 92,608 essay-type questions from 6-level Bloom's Taxonomy which were further sampled randomly to obtain 120 question samples for method evaluation. Performance evaluation using average Bilingual Evaluation Understudy (BLEU) involving five independent reviewers toward samples of these questions achieved 0.921 and 0.6 Cohen's Kappa. The relevance of Bloom's Taxonomy level of the generated questions was evaluated by means of classification model with 0.99 accuracy. The results indicate that not only are the generated questions well understood and agreed by the reviewers, they are also relevant to the expected Bloom's Taxonomy level there for the questions can be delivered to students in the respected course delivery and evaluation.

Keywords Bloom's taxonomy · Context-free grammar · Keyphrase extraction · Question generation · Question template

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1 Introduction

Question generation (QG) is a task to generate question from structured or unstructured data. This task is an interesting Natural Language Processing problem with wide potential applications in many domains. In education field, for instance, QG plays some important roles in learning process and computer-based testing (Herranen and Aksela 2019). In learning process, question generation can be used to assist students in an assisted learning system with their comprehension on learning material. By means of assisted learning system, students learn to respond to the system generated questions about facts and ideas related to the topics being studied.

In the recent years, research on question generation in education field has grown rapidly due to the availability of large scale training dataset, the advent of deep learning, and the development of GPU-based computing technology. The research topic range from enhancing theoretical aspect of question generation to improving the varieties of question generating approaches and methods (Al-Yahya 2011; Lindberg and Sc 2013; Lindberg and Sc 2013; Duan et al. 2017; Rodrigues 2017; Ye and Wang 2018; Elsahar et al. 2018; Huang et al. 2018), Automatic QG system in education is adapted from general QG with an additional constraint: the generated questions should comply with learning objectives and skills that educators set for their students in particular topic. The learning objectives of a particular course are commonly set base on Bloom's Taxonomy (Gleason 2018; Quintana and Tan 2019).

So far many QG studies have used general datasets that are not learning content and produce factual or shallow questions, whereas education and learning require in-depth questions that are following Bloom's taxonomy. Research opportunities in the QG field are still open (Heilman et al. 2011; Adamson et al. 2013; Jouault et al. 2016). The limitation of this research is that the questions generated by QG are only for lecture material that is more theoretical, but not for materials that use numbers and calculations, schemes, or program code such as mathematics, theoretical computer science, systems programming, etc.

One of the topics which attracts the attention of researchers is how to efficiently generate questions which comply with higher-level learning objectives and skills. According to (Willis et al. 2019), the main research challenge is how to generate questions to support effective teaching especially to promote critical thinking, retention, and context involvement.

Adressing this problem (Singh et al. 2017) suggest a method to generate question based-on noun phrases. The method comprises two stages. The first is extracting key-phrases from input texts. The second is generating questions based on the extracted key-phrase. The key-phrase based methods is potensial because they have ability to capture the context of the syntax and semantics of the input text. However, this method is not practical for real input text as it is not scalable to be applied for large volume of input text.

Several attempts to overcome the problem of key-phrase extraction have been proposed by (Meng et al. 2017) who proposed a question generation method based on a generative encoder-decoder model. Another method was proposed by (Yang et al. 2017) which produces key-phrases based on the semantic meaning of texts, and the question generation method use tags and linguistic rules.

One prominent QG method is construction model proposed by (Subramanian et al. 2018). The proposed model uses the probability of word order in the document as key-phrases which then acts as a target for the construction of question generation.

Although many studies on question generating for education purposes have been conducted, to the best of our knowledge, there are only few reports on keyphrase-based method which uses several levels of Bloom's taxonomy as constraint in generating questions. Therefore, the objective of this study is to propose a method that generates questions based on key-phrase which embed Bloom's taxonomic in selecting contexts for constructing questions.

Research questions that need to be analyzed with various reference methods such as information extraction, template-based questions, semantic roles, and evaluating the Question Generation method use various metrics to measure the performance of the text generation model to find solutions to research problems, namely:

1) How to identify KeyPhrase to find hidden information in semi-unstructured documents.
2) How to extract Context and Phrase from a text document to design Bloom's Taxonomy based questions.

