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A survey on question answering systems with classification

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Abstract Question answering systems (QASs) generate answers of questions asked in natural languages. Early QASs were developed for restricted domains and have limited capabilities. Current QASs focus on types of questions generally asked by users, characteristics of data sources consulted, and forms of correct answers generated. Research in the area of QASs began in 1960s and since then, a large number of QASs have been developed. To identify the future scope of research in this area, the need of a comprehensive survey on QASs arises naturally. This paper surveys QASs and classifies them based on different criteria. We identify the current status of the research in the each category of QASs, and suggest future scope of the research.

Contents

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1. Introduction

Search engines present a ranked list of relevant documents in response to users' formulated keywords based on various aspects such as popularity measures, keyword matching, frequencies of accessing documents, etc. However, they do not truly accomplish the task of information retrieval as users have to examine each document one by one for getting the desired information (Ferret et al., 2001); it makes information retrieval a time consuming process. Ideally, a search engine should return few relevant and concise sentences as answers along with their corresponding web links. A large number of QASs have been developed since 1960's (Androutsopoulos et al., 1995; Kolomiyets, 2011). Current QASs attempt to answer questions asked by users in natural languages after retrieving and processing information from different data sources even like semantic web (Vanessa, 2011; Dwivedi, 2013; Suresh kumar and Zayaraz, 2014). The format of answers is also going to be changed from simple text to multimedia (Voorhees and Weishedel, 2000). QASs developed since 1960s address different domains, data sources, types of questions, formats of answers, etc.; the number of such QASs is too large. To assess the success of these QASs and their ability to satisfy current and future needs, a systematic survey of all these QASs becomes necessary.

In this paper, we classify QASs based on explicitly identified criteria like application domains, questions, data sources, matching functions, and answers. We make a survey of the literature on QASs classified on each criterion and identify future scope of research in this area.

The rest of of this paper is organized as follows: section 2 presents related work on QASs beginning from early days of research in the form Natural Language Interface to Databases (NLIDB) to open domain QASs over text. Section 3 presents criteria identified for classification of QASs. Section 4 deals with classification of QASs based on different criteria. Section 5 makes a comparison of the proposed classification with others. In section 6, we draw conclusions.

2. Related work

In this section, we present a background on development of QASs since 1960's to the present time. The plan of developing systems that can deal with natural language questions began in the fifth generation of computer programing language (Hill I 1982). NLIDB is a system that provides facility to users for asking questions in their natural languages for getting information from databases (Androutsopoulos et al., 1995). It eases human computer interaction as users need not to learn formal languages such as SQL, Prolog, Lisp, etc. for submitting inputs. Green et al. (1961) propose BASEBALL, a QAS that provides information associated with a baseball league played in America during a particular season. This system provides answers to questions related to dates, location, etc. Woods (1973) propose LUNAR, a QAS that provides information about soil samples taken from Apollo lunar exploration. These systems transform users' questions into database queries through plain pattern matching rules and finally generates answers. These plain patterns matching rules utilize limited grammars, hard wired knowledge, and mapping rules which depend upon application domains. As a natural language supports paraphrasing, processing natural language questions through pattern matching is not a feasible solution. Both BASEBALL and LUNAR systems produce good results, but they have a limited repository of information related to their application domains.

In subsequent developments, QASs aimed on making linguistic analysis of the questions to capture the intended requirements in a natural way. One such system, MASQUE (Androutsopoulos et al., 1993) represents natural language questions in a logic representation, and then it translates the logic query into a database query for retrieving intended information from database (Androutsopoulos et al., 1995; Lopeza and Uren, 2011). It separates the task of linguistic process from mapping process. FAQFinder (Burke et al., 1997) does matching of the questions with the question list compiled in a knowledge base through statistical similarity and semantic similarity. A QAS PRECISE [Pa2002] does natural language processing of the questions; it identifies the class of questions (wh ques) and maps wh questions to their related database queries. The questions are a set of attributes or value pairs; each attribute is linked with wh-value. Another QAS, QUARC developed by Riloff and Thelen (2000) classifies questions into different wh-types and derives their expected answer types through the use of lexical and semantic clues. The problem of paraphrasing has not been solved so far. Later, the focus of developing QASs was shifted toward open domain QASs.

The research in open domain question answering from unstructured data sources was instantiated by the TREC Evaluation campaign which is taking place regularly every year since 1999 (Voorhees, 2001, 2004; Voorhees and Weishedel, 2000). The first TREC evaluation campaign provides a list of 200 questions and a document collection. The answers were known to be present in the collections. The maximum lengths of answers were allowed to be 50 or 250 characters. Systems were asked to give 5 ranked lists of answers. In the next campaign, TREC-9 held in 2000, the number of questions and size of document collections were increased. In TREC-10 in 2001, a new complexity with respect to answers, i.e., answer validation task was included as there was no assurance of all answers to be present in the document collections. The lengths of answers were reduced to 50 words. In TREC-11, held in 2002, systems were expected to give exact short answers to the questions. In TREC from 2002 to 2007, the list of questions, definition questions, and factoid questions were included in the evaluation campaigns. In TREC 2005, there was a set of 75 topics which contains various types of questions (list, factoid or others). Temporal questions were added to TREC 2005 and TREC 2006. In TREC 2007, document collections included blog collections. In a nutshell, TREC competitions progress with increasing size and complexity of document collections; increasing complexity of questions; and increasing complexity of answer evaluation strategies.

The TREC campaign provides the local data set as source of information for generating answers, but with the rise of World Wide Web, there are large collections of data on the web which may provide useful information to the users. Such a large collection can be utilized as a knowledge base for answering users' questions (Soricut and Brill, 2006). Several web based QASs have been developed (Li and Roth, 2002; Vanitha et al., 2010); these web based QASs can be categorized into Open domain QAS and closed domain QAS (Vanessa, 2011). Few examples open domain QASs are (1) Webclopedia (Hovy et al., 2000), (2) Mulder (Kwok et al., 2001), and (3) Answerbus (Zheng, 2002). The examples of restricted domain QASs are (1) Start (Katz et al., 2002), (2) Naluri (Wong, 2004), and (3) Webcoop (Benamara, 2004). Most of the questions addressed by these QASs are factoid questions. Different types of QASs use different techniques such as snippet tolerant property, keyword matching, and rules for making matching of the answers through WordNet (Miller, 1995; Carbonell et al., 2000). The responses generated by these systems are generally in the form of text, xml or Wikipedia documents (Vanessa, 2011). The QASs START (Katz et al., 2002), QAS (Chung et al., 2004) and QAS (Mishra et al., 2010) keep significant information borrowed from web on their local datasets and use it as source of generating answers for questions using linguistic techniques and rule based techniques.

