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Developing the Assessment Questions Automatically to Determine the Cognitive Level of the E-Learner Using NLP Techniques

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ABSTRACT

The key objective of the teaching-learning process (TLP) is to impart the knowledge to the learner. In the digital world, the computer-based system emphasis teaching through online mode known as e-learning. The expertise level of the learner in learned subjects can be measured through e-assessment in which multiple choice questions (MCQ) is considered to be an effective one. The assessment questions play the vital role which decides the ability level of a learner. In manual preparation, covering all the topics is difficult and time consumable. Hence, this article proposes a system which automatically generates two different types of question helps to identify the skill level of a learner. First, the MCQ questions with the distractor set are created using named entity recognizer (NER). Further, based on blooms taxonomy the Subjective questions are generated using natural language processing (NLP). The objective of the proposed system is to generate the questions dynamically which helps to reduce the occupation of memory concept.

KEYWORDS

Blooms Taxonomy, Learning Management System, Multiple Choice Questions, Named Entity Recognition, Natural Language Processing

1. INTRODUCTION

Always, Education is the best approach to achieve success in everyone's life that can be happened through online or in classroom method. In this digital world, online education is highly preferred by the leaner because of its anytime, anywhere approach which enriches the knowledge to convince the industrial expectation of the relevant domain that helps survival in the workplace. This type of education imparts the knowledge dynamically to the learner. One of the online methods is the E-Learning system which integrates the major components of E-Content for learning and the assessment part to explore the understanding level of the learner. Mitkov (2003) and Mitkov et al. (2006) projected a semi-automatic question generation in an electronic content using NLP-based methodology. The principal segment of online learning is to ask the question to discover the cognitive practice that induces advanced cognitive skill namely intellectual capacity and reasoning (Bhirangi & Bhoir, 2016).

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In education providing a quality service is more complex and challenging issues in practical (Agrawal & Sharma, 2014). Assessments are the main tool to test the skill level of the learner. It is the way to judge or assess novice's knowledge or the expert's achievement in their course. The main purpose of the assessments in E-Learning courses to identify how soundly the learner has learned the E-Content by a tutor or a supervisor. The question in the assessment is more important which is classified in two different types such as objective type and subjective type. In online education, the learner takes the self- assessments via MCQ, Quiz or through fill-up the blanks. Objective type assessment method is easy to evaluate and soon the ability level of the learner is determined quickly. One of the objective type questions is multiple choices which are the most admired type. When the learner is strong enough in the learned concept then it is easy for them to answer that helps to identify the deep understanding capacity level of the learner. MCQ boost the learner to learn more and it gives the path for active learning (Nicol, 2007). The subjective type questions are in one sentence but the answers may be one or more sentences as an explanation, or in short form of an answer. Learner tries to explain the logical concept in their own feel or based on their opinion. It helps the learner to think where the learned concept can be applied and how it can be applied? The subjective question helps to improve the cognitive level of the learner.

Bloom's taxonomy has the most important hierarchical arrangements for teaching-learning processes with the six different levels of taxonomies that are practiced. Blooms classifier is the best tool to determine the knowledge level of the learner. The six different levels are ranged from low level to high level of taxonomies which are used to find the low level of knowledge to the extreme level of knowledge. In manual process, require lots of time to prepare the assessment questions on the basis of blooms taxonomy which is the difficult task for the teacher.

In recent years, research is highly focused on the Automatic Question Generation in MCQ section. There are several methods of assessment in E-Learning. The assessment methods are Multiple Choice Questions (MCQ) checks that the learner's talent to relate understanding by the available possible answer to real-life conditions. True or false are selected, when the learner is clear and definite in the answer. This type of assessment is easily conducted. Fill-up the blanks are the type used when to recollect the specific facts for the learner. Similarly, the next type is matching the terms correctly. It assesses the learner's ability level by remembering the facts and matches the link between the terms. It will be better to generate the question automatically.

The assessments are conducted as a prerequisite in the beginning stage of the learning to check how much knowledge does the learner possess? After taking up the course check how much the learner has erudite through assessment? Then it is easy to find how much the learner has learned. Hissi et al. (2018) implemented the new technologies inclusion and its dissemination gives a very wide field of novelty in the various fields, of human and the resources such as saving time, financial profit successively. Baporikar (2016) stated that Information Technology enabled services is far better in the teaching-learning process.