2 Related work

A prominent definition of question generation was proposed by (Rus et al. 2008) Question generation is defined as the automatic generation of questions from inputs such as text, raw data, and knowledge bases. The generated questions can be in such form as factual-type, Yes/No-type, or why-type questions.

Another definition is proposed by (Yao et al. 2012). Question generation is defined as the task of generating reasonable questions from various input data such as text, database, or semantic representation. Further, (Yao et al. 2012; Nema et al. 2019) defined question generation as a system to generate rational questions from structured or unstructured data.

According to (Graesser et al. 2009; Heilman and Smith 2010; and Jouault et al. 2016; Kumar et al. 2018), various question generating systems can be categorized broadly into several categories namely:

1) Shallow question generating: QG systems designed to generate fact questions. For example question about: "who", "what", "where", "which one", "how many", and "yes/no answer". Despite the simplicity, these questions do not support deep learning and discussions (Adamson et al. 2013).
2) Deep question generating: QG systems designed to generate questions that need logical thinking to answer. For examples, questions which begin with "why", "why not", what if", "what if not", and "how"

A study by (Jouault et al. 2016; Divate and Salgaonkar 2017) concluded that there is a potential gap between the knowledge of QG system and that of human experts used to generate questions based on input text. This becomes an issue when some human experts were asked to evaluate questions generated by a QG system. While a QG

system only generates questions base on explisit representation of information from the input text, human experts can generate questions might have deep knowledge not written in the text input. To address this issue, (Jouault et al. 2016) proposed a scheme to be used by human experts to evaluate deep generated questions produced by a QG system (see Table 1).

QG approach for general applications that exploits features extracted from input text has gained wide research interests resulting in a vast number of methods. A study by (Han et al. 2018) proposed topic phrase extraction method based on features provided from the input text as a basis for question generation. A method proposed (Chao and Li 2018; Kurdi et al. 2019). refined the previous method by adding contextual information to the extracted topic phrase. (Li et al., 2019) showed some evidences that context helps improving performance of question generation.

Topic extraction is also used by (Xie et al. 2017) to set the subject and predicate in the generated questions. (Tong et al. 2019) proposed a method that uses a word and expands the word with the context structure of the word context in the input text.

In the area of QG for education, (Diab and Sartawi 2017) proposed a method that uses the semantic relationship between verbs in the generated questions and learning outcomes to evaluate compliance of a generated questions with a particular Bloom's taxonomy levels. Another study results reported by (Yang et al. 2017) proposed tags and linguistic rules to extract features as a basis for generating questions.

A study by (Emu et al. 2017) proposed a method base on structure of phrases extracting important features in the TF × IDF document representation matrix. A similar method using embedding key phrases to extract unique key phrases from scientific articles and ranking key phrases using PageRank was proposed by (Mandal et al. 2018).

The advent of deep learning algorithms has motivated many researchers to use the algorithm for QG. A recent research used deep learning model to study end-to-end

Table. 1 Deep question evaluation scheme

Question category	Evaluation criteria
C1: Questions asking facts.	Remembering
C2: Questions asking causal relations.	Comprehension
C3: Application	Questions are more complex than C2 but does not require complete integrated knowledge like C4. It requires an understanding of the topic of the questions and its context.
C4: Analysis	Questions requiring integrated knowedge of the topic as a whole. It requires knowledge of the topic of the questions as well as a general understanding of the main topic important events and theor context.
C5: Evaluation	Questions requiring a deep thinking. It requires having understanding of global history and the relations between the topic and other historical topics.

Source: (Jouault et al. 2016; Bloom 1956)

nerves to produce pairs of questions and answers through context paragraph input (Willis et al. 2019).

A study by (Gan and Yu 2018) concluded that QG is not merely the syntactical problem but more to relation between syntac-semantic. The author argue that machine-learning based methods produce low accuracy due to its limitation to capture phrase structure, scope of syllabus, difficulty level, and cognitive level as guided by Bloom's taxonomy (Kale and Kiwelekar 2013).

