**Chapter 1**

**Introduction**

## **Introduction**

The field of computer science has historically aided human in simplifying their lives. The digital era is a whole new period in human history. In the digital age, vast amounts of information are generated and stored in various forms, leading to the need for efficient methods of accessing and retrieving this data. Although traditional search engines are efficient at locating relevant content based on keywords, they frequently are unable to deliver direct answers to certain specific questions. By allowing users to ask questions in natural language and obtain clear, concise replies, question-answering systems seek to overcome this constraint.

A question-answering system uses sophisticated technology known as natural language processing (NLP) to understand user questions and provide answers that are human-like. It utilizes machine learning algorithms, semantic analysis, and information retrieval techniques to process and understand questions, search for relevant information, and generate accurate and concise answers.

There are two primary categories of question-answering systems, open-domain and closed-domain. Open-domain systems aim to provide answers to a wide range of questions on various topics, often by leveraging vast amounts of general knowledge and information from diverse sources like books, articles, and the internet. On the other hand, closed-domain systems are prepared to specific domains or subject areas, such as healthcare, educational sector, legal, or technical fields, and focus on providing specialized answers within those domains.

The functioning of a Question Answering System typically involves several steps. First, the system analyses the question's structure and language to understand its meaning and intent. It then searches through relevant data sources, such as a pre-existing knowledge base or a collection of documents, to locate relevant information. This information is then extracted and processed to generate a concise and accurate answer. In more advanced systems, machine learning techniques may be employed to improve accuracy and handle more complex questions.

There are numerous uses for question-answering systems. It is possible to use them in search engines to provide direct answers to user queries, in customer support systems to address frequently asked questions, in educational platforms to assist learners in finding specific information, and in various other domains where prompt and accurate answers to questions are required. The development of question-answering systems has been substantially aided by recent developments in the processing of natural languages, machine learning, as well as the availability of large-scale datasets. These systems are continuously developing and becoming more advanced. They are now able to provide responses that are both more specific and more complex, and they have the potential to dramatically improve information retrieval and access to knowledge for users in a variety of sectors.

## **Automated Question Answering System**

### **Definition**

An automated question answering system is an advanced software application or technology that utilizes artificial intelligence (AI) techniques to automatically process and respond to user questions or queries in a human-like manner, without the need of human intervention. This system is designed to understand natural language input and generate relevant and accurate answers by leveraging machine learning, natural language processing, and information retrieval techniques.

Automated question answering systems are capable of analysing and interpreting user queries, extracting relevant information from diverse data sources such as textual documents, databases, or the internet, and generating concise and meaningful responses. These systems aim to provide direct answers to user questions rather than providing a list of relevant documents or search results.

The core components of an automated question answering system typically include:

* **Question Understanding:** The system analyses and understands the user's question, considering the context, semantics, and intent behind it. This involves techniques such as natural language processing, syntactic parsing, and semantic analysis.
* **Information Retrieval**: The system retrieves relevant information from various sources based on the user's question. This can involve techniques such as keyword 3 matching, statistical analysis, or more advanced approaches like deep learning-based retrieval.
* **Answer Generation:** The system generates a concise and accurate response based on the retrieved information. This may involve aggregating and synthesizing information from multiple sources, performing reasoning or inference, and presenting the answer in a human-readable format.
* **Evaluation and Ranking:** In some cases, automated question answering systems may rank or evaluate the quality of different candidate answers based on their relevance, correctness, or confidence scores to provide the most appropriate response.

Automated question answering systems have diverse applications, including customer support chatbots, virtual assistants, intelligent search engines, educational platforms, and information retrieval systems in various domains. They aim to improve user experience, save time and effort by quickly providing accurate information, and facilitate effective interaction between humans and machines.

The development of automated question answering systems involves addressing challenges such as understanding complex language constructs, handling ambiguity, maintaining up-to-date knowledge bases, and continuously improving accuracy and relevance in generating answers.

### **History**

The history of Question Answering Systems dates back several decades, with significant advancements made in the field of natural language processing and information retrieval. Here's an overview of the major milestones and developments in the history of Question Answering Systems:

**1960s-1970s:** Early Question Answering Systems emerged during this period, focusing on rule-based approaches and using handcrafted patterns to match questions with predefined answers. One notable system from this era was the STUDENT system developed at Stanford University, which could answer simple science questions.

**1980s-1990s**: Research in Question Answering Systems gained momentum in the 1980s and 1990s. Systems like LUNAR and BASEBALL, developed at the University of Massachusetts, used natural language understanding and information retrieval techniques to answer questions related to specific domains (astronomy and baseball, respectively). These systems marked a shift towards more sophisticated approaches, incorporating linguistic analysis and domain-specific knowledge.

**2000s:** The Text REtrieval Conference (TREC) introduced benchmark datasets and evaluation measures for Question Answering Systems, fostering research and development in the field. In 2001, IBM's Deep Blue defeated the chess world champion, Garry Kasparov, showcasing the potential of AI in complex problem-solving tasks and inspiring advancements in Question Answering Systems.

**2003:** The development of the Watson system by IBM marked a significant milestone in the history of Question Answering Systems. Watson, designed to compete on the quiz show Jeopardy! utilized advanced techniques such as natural language understanding, machine learning, and statistical analysis to process and answer questions accurately.

**2010s:** The rise of deep learning and neural networks revolutionized the field of Question Answering Systems. Researchers began exploring models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to improve the accuracy of information retrieval and answer generation. Systems like Google's RankBrain and Microsoft's Bing started incorporating deep learning techniques into their search engines, enhancing their ability to answer user queries.

**2019:** OpenAI introduced GPT-2, a large-scale language model based on the transformer architecture. GPT-2 demonstrated impressive capabilities in understanding and generating human-like text, including answering questions. The model's release sparked widespread discussions about the potential benefits and risks associated with such advanced language models.

**Present:** Question Answering Systems continue to evolve, leveraging the advancements in deep learning, pre-training models, and large-scale datasets. Transformer-based models like GPT-3, BERT, and T5 have achieved remarkable performance in various question answering tasks, showcasing the state-of-the-art capabilities in understanding and generating answers.

As the field progresses, ongoing research focuses on improving the interpretability, explain ability, and robustness of Question Answering Systems, along with addressing challenges such as handling ambiguous queries, incorporating domain-specific knowledge, and providing reliable and trustworthy answers to users.

### **Structure of Question Answering System**

A question-answering system's design has particular, essential components. A question-answering system uses three different modules [1]:

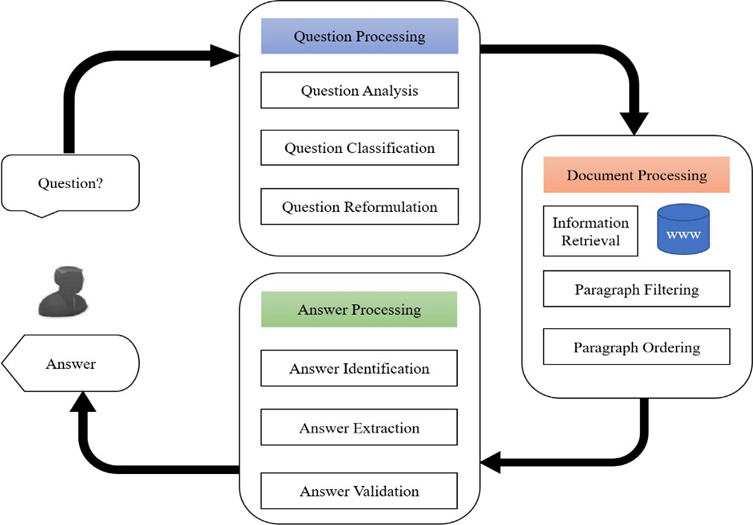
* **Query Processing Module:** This module specifies the context and focus, identifies the types of question, and sets the expectations for the type of answer that is being asked for.
* **Document Processing Module:** Information retrieval is used for locating relevant documents.
* **Answer Processing Module:** After retrieving the relevant documents, they must be parsed through to produce an acceptable and accurate response.

Figure 1: Architecture of Question Answering System, source: http://www.aliallam.net/upload/598575/documents/ECFF549932079694.pdf

Each of these modules carry out a distinct task to provide relevant answers. The full architecture is depicted in the picture below.

* **Query Processing Module:**

As already mentioned, the query processing system is responsible for three major tasks:

1. The process of analysing a question is used in order to get preliminary information from it.
2. Classify the types of questions to understand the context of the required answer. For example, Python errors should lead to coding answers, and Python bites should lead to snake bites.
3. To get relevant answers, reformulate the question. As a result, the question is transformed into a pre-trained vector that includes several examples of question-and-answer pairs. This aspect is in responsible of information retrieval.

* **Document Processing Model:**

The revised query is accepted as input by the document processing module. The document processing module maps the closest documents to the posed inquiry using an internal information retrieval (IR) method. The materials are arranged in accordance with how similar and pertinent they are to the query. Three main tasks are carried out by the document processing module.

1. Retrieve the set of documents from the Information Retrieval system.
2. Reduce the amount of text in each document and filter the set of documents obtained from the previous stage to generate a concise response.
3. Arrange the documents in order based on similarity and relevance to the question.

* **Answer Processing Module:**

The final module receives a collection of succinct documents that have been filtered and ordered by the preceding module. The set of documents is taken into consideration by the answer processing module, which then does the following three major tasks:

1. Find statements or answers within the limited set of documents.
2. Select the appropriate phrases and words that best answer the question to extract the relevant response. In the past, this was done heuristically. Heuristic algorithms are a method of problem solving where the importance of finding the optimal solution is placed. Finding a solution that comes close to the true answer is prioritized over factors like cost, complexity in terms of space and time, accuracy, or speed. When there is no known effective approach to finding a solution to an NP-complete problem, heuristic algorithms are typically applied. By entering the parameters into the method, it can be confirmed if the solution is known. As a result, creating heuristic algorithms requires switching back and forth between the algorithm and the solution it generates.

When the algorithm's solution is as effective as possible given the constraints, it is considered to perform well.

1. Validation of the answers obtained by the previous step. This is typically used for evaluating the outputs obtained by such question-answering systems as they are being designed. The evaluation metrics decrease during deployment in order to maximise the system's data flow.

