Evolution of Techniques for Question Answering over Knowledge Base: A Survey

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ABSTRACT

In this paper, a brief study of the advancements in the Question Answering domain as a type of information retrieval system is presented. Question Answering systems are responsible to provide answers to the questions proposed over a knowledge base in natural language to retrieve the required information. The promising results achieved in Question Answering in Natural Language Processing are discussed. The aim is to cover a concise yet complete understanding of the advances in Question Answering Systems classified based on domain and question type and brief information about metrics used to evaluate the system.

Keywords

Data mining, text mining, question answering, classification, named entity recognition, neural networks, pos tagging

1. INTRODUCTION

Information pertaining to numerous domains containing numerous facts is growing at a rapid rate. While this information is easily extracted and analyzed by the experts, the non-experts can't take the benefit of the same. [1], [2]. This in turn has set the platform of developing and modeling question answering and keyword search tools for Information Retrieval [3]–[6]. Question Answering Systems incorporate natural language statements or questions to retrieve information from complete document where specific pieces of information are returned as an answer. Using some ranking scheme, QA systems combine data retrieval with knowledge extraction methods to classify a range of likely candidates and then generate final answers. [7]. Question Answering has always been a promising-research area in Natural Language Processing. Question Answering systems have been widely used in various applications - information retrieval, named entity recognition, dialog systems [8]. In recent years, there has been significant increase in the amount of data being generated on a daily basis. Users bear questions for which they expect an exact, precise and short response as an answer. The response is expected to be given in the natural language without being limited to a particular query language, query training rules or even a specific information domain.

2. GENERAL ARCHITECTURE

A typical question answering system consists of following phases: Question Classification, Information Retrieval and Analysis and Answer Analysis. Question Classification is the initial phase where questions are classified by keyword extraction and semantic analysis. Queries are fired to retrieve information along with information extraction algorithms. Ranking of passages and information retrieval recall methods are used to boost information retrieval and analysis process. Answer extraction and analysis is the last phase in question answering system, which is the discrimination mark [25].

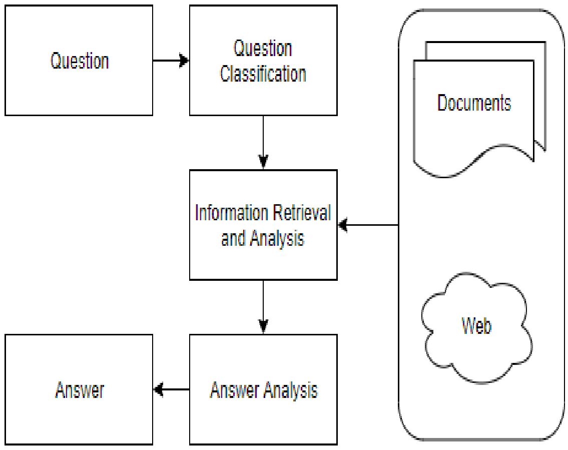

Fig. 1: General Architecture

3. TYPES OF QUESTION ANSWERING SYSTEMS

3.1 Based on Domain

Open domain Question Answering system: Systems providing short answers in natural language and no restricted to a particular domain are Open Domain Question Answering Systems. The Open Domain QA depends on information retrieved from World Wide Web and universal ontology and these sources are responsible for answers to every question asked. These systems require general vocabulary avoiding domain specific vocabulary. Open-domain data set such as Wikipedia is used for question answering. There has been significant amount of work done in Open Domain Question Answering. The data sets include Quasar [26], MS Marco [27], Triviaqa [28], Searchqa [29], SQuAD [30], Hotpotqa [31]. Research in Open Domain Question Answering has evolved since the series of competitions at the Text Retrieval Conference (TREC) [32] and researchers have started adapting neural-network-based QA models for the same tasks. Work done by Yi Tay, Luu Anh, Tuan Siu, Cheung Hui, Jian Su [33] on Searchqa [29] is ranked highest based on the results achieved on the performance metrics - F1 score and Exact Match (EM) for Open-Domain Question Answering on Searchqa. Work done by Shuohang Wang, Mo Yu, Jing Jiang, et al. [34] is ranked highest for Open-Domain Question Answering on Quasar. Work by Danqi Chen, Adam Fisch, Jason Weston, Antoine Bordes [35] is significant where their approach incorporates a search component based on the combination of bigram hashing and TF-IDF matching with a multilayer recurrent neural network model to detect answers for questions in Wikipedia Paragraphs.