3 Research method

3.1 Research framework

The research framework of this study is shown in Fig. 1. The research framework consist of: (i) translating text document to English, (ii) Phrase extraction using Context-free grammar, (iii) Question generation, and (iv) Generating question evaluation using human experts.

3.2 Dataset

The source of dataset for this study is Binus Online Learning repository. The input dataset comprises course syllabus, lecture materials, case study materials, student-lecturer discussion forum log, and student grade database for software engineering course for undergraduate program. The input textual dataset contains 127,299 characters, 19,673 words, 1347 sentences, and 225 paragraphs.

3.3 Topic extraction

Every sentence should contain a topic that reflect the semantic meaning of the sentence. The topic of a sentence is typically an object or a noun phrase. Hence, topic detection in this study is implemented by tokenization to extract noun phrases as key-phrase of a sentence. The candidates noun phrases are then used as the object of the questions combined with verbs derived from Bloom's taxonomy.

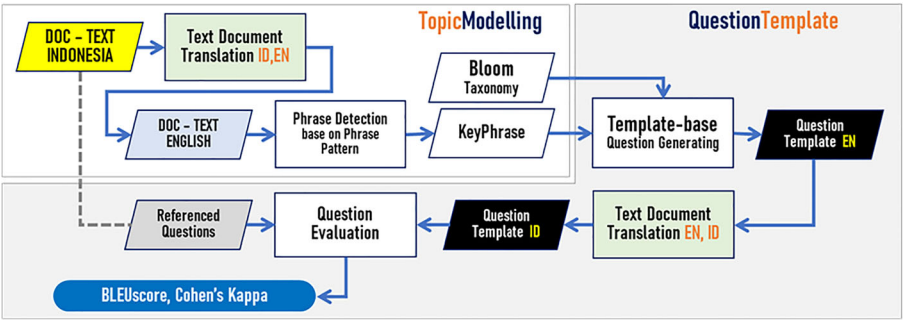

Fig. 1 Research framework

3.4 Key-phrase selection

Key-phrases can be viewed as high-level representation of a text document. They have been widely used as input for several document analysis and modeling such as document summarization, clustering, and topic analysis. Automatic keyphrase extraction, however, is a challenging task to capture the main topics of documents. Some prominent studies proposed various methods from text mining field including indexing, clustering, and summarisation.

A study by (Mikolov et al. 2013), for example, proposed a method based on probability of the two-word sequence which is measured as follows:

$$score\left(w_i, w_j\right) = \frac{count\left(w_i\, w_j\right) - \delta}{count\left(w_i\right) \times count\left(w_j\right)} \tag{1}$$

where: $count(w_i, w_j)$ is the number of a sequence of word w_i followed by w_j, $count(w_i)$ the number of word w_i, $count(w_j)$ the number of word w_j in the input document, and δ is a constant to prevent too many phrases formed by some less frequent words.

Another method is proposed by (Turney 2003) which treated the problem as a classification task. In the proposed method, the author proposed Naive Bayes model as the key-phrase classifier. The proposed method comprises three steps.

1) Document pre-processing: deleting stop words, deleting non-alpha-numerics, separating text into phrases, and stemming phrases.
2) Extracting the TF × IDF score from all sample phrases. This score is a standard metric in information retrieval to measure how specific the P phrase in document D formulated as:

$$TF \times IDF(P, D) = Pr[ph\ in\ D\ is\ P] \times (-logPr[P\ in\ a\ doc]) \tag{2}$$

where, $Pr[ph\ in\ D\ is\ P]$ is the probability of the phrase P contained in document D, and $logPr[P\ in\ a\ doc]$ is the document in corpus containing P (excluding D).

