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A Survey on Conversational AI Question answering System for Low Resource Language

Abstract: - Question-and-answer (QA) systems allow users to pose questions about the information accessible in a variety of formats, such as structured and unstructured information in natural languages. It contributes significantly to conversational artificial intelligence (AI), which has led to the creation of a novel research field on conversational question answering (CQA), in which a system is required to understand the provided context before engaging in multi-turn QA to satisfy a user's informational needs. While the majority of currently done research focuses on single-turn QA, pre-trained language models and the availability of large multi-turn QA datasets have recently made multi-turn QA more significant. This study aims to give a thorough analysis of the most recent CQA research trends, mostly based on publications that have been reviewed in recent years. Our data indicates a shift in the industry's preference for multi-turn QA over single-turn QA, which has numerous advantages for conversational AI. In order to create a solid basis for the field of CQA, this survey aims to serve as the pinnacle for the research community.

Keywords: Conversational agents, Conversational AI, Question Answering, Knowledge base, Machine learning

INTRODUCTION

The development of an intelligent dialogue system that not only matches or exceeds the capabilities of a human in conducting an interactive discussion but also offers responses to queries on a variety of topics has been one of the main goals within the field of artificial intelligence (AI) [1]. Researchers from academia and industry are becoming more interested in conversational AI, as seen by the rapidly growing number of research papers that demonstrate this. Conversational systems, often known as chatbots, are essential in a number of industries, including banking, healthcare, e-commerce, and customer service. While chatbots are quick and easy, most of them are only available for languages with a lot of resources, like English, which restricts their use to users who speak languages other than the chatbot's native tongue.

Researchers in the fields of deep learning (DL), natural language processing (NLP), and information retrieval (IR) are becoming more interested in conversational AI, which is a vital component of natural user interfaces. Conversational AI can be broken up into three groups, such as (i) task-oriented dialogue systems that must do things for the user, like make a restaurant reservation or schedule an event, (ii) chat-oriented dialogue systems that must have a natural conversation with the user, and (iii) QA dialogue systems that must give clear and concise answers to the user's questions based on information.

The research on chat-oriented and task-oriented dialogue systems has led to the development of a variety of popular dialogue agents, including Amazon Alexa, Apple Siri, and Microsoft Cortana. However, QA dialogue systems are relatively new and extensive research is still required. The fundamental components of QA dialogue systems are Conversational Question Answering (CQA) approaches. CQA, which has the ability to transform how people interact with technology, is based on the idea of asking the computer to respond to a question relying on the material that is being read.

CQA can be thought of as a condensed yet tangible conversational search environment in which the system only ever returns one correct response to a user's question rather than a collection of relevant articles or links, as is the case with traditional search engines [2]. When evaluating a machine's interpretation of textual natural

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language input, CQA is utilized as an indicator of performance since it provides a trustworthy way for humans to collect data [3]. These CQA systems are widely used in fields like customer care assistance [4] and QA dialogue systems [5, 6].

A large-scale Knowledge Base (KB) or document collection can now be queried by users using conversational Question Answering (QA) bots, which have become increasingly popular in recent years. The first are referred to as KB-QA agents, and the second, as text-QA agents. Users can interactively query a KB using KB-QA agents rather than typical SQL-like systems, making them more versatile and user-friendly. Because text-QA agents respond to user questions with brief, direct responses rather than a ranked list of pertinent pages, they are simpler to use on mobile devices than traditional search engines like Bing and Google.