Besides web and local data sets used in the literature, research in QASs is considering semantic web as a data source. Unger et al. (2012) use a template based pattern matching approach on Resource Description Framework (RDF) data by using SPARQL (Prudhommeaux and Seaborne, 2007). The author claims that the technique can be applied to semantic web.

3. Criteria for classifying question answering systems

Fig. 1 exhibits a generalized architecture of QASs. Based on the literature surveyed, we identify eight criteria in support of classifying available large number of QASs. These criteria are (1) application domains for which QASs are developed, (2) types of questions asked by the users, (3) types of analyses performed on users' questions and source documents, (4) types of data consulted in data sources, (5) characteristics of data sources, (6) types of representations used for questions and their matching functions, (7) types of techniques used for retrieving answers, and (8) forms of answers generated by QASs. Table 1 explains a brief description of each criterion, classification of QASs based on the criterion, and few examples of QASs in each class.

4. A classification of question answering systems

In this section, we discuss details of the proposed classification of QASs. We give a description of the classification; discuss pros and cons of QASs in each class along with their related research issues.

4.1. Classification based on application domain

The task of generating answers of questions is related to the type of questions asked (Moldovan et al., 2000; Voorhees and Weishedel, 2000). Some users may require general

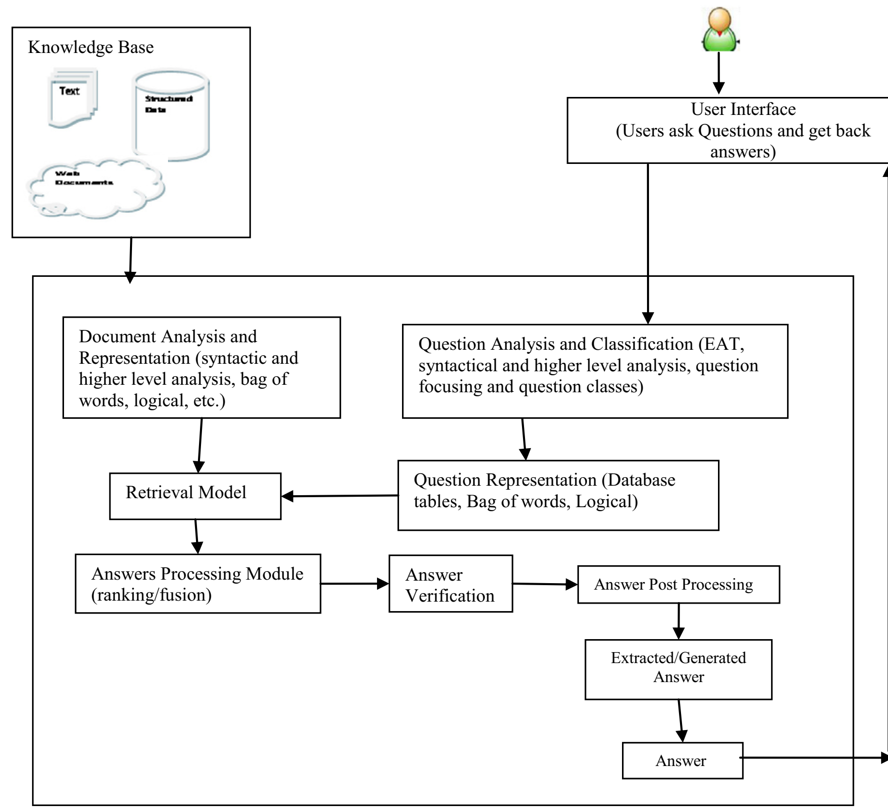

Figure 1 A generalized architecture of QASs.

information on a general topic; others may require specific information from a particular application domain. Therefore, selection of the domain as a basis of classification of QASs may be a natural choice.

4.1.1. General domain QASs

In general domain QASs, the QASs answer domain independent questions. QASs generally search for answers within a large document collection. There is a large repository of questions that can be asked in general domain QASs. QASs exploit general ontology and world knowledge in their methodologies for generating answers (Kan and Lam, 2006). Here, the quality of answers delivered by QASs is not high, and generally, questions are asked by casual users (Indurkhya and Damereau, 2010).

The pros of general domain QASs are as follows:

- There are a large number of casual users; general domain QASs are more suitable for them.
- General domain QASs do not require domain specific dictionary; they use a general dictionary.
- Users don't need to acquire knowledge of domain specific keywords for formulating questions.
- There is a large repository of questions that can be asked in general domain QASs.
- Wikipedia or news wire text can be utilized as a source of information for such QASs

The cons of general domain QASs are as follows:

- The quality of answers is low. The answers satisfaction depend upon the users.
- Domain experts require specialized information in answers, hence restricted domain QASs may be more suitable more them.

4.1.2. Restricted domain QASs

Restricted domain QASs answer domain specific questions (Molla and Vicedo, 2007). Answers are searched within domain specific document collections. The repository of question patterns is very limited; hence the systems can achieve good accuracy in answering questions. QASs exploit domain specific ontology and terminology. The quality of answers is expected to be higher. There are various restricted domain QASs developed in the literature such as: temporal domain QAS, geospatial domain QAS, medical domain QAS, patent QAS, community based QAS, etc. Different restricted domain QASs can be integrated to make General domain QASs (Vanessa, 2011; Indurkhya and Damereau, 2010). Such QASs require assigning the given question to an appropriate domain specific QAS based on the knowledge derived from keywords of the question. The state of the art faces problems in handing and forwarding the given questions to a particular restricted domain QAS as systems suffer question classification problems, ambiguity resolution problems, etc. (Indurkhya and Damereau, 2010).

The pros of restricted domain QASs are as follows:

- Restricted domain QASs suite to domain expert users as they need specialized answers.
- The quality of answers generated by restricted domain *QASs* is high; the level of satisfaction of the users depends on their domain knowledge.

Table 1 A classification of QASs.