Table 1. QAS features and techniques. adapted from [9]

QA Features	Paper	Techniques
NLIDB:(Natural Language Interfaces to Databases)	PRECISE [10]	Identifying classes of questions
	Formal semantic approach [11]	Intermediate representation language
	MASQUE/SQL [12]	Portable NL front end to SQL databases
	BASEBALL [13]	Specific domain Systems
Open Domain Question Answering	LASSO [14]– [17]	Deep linguistic analysis and iterative strategy
	FALCON [18]	Hierarchies of question types based on the types of answers sought
Over text	DIMAP [19]	Semantic categories of answers are mapped into categories covered by a NE Recognizer.
	Mulder [20]	Extracting “semantic relation triples” after the document is parsed, converting the document into triples.
Ontology based	AquaLog [21]	Allows the user to choose an ontology and then ask NL queries with respect to the universe of discourse covered by the ontology
	PowerAqua [22]	QAS focusing on querying multiple semantic Web resources
	DeepQA IBM Watson’s system [23]	Using unstructured and structured data (RDF format) to extract and score evidence
	PANTO [24]	Translates factual wh-queries into F-logic or SPARQL andevaluates them with respect to a given KB

2) Closed-Domain Question Answering: Closed domain Question Answering system involves restricted information sources and domain specific questions. Thus, limited number of questions can be asked. The quality, precision and exactness of answers in closed domain is high. Closed domain data sources include unstructured data, structured data and semi structured data like XML, JSON-annotated texts. Use of domain specific taxonomy is done in closed domain. This domain includes a linguistic requirement to understand the text of the natural language in order to provide correct responses to queries. These domains include temporal QA systems, geospatial QA systems, medical QA systems, patent QA systems and community QA systems. Closed domain QA systems can be combined to create an Open domain QA system [36] [37]. The difference between open and closed domain QA systems is the presence of domain-dependent information that can be used to better the accuracy of the system [38]. Work by [39] proposed methodology of applying semantic information to improve the precision of the information retrieval module in a closed-domain question-answering system. Felix Mikaelian, ´ Andre Farias et al. built an end-to-end closed domain question ´ answering system built on top of the HuggingFace transformers library [40].

3.2 Based on Question Type

In QA systems, the taxonomy of questions posed directly affects the responses. Classification of QA systems based on question types queried by users was first formulated by Mishra et al. [41]. This work classifies based on all the possible types of questions it identifies from literature. The classes types are: list questions, factoid questions, causal questions, confirmation questions and hypothetical type questions.

1) Factoid type questions: These questions are factual in nature and they refer to a single answer [36]. For instance, Who is known as the Father of Nation? Factoid question are wh-type questions belonging to one of these - [what, when, which, who, how].

2) List type questions: The response to a list query is a list of entities or facts in answers. For instance, list name of products available at a price less than 5 k? List type questions are considered as a series of factoid questions.

3) Hypothetical type questions: Questions having information associated to any assumed event are called hypothetical questions. For instance, questions like ’what would happen if’ fall under the category of Hypothetical questions.

4) Causal type questions: Causal questions require explanations on entities they contain. Factoid questions extract answers as named entity, whereas causal questions don’t. Pragmatic or discourse level analysis is required for the answer extraction using natural language processing. [42]– [46]

5) Confirmation type questions: Answers to the confirmation type questions are in the form of boolean response - Yes or No, True or False.

4. MOST FREQUENTLY APPLIED QUESTION ANSWERING TECHNIQUES

Researchers have used methods, algorithms, frameworks and systems related to knowledge extraction, natural language processing and machine learning to incorporate the modules of a QA architecture.

4.1 Deep Neural Networks

Recent developments in deep neural network models have shown promising results in Question Answering. With a small pipeline, these systems require a lot of training. Recurrent Neural Networks such as Gated Recurrent Unit (GRU) and Long Short-term memory (LSTM) help handling long textual matter. With use of attention mechanisms and memory networks the performance of the system can be further enhanced resulting into state-of-the-art performance for deep-learning based Question Answering. Work by [48] incorporates use of a convolutional neural network architecture for reranking pairs of short texts. Work by [49],

[50] incorporates use of natural language strings to automatically assemble neural networks from a collection of composable modules. Li Dong et al introduces multi-column convolutional neural networks (MCCNNs) to understand questions from three different aspects (namely, answer path, answer context, and answer type) and learn their distributed representations [51]. To recover from local maxima corresponding to incorrect answers Caiming Xiong, Victor Zhong, Richard Socher introduced Dynamic Coattention Network (DCN) for question answering [52], where an iterative procedure involving fusion of co-dependent representations of the question and the document is used to focus on relevant parts of both [53].