Here focusing to generate two different question patterns to test the skill level of learner. The MCQ questions are created with a set of distracters using Named Entity Recognizer and the subjective questions are created based on blooms taxonomy level using natural language techniques to find the skill level of the learner in the learned concept. Objective questions are generated automatically in the form of MCQ with a set of distractors. For a Sentence, a correct answer and the set of distractors are generated using named entity method. Based on blooms taxonomy the low-level subjective questions are developed to test the knowledge of a learner. The system has been executed in computer science domain to check the skill level of the learner.

The paper is structured as follows. The related task of generating question is described in Section 2. The system architecture and design are briefed in Section 3. The Proposed System is given in Section 4. Section 5 deals with the experimental result. In Section 6 System Evaluation is carried out and finally in Section 7 concluded with the future works.

2. RELATED WORK

Cloze question generation (CQG) described the three different modules namely the assortment of the sentences, keyword extraction and the selection of distractors. Initially, related questions are selected and followed by keyword identification from the selected sentence. Finally, the answer to the keyword is selected. The domain-specific method is the last stage in this cloze system; the system is evaluated using three modules such as assessment on the chosen sentence, retrieved keyword, and the distractors (Narendra et al. 2013).

Agarwal et al. (2011) described the discourse connectives that preferred in automatic question generation that is divided into two modules. Initially, the contents are selected from the given input text and at the end, the question formations are done. Investigator focuses on the different discourse connectives such as even though or although, 'because of',' as a result', while, for examples and instances. Why type question type will be generated when the sentence consists of the word since. The system will be evaluated by syntactic and semantic forms.

ACQ using software agents are developed where the system takes the text as an input to derive the questions based on Bloom's taxonomy (Pandey & Rajeswari, 2013). This article assists to evaluate the learner's capacity level in the subject. To process the document the system deploys the agent to perform the diverse functions which will process the document, classify the data and information and create the questions. To generate the question, the output of Information classification is considered as input in question generation. Here the template-based approach is used in keyword selection.

Mujamder and Saha (2013) developed a system to select the important sentences from the paragraph by using the topic model and similarity parse structure. The parse structure is calculated by the similarity between the input and the references parses. Mitkov et al. (2006) preferred the wordNet for similarity measures.

In the automatic multiple choice question generation system (Fattoh, 2014) based on named entities and semantic label, the system chooses the information and keywords. The distractor depends on comparability between the sentences in the data set. This system asks a list of words or remarks from the sentence comments from the sentence which might be a descriptive word, adverb or vocabulary. To generate the questions, Named Entity Recognizer (NER) and Semantic Role Labelers are used to tag the name, place and organization name. When the question is ready, the similarity measure is used to compare the question and the knowledge-based question.

Shah et al. (2017) proposed the automatic questions for intelligent tutoring system with the concept of inverse document frequency method to rank the keywords in the input, extract the keywords from the sentences and to eliminate the discourse connectives to neglect the incompletes in the sentences. The keywords of the unigram and bigram are stored in the dictionary list to generate the questions.

Stasaski and Hearst (2017) implemented the concept of ontology in multiple-choice question generation. Ontology represents the concept and the relationship between the concepts. Biological ontologies are identified and used to generate multiple choice questions. The distractors are generated based on the relationship between the concept and on the assumptions.

Brown et al. (2005) described the WordNet concept to find the synonym, definition, antonym, hyper and hyponym of a word in terms togenerate a distractor of a word in automatic generation of vocabulary assessment questions.