3) Calculating the distance of each sample phrase from the beginning of the corresponding document. The distance is calculated as the number of words preceding the first appearance, divided by the number of words in the document. The resulting feature is a number between 0 and 1 that represents the proportion of documents before the first appearance of the phrase. In this method the attribute, $TF \times IDF$ and the distance between phrases are

assumed to be independent because the $TF \times IDF$ phrase is discrete with a T value and the distance is D. Then, the probability of a unique phrase is:

$$Pr[key|T,D] = \frac{Pr[T|key] \times Pr[D|key] \times Pr[key]}{Pr[T,D]} \quad (3)$$

Where $Pr[T|\,key]$ is the probability that a Keyphrase has a $TF \times IDF$ with score T, $Pr[D|\,key]$ the probability that it has a distance D. $Pr[T|\,key]$ is the probability a priori that the phrase is Keyphrase, and $Pr[T, D]$ is the normalization factor, so that the value of $Pr[key|\,T, D]$ is between zero and one.

Figure 2 shows the relationship between phrases and the sentences containing the phrases. Each phrase is identified using a postag to determine the phrase category as nouns (NN), adjective (JJ) or verb (VB). Phrases that have been marked with a postag become key phrase and will determine the types of question. Key-phrases of the type NN will become context questions with operational verbs with correspond to Bloom's taxonomic levels.

If both noun-phrase and adjective phrase are found in a sentence, then both of them will be used to form a question. However, if there is only one adjective key phrase, the noun phrase from the previous sentence will be used to form a question.

3.5 Question template construction

Context-Free Grammar (CFG) is a class of formal grammar defined as a quadruple $G = (V, \Sigma, P, S)$, where: V is a set of non-terminal symbols. Σ is a set of terminal symbols such that $V \cap \Sigma = \varnothing$; P is a set of rules in a form of $P : V \rightarrow (V \cup \Sigma)^*$, and S is a start symbol (Hopcroft et al. 2001). In formal language, CFG rules can be seen as a set

SENTENCE	POSTAG
Software Engineering is a branch of science that focuses on theories, methods or supporting tools that develop software professionally.	[('software', 'NN'), ('engineering', 'NN')]
The software development stage from requirements analysis, planning, design, software creation, to maintenance, the costs incurred at the maintenance stage take up the largest portion.	[('maintenance', 'NN'), ('stage', 'NN')] [('requirements', 'NNS'), ('analysis', 'NN')] [('software', 'NN'), ('creation', 'NN')] [('software', 'NN'), ('development', 'NN'), ('stage', 'NN')]
Some people consider the life cycle model to be more general for a more specific category of methodology and software development processes to refer to the process chosen by an organization.	[('life', 'NN'), ('cycle', 'NN'), ('model', 'NN')] [('software', 'NN'), ('development', 'NN'), ('processes', 'NNS')] [('specific', 'JJ'), ('category', 'NN')]
The software development methodology also known as the HR framework does not appear until.	[('software', 'NN'), ('development', 'NN'), ('methodology', 'NN')]
According to Elliotts, the life cycle of SDLC system development can be considered as the oldest formal methodological framework for building information systems.	[('formal', 'JJ'), ('methodological', 'JJ'), ('framework', 'NN')] [('information', 'NN'), ('systems', 'NNS')] [('system', 'NN'), ('development', 'NN')]
The main idea of SDLC is to pursue the development of information systems in a very deliberate, structured and methodical manner, requiring every stage of the life cycle from the initial idea to the delivery of the system which must be carried out rigidly	[('information', 'NN'), ('systems', 'NNS')] [('initial', 'JJ'), ('idea', 'NN')] [('methodical', 'JJ'), ('manner', 'NN')]
Methodologies, processes and frameworks from proscriptive steps that can be used directly by organizational inactivity to flexible frameworks that the organization uses to produce a series of specific steps tailored to the needs of the project or group.	[('organization', 'NN'), ('uses', 'NNS')] [('organizational', 'JJ'), ('inactivity', 'NN')] [('proscriptive', 'JJ'), ('steps', 'NNS')] [('specific', 'JJ'), ('steps', 'NNS')]
It should be noted that since DSDM came in, all the methodologies listed above except the RUP have become agile methodologies, but many organizations, especially the government, still use a pre-agile process that is often a waterfall or similar.	[('agile', 'NN'), ('methodologies', 'NNS')] [('pre-agile', 'JJ'), ('process', 'NN')]
The development team can also approve the programming environment, such as which integrated development environment is used, and one or more dominant programming paradigms, programming style rules, or choice of software libraries or software frameworks.	[('development', 'NN'), ('environment', 'NN')] [('development', 'NN'), ('team', 'NN')] [('software', 'NN'), ('frameworks', 'NNS')] [('software', 'NN'), ('libraries', 'NNS')]
Software design can refer to all activities involved in conceptualizing, framing implementing, commissioning, and finally modifying systems or complex activities that follow the requirements specifications and before programming.	[('complex', 'JJ'), ('activities', 'NNS')] [('requirements', 'NNS'), ('specifications', 'NNS')]