Table 2: Leaderboard as of December 2019

DATASET	BEST METHOD	PAPER TITLE
SearchQA	DecaProp	Densely Connected Attention Propagation for Reading Comprehension
Quasar	Evidence Aggregation via Rˆ3 Re-Ranking	Evidence Aggregation for Answer Re-Ranking in Open-Domain Question Answering
SQuAD1.1	DrQA	Reading Wikipedia to Answer Open-Domain Questions

4.2 Graph Based

Our thanks to the experts who have contributed towards Gao have described a query graph that is similar to the knowledge base subgraphs and can be mapped directly to a logical form [54]. In their work, semantic parsing is reduced to the generation of query graphs, formulated as a problem of staged search and their method leverages knowledge base for pruning the search space at an early stage and thus simplifies the issue of semantic matching. Research by [55] proposes to enhance the visual answering of questions (VQA) with organized representations of both scene material and queries, using graphs over scene objects and query terms, and a deep neural network that exploits the structure in these representations. To address noisy expressions in questions and problem of questions involving multi-hop logic reasoning on the information graph to get answers, Yuyu Zhang et al. proposed an end-to-end variational learning algorithm which can handle noise in questions, and learn multi-hop reasoning simultaneously [56]. Junwei Bao et al. released a new data-set Complex Questions, aiming to measure the quality of KBQA systems on ‘multi-constraint’ questions which require multiple knowledge base relations to get the answer and proposed systematic KBQA method using multi-constraint query graph to answer multi-constraint questions [57].

Table 3: Open-Domain Question Answering On Quasar

Rank	F1	EM	Method	Paper Title	Year
1	42.3	49.6	Evidence Aggregation via Rˆ3 Re-Ranking	Evidence Aggregation for Answer Re-Ranking in Open-Domain Question Answering	2017
2	42.2	49.3	Denoising QA	Denoising Distantly Supervised Open-Domain Question Answering	2018
3	38.6	46.9	DecaProp	Densely Connected Attention Propagation for Reading Comprehension	2018
5	26.4	26.4	GA	Gated-Attention Readers for Text Comprehension	2016
6	25.9	28.5	BiDAF	Bidirectional Attention Flow for Machine Comprehension	2016

4.3 Named Entity Recognition

Recent textual question answering systems have named entity recognition as the important element for information extraction. Diego Molla´, Menno van Zaanen and Daniel Smith proposed a named entity recognition system that allows multiple labels to entities giving high recall. [58] Traditional QA systems tend to cut down the size of data. Filtration of documents is done until right answer to the question is found which is achieved by removing the irrelevant piece of information in the documents. So, NER is used to aid this filtration process by getting rid of the information irrelevant to the answer. After analyzing the question and it’s type, the answer is mapped to a list of entity types. The textual information is discarded if the entity type is irrelevant to the type of expected answer. [58]. Antonio Toral, Elisa Noguera, Fernando Llopis, and Rafael Mu˜noz employed similar approach for Question Anwering task in Spanish texts. [59]

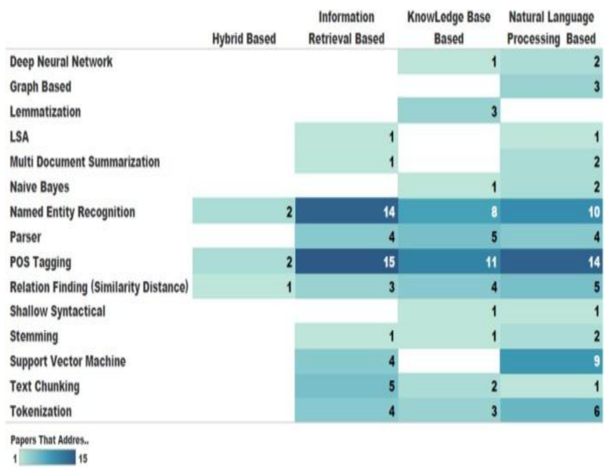

Fig. 2. Frequently used QA Techniques. Adapted from [47]

4.4 POS Tagging

W Wang, J Auer, R Parasuraman et al. hypothesized an approach [60] involving combination of syntactic and semantic features coupled with machine learning techniques for improving accuracy of question answering system on test set of Remedia Corpus [61]. In this approach, the sentences and the factoid questions are preprocessed and tagged by the parts-of-speech tagger distributed with the deep read system [61]. This tagged text is passed to the name identification module and later proper noun identified tagged text is passed to pronoun resolution module. The text is first parsed by the parser before passing it to pronoun resolution module. After this, the sentence question comparison and voting is done. Text with highest scores based on the number of votes is selected as the answer [60]. Another work by Christina Unger, Lorenz Buhmann, Jens Lehmann, Axel-Cyrille Ngonga Ngomo et al. ¨ [62], presents an approach involving parsing of the question and producing a SPARQL template [63] which is identical to the internal structure of the question. This template is then implemented using statistical recognition of entities and predicate detection [62].

5. EVALUATION METHODS

With advancements in models and techniques for Question Answering Systems increasing at a rapid rate, evaluation metrics are required for comparing the performance of these methods, models and techniques. According to Yao [64], F1 score and Accuracy are used as the performance metrics in Question Answering. F1 score is calculated on the basis of Precision and Recall. Precision and Recall are calculated using true positive (TP), true negative (TN), false positive (FP) and false negative (FN). These are the fragments of the two classes for which the data is to be classified. Accuracy is the measure of all the correctly identified cases. F1 score is the harmonic mean of Precision and Recall. It is used to give the measure of the incorrectly classified cases.

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