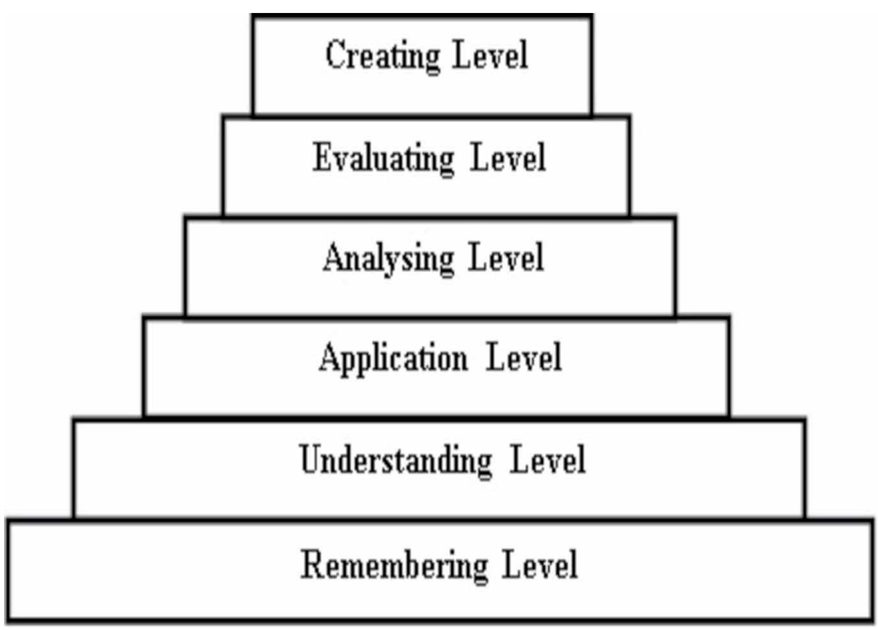
3. SYSTEM ARCHITECTURE AND DESIGN

Question Generation (QG) is the task to generate question automatically from the given paragraph that helps to judge the knowledge of the learner for the subject learned in E-Learning or in intelligent tutoring system is given by Sathiyamuruthy & Geetha (2012). Pabitha et al. (2014) stated that the test question should be based on the cognitive taxonomy level. In the proposed system, to generate the questions of both the procedural and objective, the electronic text is taken as input file and applies the preprocessing techniques using natural language processing techniques. The main objective of the proposed system is to generate questions on the basis of the blooms cognitive domain is shown in Figure 1. The learner's understanding level is determined which helps the tutor to organize the course content, a plan to provide appropriate instruction, assignment and at last to assess them. The basic level of the taxonomy is knowledge level is also known as remembering level which is used to recall some information or content from the already learned subject. Bloom's hierarchy levels are classified into two levels where the low levels are remembering, understanding and application and the higher levels are analyzing, evaluation and creating case. The learner fails to be strong in the low order skill and reaches the higher order level then the learner will not able to face all the real circumstances to solve the problems.

The knowledge level holds the list of simple verbs such as list, identifies, labels, lists, matches, names, recalls, recognizes and selects. According to this keyword set, it is enough to generate a simple multiple-choice question (MCQ) or Fill up the blank questions (FBQ). Next level of this taxonomy is comprehension which used to know how much the learner has grasped the concept and to express it in their own words. The question of this level is to justify, compare and contrast, what and when.

The text file is supplied as an input. At the first stage, the input file is pre-processed to remove the unwanted terms. Next, the file is segmented to different forms such as sentence filter, Keyword extractor and then noun filter. Finally, the pre-processed content involved in Question Generator (QG) using natural language techniques with the blooms keywords are stored separately. The keywords of different taxonomy level are maintained separately involve in generating the questions shown in Figure 2. The supervised techniques of machine learning have been used to classify the questions (Sangodiah et al. 2015, Karima et al. 2012, and Zhang & Lee, 2003). Machine learning techniques have to accomplish a very high level of precision in generating the question dynamically. Here used the Python to generate the questions.

Figure 1. Blooms cognitive hierarchical level



3.1. Input File

Iwata et al. (2011) stated that preparing the learning material is complicated since it has to meet the diverse goals and needs of the user style. E-Content of the desired topics is written in normal English languages that are stored separately. The learning content can be in paragraph format of the desired subject in structured order which prepared by the subject expert or the mentor. This input file is used by the teacher and the learner. The teacher delivers the instructions, and frame questions to the learner. The learner will study from this to gain more knowledge. Hence, the file has to be organized properly.

3.2. Document Processor

The goal of the preprocessing is to retain the input file professionally in the memory based and time-based components. It should occupy only the limited space and the time to retrieve the content should be less. The processed file has only the necessary information for further task. The original text file has to be pre-processed to remove unwanted, noisy or duplicate words from the learning content. Initially, the stemmer is preferred to take the words to the root word. Once the stemming is over then stemmed part moves to summarize where the content is in crisp. Figure 3 shows the steps involved in document pre-processing.