* **Evaluating the answers obtained:**

The criteria may differ from one paper to the next. More broadly, we desire answers from the question-answering system that are pertinent, accurate, and comprehensive. As a result, numerous evaluation measures were created to gauge such nebulous terms. These measurements include F1 scores, precision, recall, and others. Refer to this article for more information on evaluation metrics.

### **Characteristics**

Automated question answering systems possess several key characteristics that define their functionality and capabilities. Here are some prominent characteristics of an automated question answering system:

1. **Accuracy:** The system should strive to provide accurate and correct answers to user questions. It should be able to understand the question's intent and context and deliver information that is factually reliable.
2. **Relevance:** The answers provided by the system should be directly relevant to the user's query. Irrelevant or off-topic responses can lead to frustration and dissatisfaction.
3. **Natural Language Understanding:** The system should be capable of understanding and interpreting natural language queries in various forms, including variations in wording and sentence structure.
4. **Contextual Understanding:** Understanding the context of a question is crucial for generating appropriate answers. The system should be able to consider the context to provide meaningful responses.
5. **Variety of Sources:** The system should have access to a wide range of reliable and authoritative sources of information to draw from. This diversity enhances the chances of providing accurate and comprehensive answers.
6. **Consistency:** The system should deliver consistent answers to the same question posed in different ways. Inconsistencies can lead to confusion and undermine trust in the system.
7. **Speed and Efficiency:** Users expect timely responses. The system should be capable of providing answers quickly to maintain user engagement.
8. **Adaptability:** The system should be adaptable to different domains, languages, and user levels. It should be able to adjust its responses based on the specific context and user preferences.
9. **User Feedback Incorporation:** The system should have mechanisms to learn from user feedback. This can help improve the quality of answers and address any shortcomings.
10. **Handling Ambiguity:** Natural language can be ambiguous. The system should have techniques to handle ambiguity, either by asking clarifying questions or by providing multiple possible interpretations.

These characteristics collectively enable automated question answering systems to understand user queries, retrieve relevant information, and generate accurate and meaningful responses, effectively bridging the gap between unstructured data and user information needs.

### **Properties**

Properties of an automated question answering system refer to the fundamental features or attributes that characterize the behaviour and functionality of such a system. Here are some key properties of an automated question answering system:

1. **Accuracy:** An automated question answering system should strive to provide accurate and correct answers to user queries. It should employ robust algorithms and techniques to ensure the reliability of the generated responses.
2. **Relevance:** The system should prioritize relevance in its answer generation process. It should retrieve and present information that is most relevant to the user's query, filtering out irrelevant or extraneous data.
3. **Speed and Efficiency:** Automated question answering systems should aim to deliver responses in a timely manner, providing near real-time or fast retrieval and processing of information. They should optimize their algorithms and data structures to ensure efficient performance even when dealing with large volumes of data.
4. **Adaptability:** An automated question answering system should be adaptable to different domains, topics, or knowledge areas. It should have the capability to handle diverse types of questions and retrieve relevant information from various data sources, adapting to different user requirements.
5. **Scalability:** The system should be scalable to accommodate increasing user demand and larger knowledge repositories. It should be capable of efficiently handling a growing number of queries and scaling its resources to ensure consistent performance.
6. **Context Awareness:** An automated question answering system should be context-aware, taking into account the context and background information 6 provided by the user. It should be able to understand and interpret queries based on the relevant context to generate more accurate and contextualized responses.
7. **Confidence and Uncertainty Estimation:** The system should be able to assess its confidence level in providing an answer. It should be capable of estimating and conveying the degree of certainty or uncertainty associated with the generated response, indicating when it may be less confident or when further clarification is needed.
8. **Multi-modality:** Some automated question answering systems incorporate multimodal capabilities, enabling them to process and generate answers from various types of media, including text, images, audio, or video. This property expands the system's ability to handle diverse types of questions and information sources.
9. **User Interaction and Feedback:** An automated question answering system may support interactive and iterative user interactions. It should allow users to provide feedback on the generated answers, clarify their queries, or engage in a dialogue to refine the system's understanding and improve subsequent responses.
10. **Explainability:** Explainability is the property of providing explanations or reasoning behind the generated answers. An automated question-answering system may employ techniques to justify or provide evidence for the selected answer, enhancing transparency and building trust with users.
11. **Privacy and Security:** The system should prioritize user privacy and data security. It should handle user queries and data in a secure manner, ensuring the protection of sensitive information and adhering to relevant privacy regulations and policies.

These properties collectively contribute to the effectiveness, usability, and user satisfaction of an automated question answering system, empowering users to obtain accurate and relevant answers to their queries efficiently.

### **Limitation**

While automated question answering systems offer numerous benefits, they also have certain limitations that affect their performance and reliability. Here are some common limitations of automated question answering systems:

1. **Language Complexity:** Automated question answering systems may struggle with understanding and generating responses to queries that involve complex 7 language constructs, idiomatic expressions, or linguistic ambiguity. Understanding and interpreting such language nuances accurately can be challenging for the system, leading to potential inaccuracies in the generated answers.
2. **Lack of Contextual Understanding**: Despite efforts to incorporate context awareness, automated question answering systems may still struggle with fully comprehending the context of a user's query. Contextual information plays a crucial role in providing accurate and relevant answers, and the system's limitations in understanding context can lead to incorrect or incomplete responses.
3. **Inadequate Knowledge Coverage:** The effectiveness of an automated question answering system heavily relies on the breadth and depth of its knowledge base. If the system's knowledge base is limited or lacks comprehensive coverage across various domains or topics, it may struggle to provide accurate answers to a wide range of queries.
4. **Dependency on Data Availability:** Automated question answering systems heavily rely on the availability and quality of relevant data sources. If the required information is not present in the available data or if the data is outdated or unreliable, the system's performance may be compromised, resulting in incorrect or incomplete answers.
5. **Handling New or Unseen Information:** When faced with queries or topics that are outside the scope of their training data, automated question answering systems may struggle to provide accurate responses. They may not have the ability to generalize or extrapolate knowledge effectively to answer queries involving unfamiliar information.
6. **Lack of Explanation:** While generating answers, automated question answering systems may not always provide detailed explanations or reasoning behind their responses. This lack of explain ability can limit users' ability to understand how the system arrived at a particular answer, potentially reducing their trust and confidence in the system.
7. **Difficulty in Handling Multi-turn Queries:** Automated question answering systems may face challenges in handling multi-turn or complex queries that require a sequence of interactions to fully address. The system's ability to maintain context and accurately interpret user intent throughout a series of questions and responses can be limited, leading to suboptimal performance.
8. **Sensitivity to Input Variation:** Automated question answering systems can be sensitive to slight variations in the way a question is phrased or expressed. Small changes in wording, sentence structure, or synonyms may lead to variations in the system's understanding or retrieval of relevant information, potentially resulting in different or inaccurate answers.
9. **Limited Understanding of Visual or Audio Content:** While some automated question answering systems incorporate multi-modal capabilities, they may still struggle with understanding and generating answers based on visual or audio content. Extracting information from images, videos, or audio recordings poses additional challenges in terms of data processing and interpretation.
10. **Ethical and Bias Concerns:** Automated question answering systems can be susceptible to biases present in the training data or the underlying algorithms. If the training data is biased or the system inherits biases from the data sources, it can lead to biased answers or perpetuate unfair or discriminatory information.

Addressing these limitations is an active area of research in the field of automated question answering systems. Continued advancements in natural language processing, machine learning, and knowledge representation are expected to mitigate these limitations and enhance the overall performance and capabilities of such systems.

### **Application**

Question Answering Systems have numerous applications across various domains. Here are some of the key areas where Question Answering Systems are utilized:

1. **Search Engines:** Question Answering Systems are integrated into search engines to provide direct answers to user queries. Instead of displaying a list of search results, these systems aim to understand the user's question and generate a concise answer from relevant sources.
2. **Customer Support and Helpdesks:** Question Answering Systems are employed in customer support systems to address frequently asked questions. They can provide automated responses, reducing the need for manual intervention and improving response time and efficiency.
3. **E-Learning and Education:** Question Answering Systems are used in educational platforms to assist learners in finding specific information or understanding 9 complex concepts. These systems can provide instant feedback and explanations to students' questions, aiding their learning process.
4. **Virtual Assistants and Chatbots:** Virtual assistants like Siri, Google Assistant, and chatbots rely on Question Answering Systems to understand user queries and provide relevant responses. These systems enable users to interact with technology using natural language and obtain specific information or complete tasks.
5. **Knowledge Base and Document Exploration:** Question Answering Systems can be utilized to explore and retrieve information from large knowledge bases or document collections. They help users find precise answers to their questions by searching through vast amounts of data.
6. **Medical and Healthcare:** Question Answering Systems are employed in the medical domain to assist healthcare professionals in retrieving relevant information from medical literature, clinical guidelines, and patient records. They can provide accurate and up-to-date answers to medical queries, aiding in diagnosis, treatment decisions, and research.
7. **Legal and Compliance:** Question Answering Systems are used in the legal field to assist lawyers and legal professionals in searching and retrieving information from legal databases, case law, and statutes. They can help with legal research, providing relevant precedents and legal opinions.
8. **Information Access for Specialized Domains:** Question Answering Systems can be customized for specific domains like finance, technology, or engineering. These domain-specific systems leverage specialized knowledge and terminology to provide precise answers within those fields.
9. **Fact-Checking and News Verification:** Question Answering Systems can assist in fact-checking and verifying information by cross-referencing claims against reliable sources. They can help identify misinformation, improve the credibility of news articles, and enhance media literacy.
10. **Decision Support Systems:** Question Answering Systems can be integrated into decision support systems, providing relevant information and insights to aid decision-making processes. They can assist in data analysis, trend identification, and extracting actionable knowledge from large datasets.

These are just a few examples, and the application of Question Answering Systems continues to expand as the technology advances. The versatility of these systems allows them to be adapted to various domains and scenarios where accurate and timely answers to questions are essential.