Fig. 2 Sentence Key-phrase PostTag

of written recursive rules that are used to produce strings based on specified patterns. Therefore, CFG is the basis for the syntax of programming languages that provide efficient algorithms and parsing in programming languages, such as: files and data flow (Moraes et al. 2018).

In this study, CFG is used to develop question templates based on the structure of operational phrases and verbs in the Bloom's taxonomy. In this study, Structure of the question is constructed using the verb Bloom's Taxonomy and is paired with two adjacent key-phrases from the sentence in the document. The assumptions as follows:

1. Noun-phrases in general have a unique meaning or have a clear context,
2. Adjective can not stand alone; it is an explanation of a noun-phrase.

3.6 The construction of questions uses context (noun-phrase), topic (key-phrase), Bloom's taxonomy

A set of Question Templates is constructed using the following steps. The first step is, selecting key phrases in the form of noun (NN) and adjective (JJ). Adjective key-phrases are paired with noun-phrases from the previous phase. Then, the questions are formed automatically with key-phrases parsed into the procedure for making template questions (Fig. 4).

Based on the question construction in Fig. 3, the number of questions generated from the Question Generation algorithm execution is determined by the number of key-phrases found from the input document. The results of experiments on the questions generated, showed that on average there are 2 key-phrases consisting of 1 to 3 words, and an average sentence length of 140 words. Finally, the automated phrase-based question construction algorithm generated more than 92,608 questions classified in 6 Bloom taxonomic levels (see Table 2).