3.3. Sentence Filter

The sentence filter is used to split the paragraph into sentences separately. Individual sentences from the complex paragraph are filtered by the sentence tokenizer. For the implementation of the Natural Language Tool Kit, import the sentence tokenizer. Read the file to be split into the sentence. Complex sentences are split into two simpler sentences using the sentence simplifier by Abduljabbar and Omar (2015):

```
from nltk.tokenize import sent_tokenize
input = open("inputfile.txt")sentence = input.read()
print(sent_tokenize(sentence))
```

As per the input file, tokenizing has been made and the respective numbers of sentences are successfully brought out by the filtering.

3.4. Removal of Stop-Words

One of the preprocessing steps is to remove the stop-word; the natural language English consists of many stop-words namely 'is, was, are, of, be, these, by, etc.' which have only low-value information in the learning material. When we use any machine learning techniques on text processing, then it needs to remove the stop-words because they produce the noise during the text processing. Since

Figure 2. Subjective type question generation system

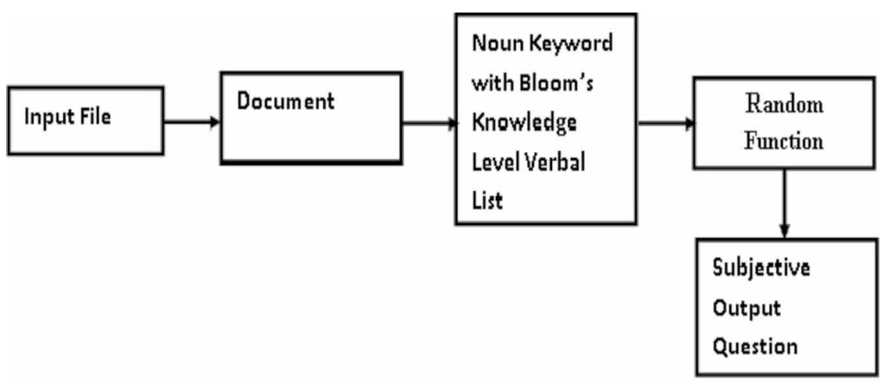
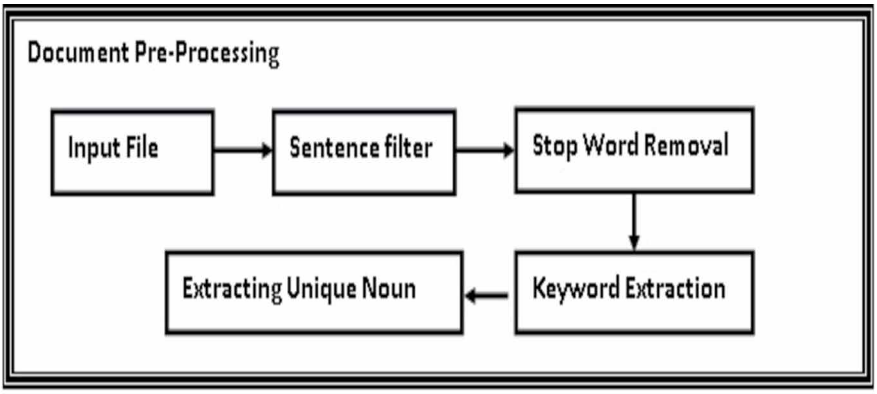


Figure 3. Document preprocessing



these stop-words will not produce a meaningful message and remove them and concentrate on the other high-value words. The stop words may be in the form of prepositions, pronouns, conjunction, preposition, and adverbs. In NLTK, there are 179 English stops-words are stored in the separate dictionary. Import the stop-words standard python library to remove the unwanted words from the paragraph which is given below:

```
stop_words = set(stopwords.words('english'))
```

After the removal of stop-words, the list of significant words from the paragraph that helps in generating the question.

3.5. Keyword Extraction

The Keyword extraction is likely to extract nearly all the significant vocabulary terms that describe the subject of an input paragraph. The extraction of the word should be done only after the removal of unwanted words from the paragraph. The identification of keywords cannot be covered in a given time, hence, used the algorithm Rapid Automatic Keyword Extraction in natural language tool also known as RAKE which is the domain-independent keyword extractor. It tries to determine the key phrases of the paragraph by examining the emergence of the vocabulary word and its amount with other words in the paragraph:

```
r = Rake()
r. extract_keywords_from_text(sentence).
```

After the removal of stop-words, the keyword words have been extracted from the paragraph based on the frequency of the occurrence from the given paragraph; the most essential words are extracted as the keyword by neglecting others. Part-of-speech of these extracted words is the mixture of the noun, verb, adjectives, etc. These keywords will move to the next stage to hold only the noun related words for the objective and subjective type of questions.