### **Advantage and Disadvantage**

**Advantage:**

Automated question answering systems offer several advantages that contribute to their usefulness and value in various applications. Here are some key advantages of an automated question answering system:

1. **Quick and Efficient Information Retrieval:** Automated question answering systems enable users to obtain immediate and direct answers to their questions without the need for extensive manual searching or browsing through multiple documents or web pages. This saves time and effort, providing users with efficient access to the information they need.
2. **Access to Diverse Data Sources:** These systems can retrieve information from a wide range of structured and unstructured data sources, including text documents, databases, websites, and knowledge bases. This enables users to access information from various domains and consolidate knowledge from disparate sources.
3. **Natural Language Interaction:** Automated question answering systems support natural language queries, allowing users to ask questions in their own words without the need for specialized query syntax or technical knowledge. This enhances user experience and facilitates more intuitive and human-like interactions with the system.
4. **User-Friendly Interface:** These systems often provide user-friendly interfaces, such as chatbots or virtual assistants, which offer a conversational experience. Users can interact with the system through familiar messaging platforms or voiceenabled devices, making it accessible and convenient for a wide range of users.
5. **Personalization and Customization:** Advanced automated question answering systems can personalize responses based on user preferences, historical interactions, or user profiles. They can tailor the answers to suit individual needs, providing a more personalized and relevant experience.
6. **Scalability and Availability:** Automated question answering systems can handle large volumes of queries and scale their resources to accommodate increasing user demand. They can operate 24/7, ensuring availability and responsiveness to user inquiries at any time.
7. **Consistency and Accuracy:** When properly trained and evaluated, automated question answering systems can provide consistent and accurate answers to user queries. They can maintain a high level of accuracy in retrieving and synthesizing information, reducing the risk of human errors or biases.
8. **Integration with Other Applications:** These systems can be integrated into various applications and platforms, including search engines, customer support systems, educational platforms, and more. Integration enhances the functionality and value of these applications, providing a seamless and enhanced user experience.
9. **Multilingual Support:** Some automated question answering systems support multiple languages, allowing users to ask questions and receive answers in their preferred language. This enables global accessibility and fosters inclusion, catering to diverse user populations.
10. **Continuous Improvement:** Automated question answering systems can be continuously improved through iterative feedback and learning processes. User feedback, system monitoring, and updates to the underlying algorithms and knowledge bases contribute to ongoing enhancements and better performance over time.

These advantages make automated question answering systems valuable tools for information retrieval, knowledge management, customer support, and various other domains where quick and accurate access to information is crucial. Continued research and development in this field are expected to further enhance the capabilities and benefits of these systems.

**Disadvantage:**

While automated question answering systems offer several advantages, they also have certain disadvantages or limitations that can impact their performance and effectiveness. Here are some common disadvantages of an automated question answering system:

1. **Limited Understanding of Complex Queries:** Automated question answering systems may struggle with understanding and accurately responding to queries that involve complex or nuanced language constructs, ambiguous phrasing, or abstract concepts. They may provide incomplete or inaccurate answers when faced with such queries.
2. **Inability to Handle Unseen or Out-of-Scope Information:** These systems heavily rely on the available data sources and knowledge bases. If a query involves information or topics that are outside the system's training or knowledge coverage, it may fail to provide meaningful answers or generate irrelevant responses.
3. **Lack of Common-Sense Reasoning:** Automated question answering systems often lack the ability to reason or understand common sense knowledge, which can result in incorrect or nonsensical answers to certain types of questions. They may struggle with interpreting implicit information or context that is obvious to humans.
4. **Vulnerability to Biases and Inaccuracies in Data:** The performance and accuracy of automated question answering systems are influenced by the quality and biases present in the training data. If the training data contains biased or inaccurate information, the system may inadvertently propagate or reinforce those biases in its responses.
5. **Difficulty in Handling Subjective or Opinion-based Questions:** These systems can struggle to handle questions that require subjective or opinion-based responses. They are primarily designed to provide factual or objective answers and may struggle to discern or generate nuanced subjective viewpoints.
6. **Lack of Explainability:** Automated question answering systems may not provide detailed explanations or reasoning behind the generated answers. This lack of explainability can make it challenging for users to understand how the system arrived at a particular answer and can impact trust and transparency.
7. **Sensitivity to Input Variations:** Minor variations in the phrasing or wording of a question can lead to variations in the system's understanding or retrieval of relevant information. Automated question answering systems can be sensitive to these input variations, potentially resulting in different or inconsistent answers.
8. **Dependence on Reliable Data Sources:** The performance and accuracy of automated question answering systems heavily rely on the availability and quality 13 of reliable data sources. If the data sources contain outdated, incomplete, or unreliable information, the system's responses may suffer in terms of accuracy and relevance.
9. **Ethical and Privacy Concerns:** Automated question answering systems may inadvertently present or propagate biased or inappropriate information, raising ethical concerns. Additionally, the processing and storage of user queries and data raise privacy and security concerns that must be addressed to ensure user trust.
10. **Lack of Human-like Interaction:** While automated question answering systems aim to simulate human-like interactions, they may still lack the depth, empathy, and contextual understanding that human interactions provide. Users may feel a disconnect or frustration when interacting with a system that does not fully comprehend their queries or emotions.

Understanding these disadvantages helps in recognizing the limitations of automated question answering systems and highlights areas that require further research and improvement to enhance their performance, accuracy, and usability.

## **Motivation**

The internet is growing every day, and this includes also the website of Assam University. Sometimes, searching on the internet takes a lot of time, and the results may not be satisfying. We're always looking for information, but there's a difference between just having information and having true knowledge.

Think about when we use a search engine. We can find relevant web pages with information based on query, but it might not give us the exact answers we want. That's where Question Answering comes in. It's a special way of searching that goes beyond just finding pages. It's about getting specific answers to user questions. Therefore, an attempt has been taken from us to create educational question answering system for web resources of educational institute.

## **Objective**

Our objective in this thesis is to develop an educational question answering system is to enhance the learning experience of students by providing them with a reliable, personalized, and comprehensive source of information. The proposed chatbot will leverage state-of-the-art machine learning models, such as deep neural networks, to enhance its understanding of user intentions, improve its accuracy, and deliver contextually relevant responses. Here are the key objectives of an educational question answering system:

* To provide accurate and timely answers to user' questions.
* To Provide information on faculty members, their research interests, and their academic achievements.
* To promote independent learning by empowering students to explore and seek answers to their questions.

By achieving these objectives, our educational question answering system can enhance the learning experience by providing accurate, personalized, and comprehensive information, fostering independent learning, and supporting students in their educational journey.

## **Organization of Thesis**

The following thesis is described in six chapters.

**Chapter 1:** In this chapter, we discussed the introduction of question answering systems, automated question answering systems, their history, structure, properties, limitations, applications, advantages, and disadvantages. We also describe the statement of the problem, the objective and motivation of our project, and the organization of the thesis.

**Chapter 2:** We present a literature review on the question-answering system in this chapter. From our literature review, we also analyse which model and technique and what type of dataset are used in question-answering systems in which domain.

**Chapter 3:** We provide a detailed explanation of our proposed model and elaborations on every model of the proposed model in Chapter 3.

**Chapter 4:** Detailed experimental setup, results and analysis of our proposed model is presented in Chapter 4.

**Chapter 5:** This is followed by the concluding remarks for the proposed model.

**Chapter 6:** Chapter 6 provides some direction for future work which is followed by the references.

**Chapter 2**

**Literature Survey**

## **A Rule-based Question Answering System for Reading Comprehension Tests by Ellen Riloff and Michael Thelen**

The author [2] has created a rule-based system, Quarc, that employs heuristic rules to locate the appropriate sentence in a short story. Quarc found the right text 40% of the time on reading comprehension exams for kids in grades 3-6, demonstrating its simplicity. Reading comprehension tests are used to gauge a child's literacy skills in the United States, and these examinations necessitate comprehensive natural language processing methods. The system called Quarc achieves 40% accuracy without in-depth knowledge of the target language by employing a set of heuristic principles developed by human experts.

Quarc, a deep learning system, achieved 40% HumSent accuracy on 115 reading comprehension tests. However, its accuracy varied across question types. When it came to questions about WHAT and WHY, Quarc scored the lowest, with only 28% accuracy. Quarc's performance was best with 55% accuracy when it came to questions about WHEN.Experiments showed that adding semantic classes, dateline rules, and specific word and phrase rules improved performance. Quarc's final version achieved 40% HumSent accuracy, comparing favourably with DeepRead's results (36%). An experiment evaluated Quarc's tie-breaking procedure, revealing improvements in performance on WHY, WHEN, and WHY questions. However, the WHO and WHERE questions remained unchanged. A better tie-breaking procedure could significantly enhance Quarc's performance by intelligently choosing between top candidates.

## **Designing an interactive open-domain question answering system By S. Quarteroni and S. Manandhar**

## This paper [3] discusses interactive question answering (QA), a rapidly developing field that makes use of dialogue interfaces to provide follow-up and clarification questions. A web search engine is utilised by the open-domain system known as YourQA in order to provide detailed responses to queries. The architecture, implementation, and evaluation of the system's chat-based dialogue interface are all topics that are covered in this discussion. The results of the Wizard of Oz study and the final evaluation show that the intended architecture is effective in accomplishing open-domain, interactive QA. This paper describes the development of the YourQA dialogue interface, an open-domain, personalised QA system. The fundamental QA component of YourQA is structured according to the three-tier partition that is at the foundation of the vast majority of cutting-edge QA systems. This partition is comprised of question processing, document retrieval, and response extraction. The conventional incapacity of standard quality assurance systems to handle the unique requirements of individual users is addressed by the introduction of a new component known as the User modelling component.

## **Bengali Question Answering System for Factoid Questions: A statistical approach By Sourav Sarker, Syeda Tamanna Alam Monisha, Md Mahadi Hasan Nahid**

An automated question-answering system is described as a programme that addresses with users in natural language, giving them the ability to understand and respond to queries in a manner that is difficult to identify for a human being. This paper [4] offers a description of such a system. Research in the field of Natural Language Processing (NLP) is becoming increasingly interested in this area because Bengali is such a common language. In order to provide candidates with prompt responses to any questions they might have throughout the admissions process at Shahjalal University of Science and Technology, a Bengali question-answering system was designed and implemented.

Since the 1960s, researchers have been exploring various question-answering systems, some of which are domain-specific while others are more generic. AnswerBus, JAVELIN, and the system developed by Abney et al. in 2000 are all good examples. Banerjee et al. developed a factoid system in Bengali that makes use of named things and anaphora-cataphora resolution, showing that study into the language of Bengal is expanding. The technology improves accuracy for both Bengali and English queries by 60% and simplifies them.

