

A SEMANTIC QUESTION CLASSIFICATION FOR QUESTION ANSWERING SYSTEM USING LINKED OPEN DATA APPROACH

¹KITTIPHONG SENGLOILUEAN, ²NGAMNIJ ARCH-INT, ³SOMJIT ARCH-INT

¹Department of Computer Science, Faculty of Science, Khon Kaen University, Thailand

²Department of Computer Science, Faculty of Science, Khon Kaen University, Thailand

³Department of Computer Science, Faculty of Science, Khon Kaen University, Thailand

E-mail: ¹kittiphong.s@psu.ac.th, ²ngamnij@kku.ac.th, ³somjit@kku.ac.th

ABSTRACT

Semantic question answering (SQA) was the research study regarding the natural language processing. The purposes of this study were 1) to encourage the users to query via the computer with the semantic natural language, and 2) to obtain the concise, accurate, and relevant to the users' needs. Recently, it was found that the research studies have encountered the problems with semantic communication, flexibility, and accuracy of processes, especially the process of question classification. It was considered the vital process of developing the semantic question answering system. Thus, this paper attempted to propose a semantic question classification for the question answering system using the linked open data approach. It proposed the problem-solving technique for question classification through semantic grammar rules derived from the questions based on principles of English grammar. Moreover, the linked open data, WordNet and DBpedia were implemented to solve the problems of words similarity and question classification through the question classification taxonomy consisting of six main classes and fifty subclasses as standards for question classification. Besides this, the dataset from the question sets of TREC with one thousand questions were also implemented. The evaluation indicated a high accuracy of question classification with the total scores of precision, recall, and F-measure, at 92.82%, 95.16%, and 93.97%, respectively.

Keywords: *Semantic Question Answering, Natural Language Processing, Question Classification, Linked Open Data, Semantic Web*

1. INTRODUCTION

Semantic question answering (SQA) was the research study concerning the natural language processing (NLP), the information retrieval (IR) and the information extraction (IE). Its purposes were to facilitate the users to access the data with the natural language, and to obtain the meaningful and concise answers relevant to the users' needs [1-4]. At the present time, the search engines were about to search the data with keywords. As the result, the answer usually came up in the form of the links of documents relevant to those keywords, but it could not provide the answer that the users really needed. Moreover, the results of retrieval were neither relevant nor meaningful to the users' needs. The users once needed to sift through the data because of a great number of the obtained data. Thus, it wasted time, discomfort, and did not enable to use the natural language questions with *What, Who, Where, How many, How long* etc. Although

some search engines attempted to develop algorithms to support the semantic search that enabled to retrieve the data with the natural language, the structures of data storage implemented with those search engines have been provided in the form of HTML instead of the ontology. Accordingly, it has not semantically retrieved the data completely yet. For example, it could not remedy all problems of the accuracy in synonyms or homonyms [5-7].

Semantic question answering system could be divided into three main processes consisting of question processing, question classification, answer query processing. For this present study, it focused on solving the problem of question classification. It was the process that emphasized the class analysis of answers from the user questions and to find out and check the answers before returning the answers to the users. Unfortunately, it still has encountered the problems of semantic communication, accuracy,

and flexibility for question classification. According to the relevant research studies [6-8], there were many research studies tried to propose the guidelines for solving the problem of question classification process through the support vector machine (SVM) and pattern matching. However, it remained to have the limitations on solving the problem of words similarity both synonyms and homonyms.

The problems found in this paper concern the way to convey the meanings, words similarity, accuracy, precision and flexibility in *Question Classification Processing*.

In this paper, we proposed the approach to solve the problem of question classification process that could analyze the class for the answers from the question structures the users keyed in order to obtain the specific and relevant answer. The answer classes were checked before returning the answers to the users. In addition, this study proposed the technique of generating the semantic grammar rules from the question structures regarding the principles of English grammar using the linked open data together with WordNet [9-11] and DBpedia [7, 12] in order to solve the problem of words similarity without limiting any domains. Moreover, the question classification taxonomy by Li and Roth [13, 14] with six main classes and fifty subclasses were implemented as the standard for the question classification process. The dataset from TREC with one thousand questions were used for testing the model and comparing to other relevant research studies.

For the contribution and strong points of this paper, it could be summarized as followings.

1) It could extract named entities from the questions, and resolve the problem of similarities of named entities through implementing the semantic extracting named entities together with WordNet and DBpedia databases.

2) It could extract properties from the questions, and resolve the problem of similarities of properties through implementing the semantic extracting properties together with WordNet and DBpedia databases.

3) It could classify the question classification from the questions to figure out the class of answers through generating *Semantic Grammar Rules* from the question structures based on English grammar by implementing the linked open data together with WordNet and DBpedia databases for resolving the problem of words similarity.

4) It could check the accuracy of the answers before returning them to the users by deploying the technique of checking accuracy answers and classes obtained from *Answer Query Processing*. Additionally, it could be checked with the class of answers obtained from *Question Classification Processing*.

The remainder of this paper was organized as follows: Section 2 described theoretical background and related works, Section 3 discussed the proposed architecture of this paper, Section 4 dealt with the semantic question answering processes, Section 5 presented the evaluation, and Section 6 provided the conclusion and plans for future work.