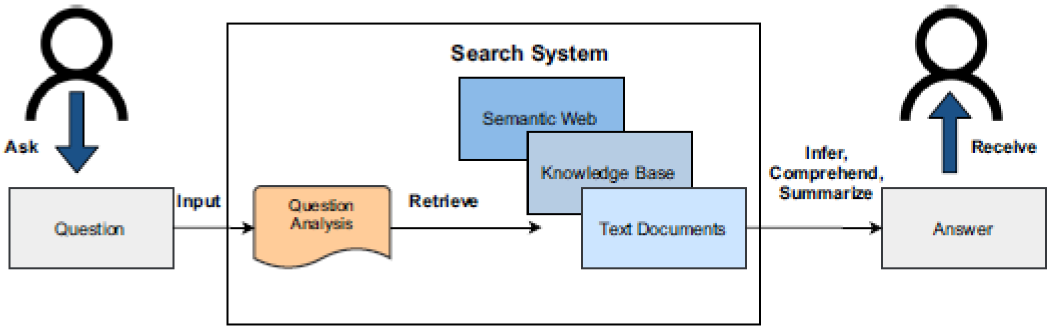

Fig 1: Generalized QA architecture

II. LITERATURE SURVEY

A factoid question-and-answer system for Task 4 of the QALD-7 shared task was presented by the author in [7]. A semantic representation of the input query is learned by our system, which is an end-to-end neural architecture. A convolutional neural network (CNN) model is used to grade the representations as they are created iteratively. We perform the highest-scoring semantic representation on Wikidata to extract the solutions. More than half of the QALD-7 Task 4 questions may be processed by our system, which generates Wikidata articles as responses [7].

In [8], the author describes a system that uses a knowledge base and a few handcrafted features to learn to answer questions on a variety of topics. Our algorithm learns low-dimensional embeddings of words and knowledge base elements and then compares natural language inquiries to potential replies using these representations. Training our system with question-answer pairs, structured representations of the responses, and question-paraphrase pairs produces results that are competitive on a recent literature benchmark carried out in [8].

Using a structured knowledge base and a character-level encoder-decoder system, it is possible to effectively answer questions, according to [9]. We use our framework for single relation query answering on the Simple Question database and demonstrate the effectiveness of our method by raising the state-of-the-art efficiency from 63.9% to 70.9% despite the use of ensembles. It's significant that our character-level model is resistant to unique entities in testing, can be learnt with significantly fewer data than past work that depends on data enhancement and has 16 times fewer parameters than a similar word-level model.

The goal of the study conducted in [12] is to evaluate the effectiveness of CQA systems in low-resource environments that are typical for the majority of non-English languages, such as small Wikipedia's or languages with few crowd workers or annotations. The authors presented their first non-English CQA database and findings, with a focus on the Basque language. The research demonstrated that cross-lingual transfer makes it possible to achieve results of high quality, on par with those of English, even with small amounts of native data.

In [13], the author proposes an entirely novel framework for dynamic neural parsing of semantics that is learned via reward-guided search with weak supervision. We use a database of 6,066 question sequences concerning semi-structured columns from Wikipedia, with an aggregate of 17,553 question-answer pairings, for our study.

Our technique outperforms cutting-edge QA systems created to respond to extremely complex questions by successfully using the sequential context.

An end-to-end adaptable memory-efficient CNN architecture known as CoCNN was presented by the author in [14] to address specific Bengali and Hindi characteristics including high inflection, morphological richness, dynamic order of words, and phonetical spelling errors. On a variety of real-world datasets, CoCNN outperforms SOTA LSTMs and pretrained BERT with 16X less parameters.

There have been prior attempts to investigate the question-answering system—Feng et al.'s proposed method [15] employed two distinct methods for answer selection. The first approach makes use of the answer's cosine similarity. The answer is shown by the cosine value with the highest value. CNN is used in the second technique. The outcome demonstrates that the approach based on deep learning produces superior results in another way.

Iyyer et al. [16] proposed that the Dependency Tree Recursive Neural Network be used to answer factoid questions that are spread out over multiple paragraphs. The model was trained using the quiz bowl competition dataset Dependency Tree Recursive Neural Network (DT-RNN). The model was tested in the quiz categories for history and literature. The test results show that the model performs better than the average human player on the history question, but worse on the literature question. According to their analysis of the research, the DT-RNN is a useful framework for question answering and may even surpass humans in several instances.

By employing the Generative Question Answering (GEN QA) model to create replies from factoids, Yin et al. [17] suggested yet another method for answering questions. Bidirectional RNN will turn the query into a representational format. By employing a CNN-based Matching Model or a Bilinear Model to determine the relevance score, the query will be compared with the knowledge base. The solution will be generated using RNN in the final step utilising the relevance score result. The results of the experiment show that the CNN model-based GEN QA outperforms the bilinear model-based GEN QA in terms of performance.

A different strategy investigated by Chen et al. [18] makes use of Wikipedia as the knowledge source to respond to the query. Using Term Frequency-Inverse Document Frequency (TF-IDF), they order the top five Wikipedia pages that are related to the problem. The articles and queries in the paragraph will be encoded using RNN. They are able to predict the span by using the term "bilinear" to describe the similarities between questions and paragraphs.

