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A Theoretical Survey on Question Answering Systems and the Future

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Abstract- Extracting the right piece of relevant information from the vast and ever-growing volume of textual data across the internet and other knowledge repositories remains significantly challenging and time-consuming task. Question answering (QA) offers an intelligent solution to the information retrieval problem by allowing users to express their quest for information in natural language statements or questions and receive precise answers as response to queries. QA represent one of the most natural ways for human-computer interaction, whereby enabling systems to provide direct response to human queries. Early QA systems were designed for restricted domains and offered limited functionalities, but modern approaches are focused handling general questions using information from multiple data sources to provide more precise answers. Quiet a given number of question answering systems have developed over the years and conducting a comprehensive review is necessary to understand emerging trends and identify future research opportunities. This study presents a theoretical survey of question answering systems and classifying them according to key characteristics, evaluation methodologies and potential future research prospects.

Index Terms- Natural Language Processing. Pattern Matching, Question Answering, Textual Entailment

1. INTRODUCTION

With the proliferation of the digital age, accessing relevant information has become a major concern. The exponential growth of online content creates difficulties in both processing and retrieving useful information (Maedche and Staab, 2001). Annually, a large volume of multimodal data is published in digital formats comprising of series of videos, images and textual document. Nevertheless, huge amount of information available on the web remains unstructured which explains the semantic gap (Mika et al. 2009). Considering this, methods to automatically retrieve and enhance different corpora structures have been the concern in terms of the semantic web idea. Hence, information retrieval approaches have been applied to retrieve relevant information. Information retrieval is a way of obtaining relevant information or resource by the user who needs information from a collection of information sources. Information retrieval deals with the organization and retrieval of information from different sets of text-based documents. Question answering techniques have been widely adopted in different application domains with some degree of success in retrieving information from large textual corpora. They are found in certain applications like modern search engines and chatbots where relevant information is retrieved from large corpora and world knowledge. However, most common architectures of question answering systems are associated with three main components. These components are question processing, information retrieval and answer processing. The question processing part analyses natural language question to identify question focus and some respective keywords and terms needed to generate the expected answer as well as question classification. With the addition of natural language processing and question analyses techniques natural language question is processed to generate queries. These queries are useful for searching source materials to retrieve the expected answer. Queries generated from the question processing phase is used for the extraction of related documents and passages which an information retrieval step is. This phase involves using both documents and web corpora as well as web search engines and knowledge bases. Next is the answer processing which has to do with processing and extracting candidate answers from the retrieved documents and passages. The results from the extraction process is classified and ranked based on candidate score and the expected answer is retrieved based on the answer selection component (see figure 1 for common architecture of question answering systems).

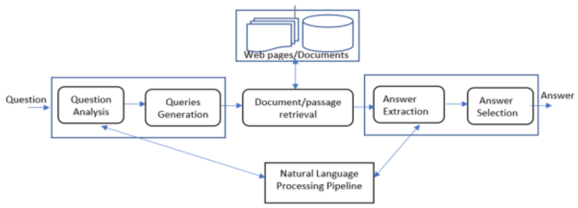

Figure 1: Common Architecture of Question Answering Systems

Question answering is an automatic way of retrieving exact information as an answer to questions presented in natural language (Harabagiu and Moldovan, 2003). Both information retrieval and question answering are rooted in Natural Language Processing and machine learning techniques. Moreover, the vast amount of textual data processed in our daily lives, and the subsequent use of natural language as our major means of communication in interchanging information makes natural language understanding and processing important in computing. Hence, the question answering community also adopted the natural language processing technique to analyse and understand questions presented in natural language form (Zouaq, 2011). Moreover, the past few years have experienced wealth of research in the subfield of question answering (Allam & Haggag, 2012). Question answering techniques help users in retrieving a small chunk of information from a pool of information based on natural language question. The concept of question answering is focused on developing a system that is capable of automatically responding to questions expressed by humans in natural language. Question answering systems have been classified into restricted and open domain, based on the kind of documents in which information is retrieved (Monroy et al. 2008).

Restricted domain

Also known as closed domain question answering deals with specific subject area such as medical domain. Here, question answering technique is confined to answering questions related to the domain of interest or retrieving domain specific collection of documents (Cavalcante et al. 2021, Dimitrakis et al. 2020). It relies on domain specific resources with focused terminology of words which makes it difficult to adopt general ontological resources for question analysis and response. Rather, the repository of questions in this approach are limited but uses domain specific ontologies whose knowledge is obtained from subject area significant words of the question (da Silva et al. 2020). Several works have been done in the close domain which includes: the legal field (Tran et al. 2013, Fawei et al. 2015), medical discipline (Sang et al. 2005), construction sector (Zhuo, 2004), and so on. However, question answering technique is associated with ambiguity and question classification problems as well as limited collection qualitatively annotated datasets in some specific domains.