2. THEORETICAL BACKGROUND AND RELATED WORKS

Semantic Question Answering (SQA)[3, 4, 6, 15] was the process that the users could employ the natural language question for semantic question answering such as *Where, What, Who, Which, Why, How many* etc., and obtain the concise answers. The research of SQA relied on the body of knowledge from different study fields namely Natural Language Processing (NLP), Information Retrieval (IR), and Information Extraction (IE) [1-3, 16] since it needed the natural language to communicate between the computer and human beings naturally.

The research studies relevant to SQA could be categorized into three aspects consisting of 1) Question Processing 2) Question Classification 3) Answer Query Processing, which were detailed as follows.

2.1 Question Processing

It dealt with analyzing and evaluating the question structure of questions that the users input to the computer. This procedure emphasized to solve the problem of words similarity for analyzing named entities and properties of the questions the users input them to the computer. Many research studies attempted to solve the problem of question process. AquaLog [17], for example, had implemented the ontology for finding out the answer from the natural language questions. Nevertheless, AquaLog had limitation that it could not support multiple resources. Besides this, it encountered the problem of accuracy in finding out the words similarity. Another study was CASIA [18]. This research study implemented a Markov logic networks algorithm for learning and creating the analysis model to sensor words and the graphic model for semantic mapping of each word. However, it was found that CASIA could not

support the evaluation of complicated questions or logical questions. Additionally, A. Ben Abacha and P. Zweigenbaum [6] had proposed the approach to solve the problem of question processing. The patients could give answers to the health questions with the semantic natural language. This helped basically examined the symptoms before going to see the doctor by implementing NLP techniques and semantic web technologies for solving the problem. As the result, it provided the flexibility for analyzing the question structure. It also solved the problem of words similarity both synonyms and homonyms. All the same, this research study still had the limitation. All data sources were documents. Moreover, the process of answer extraction took much time and risks the high percentage of failure because of unstructured texts. According to K. Sengloiluean, N. Arch-int, S. Arch-int, and T. Thongkrua [30] on a semantic approach for question answering using DBpedia and WordNet, it has proposed the approach to resolve the problem of extracting named entities and properties as well as named entities similarity and properties similarity derived from users' questions. However, the aforementioned research study has not yet brought up the question classification processing, which is considered the crucial processing of the research study concerning question answering.

2.2 Question Classification

It was the analysis process to figure out classes of answers from the questions the users input to the computer as for convenience for finding out the answers and checking the accuracy before returning the answers to the users. However, this analysis process still encountered the problems of semantic communication, accuracy, and flexibility in analyzing the answer classes. There were several studies that tried to propose the guidelines for solving the problem. It could be categorized into three groups regarding the technology implemented to solve the problems.

2.2.1 Semantic Technology

A. Ben Abacha and P. Zweigenbaum [6] had implemented NLP techniques: semantic rules languages or semantic classification to solve the problem of Question Classification. The strong point of this approach was about the flexibility of problem-solving. It could definitely resolve the problem of words similarity both synonyms and homonyms because it employed the database of vocabulary in the form of the ontology such as WordNet or DBpedia. Thus, this technique was suitable for resolving the problem of the natural language questions [4, 15, 19, 20]. Based on the

relevant research studies, many studies tried to propose the guidelines for resolving the problem of question classification using the semantic technology, NLP techniques, and semantic web technologies. The strong point of this study was the implementation of NLP techniques. It could definitely analyze the structure of the natural language. However, it was found that this approach was complicated, and it lacked the accuracy and flexibility since the questions to be testified were the natural language with high flexibility.

2.2.2 Machine learning

A. M. Hasan and L. Q. Zakaria [8] had proposed the support vector machine (SVM) and pattern matching to resolve the problem of question classification. The advantage of these techniques was about the smart system that could learn how to resolve the problem from training and testing. Notwithstanding, these approaches had the limitation that the input data were the complicated natural language questions. As the result, it could not completely resolve the problem of words similarity [8, 20-23].

2.2.3 Classification Rules

A. Mohasseb, M. Bader-El-Den, and M. Cocco [24] had proposed the machine learning algorithms together with grammar-based approach (GQCC), and classification rules to resolve the problem of question classification. The good point of this approach was that it encouraged the system to be more efficient and intelligent because it generated classification rules based on grammar and machine learning. However, it still had the limitation of resolving the problem of words similarity of the sentences written with the natural language [20, 24, 25].