A deep learning-based approach was put up by the author in [19] for sorting input questions into coarser and finer categories based on the anticipated response. This research project considers how to provide the resources needed for benchmarking and developing a baseline model, as well as the challenges of addressing queries across numerous domains and languages. We collect 500 items from the internet across six different domains. These articles offer a corpus of 250 equivalent Hindi and English documents. We have generated 5; 495 question-answer pairs from these comparable corpora, with the questions and responses being written in both Hindi and English. The query can be of the factoids or the brief description varieties. The questions are divided into 6 coarse and 63 finer categories. This is the first attempt, to our knowledge, at creating a multi-domain, multi-lingual question-answering assessment that takes into account both Hindi and English [19]. Through similarity calculations and subsequent rating, answers are extracted. We get a BLEU score of 41:37% for the brief descriptive inquiry and an MRR value of 49:10% for the factoids. According to the evaluation of the question classification model, the accuracy for the coarse and finer classes is 90:12% and 80:30%, respectively.

In [20], the author proposed a method for a Hindi-language question-answering system. The four categories of questions covered in this work are when, where, how many, and what time. The Hindi text was searched for the response to the given query. To determine its meaning, each sentence in the text was examined. In this study, the queries are represented using query logic language (QLL), a subset of Prologue. The Hindi shallow processor was used to figure out which words were nouns, verbs, and questions.

Author suggested a Hindi and English question-and-answer system in [21]. The questions were written in Hindi, and the answers were taken directly from Hindi newspapers. The English language was then used to translate these responses. The top 20 Hindi articles that were used to find potential responses were located using an

English-Hindi bilingual dictionary. In [22], the author presented a question-answering system in Telugu. The approach was dialogue-based and focused on the railroad industry. The keyword method formed the foundation of the architecture. The tokens and keywords are produced by the query analyzer. SQL statements were produced from tokens. The solution was obtained from the database using a SQL query.

The author developed a question-and-answer format in both Punjabi and English [22]. In this study, a pattern-matching algorithm was devised to identify the most relevant response from multiple sets of responses to a given query.

Systems built on AI nowadays are mostly intended for speakers of English and other European languages. High-quality corpora for these languages are readily available, which is a major factor in the development of such technologies [23]. The dearth of high-quality, large-scale text corpora, on the other hand, is impeding the development of analogous systems in other languages. With between 85 and 637 million native speakers, Asian languages such as Hindi, Bengali, Indonesian, Urdu, Marathi, and Turkish are among the most widely spoken in the world [24]. These languages are considered low-resource and low-density because there are not many native speakers and therefore not enough text corpora to use as a gold standard.

20% of the world's population, or 1.26 billion people, speak English, although only 4.8% of those people—or 369 million people—do so as their mother tongue [25]. The demand for deep learning-based NLP systems for Low-Resource Languages (LRL) is urgent given that 80% of the world's population does not speak English.

An EMDM (Entropy Minimization Dialogue Management) technique was introduced in [26]. The agent always requests the attribute value with the highest entropy among the remaining items in the KB. Without faults in language comprehension, EMDM is demonstrated to be the best option. However, it misses the distinction between questions that are straightforward for consumers to answer and those that are difficult. For example, in the movie-on-demand job, the agent could ask customers to provide the movie release ID, which is unique to each movie but easy to forget for frequent users.

The author of [27] offered KB-InfoBot, an end-to-end neural multi-turn discussion agent, as a solution to the movie-on-demand dilemma. User feedback is used exclusively to train the agent. It does not have the EMDM issue and always provides users with questions that are simple to respond to in order to aid in KB searches. Like other KB-QA agents, KB-InfoBot requires communication with a third party KB in order to get practical knowledge. Traditional methods for achieving this consist of transmitting a symbolic query to the KB to retrieve entries based on their attributes. Such symbolic activities, however, undermine the system's ability to be differentiable and obstruct the dialogue agent's end-to-end training. To get around this problem, KB-InfoBot uses an inferred posterior distribution across the KB to find the user's wanted objects for symbolic searches. The neural KB-QA techniques mentioned in the preceding sections can be used to produce the induction. Research demonstrates that combining the induction process with reinforcement learning (RL) increases task accomplishment and reward in both simulations and when used with actual users.