Open domain

It deals with several subject areas such as the web. This question answering system is domain independent. It is based on general search in a large collection of documents. Here, both general ontologies and world knowledge are exploited for generating the required answer. However, the quality of answer depends highly on the satisfaction of the user. Moreover, this question answering system does not require domain specific keywords or dictionary for formulating questions. The open domain question answering was first introduced with large text corpora in the Text Retrieval Conference (TREC) which was highly promoted (Hirschman and Gaizauskas, 2001). Early systems applied statistical techniques to extract passages containing answer like information (Davies, 2015; Barkarson et al., 2022). The later ones use both statistical and machine learning techniques for question answering whereas the most recent adopted neural networks and deep learning as well as transformers and pretrained language models to enhance contextual understanding to enable a more precise answer retrieval and generation (Zhang et al. 2022;

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Montesinos-López et al. 2022; Choi et al. 2020; Wang et al. 2023; Liu et al. 2022; Han et al. 2021)

Question answering systems can also be categorised according to the type of services they provide. These systems address questions by utilizing structured data (Atzeni et al. 2004, Fawei et al. 2015), unstructured data (Bordes et al. 2015), and a combination of both (hybrid data) (Usbeck et al. 2015), in addition to providing community-based question answering services (Bunescu and Huang, 2010). Monroy et al. (2008) presented a shallow question answering model designed to retrieve legal texts. The approach employed a graph matching strategy to identify and extract the most relevant documents within a collection of legal document repository. Monroy et al. (2009) implemented a natural language processing technique that applies lemmatization combined with manual and automated thesauri, to enhance question answering performance in document retrieval tasks. These methods are classified as shallow in the sense that they do not rely on complex algorithms to generate answers but rather applied simple mechanisms. Experimental result shows better performance than traditional information retrieval systems for legal text retrieval. Furthermore, a hybrid framework was later proposed, combining simple rule-based methods with unsupervised learning strategies to enhance question answering (Kim et al. 2014). This approach depends on deep linguistic features to determine whether a text entails a given hypothesis. The researchers used Japanese and Korean Bar examination corpus composed of legal articles and corresponding questions to evaluate the system. Every question was analysed based on negation and linguistic complexity. The underlying idea behind this system is to apply textual entailment technique for generating answers. Which faced some difficulties in handling paraphrases and complex sentence interpretation.

In recent years, question answering researchers have integrated textual entailment technique to enrich semantic interpretation, thereby aiding in the identification of precise extraction of answers from retrieved documents. Textual entailment technique provides a structured way to estimate the inferential reasoning required to answer questions effectively (Harabagiu and Hickl, 2006). The approach determines the connection between two texts, one known as the theory (T) and another the hypothesis (H), whether the content of H can be inferred from T (Fowler et al., 2005). In this context, T may consist of multiple statements while H is a concise declarative statement. Earlier works by (Fowler et al., 2005; Akhmatova, 2005) utilized logical techniques to implement textual entailment. An inference-based approach was applied in previous studies (Lin and Pantel, 2001; Segura-Olivares et al., 2013), although their performance deteriorates in noisy environment. Wang and Neumann (2008) presented an answer validation technique that employs the subsequence kernel method to support machine learning based question answering systems. Despite these successes, recent textual entailment technique falls short in extensive legal knowledge required for effective reasoning. Their limited ability in processing and inferring accurately across for both structured and unstructured datasets underscore the need for improvement tailored to legal reasoning, particularly for determining yes/no responses in legal text analysis. Other limitations of textual entailment in question answering include challenges like linguistic ambiguity (word sense disambiguation and polysemy), the complexity in question structures, scalability concerns and sensitivity to language variations such as paraphrases and idiomatic expressions.