Sr No.	Criteria	Explanations	Classifications	Examples
1	Application domains	Questions asked by users are related to restricted application domain or open domain. Repository of questions is limited in restricted domain unlike open domain questions. Different techniques are required to answer restricted domain questions which rely on domain specific ontology and terminology unlike open domain questions which rely on general ontology and world knowledge to get final answer. Hence, this classifies questions on the basis of their association with application domain	Restricted domain QAS	Start Katz et al. (2002), Naluri Wong (2004), Webcoop Benamara (2004)
			Open domain QAS	Webclopedia Hovy et al. (2000), Answerbus Zheng (2002), Mulder Kwok et al. (2001),
2	Types of questions asked by users	The expected answers depend upon the types of the questions asked by the users. Systems dealing with different types of questions require different strategies to locate answers. Hence, this classifies questions on the basis of types of question asked by user – factoid (what, who, when, which, how-quantity, quality), confirmation (is, will etc.), hypothetical (what would happen), causal (how or why)	Factoid questions	Webclopedia Hovy et al. (2000), Naluri Wong (2004), Start Katz et al. (2002), Answerbus Zheng (2002), Webcoop Benamara (2004), Mulder Kwok et al. (2001)
			List questions	Naluri Wong (2004), Start Katz et al. (2002), Webcoop Benamara (2004)
			Hypothetical questions	
			Confirmation questions	Webclopedia Hovy et al. (2000), Webcoop Benamara (2004)
			Causal questions	Webclopedia Hovy et al. (2000), Naluri Wong (2004), Answerbus Zheng (2002), Webcoop Benamara (2004), Mulder Kwok et al. (2001)
3	Types of analysis done on users' questions and source documents	Different types of analysis techniques are required to process users' questions so as to identify their requirements. Systems analyze such requirements before finding relevant answers. Source text documents are also processed and analyzed with these techniques. These approaches broadly fall into two category: statistical based approach, Rule based pattern matching approach, and hybrid approach	Morphological analysis	Webclopedia Hovy et al. (2000), Naluri Wong (2004), Start Katz et al. (2002), Answerbus Zheng (2002), Webcoop Benamara (2004), Mulder Kwok et al. (2001)
			Syntactical analysis	Webclopedia Hovy et al. (2000), Answerbus Zheng (2002), Webcoop Benamara (2004), Mulder Kwok et al. (2001)
			Semantic analysis	Naluri Wong (2004), Start Katz et al. (2002), Webcoop Benamara (2004)
			Pragmatic and discourse analysis	Naluri Wong (2004), Start Katz et al. (2002), Webcoop (Benamara (2004)
			Expected answer Type analysis	Webclopedia Hovy et al. (2000), Naluri Wong (2004), Start Katz et al. (2002), Webcoop Benamara (2004), Mulder Kwok et al. (2001)
			Focus recognition of questions	Webclopedia Hovy et al. (2000), Naluri Wong (2004), Start Katz et al. (2002), Webcoop Benamara (2004), Mulder Kwok et al. (2001)
4	Type of data consulted in data source	Large collections of the text exists in structural data source (database) and unstructured data source (report, book, article) or semi-structured data source (XML). The different types of data sources have different types of representations. Hence, this is classified on the basis of types of data source	Structured data source in QAS.	
			Semi-structured data source in QAS	Naluri Wong (2004), Start Katz et al. (2002), Webcoop Benamara (2004)
			Un-structured data source in QAS	Webclopedia Hovy et al. (2000), Answerbus Zheng (2002), Mulder Kwok et al. (2001)
			Semantic web	

(*continued on next page*)

Table 1 (*continued*)

Sr No.	Criteria	Explanations	Classifications	Examples
5	Characteristics of data source	Data sources are characterized by their source size, their language, types of data stored etc. Large scale documents are processed (analysis, representation) in different ways as compared to small scale documents. Moreover, the language used (formal or informal) also complicates the task of searching of answers. Hence, this classifies various characteristics of data source	Source size Language	Webclopedia Hovy et al. (2000), Naluri Wong (2004), Start Katz et al. (2002), Answerbus Zheng (2002), Webcoop Benamara (2004), Mulder Kwok et al. (2001)
6	Types of representation of question data and its matching function to generate candidate answers	Users' Questions and documents are expressed in natural language. They have to be transformed into machine readable form so that it can be processed further by QASs. There are different models for representation and retrieval i.e., set theoretic models treat documents as sets of words or phrases, algebraic model represents source documents and questions as vectors, matrixes, or tuples, probability model treat documents and questions in terms of probability relevance, feature based model views documents as vector of values of feature functions and combines these features into single relevance score	Set theoretic models Algebraic model Probability models Feature based models	Start Katz et al. (2002), Naluri Wong (2004), Webcoop Benamara (2004), Webclopedia Hovy et al. (2000), Answerbus Zheng (2002), Mulder Kwok et al. (2001)
7	Type of techniques used for retrieving answers	The suitability of different techniques for retrieving answers depends upon context of their usage. The context refers to complexity of questions, data sources, and answers desired by users. This classifies QASs based on techniques used for retrieving answers QASs using data mining techniques search for factual data, and generate short answers using bag of word model from data base. The QASs using information retrieval techniques search for factual information in text documents. QASs based on natural language processing techniques search for information that can be subjective or objective. QASs based on Knowledge retrieval search for understanding and creating knowledge	Data mining techniques Information retrieval techniques Natural language understanding techniques Knowledge retrieval and discovery techniques	Start Katz et al. (2002), Naluri Wong (2004), Webcoop Benamara (2004), Webclopedia Hovy et al. (2000), Answerbus Zheng (2002), Mulder Kwok et al. (2001)
8	The forms of answer generated by QAS	Answers are presented to the users in various forms that can be extracted as text snippet taken from source documents or generated answers. The form of answers generally depends upon users' question. Generally, the factoid or list questions have answers in the form of sentences. Causal, hypothetical questions have answers in the form of passages. Confirmation questions have generated answers in the form of either yes or No. some Opinionated questions have answers in the form of ratings. Dialog questions have short dialog answers.	Extracted text Snippets or other multimedia in QAS Generated answer in QAS.	Webclopedia Hovy et al. (2000), Answerbus Zheng (2002), Mulder Kwok et al. (2001) Naluri Wong (2004), Start Katz et al. (2002), Webcoop Benamara (2004)

The cons of restricted domain QASs are as follows:

- There is a limited repository of domain specific questions; such QASs can answer a limited number of questions.

4.2. Classification based on types of questions

The task of generating answers to the users' questions is directly related to type of questions asked (Moldovan et al., 2003). Hence, the classification of the questions performed in QASs directly affects the answers. Results show that 36.4% of errors happen due to miss-classification of questions performed in QASs (Moldovan et al., 2003). Li and Roth (2002) classify questions into a fine grained content based categorization but they deal with a very limited class of real world questions. Fan et al. (2010) perform function oriented classification of questions by integrating pattern matching and machine learning techniques. Benamara (2004) classify questions by taking account of their expected types of responses. We classify QASs based on types of questions asked by users. The different categories are (1) factoid type questions, (2) list type questions, (3) hypothetical type questions, (4) confirmation questions, (5) causal questions.

We explain a brief description of each category of classification in the following subsections.

4.2.1. Factoid type questions [what, when, which, who, how]

These questions are simple and fact based that require answers in a single short phrase or sentence (Indurkhya and Damereau, 2010), e.g. who is producer of the movie XYZ? The factoid type questions generally start with wh-word. Current QASs have got a satisfactory performance in answering factoid type questions (Kolomiyets, 2011; Vanessa, 2011; Indurkhya and Damereau, 2010; Dwivedi, 2013; Suresh kumar and Zayaraz, 2014).