2.3 Answer Query Processing

This process was function of generating and evaluating the query to find out the answer by employing SPARQL to query the data from DBpedia which was considered the database in the form of the ontology and check the accuracy of the answer before returning the answer to the users. Nevertheless, this process still had the problems of accuracy in querying the answer. Since DBpedia was derived from Wikipedia in the form of HTML, the obtained data were later stored in the form of the ontology or the linked open data. According to the relevant studies, they attempted to propose the guideline for resolving the problem of the answer query processing. LODQA[26], for example, was the research study that implementing the techniques for analyzing and transforming the natural language questions of the users into the form of query with

SPARQL by using the template model to query the answer. However, LODQA still had the limitation of accuracy and semantic communication to find out the answers. Additionally, it could not perfectly resolve the problem of words similarity. Another relevant research study was WIP [27]. It was the research study implementing the techniques for analyzing the structure of the natural language, and then querying it with SPARQL in order to figure out the accurate answer before returning it to the users. The advantage of SWIP was that it provided the analysis process of the question structure with the flexibility. This resulted that the query processing was more accurate. Anyhow, it was found that SWIP was short of checking the answer before returning it to the users in case the query processing provided several answers. QAKIS [28] implemented matching NL fragments, textual patterns and auto collected from Wikipedia for resolving the problem of the answer query processing. As considered the advantage of QAKIS, it employed the data from Wikipedia where was the big database. It provided the answer nearly covering all aspects. However, QAKIS still had limitation that it could only deploy with Wikipedia and the data were stored in the form of HTML instead of the ontology. Therefore, query for the answer was difficultly carried out, and it did not support the connection or mapping with other database or ontology. For another relevant study, A. Tahri and O. Tibermacine [29] deployed DBpedia extraction framework and the decision model for resolving the problem. The strong point of this study was that the accuracy of the answer was

checked with the question classification. Moreover, finding the answer type obtained more accurate answers with the decision model. All the same, the system in this study had not supported the variety of data source yet.

As the relevant studies earlier, it was found that they confronted with the problem of accuracy in analyzing the questions, the answer accuracy, semantic retrieval, words similarity, and question classification for finding the answer class and checking the accuracy before returning it to the users.

Thus, this present study proposed the certain technique for resolving only the question classification with a focus on analyzing the class of answers from the natural language questions of the users, and checking the accuracy of the answer before returning it to the users in order to obtain the most accurate answer and to meet the users' needs at most. The details were discussed in the following section.

3. PROPOSED ARCHITECTURE

3.1 Architectural Design of the System

This present study proposed the technique for generating the model of the semantic question answering using linked open data efficiently. The architectural design of the system comprised three main processes namely 1) question processing 2) question classification, and 3) answer query processing, which were shown in Figure 1.

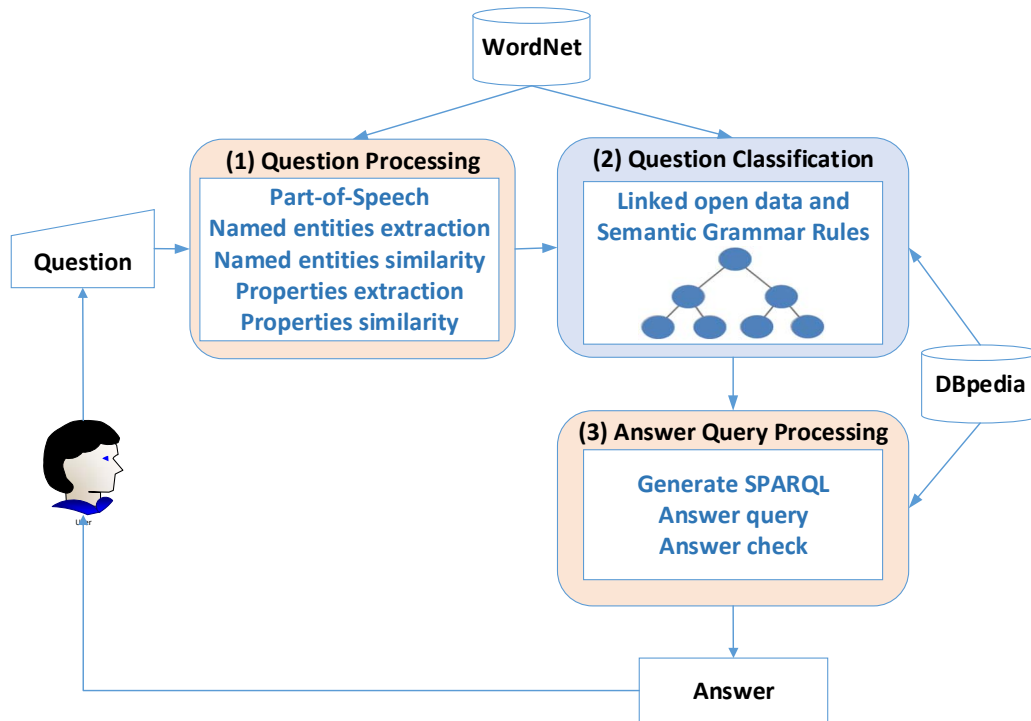


Figure 1: Architecture of Semantic Question Classification for Question Answering System

3.1.1 Question Processing

This process was function of analyzing the structures of the natural language questions. The scope of certain questions such as *What, When, Where, Who, Whose, Whom, Why, Which, and How* were defined to figure out named entities from the question structure. Named entities were then employed for finding out the answer from the linked open data. This process was proposed in [30]. It was the process extracted to figure out named entities and properties. Moreover, it resolved the problem of named entities similarity and properties similarity from the questions that obtained from the users.