2.1 QUESTION ANSWERING OVER STRUCTURED DATA

Structured data refers to an information that is organized in a standard format that allows computers to easily interpret them. Some common formats of representing such data includes resource description framework (RDF) and web ontology language (OWL) (Dima, 2013; Huang & Zou, 2013; Zheng et al., 2015). The proliferation of structured data has empowered the open domain knowledge bases, which includes DBpedia, and YAGO2 that stores millions of interlinked entities with highly accurate fact extraction. Despite the recorded success retrieving specific information remains a serious challenge for both professional and lay users. However, retrieving relevant information from such structured data sources require specialized language like SPARQL query language (Huang & Zou, 2013; Hakimov et al., 2013) to access data. Due to the syntactic and semantic complexity of SPARQL and similar languages and even users must understand the underlying data schema to define correct and efficient queries. Question answering systems allow users, regardless of expertise, to pose queries phrased in natural language. Various techniques have been proposed to translate natural language questions into SPARQL queries. Existing approaches often adopt template-based generation technique (Unger et al., 2012; Zheng et al., 2015; He et al., 2013; Yahya et al., 2012; Dima, 2013). (Unger et al., 2012) adopted the template-based approach to transform natural language questions into RDF triples that reflect the accurate representation of the internal structure of the question. A deep linguistic analysis was implemented for question translation into SPARQL template with fillable slots populated with linguistic information. (Zheng et al., 2015) applied the intersection approach to connect natural language questions to SPARQL query workloads for the automatic generation of templates. Here, a graph similarity-based technique was used to evaluate similarity measures. A hybrid linguistic method, combining shallow and deep analysis was applied in (He et al., 2013) to translate natural language questions into <subject, property, object> triples, which are subsequently matched to <class, entity, property> triple structures in DBpedia. To manage ambiguity inherent in natural language questions, Yahya et al. (2012. 2013) utilized the integer linear programming technique to resolve ambiguity in natural language question interpretation. Their approach segmented questions into smaller phrases and linked with the corresponding semantic entities, relations, and classes. The resulting mappings are then translated as SPARQL triples that directly mirrors the user question (Yahya, 2012). In a subsequent study, a relaxation mechanism was proposed in (Yahya et al., 2013) to enable partial translation of natural language questions into relaxed queries, such that missing components are reconstructed through contextual entities and relational information found in textual data. This method extends the traditional SPARQL triples into quads comprising subject, predicate object and text (SPOX) to improve contextual coverage. The system does not attempt to translate the entire question but rather focusses on translating the most relevant parts of the question. Another study proposed a prototype system that translates natural language question by aligning syntactic structures from the question to relational patterns in an RDF backend (Dima, 2013), which is analysed based on its syntactic fragments. Similarly, Huang and Zou. (2013) developed a triple-based translation approach that converts natural language questions into RDF triples mirroring SPARQL structures, uncovering the semantic relationships between entities and classes. A dependency tree parsing, and relational pattern extraction technique was employed (Hakimov et al., 2013) to convert natural language question into RDF triples.

2.2 QUESTION ANSWERING OVER UNSTRUCTURED DATA

Question answering research over unstructured data aims to design systems capable of understanding and responding to natural language questions posed by human. A number of researchers participated in the TREC2002 QA challenge, where Moldovan et al., (2002) introduced a combine approach that leverages lexical chain analysis with logic prover to re-rank potential candidate answers based on accuracy. However, combining logic prover like COGEX (Moldovan et al., 2003) is computationally expensive, due to its extensive use of linguistic rules and world knowledge resources that are expensive and time-intensive in constructing. A QA model utilizing a tree mapping strategy inspired by machine translation was proposed in (Punyakanok et al., 2004). This method depended on document retrieval. Cucerzan and Agichtein (2005) presented QA system that adapted a web-based rule rewriting technique to retrieve answers from both structured and unstructured web sources, though its overall performance remains low. Vargas-Vera and Motta, (2004) and Atzeni et al., (2004) proposed an ontology-based approach for question answering. The approach employed semantic reasoning to interpret natural language questions. Vargas-Vera and Motta (2004) adopted ontology refinement and similarity algorithms to identify relationship between query components and ontology structures combined with logic inference, NLP, and information retrieval methods to enhance answer extraction process. In addition, a related study proposed an ontology-based knowledge management and search engine that accept natural language question as input and generates a response in natural language form which is designed to align with the evolving framework of the semantic web.

2.3 QUESTION ANSWERING OVER STRUCTURED AND UNSTRUCTURED DATA

Despite the advancement of the Semantic Web which has led to an increase in publication of structured data online, a significant portion of the web information remains unstructured. This has made information access and retrieval challenging, especially when answer extraction is from both structured and unstructured data sources. For instance, the query "Which recipient of the Victoria Cross died in the Battle of Arnhem?". Such question can better be answered with an integrated information from structured and unstructured data sources (Usbeck et al., 2015). To address this difficulty, Usbeck et al., (2015) applied the Predicate-Argument Representation technique to translate natural language query into a combination of SPARQL and text queries. IBM DeepQA similarly utilized a series of algorithms to extract and evaluate candidate answers from structured and unstructured data (Ferrucci et al., 2010; Ferrucci et al., 2013). This system combined natural language processing with series of search strategies to analyse textual information and generate ranked potential answers. An enhancement of the DeepQA was later introduced to mitigate cognitive overload in healthcare professionals, who finds it difficult to coping with the rising growth of medical data (Ferrucci et al., 2013). This enhanced model seeks to support practitioners in handling the ever-increasing medical knowledge by extracting relevant information for clinical decision making.