3.6. Noun Filter

The noun is the word that represents the name, place or things, an object, either directly or indirectly, the subject of the sentence, an adjective in the sentences. Noun gives the meaningful representation of the sentences in the paragraph and it has the highest weight in generating the questions. Normally, the word tag may be the verb, adverb, adjective, and noun. The part-of-speech tagger is used to convert the given sentences into a tag form. We extract the noun keywords from the paragraph using the noun filter options. POS tagger in NLP gives the different noun format namely NNS, NNP, NNPS, and NN. In the proposed system used only the NN format to generate the questions. The tag may also have duplicate keyword and nouns:

```
nouns = [token for token, pos in pos_tag(word_tokenize(sentence))
if pos.startswith('NN')]
```

3.7. Removal of Duplicate Keyword

The filtered noun list from the sentences will definitely have the duplicate keyword tag. The duplicate tag word will produce noise and confusion in generating the question. It is better to remove the duplicate tag words from the list for the efficient question generation. Perform the following logic in python code to remove the duplicate keyword:

```
repeat the loop in noun list
        when the noun word is not in the list
                then add that word
        finally, append the list to hold the unique noun keyword
```

Now, the list has only the unique noun words. Comparatively the number of noun keywords is limited.

4. PROPOSED SYSTEM

In the proposed system produced two types of question namely the subjective type to assess the learners the deep understanding level and the objective type that helps the learner to think and recollect the data which they have learned.

4.1. Subjective Question Generation

The assessment questions can be in subjective type format where the learner will describe the answer in one or more sentences. Subjective type question helps to find the deep understanding level of the learner. Actually, for the effective subjective question, blooms taxonomy levels are to be followed. When the questions are mapped with bloom hierarchy then it is easy to determine the understanding ability level of the learner with the help of learning material (Liu et al., 2014). This taxonomy set down from the lowest hierarchy of knowledge level into the highest evaluation level of six different hierarchies (Deena & Raja, 2017, and Deena et al., 2019b). In the proposed system, the hierarchy of Benjamin Bloom is followed to generate the questions that they are the best classifier tool to determine the cognitive level of a learner. Each level carries a different set of verbs to determine the cognitive ability level of the learner. The main target is to determine the pre-requisite knowledge of the learner in the subject and how much knowledge the learner has possesses from the given material. The assessment will give a picture of the skill level of the learner before and after taking the course. The system focusing to generate the blooms knowledge level questions. This knowledge level helps to recall and recollect the information about the subject. After preprocessing; the selected noun related keyword is combined with a verbal list of bloom knowledge level to generate the questions automatically. The randomized function is used to generate the questions dynamically with the support of available verbal and noun keywords. In every execution, the learner gets a different type of questions. From the proposed system, the learner gets multiple sets of questions to determine the learner's skill level. Each execution produces a new set of question which is necessary to store the questions for further uses.

4.2. Multiple Choice Question With Named Entity Recognizer

MCQ is the best assessment method and it has its own template to test the skill level of the learner. This type of assessment helps the learner to learn more and more as reinforcement to learn, a path to motivate and challenge them to learn more to improve learner's skill level. The score of this MCQ will determine the skill level of the learner in the subject they have learned. MCQ helps to identify the cognitive level of the learner under three different blooms low level namely knowledge level, comprehension, and application level. The questions are known as a stem is the problem to be solved and each stem has a set of different options of answer list (Rakangor & Ghodasara, 2014). The stem gives some information about the sentence. In the proposed system, the stem is generated with some blank spaces where the information is not complete. A stem consists of four different choices of value. Out of four, one is the key which represents the actual correct answer of the stem. The rest three are termed as distractors which will confuse the learner to select the answer. Only when the learner has a strong understanding of the subject, they can answer correctly. It increases the cognitive understanding level of the learner. Simple sentences with key are involved to generate the MCQ. The structure of the MCQ is given in Figure 4.