## **ELIZA-A Computer Program For the Study of Natural Language Communication Between Man and Machine by Joseph Weizenbaum**

## "ELIZA" was created by Joseph Weizenbaum [5] in 1966 to aid people with psychological problems. He used the standard technique known as "key matching." With a set of preprogrammed recognising the match and its genre conditions, it properly detected the keywords and the pattern that matches. Despite making users feel as though they were conversing with humans after providing the proper response, it still did not pass the Turing test of artificial intelligence.

## **BASEBALL: AN AUTOMATIC QUESTION-ANSWERER by Bert F. Green, Jr., Alice K. Wolf, Carol Chomsky, and Kenneth Laughery**

## This paper [6] focuses on a certain programme (called Baseball) that can respond to queries over stored data in plain English. It takes queries written on cards, looks up the phrases in a dictionary to figure out their structure, and finds answers in the data set that best fits the requirements. The computer then generates the solution. While artificial languages are commonly used by men when interacting with computers, natural language communication will be essential for computer-centred systems of the future. Baseball is an AI system that can respond to queries concerning stored information in plain English. The software has two components: language processing and analysis. It functions on baseball-related data and places short-term constraints on input queries to ease syntactic analysis. The programme can provide answers to all sorts of questionable inquiries, from the most elementary to the most involved.

## **Information retrieval from documents: A survey by Mitra, Mandar, and B. B. Chaudhuri.**

## This research paper [7] discusses the findings of a large-scale literature review conducted by Doermann (1998) on the topic of document-based information retrieval. This survey covers more ground and puts more focus on how techniques for analysing images of documents might be applied to more traditional forms of IR. The breadth of approaches discussed in the paper reflects the wide variety of media types, including text and images, that need to be processed. Rather than trying to recognise the textual content of the document, the main focus of this work is on techniques that alter document images directly to accomplish information processing tasks including retrieval, categorization, and summary.

## **Deep learning-based question answering system in Bengali by Tasmiah Tahsin Mayeesha, Abdullah Md Sarwar and Rashedur M. Rahman in 23rd November 2020.**

## In this paper [8], the author explains why question answering is a significant part of natural language processing that may be put to use in a wide variety of high-value jobs since it is defined as a problem of information retrieval. A model is "trained" by being presented with a context passage and then being asked questions about that section. The recent proliferation of robust language models like BERT and its derivatives has enabled significant advancements in many areas of language processing. Because Bengali is so under-researched in NLP, this research is the first to successfully adapt the transformer model to Bengali Question Answering and establish a new standard in the field. They show that even a translation-based data collecting strategy may be used in the early stages of developing a data-heavy deep learning model, such as transformers. Since a dearth of readily available Bengali data has been one of the primary problems of academics, this opens up a greater usage of the language in NLP. The Question Answering with Translated SQuAD BERT embeddings can be applied in other contexts, and our model can be customised for newly collected corpora for specific domains like the telecoms, healthcare, and e-commerce industries. They also discuss a complete analysis of BERT and its various variants models and how they perform with a low-resource language like Bengali in both fine-tuned and zero-shot contexts. Finally, they compared the model's results to those of Bengali children in order to establish a baseline for future study, all based on common issues connected to Bengali culture.

## **A survey on question answering systems with classification by Amit Mishra and Sanjay Kumar Jain in 23rd October 2014.**

The authors [9] of the research put forth the idea that QASs provide responses to inquiries posed in natural languages. Early QASs were only designed to work in specific domains; hence, their functionality was limited. Modern QASs pay special attention to typical user inquiries, data source characteristics, and correct answer presentation styles. Since the 1960s, when the study of QASs first began, several different QASs have been created. The necessity for a comprehensive survey on QASs stems naturally from the desire to establish the future scope of research in this field. In this paper, they take a comprehensive look at QASs and categorise them accordingly. The authors categorise QASs based on several criteria (questions addressed, data sources consulted, processing performed on questions and data sources, retrieval models employed, answer formats generated, and data source features). Paraphrasing is a linguistic possibility that has not yet been fully captured by QAS. An effective QAS relies heavily on a high-quality source corpus and, consequently, well-formalised user requirements. It is easier for QASs to grasp the text without requiring them to apply advanced Natural Language Processing techniques if the corpus is well-structured and users' needs are defined. QASs’ efficacy can be affected by a number of unseen variables, such as the user's personality and level of expertise in posing the question. In order to provide findings that meet the requirements of the client, the QASs of the future will need to conduct knowledge survey tasks. In order to better serve their customers, QAS developers are working on dialogue-based models. However, there is a need for smart QASs that can analyse the browsing history and the user's behavioural activities to provide more relevant replies. In this paper, they take a comprehensive look at QASs and categorise them accordingly. The authors categorise QASs based on several criteria (questions addressed, data sources consulted, processing performed on questions and data sources, retrieval models employed, answer formats generated, and data source features). Paraphrasing is a linguistic possibility that has not yet been fully captured by QAS. An effective QAS relies heavily on a high-quality source corpus and, consequently, well-formalised user requirements. It is easier for QASs to grasp the text without requiring them to apply advanced Natural Language Processing techniques if the corpus is well-structured and users' needs are defined. QASs’ efficacy can be affected by a number of unseen variables, such as the user's personality and level of expertise in posing the question. In order to provide findings that meet the requirements of the client, the QASs of the future will need to conduct knowledge survey tasks. In order to better serve their customers, QAS developers are working on dialogue-based models. However, there is a need for smart QASs that can analyse a user's clickstream and pattern of action to provide more relevant replies.

## **A survey on question answering technology from an information retrieval perspective by Oleksandr Kolomiyets and Marie-Francine Moens in 3rd August 2011.**

An extensive and comparative survey of question-answering technology is presented in this research paper [10]. It does this by presenting the question-answering task from the perspective of information retrieval and highlighting the significance of retrieval models, which are the representations of queries and information documents, as well as retrieval functions, which are used to determine the relevance between a query and an answer candidate. The survey recommends a basic architecture for answering questions that gradually raises the level of complexity in the way that questions and information items are represented. On the one hand, natural language inquiries are converted to keyword-based searches; on the other hand, knowledge bases are accessed using structured or logical queries derived from the natural language questions, and solutions are deduced using logic. We explain the many processing steps that lead to different word-based and more complicated representations that include part-of-speech tagging, expected answer type classification, semantic roles, discourse analysis, translation into a language similar to SQL, and logical representations. The paper provides an overview of significant approaches to question-answering from recent decades. It described the challenge of answering questions as one of information retrieval when the query is presented in natural language. Considering modern heterogeneous databases that contain text, images, video, and audio, as well as information from traditional table-form databases, the requested data can be of any type or medium. In order to produce advanced content representations, we have gradually incorporated advanced forms of analysis of the question (and of documents in the case of textual material) after explaining straightforward, computationally light ways. We talked about multiple stages of processing that result in simple representations like a bag of words and more sophisticated ones like logical representation, classification of the intended answer type, semantic roles, discourse analysis, and translation of the query into a language similar to SQL. Keyword-based searches are one extreme, and complex knowledge bases are queried with structured or logical queries derived from natural language questions and responses deduced by reasoning, which are the other. The traditional divide between open-domain and restricted-domain question responses has become less distinct as a result of this development. In addition, open-domain question answering translates natural language inquiries and material into more organized forms than simple bag-of-words representations, which leads to more efficient information retrieval. The primary contribution of this study is a description of this evolution and the integration of components originating in other fields (such as information retrieval, databases, and computational linguistics). The study also identifies other research questions that should be studied in the future.

## **A Review of Question Answering Systems by Bolanle Ojokoh and Emmanuel Adebisi in 2nd May 2019.**

This paper [11] briefly examines the generic QA framework (Question Analysis, Passage Retrieval, and Answer Extraction), Q&A system issues (Question Processing, Question Classes, Data Sources for QA, Context and QA, Answer Extraction, Real-Time QA, Answer Formulation, Interactive QA, Multilingual (or cross-lingual) QA, Information Clustering for QA, Advanced Reasoning for QA, and User Profiling for QA), and Q&A system types. Based on research into QA systems, they evaluate the rationale behind each classification parameter. Modifying the generic QA architecture by adding or removing validation modules can make it more suitable for the question set at hand. Each framework module's efficiency is contingent on the efficiency of preceding modules. In other words, if a question is formulated correctly during the Question Analysis phase, it will be more likely that relevant passages will be retrieved during the Passage Retrieval phase, increasing the possibility that the correct answers will be extracted during the Answer Extraction phase. As a result, it's crucial that the QA framework's many components employ effective methodologies. New question-answering research fields have been established on the foundation of the problems with QA systems that this work has uncovered. Extensive effort has been put into automatically and manually covering Question classes. Among these are IBM Watson's contextual question answering and TREC's live question answering track for real-time questions. However, current findings reveal that additional challenges persist in the QA field. More study is needed to figure out why information isn't easily accessible. Many languages still don't have the backing they need; thus, they have to be translated into another language in order to be processed. There is still a need for investigation into issues like disambiguation, learning context, and many others. There is a need for more effective methods of merging techniques in QA systems because the performance of QA systems can be improved by using a combination of techniques to eliminate the inefficiency of individual implementations, as seen in hybridized implementations. However, this implementation can be costly for simple QA systems or quite costly and time-consuming for complex QA systems. A solid knowledge base and an intuitive grasp of user inquiries are also essential to the success of any QA system. NLP methods are used to extract this understanding. If this method fails, the system will produce inaccurate results. Optimization and modularization of currently available, higher-performing QA techniques should be the focus of future research. As a result, researchers will be encouraged to reuse high-quality modules, and they will be better able to zero in on and isolate the most pressing issues.

## **Question Answering Survey: Directions, Challenges, Datasets, Evaluation Matrices by Hariom A. Pandya and Dr. Brijesh S. Bhatt in 7th December 2021**

## In this paper [12], they have provided an overview of the latest state-of-the-art QA systems. Following an analysis of various research directions based on the types of questions, open challenges are presented, including those for low-resource languages, conversational question answering, visual question answering, and reading comprehension. Details about several research methodologies are provided. Finally, a review of datasets and assessment metrics for question-answering is provided. We have also made the observation that, while rule-based or machine-learning approaches are still widely used in low-resource languages, deep learning techniques are becoming more and more popular in resource-rich languages. Over the past decade, both internet use and information availability have increased. As a result of this digitalization, an automated response system is required to glean useful data from obsolete and ephemeral stores of information. Using natural language understanding (NLU), these systems are built to provide the user with the most relevant answer from this massive knowledge base in response to their question. The process of answering a question can include, but is not limited to, translating the user's inquiry into relevant searches, retrieving relevant information, and selecting the most appropriate answer from among the results. Current deep learning model enhancements show significant performance gains across the board. This literature evaluation categorizes the QA field's future study directions by question type, response type, evidence source, and modelling strategy. This description was followed by a discussion of the field's open issues, which included things like automatic question production, similarity recognition, and a lack of linguistic resources. The paper concludes with a survey of relevant datasets and evaluation tools.