2.4 COMMUNITY QUESTION ANSWERING

Community based question answering (CQA) platforms have been effective systems for receiving responses from both experienced and expert volunteers in problem solving. However, users of these platforms usually experience delays due to the time a suitable volunteer will provide the answer. Also, these systems accumulate large amount of previously answered questions that may match new user query. It becomes increasingly necessary to automatically identify earlier answered answers that corresponds to new user questions in order to provide timely response to queries. To address this problem several studies (Cao et al., 2008; Duan et al. 2008; and Liu et al., 2008) have explored different approaches for extracting answers from archived community questions that are semantically equivalent to user's query. A common approach to these studies is the use of semantic similarity measures. For instance, (Jeon et al., 2005a; Bunescu and Huang, 2010b; Bunescu and Huang, 2010a) applied different similarity measures to identify matching question answer pairs in the CQA repositories. One notable approach combined three similarity measures such as cosine similarity, LM-score and LM-Hrank to improve matching accuracy. In another study, (Bunescu and Huang, 2010a) utilized the supervised learning technique for ranking candidate questions. A structural information awareness utility function was implemented in (Bunescu and Huang, 2010b) for detecting paraphrased questions. The idea was to detect paraphrased questions in a corpus. Lytinen and Tomuro, (2002) proposed a metric-based strategy that classifies user questions by type and adopt four similarity metrics to identify semantically related entries. To improve the extraction of high-quality responses, LM-HRANK was employed in (Jeon et al., 2005b) to measure the level of similarity between sets of candidate answers. However, its effectiveness has been criticized for its inadequacy to capture deep semantic representation.

2.5 QUESTION ANSWERING OVER TEXTUAL ENTAILMENT

Question answering, and textual entailment have been widely researched, a hybrid framework that integrates shallow and deep analysis was implemented in (Bos and Markert, 2005) for detecting textual entailment relationship between a pair of texts. In another research, a lexical similarity measure was applied in (Jijkoun et al., 2005) to determine semantic relatedness between words to infer entailment. Yao et al., (2013) presented an integrated approach that combines linear chain conditional random field technique with tree edit distance for entailment answer extraction. A lexical and syntactic similarity measure was utilized in (Pakray et al., 2011) for textual entailment detection between a pair of sentences. Heilman and Smith, (2010) proposed a tree kernel-based model to facilitate a greedy search mechanism for recognizing entailment relationships between textual pairs. (Rios

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and Gelbukh, 2012) presented a similarity metric-based method for determining textual entailment and contradiction in a pair of texts. Bobrow et al. (2007) introduced a rule-based approach for detecting entailment and contradiction between a pair of texts. A cost-based approximation incorporated into semantic inferencing approach was introduced in (Bar-Haim et al., 2007) to determine entailment thereby applying parse trees and rule-based transformations. Kim et al., (2014) implemented a two-layered model for textual entailment exercise using the Japanese Bar Examination dataset for experimentation. However, the approach lacks deep legal knowledge to fully address legal reasoning. An integrated approach combining Support Vector Machine and Convolutional Neural Network was developed in (Do et al., 2017) to improve legal question answering and information retrieval efficiency.

III. APPROACHES TO QUESTION ANSWERING

Question answering systems apply both information retrieval and extraction techniques to deliver a more precise answer to a natural language question. The information retrieval part of the system retrieves related documents containing relevant information relating to the question after the question analysis phase. While the information extraction unit plays the role of extracting the required snippet as an answer to the question after successfully evaluating retrieved documents. However, different approaches have been applied to establish this workflow for question answering in the question answering research community. Hence, question answering systems are categorized based on the following approaches:

3.1 LINGUISTIC APPROACH

This approach applies natural language processing techniques in the analysis of natural language question. It is applied in the analysis phase to translate user question to the appropriate and precise query that specifies more exact response to the question. These approach leverages on linguistics theories and structures as well as computational linguistics to enhance the question answering process. In this approach, questions are analysed to identify constituent parts of the sentence and their relationship with each other to understand what type of answer is sorted for. Similarly, words with multiple senses are disambiguated, which helps in understanding contextual use of the words. Named entities are recognized which form the basis for identifying key information relating to the answer. Coreferences are resolved to keep track of references to same entities in the question. The decision-making process to arrive at an expected answer in this approach is more reliable, transparent and explainable. However, the challenge is that more sophisticate rules are required to resolve ambiguities as well as extensive linguistic resources like grammar rules and lexicons. The essence is that human language is vast and can be expressed in different forms like idioms, metaphors and so on which makes it difficult to parse.