The pros of factoid type questions asked in QASs are as follows:

- The expected answer types for most factoid type questions are generally named entities which could be traced in documents through named entity tagging softwares (Kolomiyets, 2011; Vanessa, 2011). They depend upon wh-category of questions. Hence, good accuracy can be achieved.
- Current QASs have got a satisfactory performance in answering factoid type questions.
- There is a large repository of questions wh- factoid type questions asked in QASs.
- QASs do not need to deploy complex natural language processing to extract answers.
- Wikipedia or news wire text can be utilized as a source of information for such QASs (ARNAUD, 2010).

The cons of factoid type questions asked in QASs are as follows:

- Identification of factoid type questions and their further sub classification automatically is itself a research issue in QASs.
- Descriptive type questions: the questions which require finding the definition or description of the term [event or entity] in the question (Cui et al., 2007; Vanessa, 2011). They normally start with 'what is'. Descriptive type's questions have diffused expected answer types that can be any event or entity.
- Fuzzy questions: questions which cannot represent information need of users correctly are termed as fuzzy questions. These questions generally have fuzzy terms and evaluative adjectives generally e.g., find set of all tall guys in town?
- Relationship or information extraction (IE): it identifies the relationship among named entities. For example, XYZ is working in ABC. Here 'XYZ' is employee and 'ABC' is company. Similarly, IE is concerned with drawing out semantic information from the text. It covers named entity recognition, co-reference resolution, relationship extraction etc.
- Dialog questions: these questions are generally incomplete and syntactically incorrect questions which make systems difficult to identify requirement of users in answers.
- Badly worded questions or ambiguous questions: these questions are either misspelled or ambiguous questions. They are difficult to get processed to generate correct answers. Such as what makes him cooooool?

4.2.2. List type questions

The list questions require a list of entities or facts in answers e.g., – list name of employees getting salary more than 5 k? QASs consider such questions as a series of factoid questions which are asked ten times one after the other. The previous answers are ignored while firing next questions by QASs. QASs generally observe a problem in fixing the threshold value for the number or quantity of the entity asked in list type questions (Indurkhya and Damereau, 2010).

The pros of list type questions asked in QASs are as follows:

- The expected answer types are named entities for the list type questions. Hence, good accuracy can be achieved.
- The techniques applied successfully to factoid types questions can work well for dealing with list type questions.
- QASs do not require deep natural language processing to extract answers of list types questions.

The cons of list type questions asked in QASs are as follows:

- QASs observe a problem in fixing the threshold value for the number or quantity of the entity asked in list type questions.

4.2.3. Hypothetical type questions

Hypothetical questions ask for information related to any hypothetical event. They generally begin with 'what would happen if' (Kolomiyets, 2011). QASs require knowledge retrieval techniques for generating answers. Moreover, the answers are subjective to these questions. There are no specific correct answers of these questions.

The pros of hypothetical type questions asked in QASs are as follows:

- Some expert users may like to search for optimal answers for hypothetical questions which require world knowledge and common sense reasoning.

The cons of hypothetical type questions asked in QASs are as follows:

- The expected answer type is diffused for hypothetical type questions asked in QASs. Hence, accuracy of QASs is low.
- The techniques applied successfully to factoid types questions don't work for dealing with hypothetical type questions.
- The reliability is low and depends upon users and context.

4.2.4. Causal questions [how or why]

Causal questions require explanations about an entity. The answers are not named entities as observed in the case of factoid type questions. QASs require advance natural language processing techniques to analyze the text at pragmatic and discourse level for generating answers (Higashinaka and Isozaki, 2008; Verberne et al., 2007, 2008, 2010; Moldovan et al., 2000).

The pros of Causal type questions asked in QASs are as follows:

- Such questions are asked by users who want explanations, reasons, elaborations etc in answers related to specific events or objects.

The cons of Causal type questions asked in QASs are as follows:

- Problems in determining relevant or unique answers- questions such as why require reason, elaboration, explanation etc as answers. Answers to why questions are subjective generally that can range from a sentence to a paragraph to a whole document. A same question can have different answers based on interpretation e.g., why X took a lecture in class 2? It has got three interpretations according to different users given below
  Why X?
  Why took lecture?
  Why in class2?
  Hence, retrieving of a answer is based on the intention of the users. It is a challenging task.
- Problems related to efficient retrieval models in why QAS-most of the current retrieval models is based on bag of words model (Verberne et al., 2007, 2008, 2010). This model has problems in the retrieval process due to polysemy, homonymy and synonymy. Hence, they cause retrieval problems in QASs. Moreover, why type questions have subjective answers which can extend from sentences to paragraphs. The identification of discourse relationship in source documents is required to generate answers for such questions.

4.2.5. Confirmation questions

Confirmation questions require answers in the form of yes or No. Systems require inference mechanism, world knowledge and common sense reasoning to generate answers.

The pros of confirmation type questions asked in QASs are as follows:

- Some expert users may like to search for information which requires world knowledge and common sense reasoning for getting new knowledge.

The cons of confirmation type questions asked in QASs are as follows:

- Such questions require a higher level of knowledge acquisition and retrieval techniques which are still under the developmental phase.

Apart from the above classification of questions, there can be opinion questions asked in QASs (Missen and Cabanac, 2010; Missen, 2009). These are the Questions which require subjective information about an entity or event. QASs use the social web to answer such questions. QASs use opinion mining techniques to generate answers to the questions.

One of the prominent opinion mining systems, SenticNet detects sentiment polarity of a single sentence by using machine-learning and knowledge-based techniques (Poria et al., 2012, 2013, 2014). The SenticNet captures the conceptual and affective information in the sentence by using the bag-of- concepts model. The system assumes that input text is opinionated. It does not deal with multiple sentences.

The pros of opinion questions asked in QASs are as follows:

With the emergence of Web 2.0, there are massive users' generated data on the web such as social networking sites, blogs, and review sites etc (Khan, 2014). These opinionated data sources contain public opinions which can help the users in making judgment about the products.

The cons of opinion questions asked in QASs are as follows:

- Informal questions- the questions put up by common users are generally informal questions. Systems find difficulty in processing questions as questions are difficult to parse and moreover, they are semantically poor.
- Opinion detection- to classify text as subjective or objective is still a research problem (Khan, 2014). Moreover, finding the relevant opinionated documents is difficult.
- Sentence boundaries are not defined. Users' comments and questions are difficult to be processed by QASs as questions are informal and they generally don't follow any grammatical punctuation.
- Detection of fake or spam content in text- systems face a problem in detecting fake or spam content which causes hurdle in truly opinion mining of the text.

4.3. Classification based on types of analysis done on questions

We classify QASs based on types of analysis done on questions by QASs. The different categories are: (1) morphological analysis, (2) syntactical analysis, (3) semantic analysis, (4) pragmatic and discourse analysis, (5) expected answer type analysis, and (6) focus recognition of questions.