Paper Name/ Authors	**Methods**	**Advantages**	**Disadvantages**	**Accuracy**
"A deep neural network framework for English Hindi question answering" Gupta, D., *et al.*[1] October 2019	Unified deep neural network (DNN)	This is a generic framework with the flexibility of being adaptable to any number of languages and this scheme introduced an effective language-independent snippet generation algorithm.	This approach failed to handle the descriptive and multi-step reasoning questions in a multilingual environment.	50.11 EM, 53.77F1
"English Intelligent Question Answering System Based on	Elliptic equation+ intelligent question-answering system	This model was explained the English proficiency answer	This model failed to improve the consistency of the	

elliptic fitting equation" Zhang, S. and Jaamour, Q., [2] June 2022		model and the capabilities and functions of each model within each model and provided design and development processes, mathematics, and used important English questions.	algorithm and did not strengthen the functionality of the system to see user needs more quickly.	81%
Gupta, S. and Khade, N.,[3] June 2020	Multilingual-Bidirectional Encoder Representations from Transformers (m-BERT)	This scheme used a multilingual training set revealed the larger improved results and indicated an improvement in multilingual comprehension of m-BERT for Hindi QA.	This model failed to construct XQuAD for training by incorporating the entire SQuAD corpus.	52.93 EM, 64.51 F1
"Qald-9-plus: A multilingual dataset for question answering over dbpedia and wikidata translated by native speakers" Perevalov, A., *et al.* [4] Feb 2022	KGQA+ QALD-9-plus	This model utilized DBpedia SPARQL queries from QALD-9 was transferred to Wikidata to improve the usability of the data.	The deduced scheme did not increase the coverage of languages and failed to extend the number of languages in the dataset.	Micro F1 accuracy per dataset
"A Turkish question answering system based on deep learning neural networks" Gemirter, C.B. and Goularas, D., [5] March 2021	Deep Neural network (DNN)	The devised methodology was successfully used in QA tasks for any language and any domain.	This approach required the use of various and large data sets. The accuracy of the network was varied according to the training parameters.	EM 57, F1 69 For Turkish banking sector data set
"Synthetic Data Generation for Multilingual Domain-Adaptable Question Answering Systems" Kramchaninova, A. and Defauw, A., [6] 2022	SQuAD 2.0 + multilingual-Bidirectional Encoder Representations from Transformers (m-BERT)	Achieved improved performance on domain-specific test sets that included semantically complex questions, both in English and Dutch.	This approach attained poor performance in quality monitoring of the generated synthetic questions, especially for languages other than English.	
"A Conceptual Framework For Malay-English Mixed-language Question	Convolutional Neural Networks (CNN)	This model reduced the data complexity and improved the performance of the	The language identification stage relied on the Malay corpus, which may	

Answering System" Lim, H.T., *et al.* [7], 2021		mixed-language question-answering system.	lead to identification errors.	
"Towards developing a multilingual and code-mixed visual question answering system by knowledge distillation" Khan, H.R., *et al.* [8], 2021	Learning Cross-Modality Encoder Representations from Transformers (LXMERT)	The presented model utilized rich information and devised effective distillation objectives to encourage the student model to learn from the teacher through a multi-layer distillation process.	Training models for multilingual setups demand high computing resources.	70.26
"Arabic Question Answering Using Ontology" Ali Albarghothia, Feras Khatera, Khaled Shaalana Elsevier 2017[24]	SPARQL with RDF	The devised methodology was successfully used to generate keywords by processing questions by using Jena framework with SPARQL queries	SPARQL queries are complicated with compound questions that have multiple questions at the same time. This complexity of proposed questions was resolved by adding more rules that can handle these kinds of questions.	Precision - 81%
"QUESTION ANSWERING SYSTEM USING ONTOLOGY IN MARATHI LANGUAGE" Sharvari S. Govilkar1 and J. W. Bakal International Journal of Artificial Intelligence & Applications · July 2017[25]	Query triple extraction	Performance of MQAS was evaluated by measuring its ability to retrieve all and only relevant information. MQAS performance is strongly dependant on POS Tagging and correct processing of the queries.	The dataset considered under study was very small in size and also for very few domains of Marathi language. The research can be further extended for handling of 'कसं' and 'का' type questions which are most difficult type questions as these questions require deep semantic processing of the sentences to extract answer.	The system shows average accuracy as 93.66%, 44.61 and 29.82%
"Natural language processing based new approach to design factoid question answering system"	Deep Learning network	This model reduced the data complexity and improved the performance based on the SQUAD dataset for question-answering system.	Training models for multilingual setups demand high computing resources.	