3.2 STATISTICAL APPROACH

Statistical approach adopts probability models and statistical methods to proffer most probable answers to questions with respect to answers found in a corpus. This approach depends on large corpora and linguistic patterns to delineate and identify the possible correct answers to questions. This approach does not rely on structured query language but can formulate natural language queries to find answers to questions. It works by treating each term independently which makes it a useful method for classification. Statistical techniques are more applicable in large scale question answering systems where pre-defined answers are not provided. However, different statistical techniques are applied in the question answering subfield to analyse sentence structure as well as rank potential answers with respect to their likelihood estimation. Some of these methods includes probability models like Naive Bayes, Term Frequency Inverse Document Frequency (TF-IDF) models and so on.

Probability models apply probability distribution to classify and select the most appropriate answer to natural language question. An estimation function is used to predict the likelihood of a candidate answer to a question by assigning probabilities to candidate answers with respect to corpus evidence. The approach offers a robust framework for managing uncertainty in natural language in question answering systems. The fundamental approach involves the following:

Naïve Bayes Classifier: delivers a simple and effective way for question answering especially for questions with structured dataset. It is easy to train and calculate probabilities and most importantly works with sparsely distributed dataset. It works first by learning word probabilities with estimation and uses the learned knowledge and estimation to answer new questions.

$$P(A|Q) = \frac{P(Q|A)P(A)}{P(Q)}$$

Where A is candidate answer, Q question, P(A) is the probability of an answer, P(Q) is the probability of the question, P(A|Q) is the probability of an answer given the question and P(Q|A) is the probability of the question given an answer. With a prior knowledge that a given answer will be possibly correct based on historical information, then the new information is updated as observed in Bayesian inference.

1. Term Frequency Inverse Document Frequency (TF-IDF) is a statistical technique that attribute weights to words in accordance to their significance or importance. The words associated with high tf-idf scores are identified as relevant and relative. This technique is useful for document classification where it represents a document as a vector of words with respective weights which allows text comparison and content similarity check. The formula for TF-IDF is given as

$$TF - IDF = TF \times IDF$$

$$TF = \frac{Number\ of\ term\ occurance\ in\ document}{Total\ number\ of\ terms\ in\ document}$$

$$IDF = \log(\frac{Total\ number\ of\ documents}{Number\ of\ documents\ containing\ term})$$

3.3 PATTERN MATCHING APPROACH

Pattern matching approach identifies and retrieve answers with respect to some previously defined patterns or templates. This approach works by classifying and mining related answers from natural text and matching question patterns or answer patterns (Shen et al. 2005; Zhu et al. 2021). It involves fixed or partial pattern matching for simple and complex questions. Patterns could be defined based on keywords and named entities or syntactic relational structures. These systems will be able to identify and retrieve relevant information in a more accurate form.

3.3.1 FIXED PATTERN MATCHING

This technique involves locating and extracting already established patterns identified within the questions by matching them to the related text in order to generate corresponding answer to the question. This approach is useful in retrieving relevant answers for questions with clear answer formats like those that necessitate retrieving simple facts or matching corresponding terms in the text to options (Anggraeni et al. 2019; Akermi et al. 2020; Wu et al. 2003). The process works by matching keywords, phrases or precise data presentation structure. For example, given a question "What is the name of the president of Nigeria?" and a pattern existing in the text like "The president of Nigeria is Tinubu." In matching the text and the questions together "Tinubu" would be identified as the answer to the question. This method is very simple and efficient; however, it is limited in answering deep and complex questions requiring good understanding.

3.3.2 PARTIAL PATTERN MATCHING

This approach deals with more complex questions where the answers to the question will be within related keywords or synonyms in the text. In its matching operations it gives room for some level of mismatch or variation (Shen et al. 2005; Wu et al. 2003), It provides complete tolerance to the variation in words arrangement in text and accommodates slight difference in phrasing. Named entity recognition and query expansion techniques can be adopted to better the performance of partial pattern matching. It works by identifying specific patterns in text like phrases or syntactic structures and associate them with the corresponding answers by partially matching them to text to retrieve the relevant answer. The match could be exact or partial. For example,
User question: Who established the first private refinery in Nigeria?

Template pattern: Aliko Dangote is the founder of private oil company in Nigeria?