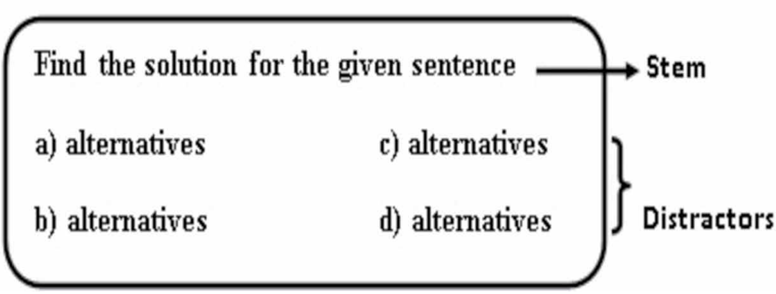
$S = \{S_{1,} S_{2,\ldots} S_n\}$ problem to be solved as stem which selects in Figure 4, the set of alternatives are given for the problem to be solved. Zekri et al. (2017) stated that questions can also be generated from the images. A learner has to think and recollect the concepts from the learned material to answer the question. In the proposed system, the stem and set of alternatives have been generated automatically and dynamically. Named entity recognizer is used to generate the appropriate set of distractors and the answer key. The Named Entity Recognition (NER) is an NLP technique used to extract the noun phrases of the information such as Person Name, Organization, Products, Country Name, Location, Time, Date, Percentage value and Monetary value. It is used to extract the meaning of the word, to split or chunk the information into a small piece in turn; it is divided into two parts as Entity names and its Entity type. The entity name and entity type of the chunked data are identified using the tagged_tree.leaves() and tagged_tree.label() respectively. The chunked data are classified under the classes of predefined one in NLTK which involve in generating the MCQ. The named entities are identified and classified by the NLTK. The 'Has' attribute returns the true value when the object name is identified as a false value. Retrieve the category of named entity by tagged_tree.label() is used to retrieve the named entity category of the terms in the paragraph. After every retrieval, appends the named entity for each word in the sentences creates a list to helps distractor generation. Component of MCQ is given as:

```
MCQ = {S, A, Q} where, S from the paragraph,
A = a key answer of the stem,
```
$Q = \{Q_{1,}\ Q_{2\ldots}Q_n\}$ Q represents the distractor of the stem.

4.3. Stem Selection

A stem is a question or the problem to be solved. The sentences involved in generating the questions are termed as the stem. Swali et al. (2016) suggested that the stem plays an important role in assessing the learner's cognitive level. Deena & Raja (2019a) presented on selecting the relevant sentences from the paragraph to generate the question automatically using Latent Semantic Analysis (LSA). The entire sentences in the paragraph will not have the semantic sense to raise the questions. LSA is used to select the sentence based on the score value. The highest score value implies the highest priority sentence of the paragraph. The stem will frame from the high priority sentence to low priority

Figure 4. Structure of the MCQ



sentence. In the proposed system, the sentence as it is from the paragraph is considered for the stem creation where the noun terms alone are replaced by the blank space. The learner will take the self-assessment as a number of times to strengthen the subject knowledge. The system itself will produce the stem repeatedly without any human intervention.

4.4. Distractor Selection

The distractor selection is most important for the MCQ and it is a challenging task. The relevant distractor has to be set for the stem (Liang et al., 2017; Bhatia et al., 2013; Alvarez & Baldassarri, 2018). The distractors will confuse the learner in finding the answer to the stem. This will indirectly motivate the learner to recollect and think the subject during answering. Distractor has to be designed appropriately to answer key which helps for the quality stems to assess the cognitive level of the learner. Miller (1995) used the WordNet concept to create the distractor. Rakangor and Ghodasara (2014) proposed the named entity such as entity type and entity names for the "Wh" type questions such as the example "who is the prime minister of India?" Here they set a standard template to generate the question from the named entities. All the distractors are selected from the entity type of personal name. In the proposed system, used the Named entity for the distractors selection in the stem to create a blank space which will replace the noun related terms in the sentence and that particular noun word is the answer key and alternatives are selected from the named entity set. Two alternatives are selected from the entity name, other than answer key one alternative is included from the noun list. Another alternative is the answer key.

4.5. Random Function

In the proposed system, for both the objective and subjective type questions, different set questions are generated for every execution. The numbers of a possible set of questions are high for the same document which helps the learner in self-assessment. A random function is used to select a noun word in the stem. Every time, this random function helps to replace the noun term in the stem so the new set of question is created dynamically. It is not necessary to hold any database for the question generation.