## **Question Answering System, Approaches and Techniques: A Review by Ajitkumar M. Pundge, Khillare S.A., C. Namrata Mahender in 3rd May 2016**

This paper [13] highlighted that as technology advanced, more and more data became available online, leading to a dramatic increase in internet usage. Information retrieval and text processing have subfields, one of which is question-answering. Depending on the context, the question-answering system can be used for a variety of tasks, such as text mining, language instruction, online testing, and more. There has been a rise in the number of people who utilize the internet during the past decade. In QA, the user poses a variety of questions to a question-answering system in the hopes of receiving useful responses. When users want answers to their inquiries but prefer to phrase them in natural language rather than a query, Question Answering is there to save the day. The QA of the English, Chinese, Japanese, Korean, etc. languages has made significant strides. Information retrieval has a particular domain known as question answering. There are numerous systems available for answering questions, each with a specific use case. Based on the source of the responses, the Question Answering System (QAS) offers a wide range of uses. such as information extraction from documents, language learning, an online testing system, interaction between humans and computers, document management, document classification, and many others. Data in a question-and-answer system can be categorized as structured or semi-structured. A question-answering system's primary goal is to obtain answers to queries rather than the entire document. Open-domain and closed-domain question-answering systems are two different categories. While closed-domain systems have a narrow range of job areas (such as medical, weather forecasting, etc.), open-domain systems are primarily web-based and have no age restrictions. The study of question-answering strategies is covered in this essay. Details of methods are offered after the structure of the question-answering system is introduced. The conclusion of this essay is finally here. In this global era, we need a QA system that can address closed-domain problems and provide pertinent answers to inquiries. The QA system can be a learning companion; it can aid in our educational system. It can be built into systems that evaluate or grade responses and produce outcomes that are consistent with human performance. The educational system now has new options that let students learn at their own pace. The researcher has several significant obstacles, including knowledge representation, precise representation for proper understanding, paraphrasing, conceptual learning, online access to descriptive questions, evaluating replies, and including figures, tables, and mathematical equations. The problems involved are complicated, making the solutions much more challenging, but the demands for the applications are great. Therefore, there is a lot of room to explore the difficulties in the QA area.

## **Research and reviews in question answering system by Sanjay K Dwivedia and Vaishali Singh in 2013.**

## In an effort to face the issues brought on by the explosion of information in the age of information and communication technology, we have taken a thorough review of the question-answering research [14]. The selection of a technique is highly problem-specific, as we have shown. A hybrid method, which skilfully combines seemingly unrelated techniques, frequently yields better outcomes in the form of greater relevance, speed, precision, and recall metrics. However, it is acknowledged that methods for answering questions that rely on linguistic, statistical, and pattern-based approaches will continue to be in the spotlight and attract a lot of QAS researchers' attention. Question Answering (QA) systems are an automated method of getting accurate answers to queries posed in natural language by humans. The primary goal of the QA system is to facilitate human-machine interaction. In this article, we offer a taxonomy for describing question-and-answer (QA) systems, give a quick overview of the main QA systems that have been discussed in the literature, and conduct a qualitative study of them. Finally, in order to provide insight into the research horizon in this direction, a comparison between these methodologies based on specific QA system properties that were deemed crucial in our study has been conducted.

## **A Survey on Question Answering System by Biplab Ch. Das**

In this report [15], the author reviews the development of question-and-answer systems before talking about IBM Watson, a QA system created at the IBM Research Labs. The classification of questions is examined, granting Bloom's Taxonomy in Learning Domains. A common NLP application is answering queries. A task that a question-answering system does is the discovery of the precise answer to the query given a question and a set of documents. It aims to understand the many problems in natural language understanding and representation as well as to design a natural language interface for computers. These two objectives are complementary. In the past forty years, question-answering systems have undergone significant advancements on par with the rest of natural language processing. The first famous QA book was released in 1978. Lehnert's thesis, in which she presented a question-answering system based on semantics and logic, served as the foundation for the project. It is imperative that we do not err; the tale of question-answering systems dates back to the sixties (Tomek Strzalkowski and Sanda Harabagiu, 2010). The question-answering systems were in place long before the publication of the book. Over the course of the past four decades, we have seen the development of hundreds of different question-answering systems. Even before 1978, the first of these kinds of systems were natural language interfaces that were peripheral to database access. The natural languages that were supported were limited, and the scope of the topics that could be addressed by the question-answering system was narrowed. These algorithms did their work by converting the limited natural language questions into database questions. In the first part of this chapter, we will go over a brief history of Watson as well as the pipeline of the IBM Watson Architecture. The next step is for them to look at articles written by IBM Watson. Following the road map that was shown at the beginning of the chapter, we bring the conversation to a close with Watson Beyond Jeopardy, which focuses on Watson's applications in the medical field.

## **Comparison of existing works**

Table 2: Comparison of existing work

|  |  |  |
| --- | --- | --- |
| **Authors** | **Advantages** | **Disadvantages** |
| Ellen Riloff and Michael Thelen | He created Quarc, a rule-based system that employs heuristic criteria to locate the appropriate sentence in a short tale. | The main demerit is that it does not use deep language understanding techniques. |
| S. Quarteroni and S. Manandhar | They discussed interactive question-answering (QA), a developing field that employs dialogue interfaces for clarification and follow-up. | No pattern matching algorithm is used. |
| Sourav Sarker, Syeda Tamanna Alam Monisha, and Md. Mahadi Hasan Nahid | For the purpose of admissions exams at Shahjalal University of Science and Technology, a Bengali question-answering system was designed to deliver immediate responses to candidates' inquiries. | The system provides 60% accuracy for Bengali and English queries. |
| Joseph Weizenbaum | ELIZA (QA) for the people who have psychological issues. | This QA system generally does not use any Machine learning algorithms. |
| Bert F. Green, Jr., Alice K. Wolf, Carol Chomsky, and Kenneth Laughery | They created a computer program (called Baseball) that can respond to questions regarding data in plain English. It takes in queries from cards, analyzes their phrase structure with the help of a dictionary, and then finds answers in the data set that best fits the requirements. | Men use artificial languages to communicate with computers, but future systems will need natural language. |
| Tasmiah Tahsin Mayeesha, Abdullah Md Sarwar and Rashedur M. Rahman | Question answering, defined as an information retrieval issue, is an important part of NLP with many high-value applications. | Only one language was used to train this QA system. |
| Amit Mishra and Sanjay Kumar Jain | This study examines QASs and categorizes them according to several standards. The authors categorize QASs according to a number of factors, including the types of data sources used, how questions and data sources were processed, the models used for retrieval, how answers were produced, and the features of the data sources. | We do not intend to use performance measurement as a criterion for identifying QAS because we are unaware of the performance specifics and truth corpora of different QAS. |
| Oleksandr Kolomiyets and Marie-Francine Moens | An extensive and comparative survey of question-answering technology is presented in this study. It presents the task of answering questions from the perspective of information retrieval and highlights the significance of retrieval models, or representations of queries and information documents, and retrieval functions, which are used to determine the relevance between a query and an answer candidate. | It does not provide knowledge about AI. |
| Bolanle Ojokoh and Emmanuel Adebisi | This paper examines numerous QA systems and makes extensive use of NLP approaches. | The evaluation procedure is not discussed in this paper. |
| Hariom A. Pandya and Dr. Brijesh S. Bhatt | This paper surveys question-answering datasets and talks about evaluation measures. | This paper uses an old technique of pattern matching. |
| Ajitkumar M. Pundge, Khillare S.A., C. Namrata Mahender | Question answering is discussed in this work as a subfield of both information retrieval and text processing. Depending on the context, the question-answering system can be used for a variety of tasks, such as text mining, language instruction, online testing, and more. | Research on methods for answering queries is presented in this work, but no ideas for Validation are offered. |
| Sanjay K Dwivedia and Vaishali Singh | This study provides a taxonomy for classifying QA systems, a brief survey of the most prominent QA systems discussed in the literature, and a qualitative evaluation of them. | The methods and approaches to answering questions are presented in this work, but no validation principles are offered. |
| Biplab Ch. Das | This paper provides a historical context for QA systems before discussing IBM Watson, a QA System developed by IBM Research Labs. | The supporting natural language and question-answering systems were domain-specific. |
| Bolanle Ojokoh and Emmanuel Adebisi | This paper discusses the generic QA framework, including Question Analysis, Passage Retrieval, and Answer extraction, as well as QA system issues like Question Processing, Question Classes, Data Sources, Context and QA, Answer Extraction, Real-time Question Answering, Answer Formulation, Interactive QA, Multilingual (or cross-lingual) question answering, Information Clustering, Advanced Reasoning, and User Profiling. The study classifies QA systems by application domain, question type, data source, answer form, language paradigm, and methodologies. | This paper examined why research is needed to address challenges such as accessing knowledge in a natural way, language resource limitations, and problems like disambiguation and learning context. |

## **Analysis of Literature Survey**

Quarc is a rule-based system created by Ellen Riloff and Michael Thelen that uses heuristic principles rather than deep language understanding to choose the appropriate sentence in a short story. Quarc did best on questions pertaining to WHEN (55% accuracy), and did worst on questions pertaining to WHAT and WHY (28% accuracy). Studies revealed that performance was enhanced by the addition of semantic classes, dateline rules, and particular word and phrase rules.

An emerging field that uses dialogue interfaces for follow-up and explanation, interactive question answering (QA) was presented by S. Quarteroni and S. Manandhar. They contributed suggestions to the development of the YourQA open-domain, customizable QA system's discussion interface. YourQA's central QA features are split into the three main categories of modern QA systems, which are question processing, document retrieval, and answer extraction. The standard incapacity of QA systems to adapt to specific users' preferences is addressed by introducing a new part called the User modeling part.