Here, a partial match will recognise "refinery" as "oil company" and "established" as a synonym for "founder" and returns "Aliko Dangote". If multiple matches are found, then an answer ranking technique is applied based on contextual relevance and other features to retrieve most relevant answer (Cui et al. 2007; Vargas-Bianchi, 2025). A partial matching technique was applied in (Er, 2009) for matching factoid questions in Turkey language. Templates were predefined to recognise and extract short and factual answers from text. A machine learning approach that adopt a slackly defined lexical and syntactic patterns for question answering (Cui et al, 2007). The tool uses statistical and linguistic patterns to match and extract possible answer from a pool of text. The approach works better for definitional questions.

3.3.3 TEMPLATE BASED MATCHING

This approach works by using predefined templates to identify the structure of the question and relate them to more fitting answers. Often the templates are manually or semi-automatically curated with fillable slots that matches a type of question. An input natural language question is translated into a proper query template that matches the handcrafted or semi-automatic templates (Fabbri et al. 2020). Once a template matches the question, the system fills template placeholders with entities from the question and then searches the text corpus to extract the correspond answer. For example, we have a question template as:

Template: "Who is the president of <Nigeria>?"

In instantiating question to query template, we have:

Query: SELECT president FROM countries WHERE name <Nigeria>.

The template matching based approach have been applied by different researchers in the domain for question answering exercise where retrieval is either from a text corpus, knowledge base or knowledge graph (Formica et al. 2024, Athreya et al. 2021, Lan et al. 2019, Jiao et al. 2021). Unger et al. (2012) adopted the template based matching technique to map natural language questions to SPARQL queries. The research used linguistic analysis to create matching syntactic templates containing semantic information that corresponds with knowledge graph to retrieve relevant answers. An unsupervised template driven question generation approach was applied in (Fabbri et al. 2020). Their technique extracts answer related sentence and transform it into a WH-question based on template tailored answer type like "when" or "where". Cui et al. (2007) employs soft pattern matching technique to enhance question answering system to handle definitional questions. The approach recognised patterns within text by leveraging probabilistic pattern matching to identify relevant definitions in large corpora. A question answering system that aligns natural language questions to predefined SPARQL query templates for question answering was proposed in (Punjani et al. 2018). The approach depends on natural language question templates that matches some specific query patterns which handles geospatial question with minimal ambiguity. A template-based approach for question answering was introduced in (Lu et al. 2021). In their method the predefined template captures user intention and generates structured queries that corresponds to RDF query format. Other pattern matching examples for question answering could be seen in the SQuAD dataset (Rajpurkar et al. 2016). These datasets were much larger than previous ones and are manually labelled reading comprehension dataset. A baseline model and assessment method were provided to show machine performance. However, in application of SQuAD dataset, Rondeau and Hazen, (2018) highlights specific concerns about the dataset with respect to machine comprehension system. The authors stressed the need for enhanced reasoning and language understanding abilities in question answering systems.

3.4 RULE-BASED APPROACH

Involves adopting rules, logic and handcrafted patterns to capture and response to user questions. Rules are often defined based on linguistic patterns, semantics and relationships which enables the system to capture information that are relevant from text or knowledge bases to analyse question and extract relevant answers (Katyayan and Joshi, 2023; Zhang et al. 2025; Ni et al. 2024). Rule based systems mimic the human reasoning and decision-making process by systematically adhering to series of logical steps. These systems are deterministic in nature in that the same input will arguably generate the result. Alazani and Mahender (2021) applied a rule-based technique in question generation for Arabic text question answering. The approach worked based on Arabic linguistic rules thereby performing key steps in linguistic pipeline such as tokenization, stemming, parts of speech tagging and so on to identify key sentence components to generate aligning answers to questions presented in natural language form. An integrated approach was applied in (Mitra and Baral, 2016), where data driven natural language processing with explicit rule learning and logical reasoning tools were combined to produce a more robust understanding in Artificial Intelligence agents. The combination propelled the development of question answering systems with advanced cognitive abilities.