3.1.2 Question Classification

It was the process that discussed the details of this present paper. The answer class was analyzed to facilitate the users to obtain the answer, and to check the accuracy of the answer before returning it to the users by employing semantic grammar rules from the question structure based on the principles of English grammar. The linked open data and WordNet and DBpedia were also implemented to resolve the problem of words similarity, and figure out the answer class as detailed in Section 4.

3.1.3 Answer Query Processing

In this process, it served as the query to find out the answer using named entities and properties derived from *Question Processing* in order to generate SPARQL. Then, it queried to find out the answer from DBpedia and to check the accuracy of the answer obtained from *Answer Query Processing*. The obtained answer and answer class were deployed to check the accuracy of the answer class from *Question Classification*, which was earlier analyzed to check the accuracy of the answer before returning it to the users.

4. SEMANTIC QUESTION ANSWERING PROCESSES

According to the architectural structure in Section 3.1, it could show the details of procedures of Question Classification and Answer Query Processing as the followings.

4.1 Question Classification

For this process, the answer class was analyzed as convenience for finding out the answer and checked the accuracy of the answer before returning it to the users by deploying semantic grammar rules from the question structure based on

the principles of English grammar as shown in Table 1. In this process, the linked open data, and WordNet and DBpedia were implemented to resolve the problem of words similarity. Moreover, the question classification taxonomy by Li and Roth [13, 14] consisting of six main classes and fifty subclasses was implemented as standards for the question classification as illustrated in Table 2.

Besides this, the dataset from the question sets of TREC with one thousand questions was deployed for the test. This was considered the standard that the researchers on the fields of question classification acknowledged. This process was presented in the form of algorithm as demonstrated in Algorithm 1.

Algorithm 1 Question Classification

Input: POS is a finite set of Part-of-Speech from Algorithm of Question Processing [30]

Output: C is a finite set of class of answer for question

Let $T \subseteq POS = \{t_i \mid \forall i = 1 \dots n\}$ was a finite set of question type from POS

Let FNP = a finite set of first noun phrases)NP(

Let CFNP = a finite set of class of first noun phrases)NP(from WordNet and DBpedia

Let C = a finite set of class of answer for question

```

procedure: QuestionClassification(POS) // eg., POS={ What(WDT), country(NN), is(VBZ), the(DT),
Baltra(NNP), Island(NNP)}
  Include QuestionProcessing() // Include QuestionProcessing() from Algorithm of
  Question Processing [30]
  T = questionType(POS) // eg., T = {What}
  FNP = findFirstNP(POS) // eg., FNP = {country(NN)}
  if (T = "What / Which") then
    CFNP = findClassFirstNP(FNP) // e.g., CFNP = {Location}
    C = semanticGrammarRules(CFNP) // e.g., C = {Location: country}
    return C // Class of answer = Location: country
  else (T = "When / Where / Who / Whose / Whom / Why") then
    C = semanticGrammarRules(T)
    return C
  else (T = "How") then
    C = semanticGrammarRules(T)
    return C
  else (T = "How [Num_Words]") then
    C = semanticGrammarRules(T)
    return C
  end if
end
    
```

According to Algorithm 1, the results obtained from Part-of-Speech processing in Question Processing [30] were analyzed as shown in Figure 2.

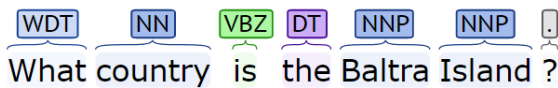


Figure 2: Part-of-Speech processing

Step 1: Analyzing the question to see the concordance of semantic grammar rules

This step dealt with analyzing the question structure based on semantic grammar rules. As considered the examples of questions in Figure 2, it showed that the question starting with *What* was categorized in the rule of the *What/Which* group. The question *What* could come up with the various kinds of classification and it could be possible for all classes.

Step 2: Analyzing Class of answer

According to semantic grammar rules in Table 1, the *What* group mainly focused on the first noun phrase of the question. As considered the example in Figure 2, the first noun phrase was *country* (NN). The class of country was checked from WordNet and DBpedia (country (NN) = Location). After matching and the question

classification taxonomy by Li and Roth shown in Table 2, it could be summarized that the class of answers of the question “*What country is the Baltra Island?*” was considered LOCATION: Country.