An automated question-answering system was introduced by Sourav Sarker, Syeda Tamanna Alam Monisha, and Md. Mahadi Hasan Nahid. It is a program that converses with users in natural language, enabling them to comprehend and respond to inquiries in a way that is difficult to distinguish from a human. They developed a quality assurance method that reduces complexity for Bengali and English while also offering 60% accuracy.

The ELISA (QA) system was created by Joseph Weizenbaum for those with psychological problems. He used the key-matching strategy. With a set of preprogrammed recognizing the match and its genre conditions, it properly detected the keywords and the pattern that matches. Although it gave users the impression that they were speaking with humans after responding appropriately, it failed the Turing test, which measures how intelligent a machine is.

A computer program was presented by Bert F. Green Jr., Alice K. Wolf, Carol Chomsky, and Kenneth Laughery that responded to queries concerning stored data in common English. It reads questions from cards, analyzes sentence structure using a dictionary, and extracts information from data that complies with the requirements. The answer is then printed by the application. Men frequently use artificial languages to converse with computers, yet natural language communication will be necessary in future computer-centered systems.

Doermann's extensive survey (1998) of the research findings in the broad field of document-based information retrieval is described by Mitra, Mandar, and B. B. Chaudhuri. This survey's focus is also a little bit broader, and it places more of an emphasis on how document image analysis techniques relate to traditional IR techniques. The paper's survey includes a wide range of techniques needed to deal with various file formats, including text and image. The paper's main focus is on approaches that directly alter document images and carry out information processing tasks like retrieval, categorization, and summary without making an effort to fully comprehend the textual content of the document.

A QA model was created by Tasmiah Tahsin Mayeesha, Abdullah Md Sarwar, and Rashedur M. Rahman and trained to be able to respond to inquiries about the text in question. All kinds of language processing tasks have advanced significantly as a result of the recent emergence of potent language models like BERT and its variations. Bengali is currently an understudied language in NLP, so much so that this work establishes a milestone by being the first to successfully apply the transformer model to Bengali question answering.

On October 23, 2014, Amit Mishra and Sanjay Kumar Jain made the suggestion that question-answering systems (QASs) produce responses to inquiries made in natural languages. This study examines QASs and categorizes them according to several standards. The authors categorize QASs according to a number of factors, including the kinds of questions they deal with, the kinds of data sources they consult, the kinds of processing they do on the questions and data sources, the kinds of retrieval models they use, the kinds of responses they produce, and the features of the data sources. Languages allow for paraphrase, which QASs currently struggle to detect. The effectiveness of a QAS is strongly influenced by a high-quality source corpus and, consequently, by well-articulated user needs.

A thorough and comparative analysis of question-answering technology is provided by Oleksandr Kolomiyets and Marie-Francine Moens. It presents the task of answering questions from the perspective of information retrieval and highlights the significance of retrieval models, or representations of queries and information documents, and retrieval functions, which are used to determine the relevance between a query and an answer candidate. The survey recommends a basic architecture for answering questions that gradually raises the level of complexity in the way that questions and information items are represented. On the one hand, natural language inquiries are converted to keyword-based searches; on the other hand, knowledge bases are accessed using structured or logical queries derived from the natural language questions, and solutions are deduced using logic.

Questions, Question Classes, Data Sources for QA, Context and QA, Answer Extraction, Real-Time Question Answering, Answer Formulation, Interactive QA, Multilingual (or cross-lingual) question answering, Information Clustering for QA, Advanced Reasoning for QA, and User Profiling for QA were all covered in detail by Bolanle Ojokoh and Emmanuel Adebisi. Through research into the literature around QA systems, they generate an educated opinion regarding the validity of each classification criterion. Modifying the generic QA architecture by adding or removing validation modules can make it more suitable for the question setting at hand. Each framework module's efficiency is contingent on the efficiency of preceding modules. In other words, if a question is formulated correctly during the Question Analysis phase, it will be more likely that relevant passages will be retrieved during the Passage Retrieval phase, increasing the possibility that the correct answers will be extracted during the Answer Extraction phase.

Question-answering datasets and evaluation metrics were surveyed by Hariom A. Pandya and Dr. Brijesh S. Bhatt. The process of answering a question can include, but is not limited to, translating the user's inquiry to relevant searches, retrieving relevant information, and selecting the most appropriate answer from among the results. Current deep learning model enhancements show significant performance gains across the board. This literature evaluation categorizes the QA field's future study directions by question type, response type, evidence source, and modeling strategy. This description was followed by a discussion of the field's open issues, which included things like automatic question generation, similarity detection, and a lack of linguistic resources. The paper concludes with a survey of relevant datasets and evaluation measures.

The study on question-answering methodologies and their methods is presented by Ajitkumar M. Pundge, Khillare S.A., and C. Namrata Mahender. Details of methods are offered after the structure for the question-answering system is introduced. The conclusion of the paper is finally here. In this global era, we need a QA system that can address closed-domain problems and provide pertinent answers to inquiries. The QA system can be a learning companion; it can aid in our educational system. It can be built into systems that evaluate or grade responses and produce outcomes that are consistent with human performance. The educational system now has new options that let pupils learn at their own speed. The researcher has several significant obstacles, including knowledge representation, precise representation for proper understanding, paraphrasing, conceptual learning, online access to descriptive questions, evaluating replies, and including figures, tables, and mathematical equations. The problems involved are complicated, making the solutions much more challenging, but the demands for the applications are great. Therefore, there is a lot of room to explore the difficulties in the QA area.

A taxonomy for classifying question-answer (QA) systems was proposed by Sanjay K. Dwivedia and Vaishali Singh. Additionally, they did a quick study of the major QA systems published in the literature and offered a qualitative analysis of these systems. In conclusion, a comparison of various methodologies has been done in order to bring insight to the research scope in this particular direction. The comparison is based on key aspects of the QA system that were determined to be essential in our study.

A question-answering system that was developed by Biplab Ch. Das that was based on semantics and reasoning was presented. These algorithms did their work by converting the limited natural language questions into database questions. In the first part of this chapter, we will go over a brief history of Watson as well as the pipeline of the IBM Watson Architecture. The next step is for them to look at articles written by IBM Watson. Following the road map that was shown at the beginning of the chapter, we bring the conversation to a close with Watson beyond Jeopardy, which focuses on Watson's applications in the medical field.

Answer Extraction, Real-time Question Answering, Answer Formulation, Interactive QA, Multilingual (or cross-lingual) question answering, Information Clustering for QA, Advanced Reasoning for QA, and User Profiling for QA were some of the topics that Bolanle Ojokoh and Emmanuel Adebisi investigated in their study of the generic QA framework. Other topics that they looked into included Question Processing, Question Classes, Data Sources, Context and QA, and Answer Extraction.

**Chapter 3**

**Methodology**

## **Overview of Proposed Model**

Several model and techniques have been used to make our question-answering system. We have taken the information from the web page of Triguna Sen School of Technology (TSSOT), Assam University as data resources. We have used deep neural network for training the model for intent classification. Extracted data from the web pages have been used as the features for training the model for intent classification of user query. We are using Pre-trained Bert model to retrieve the specific answer from the dataset based on user query.

Figure 1: Flowchart of the model

### **Dataset Generation Process**

We used the following process to create the dataset for our question Answering System.

1. **Web Resources:**

Assam University website consists of many web pages for each department and admin also from which we choose web resources of Triguna Sen School of Technology to extract all the information in text format. The following Link are given below that have been used for web scrapping.

* 1. [**http://www.aus.ac.in/tssot-cse/**](http://www.aus.ac.in/tssot-cse/)
  2. [**http://www.aus.ac.in/tssot-ece/**](http://www.aus.ac.in/tssot-ece/)
  3. [**http://www.aus.ac.in/agriculturalengg-department/**](http://www.aus.ac.in/agriculturalengg-department/)

1. **Web Scrapping:**

Web scraping enables the collection of data from multiple sources on the internet, which can then be used for various purpose. We used web scrapping using python library to retrieve the text data and store it to generate the dataset for our question answering system. The extracted data has only text information related to TSSOT.

We used requests, pathlib, and bs4 as Beautiful Soup 4 libraries of python for web scrapping. Request library has been used to get HTTP requests of the web pages. Beautiful Soup library convert the HTML content to the BeautifulSoup format using parsing.

**Pathlib:** Pathlib is a module in Python’s standard library that provides classes for working with file system paths. It was introduced in Python 3.4 as an alternative to the older os.path module for path manipulation and file system operations. The pathlib module offers a more objective-oriented and intuitive approach to handling file path and simplifies many common file operations.

**Beautiful Soup:** Beautiful Soap is a popular Python library for parsing HTML and XML documents. It provides a convenient way to extract and navigate data from web pages or XML files. Beautiful Soup makes it easy to scrape and process web content by providing a straightforward API. Beautiful Soup provides several methods and attributes to navigate and search the parsed document. You can use find() and find\_all() to search for specific tags; select() to use CSS selectors for more complex queries; and various other methods to traverse the HTML or XML tree.

A request sent to the specific URL using request library to retrieves the HTML content of the page and parses it using BeautifulSoup. Then all links are extracted that start with ‘http://’ from the parsed HTML and stored them for text extraction.

For each extracted link, it sends an HTTP GET request to the URL and the HTML content of response is parsed using ‘BeautifulSoup’. Then we extract specific content from the webpage and pre-processing on the extracted information and store it in a text file.

**Preprocessing:** Preprocessing involves removing inaccessible links, the extra space and utf-8 characters from the extracted text information. It also removes irrelevant characters that has been occurred in the paragraph during web scrapping.

The number of words extracted from the above-provided link are,

Table 2: No. of words

|  |  |
| --- | --- |
| **Department** | **No. of Words** |
| Computer Science & Engineering | 7788 |
| Electronics Communication Engineering | 6366 |
| Agriculture Engineering | 7273 |
| **Total no. of words** | **21427** |

1. **Question generation:**

We use Haystack Pipeline as an automatic question generation model to generate question to save time and effort compared to manual question generation. Human being needs more effort to generate relevant questions from large chunks of the data in text file so we are using the BM 25 algorithm with Haystack pipeline to generate set of questions from the relevant context.

**Haystack Pipeline:** The Haystack pipeline for question generation is a structured sequence of automated steps that leverages natural language processing and machine learning techniques to extract relevant information from documents, rank passages, and then generate meaningful questions from those passages.