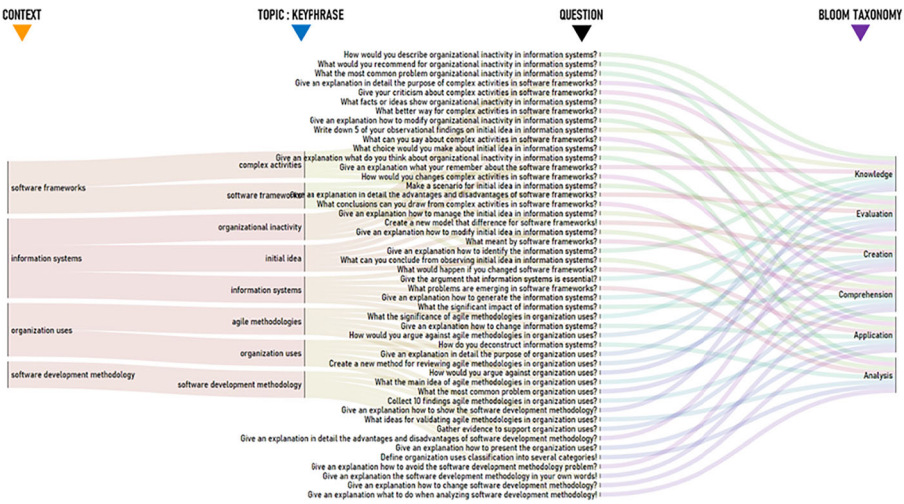

Fig. 3 Question template construction

Table 2 Output from question template algorithm

No	ID_Quest	KEY-Phrase	Question Generating	BLOOM Level
1	20_04	software engineering	What can observe about software engineering?	Comprehension
2	30_11	software engineering	What information is useful for software engineering?	Application
3	40_01	software engineering	How to sort the parts software engineering?	Analysis
4	50_06	software engineering	What changes to software engineering as recommendation?	Evaluation
5	60_08	software engineering	Determine the formula to solve the problem of software engineering!	Creation
6	20_06	software engineering	What is the significant impact of software engineering?	Comprehension
7	30_04	software engineering	How to modify software engineering?	Application
8	40_05	software engineering	Find a number of ways to problem-solving of software engineering!	Analysis
9	50_12	software engineering	How to overcome software engineering weaknesses?	Evaluation
10	50_07	important part	How to handle important part in Software Re-engineering?	Evaluation
11	60_02	special attention	What must change to revise special attention in software engineering?	Creation
12	10_03	state expenditures	How to identify the state expenditures?	Knowledge
13	30_10	state expenditures	What are the instructions for state expenditures?	Application
14	60_07	state expenditures	Develop a proposal that would produce state expenditures!	Creation
15	50_12	state expenditures	How to overcome state expenditures weaknesses?	Evaluation
16	40_01	state expenditures	How to sort the parts state expenditures?	Analysis
17	40_08	significant portion	What was the underlying problem with significant portion in state expenditures?	Analysis
18	20_07	software development	What software development are most popular?	Comprehension
19	30_05	software development	Base on experience implement for the development of software development?	Application
20	40_06	software development	What are some of the problems of software development?	Analysis
21	50_12	software development	How to overcome software development weaknesses?	Evaluation
22	40_11	overall development	What we must know about overall development in software development?	Analysis
23	10_08	software development	How to indicate a software development?	Knowledge
24	60_01		What alternative to suggest for software development?	Creation

Table 2 (continued)

No	ID_Quest	KEY-Phrase	Question Generating	BLOOM Level
		software development		
25	20_02	requirements analysis	How to express requirements analysis?	Comprehension
26	30_02	requirements analysis	How to present requirements analysis?	Application
27	40_02	requirements analysis	What do you infer about requirements analysis?	Analysis
28	50_05	requirements analysis	How to effectively is requirements analysis?	Evaluation
29	60_04	requirements analysis	What can invent requirements analysis?	Creation
30	20_06	software creation	What is the significant impact of software creation?	Comprehension

4 Model performance evaluation

4.1 Quality evaluation of the generated questions

This evaluation stage aims to evaluate the quality of the generated questions compared to the manually generated questions (reference questions) by human experts. In this study, this evaluation step involve five human independent reviewers who have competence in the field of study or discussion materials used as questions. Each reviewer independently evaluated a number of generated question samples. The measurement used BLEU score and Cohen's Kappa metrics.

4.2 Evaluating the effect of context on question quality

This evaluation step aims to evaluate the effect of context on the generated question quality using statistical test. The hypotheses to be tested are: (i) significant of mean BLEU test from questions without context, (ii) significant of mean BLEU test from questions with context, and (iii) significant difference of mean BLEU test from questions with context and without context.

In this study, the design of this performance evaluation is implemented as follows:

1) The tested questions are those generated by the system using question template represented by context-free grammar rules and each input text document is represented by N-gram.
2) BLEU score is computed based on system generated question and referenced question constructed manually by each reviewer.
3) The number of independent reviewer is 5. Each reviewer understands the course materials.
4) The number of question samples is 120 chosen randomly from the total of 92,608 generated questions

4.3 Evaluation the predicted Bloom's taxonomy of the generated questions

This test aims to evaluate how good the proposed key-phrase based model is in generating questions that comply with Bloom's taxonomy levels. This task is viewed as a classification problem using input data as a labeled data set $S = \{x_i, y_i\}_1^n$ where $x_i \in X$ is a representation of question, $y_i \in Y$ is Bloom's taxonomy level of a questions, X and Y are domain of question representation and question label respectively, and n is the number of sample data. It is assumed that there is a mapping $F : X \rightarrow Y$.

A classification model based on machine learning G is trained using supervised learning technique to approximate F so that a new question is generated? q then its Bloom's taxonomy level can be predicted as:

$$G(q) = \widehat{F}(q)$$

Performance of the trained classification model is measured using accuracy, precision, and recall metrics.