Table 1: Summary of Semantic Grammar Rules

Question type	Grammar structure	Class of answer
When	When (V.to do /AUX) NP VP X?	NUMERIC: Date
	<i>Ex. When was Barack Obama born?</i>	NUMERIC: Date
	Description: It was the question about time, so the possible answer class was NUMERIC: Date.	
Where	Where (V.to do /AUX) NP VP X?	LOCATION: Country / State / City / Other
	<i>Ex. Where was Barack Obama born?</i>	LOCATION: Other
	Description: It was the question about a location, so the possible answer class was LOCATION: Country/State/City/Other as considered NP and VP.	
Who / Whose / Whom	(Who / Whose / Whom) [V.to do / AUX] [VP] [NP] X?	HUMAN: Individual/Group
	<i>Ex. Who is the wife of Barack Obama?</i>	HUMAN: Individual
	Description: It was the question about an individual or an organization, so the possible answer class was HUMAN: Individual/Group as considered NP and VP.	
Why	Why [V.to do / AUX] NP [VP] [NP] X?	DESCRIPTION: Reason
	<i>Ex. Why is the grass green?</i>	DESCRIPTION: Reason
	Description: It was the question about a reason, so the possible answer class was DESCRIPTION: Reason to describe the reason.	
What	What [NP] [V.to do / AUX] [NP] [VP] X?	HUMAN / LOCATION / ENTITY / NUMERIC / DESCRIPTION
	<i>Ex. What country is the Baltra Island?</i>	LOCATION: Country
	Description: It was too broad question, so it could possibly be all classes of answers. For the analysis, the class of the first NP obtained from WordNet and DBpedia was taken into consideration.	
Which	Which [V.to do / AUX] NP X?	HUMAN / LOCATION / ENTITY
	<i>Ex. Which company created the Opera Browser?</i>	HUMAN: Group
	Description: It was too broad question, so it could possibly be many answer classes. For the analysis, the class of the NP obtained from WordNet and DBpedia was taken into consideration.	
How	How [V.to do / AUX] NP VP X?	DESCRIPTION: Manner
	<i>Ex. How does she go to school?</i>	DESCRIPTION: Manner
	Description: It was the question about the description of some process, so the possible answer class was DESCRIPTION: Manner.	
	How [fast / long / many / much / far /...] X?	NUMERIC: X
	<i>Ex. How many populations in London?</i>	NUMERIC: Count
	Description: It was the question about the numeric value, so the possible answer class was NUMERIC such as NUMERIC: Count, and NUMERIC: Money.	

*** AUX, NP, and VP were defined as auxiliary verbs, noun phrases, and verb phrases respectively. The symbols “/” referred to “Boolean OR” and “X” referred to a modifier.

Table 2: Question Classification Taxonomy by Li and Roth [13, 14]

Coarse class	Fine classes
ABBREVIATION	abbreviation, expression
ENTITY	animal, body, color, creative, currency, disease, event, food, instrument, language, letter, other, plant, product, religion, sport, substance, symbol, technique, term, vehicle, word
DESCRIPTION	definition, description, manner, reason
HUMAN	group, individual, title, description
LOCATION	city, country, mountain, other, state
NUMERIC	code, count, date, distance, money, order, other, period, percent, speed, temperature, volume, weight

4.2 Answer Query Processing

The process dealt with the answer query of question. The results obtained from *Question Processing* [30] and *Question Classification* were implemented to generate SPARQL for querying the data from DBpedia and checking the accuracy of

the answer before returning it to the users. The answer classes obtained from *Answer Query Processing* and *Question Classification* were checked whether they were identical before returning the answers to the users later.

Algorithm 2 Answer Query Processing

Input: *ES* is a finite set of named entities extracted from Algorithm of Question Processing[30]
PR is a finite set of properties extracted from Algorithm of Question Processing[30]
C is a finite set of class of answer for question from Algorithm 1 Question Classification
Output: *A* is a finite set of answer for a question

Let $AC = \{ac_i | \forall i=1 \dots n\}$ was a finite set of class of answer from an Answer Query Processing
 Let $QC = \{qc_i | \forall i=1 \dots n\}$ was a finite set of class of answer from a Question Classification
 Let $A = \{a_i | \forall i=1 \dots n\}$ was a finite set of answer for a question

```

procedure: AnswerQueryProcessing (ES, PR, C)
    Include QuestionProcessing() // Include QuestionProcessing() from Algorithm of Question Processing [30]
    Include QuestionClassification() // Include QuestionClassification() from Algorithm 1 Question Classification

    for  $es_i \in ES$  // e.g.,  $ES = \{Baltra\ Island\}$ 
        for  $pr_i \in PR$  // e.g.,  $PR = \{country\}$ 
             $A = A \cup sparqlQuery(es_i, pr_i, ?ans)$  //  $SELECT ?ans WHERE (es_i, pr_i, ?ans)$ 
             $AC = AC \cup answerClass(A)$  // e.g.,  $AC = \{Ecuador(Country)\}$ 
             $QC = QC \cup answerCheckClass(AC, C)$  // e.g.,  $Country \cong Location: country$ 
        end for
    end for
    return  $A$  // e.g.,  $A = \{Answer: Ecuador\}$ 
end
    
```

As for Algorithm 2, the results obtained from *Question Processing* including named entities (ES) and properties (PR) were input in the process. The results obtained from Algorithm 1, Class of answer (C), were also input in the process.

Step 1: Generating SPARQL processing

Named entities: *Baltra Island*
 Properties: *country*
 Class of answer: *Location: country*

Generate triple: (*Baltra Island, country, ?Answer*)
 Generate SPARQL:

```

SELECT DISTINCT ?Answer WHERE
{
    <http://dbpedia.org/resource/Baltra_Island>
    <http://dbpedia.org/ontology/country> ?Answer .
}
    
```

Figure 3: SPARQL for Answer Query from DBpedia

Step 2: Answer query processing

Answer Query: *Ecuador (Country)*

Step 3: Class of answer check

This step was the process of evaluating and checking the accuracy of the answer before returning it to the users. The answer classes obtained from Answer Query Processing and Question Classification were checked to see whether they were identical before returning the answers to the users.