4.3.1. Morphological analysis

This type of analysis aims at separating words into individual morphemes and assigning a class to the morpheme e.g., plays, plays, played is assigned to 'play' class. The stemming and lemmatization of words are performed for making morphological analysis of the text.

The pros of morphological analysis are as follows:

- Such analysis is required for effective searching as it takes account of different forms of words. Hence, redundancy is removed at word level during information retrieval process.

The cons of morphological analysis are as follows:

- Sometimes, performing stemming of the words yield incorrect results in searching, e.g., computer, compute, computation will lead to the same stemmed word 'compute'. But these words are semantically different. Hence, sometimes searching after the stemming of words could yield incorrect results.

4.3.2. Syntactical analysis

This type of analysis identifies grammatical construction of words in questions and source documents. Usually, a sentence consists of content bearing keywords (noun, verbs, adjectives or adverbs) which are connected with function words (determiner or prepositions). In this type of analysis, QASs generate parse trees after processing questions and documents. QASs attempt to reduce the search space in documents hence helps in effective searching. For example, which play did xyz work? QASs will search for 'play' word which behaves as a noun not a verb.

The pros of syntactical analysis done in QASs are as follows:

- Such analysis is required for effective searching as it takes account of words different parts of speech; hence redundancy is removed at the word level during the information retrieval process.

The cons of syntactical analysis done in QASs are as follows:

- There can be syntactical ambiguity when analyzing questions e.g., List the name of staff working in XYZ corporation having a driving license. Here, there is a syntactical ambiguity observed by systems as systems link License with XYZ company not with staff; this is not true in the real interpretation of the question.

4.3.3. Semantic analysis

This analysis deduces the possible meaning of questions based on the words used in the questions. It generally analyzes the parse tree generated in syntactical analysis phase and interprets the possible meaning of the question based on the tree. Current QASs operate at lexical and sentence level for deducing the meaning of questions (Kolomiyets, 2011; Alexander Clark, 2010; Saeedeh Momtazi, 2011; Suresh kumar and Zayaraz, 2014).

One of the semantic analysis tasks is Semantic role labeling in text. The Semantic role labeling [shallow semantic parsing] aims at identification and labeling of arguments in the text (Daniel and Daniel, 2000). Such techniques are useful in making semantic analysis of the questions.

The pros of semantic analysis done in QASs are as follows:

- Semantic analysis solves problems of finding semantic class of questions and answer types.
- Semantic analysis based searching provides effective searching for answers in contrast with keyword based searching.

The cons of semantic analysis done in QASs are as follows:

- Current QASs operate at lexical and sentence level for deducing the meaning of the text. To the best of our knowledge, we don't find any work which does semantic analysis at document level.
- The problems observed in co-reference resolution, name entity recognition, relation extraction, parts of speech tagging etc. makes the task of performing the semantic analysis of text difficult.

4.3.4. Pragmatic and discourse analysis

In this analysis, the questions and documents are interpreted at sentence or higher level. Syntactical analysis is a function of one argument i.e. sentence, whereas, pragmatic interpretation is a function of utterance and context with which the sentence is expressed. e.g., I need a mobile with a good camera and nice sound quality. I found nokia in the market. Why should I buy it? Here 'it' refers to nokia which is a mobile.

Discourse analysis – a discourse is generally a string of language that is more than one sentence long. In this type of analysis, systems identify the discourse structure of the connected text i.e. types of discourse relationship existing in between sentences (elaboration, explanation, contrast)in text (Verberne et al., 2010; Mishra and Jain, 2014, 2015).

Such type of analysis is generally required when searching for long answers to complex questions like why and how.

It does the following tasks:

- Anaphora resolution – replacements of words like pronouns which are semantically blank with proper nouns in text.
- Discourse structure recognition – it identifies the logical connectivity of sentences within the text. e.g., newspaper article can be fragmented into headings, main story, previous events, evaluation etc. This type of analysis is generally required in the case of opinionated, causal, hypothetical and yes–no questions.

The pros of pragmatic and discourse analysis done in QASs are as follows:

- Such analysis is required for finding answers to complex questions like why or opinion questions. The relations like elaboration, explanation; contrast etc. existing in between sentences can help QASs in tracing answers.
- Such analysis is helpful in deducing the meaning of the text.

The cons of pragmatic and discourse analysis done in QASs are as follows:

- Current technology uses inter sentential and intra sentential discourse structure of sentences. Hence, the technology is still far from ideal discourse analysis of text (Ziheng et al., 2014).
- The problems observed in co reference resolution, name entity recognition, relation extraction, parts of speech tagging etc. makes the task of discourse analysis much tougher.

4.3.5. Expected answer type analysis

QASs determine the entity (answer type) which is required in answers based on the category of questions e.g., who is author of book XY? Here, the expected answer type is person. Hence, expected answer type analysis helps in generating answers to factoid type questions and list type questions. As we discussed, there are some sets of questions like 'why', 'how' which have no unique answer types. Hence this type of analysis does not help QASs directly for such questions.

4.3.6. Focus recognition of questions

Identification of focus in the questions is important in deriving correct answers. e.g. in a question like 'if I need mobile with good camera and nice sound quality. I found nokia in market. Why should I buy Nokia?' here, the focus of the question is 'need mobile, nice sound quality, buy nokia, good camera'. Hence recognition of the focus in the question is significant in deriving correct answers.

Different types of questions require different processing techniques for focus recognition. There are various aspects while analyzing the natural language questions such as target extraction, pattern extraction and parsing (Saeedeh Momtazi, 2011).

Classification based on approaches used for analysis of questions and source documents. The performance of a QAS is dependent on well formalized users' questions. A natural language like English is full of ambiguities (Indurkhya and Damereau, 2010). Hence, systems have an extra burden to make a proper logical representation of natural language questions.

Based on the literature review (Manning and Schütze, 1999; Frederik, 2010; Dwivedi, 2013), there are broadly three approaches for making analysis of natural language questions and source documents. These are: Statistical based approach, Rule based pattern matching approach and hybrid approach.

Statistical based approach: these are a data driven approach. They use quantitative relations to discover statistical relations existing in questions and documents (Suresh kumar and Zayaraz, 2014). They include probabilistic modeling, linear algebra and information theory etc.

Statistical query are generally keywords derived from questions, hence they are not artificial query languages. Statistical based approaches require large data for correct statistical learning. Upon learning, they could produce promising results.

Pros of statistical approaches in QASs.

- No expert knowledge is required.
- Natural language problems like leaking grammar, paraphrasing are ignored.
- Large amounts of data containing answers could be dealt with easily.
- Deal with complex questions more effectively.
- Could deal with heterogeneous data sources.

Cons of statistical approaches in QASs.