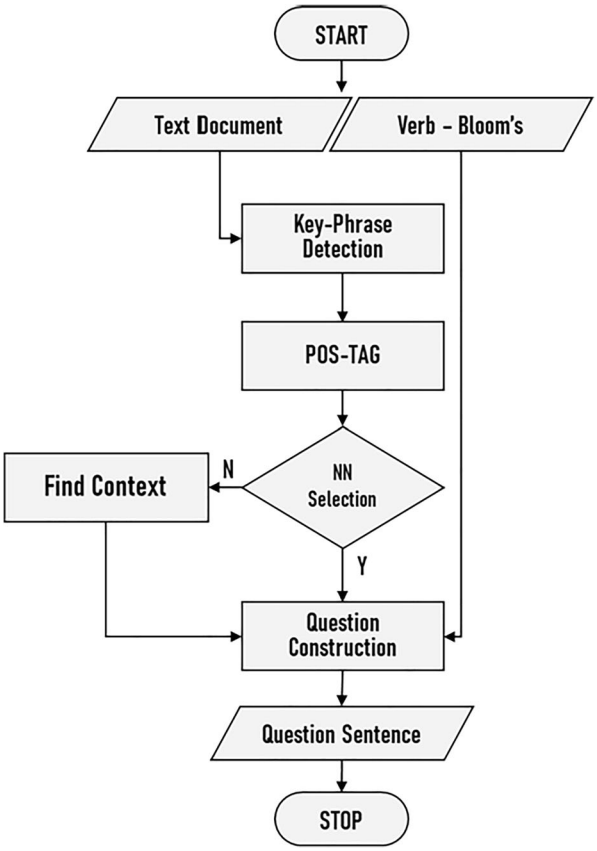

Fig. 4 Question construction process flow

5 Research result and discussion

5.1 Evaluation of the generated question quality

The average BLEUscore obtained from questions The score is 0.921 context seems higher than questions without context 0.861. This shows that the Question Generation Algorithm is able to generate questions using words that resemble the questions compiled by reviewers when making similar questions. (see Table 3).

The Cohen's Kappa score of questions using the 0.627 context seems smaller than the questions without the 0.760 context. However, both of these scores are in the good category, which means that the reviewers have a good agreement in capturing the context of the question.

The measurements of BLEUscore and Cohen's Kappa involve human reviewers who have competence in the field of study or discussion material used as questions.

5.2 Evaluating the effect of context to question quality

The statistical testing evaluation the following results:

Test #1:

$$H_0 : \overline{B}_{woc} = 0, H_1 : \overline{B}_{woc} > 0,$$

With number of samples $(n) = 5$, mean of BLEU score without context $\left(\overline{B}_{woC}\right) = 0.86$, standard deviation $(s_{woC}) = 0.03$,

$Z = \frac{\overline{B}_{woC}}{s_{woC}/\sqrt{n}} = 64.10 > 1.96$ (α= 0.10).

Conclusion: mean of BLEU score without context is not equal to 0.

Test #2:

$$H_0 : \overline{B}_{wc} = 0,$$

$$H_1 : \overline{B}_{wc} > 0,$$

With number of samples $(n) = 5$, mean of BLEU score with context $\left(\overline{B}_{wc}\right) = 0.92$, standard deviation $(s_{wC}) = 0.03$,

$Z = \frac{\overline{B}_{wc}}{s_{wC}/\sqrt{n}} = 68.57 > 1.96$ (α = 0.10).

Conclusion: mean of BLEU score with context is not equal to 0.