Class of answer from answer query processing \cong
Class of answer from question classification

Ex., *Country* \cong *Location: country*

Step 4: Returning the answer to users

At this step, the answer to the question was returned to the users, so the result could come up as below.

For example 1: *What country is the Baltra Island?*

Answer: *Ecuador*

the standard of the question classification taxonomy by Li and Roth so that the system was accurate, and covered the natural language at most.

5.2 Measurement and Evaluation

F-measure was employed to measure the efficiency. It was typically used to measure the basic efficiency of data which combined *Recall* and *Precision* for calculation. F-measure represented *Precision* and *Recall*.

$$Precision = \left(\frac{ce}{ce + te} \right) 100 \quad (1)$$

While *ce* referred to the accurate value of data obtained from question classification, and *te* referred to the inaccurate value of data but it was classified.

$$Recall = \left(\frac{ce}{ce + fe} \right) 100 \quad (2)$$

While *ce* referred to the accurate value of data that was classified, and *fe* referred to the inaccurate value of data and it was not classified.

$$F - measure = 2 \left(\frac{Precision * Recall}{Precision + Recall} \right) \quad (3)$$

The evaluation indicated a high accuracy of question classification with the total scores of precision, recall, and F-measure, at 92.82%, 95.16%, and 93.97%, respectively as shown in Table 3. The efficiency of question classification from the dataset was measured and classified into nine groups of question types consisting of *When, Where, Who, Whose, Whom, Why, How, Which, and What*. The efficiency of precision, recall, and F-measure was detailed in Table 3. However, the reason why precision, recall, and F-measure scores were not resulted 100% because this present study was the study about the question answering regarding the natural language of human beings. In other words, both the input questions from the users and question answering process were concerned about the natural language with a high flexibility. Some words could not be searched in DBpedia and WordNet.

5. EVALUATION**5.1 Experimental Design**

This part of the present study discussed the experimental design based on the architecture of a semantic question classification for question answering system using linked open data approach. The questions employed for the test were the question sets from TREC [31-33] with one thousand questions, which were considered the standardized question sets for the test and acknowledged by most researchers. To obtain answer from the query, the DBpedia was employed as the immense knowledge source with the increasing information by the users from all over the world. For resolving the problem of words similarity, the database of WordNet [9-11] and DBpedia were implemented to enable the system to cover the natural language at most, whereas the semantic grammar rules were deployed to resolve the problem of the question classification. The English grammatical structure and the linked open data together with WordNet and DBpedia were employed to find out the class of answers regarding

Table 3: Results of the Approach within Various Datasets in the Process of Question Classification

Question type	Precision	Recall	F-measure
When	93.55	96.67	95.08
Where	89.47	92.73	91.07
Who	95.58	97.30	96.43
Whose	100.00	100.00	100.00
Whom	100.00	100.00	100.00
Why	88.24	93.75	90.91
How	90.83	92.37	91.60
Which	86.96	90.91	88.89
What	90.77	92.70	91.73
Total	92.82	95.16	93.97

5.3 Comparison with Other Approaches

The results of this present study were compared to other relevant research studies discussed in Section 2. Each research study had

experimented with the same data group. The efficiency evaluation of each research study could be summarized in Figure 4.

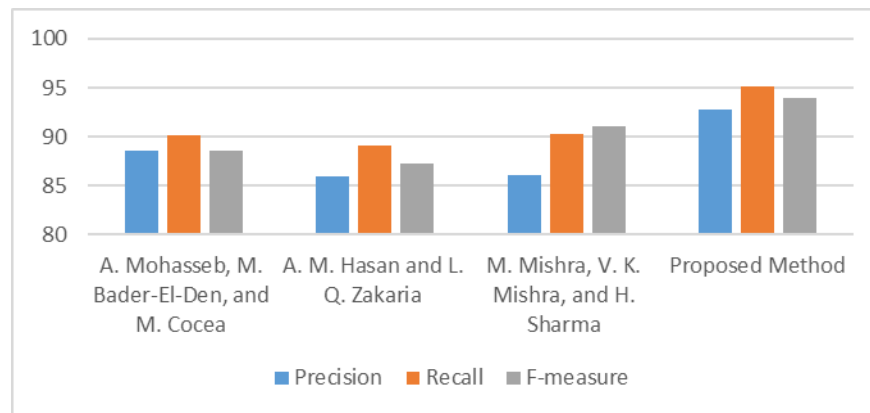


Figure 4: Comparison with Other Approaches

The results of efficiency evaluation of the proposed techniques were at the high level and different from other research studies that were discussed as follow.

A. Mohasseb, M. Bader-El-Den, and M. Cocea [24] conducted the research on the question categorization and classification using grammar based approach. This study proposed the approach for resolving the problem of question classification through grammar-based approach (GQCC) by analyzing the structure of English grammar. Additionally, machine learning algorithms were employed to resolve the problem of question classification. The results of efficiency evaluation of Precision, Recall, and F-measure were 88.50%, 90.10%, and 88.50% respectively.