- Require a large amount of data for training purpose.
- Do not take account of semantics and context of words and sentences.

Rule based pattern matching approach. Pattern-based approaches make combined use of linguistic rules and human knowledge in information retrieval processes. In this approach, predefined patterns are built for questions and answers. Extraction of answers is performed on the basis of matching of predefined patterns. These patterns could be lexico-syntactic or lexico-semantic patterns (Ravichandran and Hovy, 2002; Zheng, 2002).

Pros of pattern based approaches in QASs.

- Less training data are required. No expert knowledge is required.
- Large amounts of data containing answers could be dealt with easily.
- Does not influenced by types of query language.
- Deal with complex questions more effectively.

Cons of pattern based approaches in QASs.

- Expert or domain knowledge is required.
- Building patterns is a cumbersome and non-trivial task.
- Natural language does not follow a definite pattern, hence developing the correct pattern is difficult.

Hybrid approaches: statistical based approach and pattern based approaches are good in their respective domains. The pattern based approach needs bootstrapping or initial clustering which is done through the use of statistical methods. Statistical based approaches require a large amount of data for correct learning. Some researchers use hybrid approaches in QASs. Kwok et al. develop MULDER, a QAS (Kwok et al., 2001) which consults the web as a source of information. The system makes use of linguistic and statistical techniques for generating answers. Chakrabarti et al. develop a QAS (Chakrabarti et al., 2004) which makes use of a linguistic and pattern based approach for answer finding.

Pros of hybrid approaches in QASs.

- The limitations observed in statistical based approaches and pattern based approaches could be minimized through hybrid approaches.

Cons of hybrid approaches in QASs.

- More data are required as compared to rule based approaches.

4.4. Classification based on types of data sources

We classify QASs based on types of data present in the source text. The different categories are: (1) structured data source, (2) semi-structured data source, and (3) unstructured.

4.4.1. Structured data source

In structured documents, data are structured in the semantic set (entities). Similar entities are collected in the relations.

Entities in same relation have the same attributes. Description of all entities in a unit is called schema. The arrangement of data has got a defined format. The matching of query with structured data source is exact. The corresponding query language is artificial.

The pros of structured data source in QASs are as follows:

- The reliability of answers is higher as correct information is stored in the data source.
- QASs do not require complex natural language processing of these data sources.

Based on the literature reviewed, cons of structured data source in QASs are as follows:

- There can be a limited information stored on a structured data source
- There can be reference reconciliation in data sources.
- The data source is labor intensive to build.
- Different structured data sources like MySql, SQLite, DB2 etc follow different representations and accept different query languages, hence the systems have to transform questions into queries depending upon the type of data sources.

4.4.2. Semi-structured data source

In the semi-structured data source, there is no such partition in between stored data and the schema.

The pros of semi-structured data source in QASs are as follows:

- Representation of information in data sources that is constrained by schema.
- It provides a flexible format for making data exchanges in between different types of databases.
- It transforms structured data into semi-structured (for web browsing purposes) format.

Cons

- There can be reference reconciliation in these data sources.
- The data source is labor intensive to build.

4.4.3. Un-structured data source

Data can be of any type. Data are not structured in any semantic set. There are no strict rules for arrangement of data in this data source. QAS dealing with un-structured documents requires the use of natural language processing and IR technologies to find answers.

The pros of un-structured data sources in QASs are as follows:

- Information can be easily added or updated.

The cons of un-structured data source in QASs are as follows:

- Representation of unstructured data sources is a big problem here.
- The reliability of answers is low here.
- Paraphrasing is prominent here.

4.5. Classification based on types of matching functions used in different retrieval models

We classify QASs based on types of matching functions used in different retrieval models. The different categories are: (1) set theoretic models, (2) algebraic models, (3) probability models, (4) feature based models, (5) expected answer type analysis, and (6) conceptual graph based models.

4.5.1. Set theoretic models

Set theoretic models treat documents as sets of words or phrases. Matching is performed on the basis of operation carried out in between sets. Some of the set theoretic models are dealt in the following subsections.

4.5.1.1. Standard Boolean model. The pros of the Boolean model in QASs are as follows:

- Easy implementation: As Boolean operator is used in making a query, hence the keyword matching is easy to implement.

The cons of Boolean model in QASs are as follows:

- Partial matching of query with document is not done here i.e., Systems face inability to rank the output if there is a little matching in between document words and keywords of questions.
- Users have to formulate Boolean expression in their questions which could be difficult for most users.
- The Boolean model generally provides either too few or too many documents which is not desirable.

4.5.2. Algebraic models

This model represents source documents and users' questions as vectors, matrixes, or tuples. The matching is performed as a scalar value.

- Vector space.
- Generalized vector space model.
- Topic based vector space model.
- Latent semantic indexing.
- Extended Boolean model.

4.5.3. Probability models

Probability model treats documents and questions in terms of probability relevance.

- Binary independence model.
- Probabilistic relevance model.
- Uncertain inference.
- Language models.

The pros related to vector space and probability model QASs are as follows

- Ranked list of documents: these models generate a ranked list of documents after performing matching with a question hence better results are presented to the users.

- Use of natural language: the input query language is simple. Hence, it is convenient for the common users to express their need in natural language.

The cons related to vector space and probability model QASs are as follows

- The limited expressiveness of input: the input query has got limited expressiveness e.g. use of NOT operator is not allowed.
- No representation of phrases: these models lack capability to represent some linguistic features such as phrases or proximity constraints which can be basis to search of information.
- Prior Knowledge required: In the case of a probabilistic model, there should be prior estimation of the probabilities for words of documents and questions. Hence, computation of relevancy is costly.
- Boolean relations are lost: Boolean relations are lost in these models such as NOT.

4.5.4. Feature based models

Feature based retrieval model views documents as a vector of values of feature functions and combines these features into a single relevance score.

The pros related to Feature based model QASs are as follows:

- Feature based analysis can be performed to enable searching for feature specific information.

The cons related to Feature based model QASs are as follows:

- Learning to rank model: problem here is to identify values of features functions and their computation.

4.5.5. Conceptual graph based models

These conceptual graph based models represent the sentence of the text with a structure formed by vertices and edges in graph (Sowa, 1976). It provides a higher level of understanding of the text by capturing semantics in the text. Questions and sentences must be modeled into conceptual graph formalism for finding answers. Systems face difficulty in modeling complex questions and documents in conceptual graph formalism and find relevancy between them.

4.6. Classification on the basis of characteristic of data sources

We classify QASs based on characteristics of data sources. The different categories are: (1) source size, (2) language, (3) heterogeneity, (4) genre, and (5) media.

4.6.1. Source size

The task of searching for answers within documents is related to their source size and number of documents. Large document collections have both merits and demerits with respect to finding correct answers. If there is a large number of documents, then answers can be in different structural forms, hence the matching of the answers with the structure of questions could be performed. Secondly, the more the occurrence of answers in different documents; there is a high justification of correctness of such answers.