Table 3 ComputedScore BLEU dan Cohen's Kappa

(+) CONTEXT							(−) CONTEXT						
N-Gram	N-Gram	BLEU 1	BLEU 2	BLEU 3	BLEU 4	BLEU 5	AVERAGE	BLEU 1	BLEU 2	BLEU 3	BLEU 4	BLEU 5	AVERAGE
1	1	0.9363	0.9209	0.9219	0.9387	0.9699	0.9375	0.9646	0.9543	0.9510	0.9551	0.9882	0.9626
2	2	0.9040	0.8861	0.8825	0.9039	0.9508	0.9055	0.9475	0.9318	0.9275	0.9345	0.9830	0.9449
3	3	0.8757	0.8587	0.8516	0.8772	0.9341	0.8794	0.9346	0.9155	0.9089	0.9190	0.9786	0.9313
4	4	0.8522	0.8366	0.8298	0.8549	0.9190	0.8585	0.9238	0.9022	0.8950	0.9072	0.9755	0.9208
5	5	0.8316	0.8173	0.8125	0.8350	0.9055	0.8404	0.9145	0.8907	0.8832	0.8972	0.9732	0.9118
6	6	0.8130	0.7990	0.7975	0.8165	0.8925	0.8237	0.9057	0.8801	0.8727	0.8883	0.9716	0.9037
7	7	0.7980	0.7848	0.7859	0.8011	0.8824	0.8104	0.8984	0.8705	0.8637	0.8812	0.9715	0.8970
8	8	0.8171	0.8037	0.8094	0.8213	0.9115	0.8326	0.8965	0.8664	0.8607	0.8800	0.9771	0.8961
AVERAGE	AVERAGE	0.8535	0.8384	0.8364	0.8561	0.9207	0.8610	0.9232	0.9014	0.8953	0.9078	0.9773	0.9210
Cohhen Kappa with CONTEXT: 0.62728							Cohen Kappa with-out CONTEXT: 0.76067						

Test #2:

$$H_0 : \overline{B}_{wc} - \overline{B}_{woc} = 0,$$

$$H_1 : \overline{B}_{wc} - \overline{B}_{woc} > 0,$$

With number of samples (n) = 5, mean of BLEU score without context $\left(\overline{B}_{woC}\right) = 0.86$, BLEU score with context $\left(\overline{B}_{wc}\right) = 0.92$, $s_{woC} = s_{wC} = 0.03$,

$Z = \frac{\overline{B}_{wc} - \overline{B}_{woC}}{\sqrt{\left(\frac{s_{wc}{}^2}{n} + \frac{s_{woC}{}^2}{n}\right)}} = 3.16 > 1.96$ (α = 0.10).

Conclusion: mean of BLEU score with context is higher than that without the context.

5.3 Evaluation the predicted Bloom's taxonomy of the generated questions

The following model are trained using 74,881 (80% of the whole generated questions as input dataset) as training dataset and 18,721 samples (20% of the input dataset) as testing dataset. Performances of several classification models are summarized into the following table Table 4.

6 Conclusions and future work

Question generation in the online learning field is a task to generate questions which are relevant to the text input documents and Bloom's Taxonomy of the expected learning output. This task remains a challenging problem.

The main challenges are as follows: (i) there exists a potential gap between the knowledge that question generation system and human experts use to generate questions based on input text, and (ii) the generated questions are expected to promote critical thinking, retention, and context involvement of the students.

This study proposes a question generation model based on key-phrase extracted from text input documents through syntactic parsing using predefined context-free grammar rules. The proposed model was tested using learning materials from Bina

Table 4 Testing performance of classifier model

Model	Acc.	Prec.	Recall	F1
Decision Tree	1.00	1.00	0.99	0.99
Random Forest	0.99	0.99	0.99	0.99
Gradient Boosting	0.99	0.99	0.99	0.99

As can be seen from the above table, the proposed key-phrase model can generate questions with strong relevance to Bloom's taxonomy

Nusantara University's Online Repository that generates 92,608 essay-type questions from 6-level Bloom's Taxonomy.

Performance evaluation using average Bilingual Evaluation Understudy (BLEU) involving five independent reviewers toward samples of these questions achieved 0.921 and 0.6 Cohen's Kappa. The relevance of Bloom's Taxonomy level of the generated questions is evaluated by means of classification model with 0.99 accuracy. These results indicate not only were that the generated questions well understood and agreed by the reviewers they were also relevant to the expected Bloom's Taxonomy level so that the questions can be delivered to students in the respected course delivery and evaluation. Generated questions have been tested in the software engineering course and are proven (1) to assist teachers in guiding asincronous learning, namely online discussions, (2) to assist teachers in providing learning practice questions.

In future work, we plan to investigate a method of extracting answers from corpus text based on machine-generated questions. We also plan to investigate the performance of a questioner model with a variety of Encoder-Decoder to extract answers to questions.

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