5. EXPERIMENTAL RESULT

In the Learning Management System (LMS), to recognize the learner's skill level an assessment has to be conducted as pre-requisite of the concept and post-test after completing the course. Traditionally the test question was generated manually by the domain expert or by the subject expert. The system to generate the assessment questions automatically. In an implementation, Natural Language Techniques is used in Python language. An input file with actual learning content is stored separately in the memory. It is clearly understood that organizing learning material is very hard to meet the various expectations levels, goals, and interests of all the learners. Critical care has to be considered in organizing the learning material. The quality in education is measured in different facets with different contexts given by Baporikar (2015).

In this system derived an essential noun keyword from the given material. To produce, the question creates a list of verbs of each level based on blooms taxonomy. Liu et al. (2014) presented the mapping of questions with blooms is easy to determine the understanding ability level of the learner in the learning material. This taxonomy delineates a hierarchy of six different levels from the low knowledge level into the higher evaluation level. Levels are used in cognitive learning to identify the understanding ability level of the learner (Deena & Raja, 2017). Each level carries a different set of verbs to determine the cognitive ability level of the learner. Procedural type questions help to answer in one or two lines of the learned concept. It helps to identify the learner's knowledge level on the study material.

5.1. Knowledge Level

It is the low-level taxonomy that helps to recollect the previously learned material, to know the subject knowledge of the learner before and after taking up the course. This level has to default verbal list which acts as keys to know the cognitive level of the learner. Each subjective question is framed based on the verbal list and noun keyword of the subject. The blooms verbal list is created using python language. In general, there is around 21 verbal in the knowledge level of blooms. Here only a few verbal words are included as the sample for subjective type questions. The list in python as given below:

Blooms knowledge verbal list = [Arrange, List, Define, Label, Recognize, label, relate, recall, memorize]

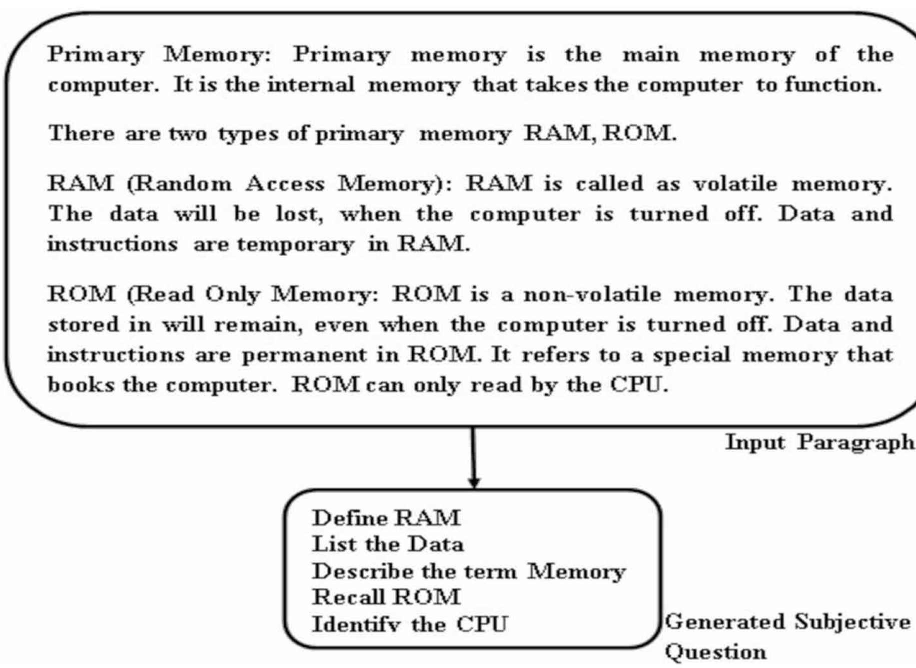
The System executed for the sample input paragraph of the concept of memory in the computer science domain. The sample output of subjective type questions is shown in Figure 5. The steps of instructions are followed to execute the code:

1. Repeat the loop until the length of blooms list;
2. Next, Check the condition, if any of verbal is present, then;
3. Random function combined with noun keyword to generate the subjective question;
4. Finally, continue until the condition fails.