3.5 MACHINE LEARNING APPROACH

Machine learning approach has greatly impacted the way question answering systems functions in retrieving a piece of information as an answer to a natural language question. These systems utilize techniques like natural language processing (NLP) to evaluate questions in order to extract relevant answer from a pool of text. The importance of these systems is their ability to understand questions; extraction of relevant passages and the subsequent retrieval of the expected answers make them unique and interesting. The classical machine learning approaches applies statistical and linguistic engineering techniques to retrieve relevant patterns from data. These systems work based on three well defined steps as question processing, information retrieval and answer processing. Question processing is intricate and complex task that involves determining the type of question and retrieving linguistic patterns by performing tokenization, parts of speech tagging and syntactic parsing. Whereas understanding the question type is deeply interconnected with the kind of expected answer. The information retrieval step applies conventional information retrieval techniques to find and extract documents and pages relating to the question type. Queries are analysed to extract the semantic information contained in the query which is required to retrieve the expected answer as a way of understanding user question. Support Vector Machine methods are often used for context-based ranking formed from their relevance to enhance question answering systems effectiveness (Kim et al. 2014; Yen et al.2013; Sarrouti and El Alaoui, 2017; Purwarianti et al. 2007). These tools are trained on lexical, syntactic and semantic features as well as named entities and concepts in order to understand the context of the question or the type. In the same way most authors interpret the answer selection task as classification problem and applies SVM in selecting expected answer (Suzuki et al. 2002, Wu et al. 2007, Pota et al. 2016). Also, SVM is useful for classification task in identifying an answer type (Zhang and Lee, 2003). For passage and paragraph retrieval and feature based ranking among many retrieved to extract the most likely to contain the answer, the Latent Semantic Indexing (LSI), Manhattan distance, and Jaccard similarity as well as Palmer Wu similarity are used for ranking task (Do et al. 2017).

While machine learning algorithms are utilized to determine the most suitable answer based on the retrieved content in the answer processing phase, (Kumar et al. 2003) adopts a machine learning technique to return exact responses to natural language questions presented in Hindi language. Their idea is built upon combining the techniques of information retrieval, natural language processing and machine learning to analyse user questions and generate more appropriate and precise response as an answer. A support vector machine (SMV) based machine learning technique was applied in (Ahmed and Ajusha, 2017). Here, user queries are categorized based on expected answer type by SVM trained on lexical and syntactic characteristics, which leads to the answer extraction process. Then an SVM based classifier is applied for ranking and candidate answer selection. A linguistic and statistical feature extraction method was applied in (Dominguez-Sal and Surdeanu, 2006) for concise fact seeking questions for factoid question answering. However, most conventional machine learning approaches for question answering are known as supervised learning, which requires extensive human involvement in the training process. A serious manual effort is needed in labelling hundreds and thousands of data for question answering and achieving quality result accuracy highly depends om having broad and sufficiently diverse dataset.

3.6 DEEP LEARNING

Deep learning is a branch of machine learning technique that leverages artificial neural networks to process data to extract useful insight like human learning. The deep learning process is an unsupervised learning method that contains multiple layers of processing units. These layers include the input, hidden and output layers. An artificial neural network is made of different nodes that process input data, which jointly form the input layer of the network. The hidden layer process data at several levels and fine-tune their functionalities as they encounter newly introduced data. It contains hundreds of layers that are used to analyse a problem from multiple angles. The nodes that generate the results are contained in the output layer, which produces binary response in the form of "yes" or "no". For information extraction, the main entities are identified in the natural language question as well as the possible answers based on topic entities. The question is then converted into feature vectors alongside with the entities and relations found in text or knowledge base. This process allows for direct similarity matching task between question-and-answer vectors for corresponding entities and relation. A bi-LSTM model was introduced in (Sharma & Gupta, 2018) with an attention mechanism which translates both question and candidate answers into a vector representation, which then applies cosine similarity measures to determine matches. The system was tested with the TREC-QA and shows high score in evaluation with Mean Average Precision (MAP). An integration of convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory networks (BiLSTM) was implemented in (Cai et al. 2020) alongside with a combination of co-attention and attention mechanisms to analyse question to extract deep semantic information as well as to improve understanding of the relationships in the question pairs. With this approach, the system connects to previously answered question with similar meaning. Tahsin Mayeesha et al. (2021) applied recurrent neural networks (RNN) and long short-term memory (LSTM) models to retrieve semantic information and extract answers from Bengali text. In addition, they implemented it on a dedicated dataset specifically built for Bengali question answering tasks, to handle the Bengali's language multifaceted morphological structure through preprocessing and applied embedding techniques to generate an efficient word representation. The research demonstrates that the implementation of the deep learning method significantly enhanced accuracy over traditional rule based and statistical techniques. An integrated approach was implemented on a humanoid robot in (Budiharto et al. 2020) to integrate natural language processing technique with convolutional neural network and recurrent neural network to process and answer user questions. The authors demonstrate that the approach boosted the robot's ability to understand user questions based on context and respond accordingly.