A. M. Hasan and L. Q. Zakaria [8] did the research on question classification using support vector machine and pattern matching. This study proposed the approach for resolving the problem of question classification using the support vector

machine (SVM) and pattern matching. The results of efficiency evaluation of Precision, Recall, and F-measure were 85.92%, 89.07%, and 87.27% respectively.

M. Mishra, V. K. Mishra, and H. Sharma [19] studied about question classification using semantic, syntactic and lexical features. This study proposed the approach for resolving the problem of question classification by deploying the machine learning techniques, syntactic, and lexical features. Then, the results of question classification were compared with three types of machine learning algorithms consisting of Naive Bayes, SVM, and kNN. This was done to indicate the pros and cons of each proposed approach. The efficiency evaluation of the accuracy of this study was 91.1%.

Actually, this present study had the strong points and differed from other research studies in the following aspects. Firstly, it could extract named entities from the question and resolve the problem of similarities of named entities. In

addition, it could extract properties from the question and resolve the problem of similarities of properties. It could also classify questions to find out the class of answers and check the accuracy of the answers obtained from *Answer Query Processing* and *Question Classification* before returning the answers to the users. According to the results of efficiency evaluation in Table 3, it assured that this present study had the accuracy and efficiency at the high level for resolving the problem of question classification.

As compared to the aforementioned research study [30] on a semantic approach for question answering using DBpedia and WordNet, it mainly focused on *Question Processing* and proposed an approach to resolve the problem of extracting named entities and properties, and entities similarity and properties similarity obtained from user's questions. However, in this paper, it mainly focused on *Question Classification* through the technique of generating *Semantic Grammar Rules* from the question structures based on the English grammar. Moreover, the linked open data together with WordNet and DBpedia databases were implemented to resolve the problem of words similarity and find out the class of answers.

6. CONCLUSION

This paper presented a semantic question classification for the question answering system using the linked open data approach, which was considered the great vital process for developing the semantic question answering system. It proposed the technique to find the class of answers from the question that the users input in the computer as the convenience for finding and checking the accuracy of the answer. Lastly, the efficiency of accuracy of *Question Classification* was evaluated. To ensure the capability of the proposed approach, the experiment was conducted within the dataset of 1,000 questions. The evaluation indicated a high accuracy of question classification with the total scores of precision, recall, and F-measure at 92.82%, 95.16%, and 93.97% respectively.

In the future, it was anticipated to continue developing the semantic question answering system by natural language questions in order to resolve the remained problems of *Answer Query Processing* with more complicated questions and words similarity. Moreover, it was to encourage the system to be more accurate and efficient so that the obtained answer was more semantic and relevant to the users' needs.

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REFERENCES:

- [1] S. J. Athenikos and H. Han, "Biomedical question answering: A survey," *Computer Methods and Programs in Biomedicine*, vol. 99, pp. 1-24, 7// 2010.
- [2] A. M. N. Allam and M. H. Haggag, "The question answering systems: A survey," *International Journal of Research and Reviews in Information Sciences (IJRRIS)*, vol. 2, 2012.
- [3] A. Bouziane, D. Bouchiha, N. Doumi, and M. Malki, "Question Answering Systems: Survey and Trends," *Procedia Computer Science*, vol. 73, pp. 366-375, 2015/01/01 2015.
- [4] S. Hazrina, N. M. Sharef, H. Ibrahim, M. A. A. Murad, and S. A. M. Noah, "Review on the advancements of disambiguation in semantic question answering system," *Information Processing & Management*, vol. 53, pp. 52-69, 1// 2017.
- [5] P. Raj, "Architecture of an Ontology-Based Domain-Specific Natural Language Question Answering System," *arXiv preprint arXiv:1311.3175*, 2013.
- [6] A. Ben Abacha and P. Zweigenbaum, "MEANS: A medical question-answering system combining NLP techniques and semantic Web technologies," *Information Processing & Management*, vol. 51, pp. 570-594, 9// 2015.
- [7] M. A. Paredes-Valverde, M. Á. Rodríguez-García, A. Ruiz-Martínez, R. Valencia-García, and G. Alor-Hernández, "ONLI: An ontology-based system for querying DBpedia using natural language paradigm," *Expert Systems with Applications*, vol. 42, pp. 5163-5176, 7/15/ 2015.
- [8] A. M. Hasan and L. Q. Zakaria, "Question classification using support vector machine and pattern matching," *Journal of Theoretical and Applied Information Technology*, vol. 87, p. 259, 2016.
- [9] H. Liu, H. Bao, and D. Xu, "Concept vector for semantic similarity and relatedness based on WordNet structure," *Journal of Systems and*