The demerits are that there will be more time required for processing a large number of the documents. Moreover, redundancy of answers can lead to problems in ranking of answers.

The pros related to source size in QASs are as follows:

- The larger the size of the data source, the greater is the description related to events and objects hence, searching for satisfactory answers could be done here.
- The larger the size of the data source, the accuracy of Statistical and pattern based approaches in QASs is increased and better accuracy is achieved.

The cons related to source size in QASs are as follows:

- There can be an indexing problem in big data.
- There is burden on natural language processing tasks when the size of data sources is larger.

4.6.2. Language

If the documents are multilingual, then the task of generating answers is difficult as different languages follow different syntax and rules. There is no common linguistic rule by which all natural languages could be understood.

The pros related to Language in QASs are as follows:

- Large information is scattered in different languages which can be combined to get more knowledge.

The cons related to language in QASs are as follows:

- Languages follow different syntax and rules hence different language processing techniques are required.
- Some languages have no rules of grammar. Some languages also are not Turing-recognizable. Hence, processing such languages is difficult.

4.6.3. Heterogeneity

A large amount of information is stored on different sites and in different formats. There is no common representation model that can model different types of data sources. Hence, Systems face problems in dealing with heterogeneous data sources. Data space systems could get benefit out of heterogeneity by providing pay-as-you-go integration of data sources which are populated as a set of participants (Singh and Jain, 2011). It reduces the labor intensive effort needed to build up a data integration system.

The pros related to Heterogeneity in QASs are as follows:

- Large information is scattered in different formats such as databases, text, and multimedia which can be integrated to get more knowledge.

The cons related to Heterogeneity in QASs are as follows:

- Modeling: there are different types of data sources with different representations. These representations have got their respective Pros and, cons.
- Querying: different data sources understand different query languages. Hence, QASs face a problem in transforming natural language questions to a suitable query language based on data sources.
- Populating new data sources: automatically populating new data sources into data space based on the information content is a difficult task.

4.6.4. Genre

The language used in data sources can be linguistically correct or incorrect (formal, informal). Informal language is difficult to process for systems as they do not follow any syntax or formalism. Processing of such data sources is difficult as there is an incorrect parse tree generated. Hence, retrieving of answers is a difficult task.

4.6.5. Media

Most of the research done in question answering consult text based document collections. Retrieving answers in the form of multimedia i.e., audio, video, sound is a tough task (Indurkhya and Damereau, 2010).

4.7. Techniques used in QASs

Ackoff (1989) states that the content of human mind could be assembled into five categories i.e., Data, Information, Knowledge, understanding and wisdom. Data are symbols and raw facts. It represents facts and events without having a relationship with others things. Information is meaningful processed data and it generally generates answers to simple questions such as who, what, which, where, when questions. Information is a meaningful collection of data embodied through a relational connection. Knowledge represents patterns that provide a high level of predictability. Knowledge requires integration of various domains' knowledge so as to gather more knowledge. It requires analytical ability and true cognitive ability as possessed by human beings.

With the emergence of WEB 2.0, there is a large number of users' generated content on the web such as sites, blogs, and review sites etc (Cambria and White, 2014). On the Social web, users interact and collaborate with each other and share their experiences. Such resources could contain fake opinions or false information (Cambria and White, 2014). This gives rise to demand for such QASs systems that use factual information on the web along with opinion base information by incorporating various components of knowledge discovery, knowledge survey, and knowledge selection in making decisions related to answer generation (Kan and Lam, 2006). Based on the literature review discussed in this section, we classify QAS on the basis of technology used in Table 2.

With the emergence of WEB 2.0, there is a large number of users' generated content on the web such as sites, blogs, and review sites etc (Cambria and White, 2014). These data sources could contain public comments, opinions etc which could help other users in getting useful information. On the Social web, users interact and collaborate with each other and may provide useful information that could create new knowledge related to different concepts. Such resources could contain fake opinions or false information (Cambria and White, 2014). This gives rise to demand for such QASs systems that use factual information on the web along with opinion based information by incorporating various components of knowledge discovery, knowledge survey, and knowledge selection in making decisions related to answer generations (Kan and Lam, 2006).

Table 2 Classification of QASs based on techniques.

Aspects	QAS based on data mining	QAS based on information retrieval	QAS based on natural language understanding	QAS based on knowledge retrieval and discovery
Searching	Searching for factual data	Querying for factual information	Querying for information that could be subjective opinionated or fact based	Understanding knowledge, creating knowledge and searching for useful correct answers
Matching	Exact	Best match	Best match	Best correct match
Technology	Artificial intelligence and database	Information retrieval and natural language processing	Natural language processing and understanding	Natural language understanding, knowledge acquisition, mining
Form of answers	Short answers	Mixed answers	Mixed answers	Mixed answers
Types of questions	Simple-find	Wh questions- what, where, which, when	Definitional questions	Complex questions- how, why, hypothetical, yes–no
Relevancy	Objective	Subjective	Subjective	Subjective
Techniques	Pattern matching, syntactic analysis	Relevancy ranking, pattern matching, syntactic analysis	Relevancy ranking, pattern matching, syntactic, semantic analysis	Understanding knowledge, creating knowledge, discourse analysis, pragmatic analysis, and application of deductive techniques
Knowledge source	Data base	Syntactic Web	Syntactic and pragmatic web	Semantic and pragmatic web
Models used in retrieval process	Bag of word	Bag of word	Bag of concepts	Bag of knowledge
Reliability	Very Good as schema is designed by domain experts	Less as lots of fake information seen on the web	Less	Good

Based on the literature review discussed in this section, we classify QAS on the basis of technology used in Table 2.

We classify QASs based on techniques used in QASs for generating answers. The different categories are: (1) QASs using data mining techniques, (2) QASs using information retrieval techniques, (3) QASs using natural language processing and understanding techniques, (4) QASs using knowledge retrieval.

The different techniques for retrieving answers are good in their respective scenario. The scenario refers to complexity of questions, data sources, and answers desired by users. This classifies QASs based on techniques used for retrieving answers.

QASs using data mining techniques search for factual data, and generate short answers using bag of word model from data base. QASs using information retrieval techniques search for factual information in text documents. QASs based on natural language processing techniques search for information that can be subjective or objective. QASs based on Knowledge retrieval search for understanding and creating knowledge.

4.8. Classification based on forms of answer generated by QASs

We classify QASs based on forms of answers generated by QASs. The different categories are: (1) extracted answer, (2) generated answer.