IV. EVALUATION METRICS

For evaluation of question answering systems, statistical techniques have been commonly applied in evaluating the performance of question answering tools. These techniques comprise of precision, recall, F1 measure, accuracy, mean reciprocal rank (MPR) and so on. Often dataset used for question answering research contains correct and incorrect answers especially for multiple choice question answering task (Fawei et al. 2017). During evaluation the correct cases that the system could successfully identified are referred to as True Positive (TP) while the correct cases that the system could not identify are known as False Negative (FN). The incorrect cases that the question answering system identified as incorrect are called True Negative (TN) whereas the cases the system fail to identify as incorrect referred to as False Positive (FP).

- Precision measures the number of retrieved answers that are truly correct from the pool of answers. It defines the correctness of the system in retrieving the correct answer. It is calculated as the ratio of the correct answers and to all the correct and incorrect answers. The formula for precision is given as:

$$Precision = \frac{TP}{TP + FP}$$

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- Recall is the metrics that measures the fraction of the actually correct answers that were captured during the answer retrieval process of the system. High recall score indicates that the system is performing well in retrieving the correct answers. Its measurement scale is between 0 to 1 or as a percentage. The recall score is at maximum if its value reaches 1.0, which means the system successfully identifies all the correct answers present in the dataset. The formula for recall is given as:

$$Recall = \frac{TP}{TP + FN}$$

- Accuracy measures the overall correctness of the question answering systems retrieval of the correct and incorrect answers. It is measured in a scale of 0 to 1. Better performance is achieved with an increasing level of accuracy score. Accuracy is actual an expression of the systems' ability to retrieve the correct and incorrect answers. The formula for accuracy is given as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- F-measure metrics jointly evaluate the harmonic mean of precision and recall. It evaluates the quality of retrieval from the perspective of an author who equates precision and recall equally important in the analysis phase. The formula for F-measure:

$$F1 - measure = \frac{2 * P * R}{P + R}$$

- Mean Reciprocal Rank (MRP) measures the position of the correct answer in the ranked list of outputs. It is used to determine how effective is the question answering system in retrieving the correct answer by evaluating how well the system ranks the first correct answer in the rankings of the retrieved answers. MRP formula is:

$$MRP = \frac{1}{n}\sum_{n=1}^{n}\frac{1}{rank_i}$$

V. CHALLENGES AND FUTURE DIRECTION

Despite the progressive success in question answering research, it is faced with different challenges such as understanding human language, precise and fluent answer generation and so on. Natural language is vast, complex and not very precise enough, hence, handling issues of ambiguity in words and phrases, domain specific language, complexity in question structure as well as coreference resolution problems are the issues to deal with. Ambiguity makes language comprehension difficult, which includes lexical, syntactic, semantic and pragmatic (Rodd, 2020; Höffner et al. 2017; Zait & Zarour, 2018; Abd Al-hussein & Mayuuf, 2021). For example, the word "scrub" could have different meaning like "to clean", "exfoliator" or "a kind of special cloth worn by surgeons". In same way when the structure of a sentence leads more than a single interpretation makes it hard for question answering systems to capture the underlying interpretation of the given sentence (eg the sentence "visiting relatives can be time consuming" can mean you visiting relatives or relatives visiting you). Also, intent driven sentence could often be missed by question answering systems (eg the sentence "could you pass me the ball" can structurally mean a yes/no question but contextually meant as a request). Similarly, specialized language (vocabulary, terminology and expressions) tailored to solving problems in a particular field of study. In contrast to everyday language, domain specific language depends on precise vocabulary that is uniquely exclusive within its context. For example, "what duration does paracetamol take to reach its half-life in children?" would be a struggle for general question answering systems to extract the required answer. But, as used here paracetamol and half-life are medical domain specific terminology, which could be correctly interpreted and answered by a medical question answering system.

However, the advancement in question answering systems would involve making them more open, intelligent and real-world applicability. More broadly, integrating structured and unstructured data with real-world knowledge would better interpret implied meanings of figurative expressions as well as multilingual and cross-lingual problems in question answering systems. This will help in streamlining question answering systems to move from correlation-driven question answering to comprehend casual dependencies. Moreover, other areas of investigation are enabling question answering systems to justify their answers by referencing supporting evidence from multiple sources as well as addressing voice-based questions, analysing audio content, thus, facilitating conversional clarification when questions are ambiguous.

VI. CONCLUSION

In this study, we present an overview of some well-known question answering methodologies and the associated services they provide. The survey details various computational approaches used within the question answering field for question interpretation, evidence retrieval and extraction of concise, contextually appropriate natural language answer. The review additionally offers a theoretical overview of statistical frameworks commonly employed to measure question answering systems effectiveness. Based on gained insight, we outline prospective direction for future research. In future, we intend to explore emerging trends identified in this study to engineer novel question answering architectures capable of addressing domain specific questions and associated knowledge bases relevant to the research challenges identified in the review.

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