- Software*, vol. 85, pp. 370-381, 2012/02/01/ 2012.
- [10] D. Tufiş and D. Ştefănescu, "Experiments with a differential semantics annotation for WordNet 3.0," *Decision Support Systems*, vol. 53, pp. 695-703, 2012/11/01/ 2012.
- [11] A. Amalanathan, S. Shanmugam, M. Senthilnathan, and S. Harikumar, "Semantic Annotations for Customizing Geographical Maps Based on WordNet," *Procedia Technology*, vol. 4, pp. 375-383, 2012/01/01/ 2012.
- [12] X. Zhang, X. Liu, X. Li, and D. Pan, "MMKG: An approach to generate metallic materials knowledge graph based on DBpedia and Wikipedia," *Computer Physics Communications*, vol. 211, pp. 98-112, 2017/02/01/ 2017.
- [13] X. Li and D. Roth, "Learning question classifiers," in *Proceedings of the 19th international conference on Computational linguistics-Volume 1*, 2002, pp. 1-7.
- [14] X. Li and D. Roth, "Learning question classifiers: the role of semantic information," *Natural Language Engineering*, vol. 12, pp. 229-249, 2006.
- [15] M. Neves and U. Leser, "Question answering for Biology," *Methods*, vol. 74, pp. 36-46, 3/1/ 2015.
- [16] M.-C. Yang, D.-G. Lee, S.-Y. Park, and H.-C. Rim, "Knowledge-based question answering using the semantic embedding space," *Expert Systems with Applications*, vol. 42, pp. 9086-9104, 12/15/ 2015.
- [17] V. Lopez, V. Uren, E. Motta, and M. Pasin, "AquaLog: An ontology-driven question answering system for organizational semantic intranets," *Web Semantics: Science, Services and Agents on the World Wide Web*, vol. 5, pp. 72-105, 6// 2007.
- [18] S. He, S. Liu, Y. Chen, G. Zhou, K. Liu, and J. Zhao, "CASIA@ QALD-3: A Question Answering System over Linked Data," in *CLEF (Working Notes)*, 2013.
- [19] M. Mishra, V. K. Mishra, and H. Sharma, "Question classification using semantic, syntactic and lexical features," *International Journal of Web & Semantic Technology*, vol. 4, p. 39, 2013.
- [20] A. Mishra and S. K. Jain, "A survey on question answering systems with classification," *Journal of King Saud University - Computer and Information Sciences*, vol. 28, pp. 345-361, 2016/07/01/ 2016.
- [21] Z. Yu, L. Su, L. Li, Q. Zhao, C. Mao, and J. Guo, "Question classification based on co-training style semi-supervised learning," *Pattern Recognition Letters*, vol. 31, pp. 1975-1980, 2010/10/01/ 2010.
- [22] M. Razzaghoori, H. Sajedi, and I. K. Jazani, "Question classification in Persian using word vectors and frequencies," *Cognitive Systems Research*, vol. 47, pp. 16-27, 2018/01/01/ 2018.
- [23] D. Zhang and W. S. Lee, "Question classification using support vector machines," presented at the Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval, Toronto, Canada, 2003.
- [24] A. Mohasseb, M. Bader-El-Den, and M. Cosea, "Question categorization and classification using grammar based approach," *Information Processing & Management*, 2018/05/29/ 2018.
- [25] W. Xia, W. Zhu, B. Liao, M. Chen, L. Cai, and L. Huang, "Novel architecture for long short-term memory used in question classification," *Neurocomputing*, vol. 299, pp. 20-31, 2018/07/19/ 2018.
- [26] J.-D. Kim and K. B. Cohen, "Natural language query processing for SPARQL generation: A prototype system for SNOMED CT," 2013.
- [27] C. Pradel, O. Haemmerlé, and N. Hernandez, "Swip: A Natural Language to SPARQL Interface Implemented with SPARQL," in *Graph-Based Representation and Reasoning: 21st International Conference on Conceptual Structures, ICCS 2014, Iaşi, Romania, July 27-30, 2014, Proceedings*, N. Hernandez, R. Jäschke, and M. Croitoru, Eds., ed Cham: Springer International Publishing, 2014, pp. 260-274.
- [28] E. Cabrio, J. Cojan, A. P. Aprosio, B. Magnini, A. Lavelli, and F. Gandon, "QAKiS: an open domain QA system based on relational patterns," presented at the Proceedings of the 2012th International Conference on Posters & Demonstrations Track - Volume 914, Boston, USA, 2012.
- [29] A. Tahri and O. Tibermacine, "DBPEDIA BASED FACTOID QUESTION ANSWERING SYSTEM," *International Journal of Web & Semantic Technology*, vol. 4, p. 23, 2013.
- [30] K. Sengloiluean, N. Arch-int, S. Arch-int, and T. Thongkrau, "A semantic approach for question answering using DBpedia and WordNet," in *2017 14th International Joint*

Conference on Computer Science and Software Engineering (JCSSE), 2017, pp. 1-6.

- [31] A. Ittycheriah and S. Roukos, "IBM's statistical question answering system-TREC-11," IBM THOMAS J WATSON RESEARCH CENTER YORKTOWN HEIGHTS NY2006.
- [32] H. T. Dang, D. Kelly, and J. J. Lin, "Overview of the TREC 2007 Question Answering Track," in *Trec*, 2007, p. 63.
- [33] E. M. Voorhees, "Question answering in TREC," presented at the Proceedings of the tenth international conference on Information and knowledge management, Atlanta, Georgia, USA, 2001.