**Elasticsearch Document Store:** The Elasticsearch Document Store is a component within the Haystack framework that serves as a storage and retrieval system. It uses Elasticsearch, a powerful search and analytics engine, to store and index documents, making them easily accessible for various natural language processing tasks, including question generation. This store efficiently manages the storage and retrieval of documents, enabling quick and accurate access to relevant information during the question generation process.

**BM25 Algorithm:** The BM25 algorithm, often used in information retrieval, is a ranking function that assesses the relevance of documents to a query. In the context of question generation, BM25 helps identify passages from a collection of documents that are most pertinent to a given query. It assigns higher scores to passages containing query-related terms while considering factors like term frequency and document length. BM25 aids in selecting relevant content for generating questions from text, improving the quality of questions by focusing on contextually important information.

We used BM25 algorithm for generating questions and Elasticsearch Document Store have been used for storing and retrieving document in Elasticsearch. Around five hundred words are taken as chunks from the paragraph text stored in a text file to generate multiple questions. No of generated question depend on the taken chunk.

The BM25 takes an input text or context and pre-processes it to ensure compatibility with the language model. It generates questions using predefined templates, where missing words or phrases are predicted by the language model. The generated questions are scored based on relevance or quality using techniques like perplexity or rule-based scoring. The top-scoring questions are selected as the output, forming a list of relevant and high-quality generated questions.

The BM25 algo utilizes a pre-trained language model to generate questions from a given text or context, providing a convenient way to automatically generate questions for further analysis or information retrieval tasks.

Sample of generated questions based on relevant paragraph is given below, -

**Paragraph:**

*The Department of Computer Science and Engineering (formerly Department of Information Technology) is one of the three departments at Triguna Sen School of Technology established in the year 2006. It offers bachelor’s programs along with master’s and doctoral degree programs in Computer Science and Engineering. It provides a comprehensive program that emphasizes on algorithms and theory, advanced computer architecture, computer vision and pattern recognition, data mining and machine learning, information retrieval & NLP, operating systems and computer networks, computer security, and scientific computing. The CSE department’s many strengths include its high faculty-to-student ratio, state of the art facilities, strong focus on undergraduate education and emphasis on leadership, service, and ethics. Faculty and students often collaborate on projects, working side-by-side with researchers from other colleges and departments across the campus, such as ISI, Kolkata, IIT Guwahati and NIT Silchar to name a few. In addition, quality research opportunities available through the department, as there is a real sense of community and teamwork here.*

**Questions:**

*“What was the previous name of the Department of Computer Science and Engineering?",*

*"When was the Triguna Sen School of Technology established?",*

*"What type of degree programs are offered in Computer Science and Engineering?",*

*"What are some of the topics taught in the computer science and engineering program?",*

*"What are some of the strengths of the CSE department?”,*

*What is the high faculty-to-student ratio in the department of CSE?",*

*"What type of projects do students often work side-by-side with researchers from other colleges and departments across the campus?",*

*"What is a real sense of community and teamwork? What kind of sense of community and teamwork is there?*

1. **Creating Dataset in JSON format:**

We merged the preprocessed text and generated question based on the chunk of related data to create a dataset into JSON format for training and intent classification for user query after training the deep neural network model using feature engineering and training process. The prepared dataset includes intent, tag, patterns and responses.

**Tag:** Each intent is assigned a unique tag, which serves as a label or identifier for that specific intent.

**Patterns:** Patterns represent different ways or variations in which a user might express a particular intent. Patterns are the generated question from Haystack module for the specific chunk.

**Responses:** Responses are the predefined answers or actions associated with each intent. They provide the appropriate information or actions that the system should take in response to a specific user query. Here, responses are those specific chunks used in question generation task.

**Context set:** The context set field in our dataset is empty, indicating that no specific context has been assigned to any intent.

Snapshot:

Figure 2: JSON format Dataset

### **Intent Classification Model**

1. **Dataset Collection:**

We are using JSON format data set which is created by merging text and generated question based on the chunk of related data.

1. **Feature Extraction*:***

Feature extraction involves converting the textual patterns into a numerical format that the model can understand. We have used Bag-of-Words for feature extraction to train deep neural network model using TensorFlow.

**input Set:** Words which are present in patterns in JSON file is converted into bag of words to represent numerical structure.

**output\_set:** All the tags in our corpus are converted into Bag-of-Words by initializing all the position with zero and change the corresponding position with one for corresponding tag.

#### **Training process**

We are using ‘input set’ and ‘output set’ for the training process with DNN class present in Python TensorFlow models. There is one input layer, two hidden layer and one output layer with softmax function. Show metrics is used to show the loss and accuracy during the training process.

batch size = 8

No. of epoch = 200

Softmax function is commonly used in multiclass classification problem to convert row predicted values into probabilities.

Softmax (x\_i) = exp (x\_i) [ sum (exp (x\_j)) for all j]

We trained and saved the model using above features.

### **User Query Processing**

We are using saved deep learning model to process the user query. User provides input in the Google Collab as interface. User’s input is converted to numerical form using feature extraction technique as bag of words. Bag of words represent the vector from of the user query.

After representing the user query using bag of words. It sent to the intent classification model to specify the relevant tag of the exact paragraph which holds the answer of user question. The pre-processed input is passed through the neural network architecture in a forward propagation process. Each layer in the network performs a weighted sum of its inputs, applies an activation function, and passes the result to the next layer. The activation functions introduce non-linearity, allowing the model to capture complex patterns and relationships in the data. The output layer of the neural network represents the predicted probabilities for each class or tag. The final layer typically uses an activation function appropriate for the specific task, such as the softmax function for multi-class classification. The softmax function normalizes the outputs into a probability distribution, where each value represents the model's confidence in predicting a particular tag. The predicted probabilities from the output layer are examined to determine the most likely tag. This is often done by selecting the tag with the highest predicted probability, using techniques like argmax to find the index of the maximum value. The corresponding tag is then considered the predicted tag for the user's query. After retrieving the most likely tag of user’s query, JSON dataset has been used to store the paragraph of most likely tag. We extract the paragraph which consist of multiple answers and it also has the specific answer of user query that has been processed using Information retrieval model.

### **Passage Retrieval**

We are using default pipeline from the Bert Transformer to extract the exact answer of user query.

Default pipeline commonly used for question answering tasks is based on the DistilBERT model (specifically, the DistilBERT base uncased version). DistilBERT is a variant of the BERT (Bidirectional Encoder Representations from Transformers) model that has been distilled for efficiency while retaining much of its performance.

**BERT:** BERT (Devlin et al., 2018) refers to a neural network pretraining technique called Bidirectional Encoder Representation from Transformers. Due to its excellent performance in several NLP tasks on GLUE (Wang et al., 2019) including SQuAD 1.1 and SQuAD 2.0. There have been many other architectures that are variants of BERT. It has recently been included in Google Search too. BERT is based on transformers which processes words in relation to all the other words in a sentence instead of looking at them one by one. This allows BERT to look at contexts both before and after a particular word and helps it to pick up features of a language.

**Input representation:** Input representation for BERT can handle both a single sentence and a pair of sentences representation e.g (Question, Answer) in a single token sequence. A sentence is considered to be an arbitrary span of contiguous text rather than a linguistic sentence. A sequence can be one sentence or two sentences concatenated together. Word piece tokenization is used with a 30k vocabulary. First token of every sequence is always a special token called the [CLS] token. For classification tasks the final hidden state assigned to the CLS token is used as input. If pair of sentences are given as input then the sentences are separated using a separator token [SEP]. Segment embedding are also used to indicate whether a sentence is from sentence 1 or 2. The final input to the model is the summation of the token embedding, segment embedding and positional embedding.

**DistilBERT:** DistilBERT (Sanh et al., 2019) is a compressed version of BERT where knowledge distillation technique was used to compress the BERT architecture. Using knowledge distillation in the pretraining phase of BERT it was possible to reduce the size of a BERT model by 40% while retaining 97% of its language understanding capabilities and being 60% faster. For training it uses a triplet loss combining language modelling, distillation and cosine embedding loss. Model compression techniques like knowledge distillation is motivated by the desire to deploy massive architectures like transformers to low computing resource environment as well as reducing training time and computational cost.

**Knowledge distillation:** Knowledge Distillation (Hinton et al., 2015) is a compression technique where a smaller compact model is trained to reproduce the behaviour of a larger model or an ensemble of models. The larger model is often called the teacher and the smaller model is called the student. In knowledge distillation the student network minimizes a loss function where the target is the distribution of class probabilities predicted by the teacher. This probability distribution generally has the correct class at a high probability while the other classes have near zero probability. Knowledge Distillation can be thought of the teacher network teaching the student how to produce outputs like itself. Both of the networks are fed same input. While the target of the teacher network are the actual labels, the student network is rewarded for mimicking the behaviour of the teacher network. The student is trained with a distillation loss over the soft target probabilities of the teacher.

**DistilBERT architecture:** The student network is a small transformer architecture which is trained with the supervision of a larger transformer architecture (BERT-base) and initialized from the layers of the teacher architecture. The number of layers is reduced by a factor 2 and other minor modifications like removing token type embedding and poolers are also done. DistilBERT was also trained on the same corpus like the original BERT model, a concatenation of English Wikipedia with other large datasets. The training loss is a linear combination of distillation loss and supervised training loss (in this case masked language modelling loss) as the next sentence prediction objective was dropped. A cosine embedding loss was also added to align the embedding of the student and the teacher transformer network.

### **Answer Extraction**

We are using distillbert unlarge case model to extract the specific answer from the relevant response paragraph using user’s query as question. It is pretrained Bert model which uses attention mask and self-attention to the input representation. Input represent both user’s query and response from the intent classification model. Where the first token is CLS and the SEP token represent the boundary of question ending in each sequence as combined input of user query and response. The following process are performed for answer retrieval.

1. **Tokenization:**

The input question and response are tokenized into individual tokens using WordPiece tokenization. WordPiece tokenization breaks down the input text into subword units, allowing the model to handle out-of-vocabulary words and capture more fine-grained information.

1. **Embedding:**

The tokens are converted into dense vector representations called embeddings. The DistilBERT model utilizes pre-trained word embeddings and positional embeddings to capture the meaning and position of the tokens in the input.

1. **Contexttual Representation:**

The model generates contextualized representations of the token embeddings by considering the bidirectional context through multi-layer self-attention mechanisms.DistilBERT compresses the original BERT model by reducing the number of layers and parameters while maintaining similar performance.