4.8.1. Extracted answer

- Answers in the form of sentences. Here, the source documents are segmented into individual sentences. The sentence which qualifies most as answer will be presented to the user. Generally, factoid questions or yes–no type questions have extracted text answers. QASs face a problem in detecting sentence boundary in the case of informal documents like blogs, social networking sites etc.
- Answers in the form of a paragraph. Here, source documents are segmented into individual paragraphs. The paragraph which qualifies most as answer will be presented to the user. Generally causal or hypothetical type questions fall in this category. Here, topicalization is the big issue.
- Answers in the form of multimedia. Here, answers in the form of multimedia such as audio, video, sound clip are presented to the user.

4.8.2. Generated answer

- Answers in the form of yes or no. here answer is generated by QASs in the form of yes or no through verification and justification.
- Opinionated answers or ratings are generated by the QASs which give star ratings to the object or features of the object.
- Dialog answer. QASs generate answers to the questions of users in the form of a dialog.

5. Comparison with other classifications

Vanitha et al. (2010) classify QASs as web based QASs, information retrieval or information extraction based QASs, restricted domain QASs and rule based QASs.

Goh et al. classify QASs into two groups based on approaches used (Goh and Cemal, 2005).

- Natural language processing (NLP) and information retrieval (IR).
- Natural language understanding and reasoning (NLU).

One category of QASs such as Webclopedia, Answerbus, Mulder etc use NLP and IR techniques for generating answers. They use syntax processing, semantic analysis, named entity recognition, information retrieval, etc. Such QASs consult text based documents as source documents. Questions are open domain simple wh-questions. Another category of QASs use NLU techniques such as semantic analysis, discourse or pragmatical analysis along with syntax processing. The answers are synthesized results. QASs perform subjective evaluation. There are various QASs falling under this category such as Webcoop, Naluri, Start etc.

Hovy et al. (2000) classifies QAS into two groups based on approaches used:

- Pure information retrieval.
- Pure natural language processing.

Pure information retrieval approach assumes documents as collection of mini documents. It retrieves the mini document as an answer which is best matched with query. Systems face challenge in making mini documents size small enough to be answer-sized.

Pure Natural language processing matches syntactical and semantic interpretation of the users' questions with syntactical and semantic interpretation of the sentences present in the documents and generates the best matched sentence as the final answer. The main challenge for the system is to perform syntactical and semantic interpretation of the large number of documents in less time.

Benamara (2004) classify questions by taking account of their expected types of responses into two categories:

- Questions (yes or no, factoid question) giving atomic or enumerative responses i.e. short answers.
- Questions (causal, descriptive, comparison questions) giving narrative responses i.e., long answers.

Vanessa (2011) classify QASs according to various criteria

- Types of questions dealt by the system.
- Types of data sources consulted.
- Scope (open domain or restricted domain).
- Adaptability to various intrinsic problems (ambiguity, heterogeneity etc.).

Moldovan et al. (2003) classify QASs taking into account the complexity of questions and difficulty faced by QASs in generating correct answers and classifying them into different types:

- QAS capable of answer factoid type questions.
- QAS capable of support reasoning mechanism.
- QAS capable of fuse answers extracted from different sources.
- QAS capable of answer questions in context of earlier interaction with users.
- QAS capable of supporting analogical reasoning.

Table 3 Comparison of the proposed classification with other classifications.

Literature	Criteria	Details	Observation
Vanitha et al. (2010)	Data sources, application domain, Techniques used	Web based, information retrieval or extraction based , restricted domain, rule based	Classification not orthogonal. Research issues in different categories are not discussed
Goh and Cemal (2005)	Techniques used	NLP and IR, NLU	Classification based on one criterion. Research issues in different categories not discussed
Hovy et al. (2000)	Techniques used	Pure IR, pure NLP	Classification based on one criterion. Research issues in different categories not discussed
Benamara (2004)	Answers' size	Questions giving atomic answers, questions giving narrative responses	Classification based on one criterion. Research issues in different categories not discussed
Lopez (2007)	Types of questions, data sources, application domain, adaptability to various intrinsic problems	Types of questions, types of data sources consulted, scope, adaptability to intrinsic problems,	Classification not orthogonal. Research issues in different categories not discussed
Moldovan et al. (2003)	Types of questions, forms of answers, types of techniques used	QASs dealing with factoid type questions, QAS dealing with reasoning mechanism, QAS fusing answers from different sources, QAS supporting dialog questions, QAS supporting analogical reasoning	Classification not orthogonal. Research issues in different categories not discussed
Vicedo and Mollá (2001)	Techniques used	QASs do not employ NLP techniques, shallow NLP techniques, and deep NLP techniques	Classification based on one criterion. Research issues in different categories not discussed
Proposed Classification	Types of questions, Data sources, types and forms of answers, matching functions used in different models, techniques used	Types of questions, Data sources, types and forms of answers, matching functions used in different models, techniques used	Comprehensive overview of QASs with classification. Research issues in different categories are discussed

Vicedo and Mollá (2001) classify QASs on the basis of level of natural language processing techniques involved in generating answers.

- QASs that do not employ NLP techniques.
- QASs that employ shallow NLP techniques.
- QASs that employ deep NLP techniques.

Our work of classification gives a comprehensive overview of QASs based on all common known approaches used in the literature surveyed. We identify research issues in each identified QASs category. We present the classification in Table 3.

6. Conclusions

We classify QASs on the basis of various criteria (types of questions dealt, type of data sources consulted, and types of processing done on question and data sources, types of retrieval model, forms of answers generated, and characteristics of data sources). Languages permits paraphrasing which is still not captured successfully by QASs. The performance of a QAS is highly dependent on good source corpus and accordingly well formalized users' requirements. If the corpus is structured and users' requirements are well formalized, then the burden on the QASs to use complex Natural Language Processing techniques to understand the text is reduced.

There are some hidden factors which affect the performance of QASs i.e. Psychology and the skill of the user who is asking the question etc. The future QASs should perform knowledge survey tasks in order to give results which could satisfy the needs of the customer. Dialog based QASs are being developed to understand th eneed of users. But, there are requirements of intelligent QASs that can track th ebrowsing history and behavioral activities of users and present answers to questions in a more effective manner.

QAS can enable users to access the knowledge in a natural way by asking natural language questions and get back relevant correct answers. The major challenges in QASs are: understanding natural language questions regardless of their types or representation; understanding knowledge derived from the documents (structured, semi structured, unstructured to semantic web) and searching for the relevant, correct and concise answers that can satisfy the information needs of users.

We face problems in making a general hierarchical classification of QASs. We created a mind map which is more suitable to classify QASs. Our different classification criteria are not disjoint i.e., some can overlap with each other {questions' domain, types of questions} and, {types of processing done on question, type of retrieval models.}; {characteristics of data sources, type of data sources; type of processing done on documents}. As, we don't know about the performance details and truth corpora of various QAS, we do not aim at measuring performance as criteria for classifying QAS.

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