5.2. Objective Type Questions-MCQ

Deena & Raja (2019a) implemented only the procedural type question. The proposed system have enhanced the same input file for objective type question such as multiple choice questions which

Figure 5. The output of subjective questions



carries the correct answer and set of distractors that confuse the learner to select the answer from the alternatives (Goto et al., 2010).

The stems are generated dynamically with empty blank spaces in the same subjective type inputs. Normally, MCQ will not have the blanks spaces. In the proposed system, with the help of the random Choice, the noun terms are replaced by the blank space in the stem. The distractors are randomly generated for the stem without any human Intervention. In every execution, it produces a different MCQ questions as output and the sample retrieved output is given in Figure 6.

6. SYSTEM EVALUATION

Both the generated subjective and objective type questions were verified with around 20 computer science teachers from different institutions. The evaluated output and suggestions are given in Table 1. Questions were given to 55 students of different schools with different categories to check whether the student can able to understand the questions. About 44 students were able to understand and answer the questions without any support. 11 students were not able to understand the questions and rest were not able to understand the distractor set.

Overall, 80 sentences were considered from the computer science domain for the evaluation purpose, the system generates 70 number of objective questions with distractors. Out of which 59 questions were relevant when compared with the human style. The exactness of the questions is measured by precision. The overall exactness of the output is 84% and the completeness of the output is 73%:

Precision (P) = 59/70
= 0.84

Figure 6. Sample MCQ output

a) Primary Memory: Primary memory is the main memory of the __________
1) Random Access memory   2) computer
3) Data   4) instructions

b) The data will be lost, when the __________ is turned off.
1) RAM   2) computer
3) ROM   4) books

c) ________ can only read by the CPU.
1) ROM   2) function
3) CPU   4) memory

Table 1. MCQ executed status

No. of Evaluator	Total No. of Examinees	No. of Examinees Attended	No. of Examinees not Attended
20	55	44	11

The recall (R) is measured as the relevant questions over the total number of questions. It is also known as sensitivity of the instances. The completeness of system is measured by Recall:

Recall (R) = 59/80
= 0.73

Further, four different materials were executed to generate objective questions from the computer science domain. They are measured in terms of precision and recall shown in Table 2.

The graph is shown in Figure 7, with the precision and recall value of each document.

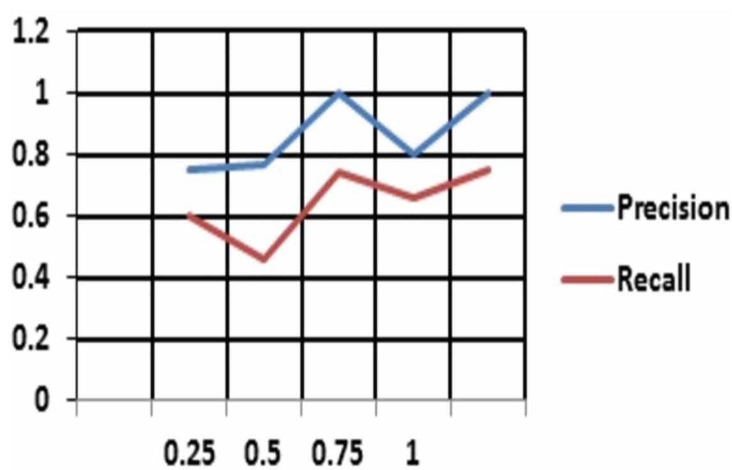
7. CONCLUSION AND FUTURE WORK

In the proposed system, the objective and subjective type questions for an E-Learning environment is generated. In an objective type, multiple choice questions were created with the distractors set are developed using the named entity recognizer. The random function is used in both the objective and subjective type questions to generate the questions randomly without human intervention. The subjective type questions are generated as per the blooms taxonomy. The proposed system is tested with various samples and the exactness of questions is always above the 75% of the precision. The generated outputs are measured by the exactness and completeness value where the achievements are

Table 2. MCQ relevancy report

Document Number	No. of Sentences From Documents	Total No. of Questions Generated	Relevant Question	Precision	Recall
1	10	8	6	0.75	0.6
2	15	9	7	0.77	0.46
3	7	5	5	1.0	0.74
4	12	10	8	0.8	0.66

Figure 7. Precision and recall



84% and 73% of precision and recall value respectively. For every execution, a set of new questions has been generated which helps to reduce the memory. In future, the work will be carried to improve the accuracy level of the stem and distractors to improve the recall value.

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