Question types:

Depending on their complexity, the expected type of response, or the methods that should be used to respond to them, questions can be easily categorised into different groups [28]. According to the questions that customers frequently ask, the categorisation is as follows:

Factoid questions: Questions that anticipate the algorithm to find a straightforward and fact-based answer in a short statement, such as “who played Chandler in FRIENDS.” Factoid queries frequently start with the letter “wh.” The factoids' answers can be discovered using a variety of extraction methods. In order to find the answer in the text provided, the strategies first uncover latent or buried information in the given question using either structure matching [29] or reasoning [30]. One example of a factoid QA dataset is FreebaseQA [31].

Casual questions: Casual inquiries—which typically begin with the words “why” or “how,” depending on the entity—require thorough explanations specific to that entity. Casual questions don't always yield clear or succinct responses. For this generation of in-depth responses, powerful natural language processing algorithms that can comprehend the query at many levels of sophistication, such as semantics and syntax, are required [32]. “Why do earthquakes occur?” is an example of such a question.

Unanswerable questions: These are the inquiries for which the source text does not yield any conclusions or answers. Any of the previously specified question categories could be unanswerable. The QA system should notify that the query is unanswerable for these inquiries. With almost 50,000 unanswerable questions, SQuADRUn [33] is an expansion of the SQuAD dataset [34], which was created to help QA efforts.

Listing questions: The answers to these questions must include a list of individuals or facts, for example, “list the names of all former presidents of America.” The methods used to respond to factoids are effective for answering listing inquiries. The explanation for this is that such inquiries are handled by QA systems as a series of factoids that are asked repeatedly [28].

Complex questions: Complex questions are those that call for various sorts of knowledge or multiple steps to be taken in order to be answered. They are challenging to respond to and call for many system interactions or access to various documents [35]. How many Chinese cities have a population greater than New Delhi, for example? Requires the system to calculate the population of New Delhi first, and then compare it to the populations of several Chinese cities. As a result, complex strategies such iterative query generation [36], multi-hop reasoning [37], breakdown into subquestions [38], and mixing clues from many documents [39] are needed to answer complex questions. Some examples of complicated QA datasets include the Large-Scale complicated Question Answering Dataset (LC-QuAD) [40] and the Complex Sequential Question Answering (CSQA) [41-43].

Data Sources types:

CQA systems can be categorized according to the underlying data sources used to arrive at a conclusion. These could be the underlying data sources:

Structured data source: Data is kept in the form of entities and kept in a structured document. These things make up a different table. A table's entities can each be connected with a number of characteristics. The metadata for these properties is kept in a schema and is referred to as the definition of these attributes. Accessing the data and obtaining pertinent data from the schema requires the usage of a query language. Resource Description Framework (RDF) graphs and databases are two examples of structured data sources. For the purpose of providing answers, Question Answering over Linked Data (QALD) and LC-QuAD [40] make use of structured data sources, specifically RDF graphs.

Semi-structured data source: The semi-structured data sources need a lot of labor to develop because there is no distinct line separating the stored data from its schema. XML is one type of semi-structured data source.

Unstructured data source: For the purpose of storing the data in this specific configuration, there are no set guidelines. Unstructured data sources might contain any type of data, so to find the right response, sophisticated

NLP algorithms and information retrieval techniques must be used. However, compared to sources of structured data, the accuracy of the answers is not as reliable.

III. CONCLUSION

Conversational Question Answering (CQA) methods have emerged as a crucial technology to close the interconnected gap between machines and people as a result of the establishment of pre-trained language models and the creation of conversational datasets. This advancement makes it easier for other application areas to develop and advance, such as search engines, interactions with IoT devices in smart environments, and online customer assistance, allowing CQA to realise its social and economic implications. The successful absorption of contextual data, the ability to infer the queries, and the capability to ask appropriate clarification questions are the main challenges confronting the field of CQA.

Users can obtain knowledge naturally through QA by asking questions in everyday language and receiving pertinent, correct answers. The main challenges in QAs are understanding natural language questions, no matter how they are written or formatted, understanding knowledge from documentation (structured, semi-structured, unstructured, and semantic web), and looking for relevant, accurate, and brief answers that can meet users' informational needs.

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