1. **Attention Mechanism:**

The model applies self-attention mechanisms to capture the contextual relationships between tokens.Self-attention allows the model to attend to different parts of the input text, attending more to informative tokens for the given question.

1. **Answer Extraction:**

DistilBERT can perform answer extraction using token classification or span prediction techniques.Token classification involves assigning a probability score to each token, indicating the likelihood of it being part of the answer.Span prediction involves predicting the start and end positions of the answer span within the context.

1. **Post-processing:**

The predicted answer span or tokens are post-processed to generate a final answer.This typically involves removing unnecessary tokens, handling special characters, or applying additional heuristics.

### **Response Generation:**

Once the answer span is obtained, it can be used to generate a response. This could involve directly returning the answer span as the response or further processing it to generate a more user-friendly or natural language response. Additional techniques like text generation, template-based responses, or language modelling may be employed to generate coherent and informative responses. After generating the response, the response is given to the user.

**Chapter 4**

**Result and Discussion**

## **Result**

We are receiving proper responses to some queries, but we are not receiving proper responses to some. The system’s output is shown in following figures.

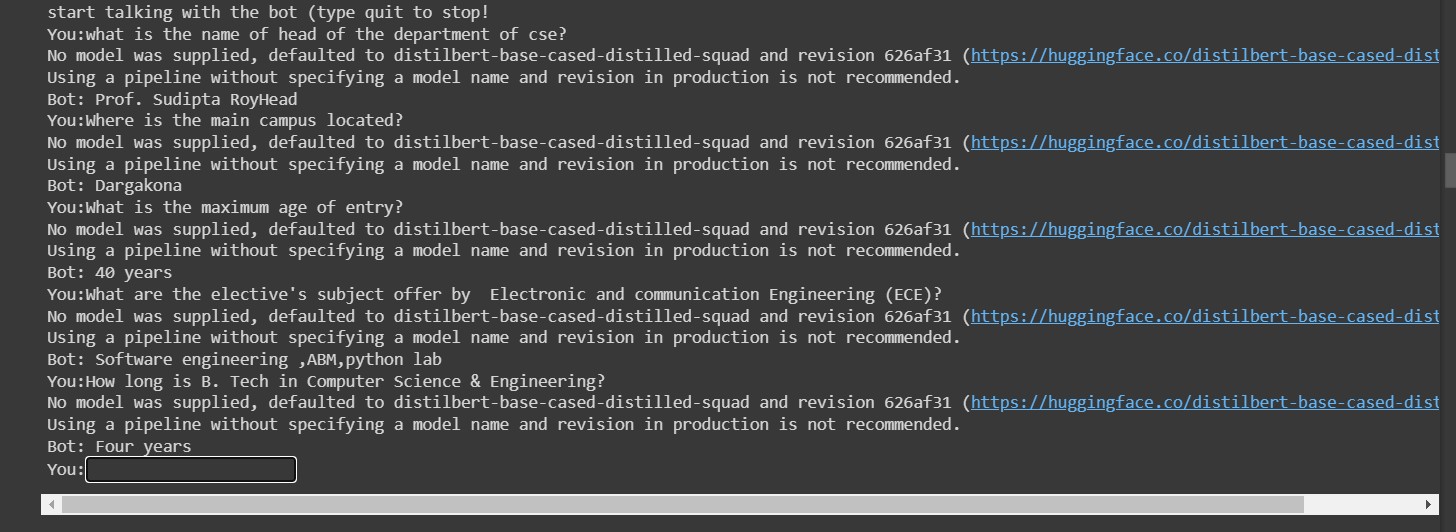


Figure 4.1: Accurate response

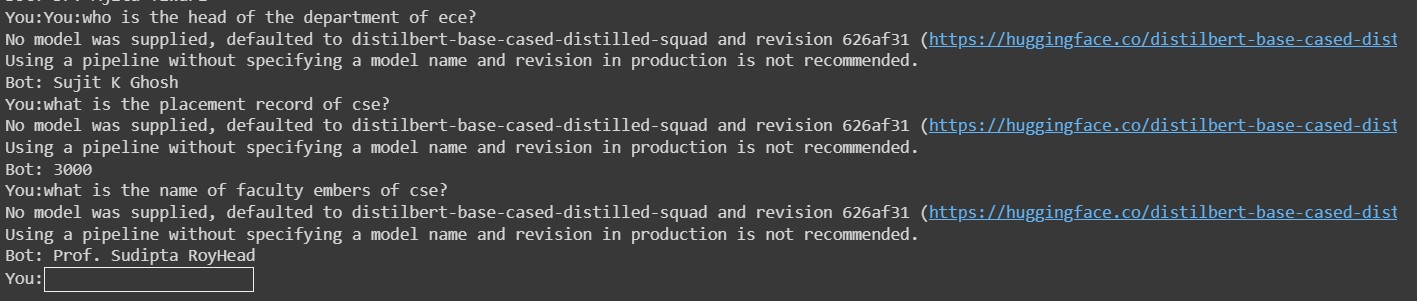


Figure 4.1: Non-accurate response

## **Evaluation:**

At first, we created a csv file for preparing annotated dataset which contain context, question and answer. Then it is converted into JSON format and again from JSON format it is converted to squad\_sot.json format for evaluation of our DistilBERT model.

We have taken 25.89% question from our main dataset to generate squad\_sot.json file.

#### **Process of Evaluation:**

* + The goal of the evaluation is to assess the performance of a question- answering pipeline on a specific task.
  + An annotated dataset is used for evaluation, which contains contextual information (paragraphs) and corresponding question-answer pairs.
  + The pipeline's performance is measured by comparing its predicted answers to the ground truth answers provided in the dataset.
  + The evaluation process involves iterating through the examples in the dataset. For each example, the context and question-answer pairs are extracted.
  + Each question-answer pair is examined individually. The question is used as input to the question-answering pipeline, along with the corresponding context, to generate a predicted answer.
  + The predicted answer is compared to the ground truth answer for that question. The comparison may involve measuring the similarity or matching between the two answers.
  + The evaluation metrics used in this process include accuracy and fuzzy matching scores. Accuracy represents the proportion of correctly predicted answers, while fuzzy matching scores assess the similarity between predicted and ground truth answers.
  + A confusion matrix is constructed to provide an overview of the pipeline's performance. The confusion matrix shows the distribution of predicted and true answers, allowing for an analysis of correct and incorrect predictions.
  + Visualization techniques, such as heatmaps, can be used to present the confusion matrix in a more accessible and understandable format.
  + The evaluation results, including accuracy, fuzzy matching scores, and the confusion matrix, provide insights into the strengths and weaknesses of the question-answering pipeline for the given task.
  + These findings can be discussed in a research paper to analyze the effectiveness of the pipeline, identify areas for improvement, and suggest potential future work.

We are getting **48.54%** accuracy and Fuzzy F1 Score **83.70%.**

The formula for calculating accuracy in the context of a question answering system can be represented as follows:

Accuracy = (Number of Correctly Predicted Answers) / (Total Number of Examples)

To break it down further:

* Number of Correctly Predicted Answers: This refers to the count of answers predicted by the chatbot that match the ground truth answers.
* Total Number of Examples: This is the total number of examples or questions in the dataset that were evaluated.

The accuracy score is a measure of how well the chatbot performs in providing correct answers compared to the ground truth answers in the dataset. It is expressed as a value between 0 and 1, where 1 indicates a perfect match between predicted and ground truth answers, and 0 indicates no correct answers.

In the provided code snippet, the accuracy is calculated using the `accuracy\_score` function from the `sklearn.metrics` module, which compares the predicted answers (`predicted\_answers`) with the ground truth answers (`ground\_truth\_answers`) and returns the accuracy score. The accuracy score is then printed as the output.

Predicted Answer vs Ground Truth Answer

|  |  |  |  |
| --- | --- | --- | --- |
| Sl No. | Question | Predicted Answer | Ground Truth Answer |
| **1.** | When did Assam University come into existence? | 1994 | 1994 |
| **2.** | Where is the main campus located? | Dargakona | Dargakona |
| **3.** | What was the name of the Vice Chancellor? | Topodhir Bhattacharjee | Prof. Rajive Mohan Pant |
| **4.** | What year was the Department of Agricultural Engineering established? | 2006 | 2006 |
| **5.** | What is the name of the head of the Department of Agricultural Engineering? | Dr. Ajita Tiwari | Dr. Ajita Tiwari |
| **6.** | What was the previous name of the Department of Computer Science and Engineering? | Department of Information Technology | Department of Information Technology |
| **7.** | When was the Triguna Sen School of Technology established? | 2006 | 2006 |
| **8.** | Who is the head of the Department of CSE? | Prof. Sudipta RoyHead | Prof. Sudipta RoyHead |
| **9.** | What does the Department of Computer Science Engineering offer? | Undergraduate, Postgraduate and Doctoral programmes | Undergraduate, Postgraduate and Doctoral programmes |
| **10.** | What is the name of the hod of Electronic and communication Engineering (ECE) ? | Head of the Department | Dr. Richik Kashyap, HoD(Head of the Department) |
| **11.** | In what year was the Department of Electronics and Telecommunication Engineering established? | 2011 | 2011 |
| **12.** | How long is the duration of the Under Graduate B. Tech in Computer Science & Engineering? | Four years | Four years |
| **13.** | How many acres of campus does the university boast? | 600 | 600 |
| **14.** | When is the 30th Foundation Day of Assam University? | January 21, 1994 | 31st October 2022 |

**Fuzzy F1 Score:**

F1 Scores Table:

|  |  |  |
| --- | --- | --- |
| **Sl. No.** | **Accuracy Metrics** | **Values** |
|  | Precision | 0.961235 |
|  | Recall | 0.390756 |
|  | F1-score | 0.367947 |
|  | Support | 238.0000 |
|  | Average F1 score | 86.163866 |

No of classes are 210 for evaluation of F1 score.

Individual F1 Score:

|  |  |  |
| --- | --- | --- |
| **Sl. No.** | **Class Name** | **F1 Score** |
|  | Navajyoti NathAssistant Register | 0.666666 |
|  | New Delhi | 1.0 |
|  | Notification for walk-in-interview | 0.666666 |
|  | Subrata SinhaSystem | 1.0 |
|  | Silchar Circuit House | 0.0 |
|  | Prof. Sudipta RoyHead | 1.0 |
|  | [amitmcs@gmail.com](mailto:amitmcs@gmail.com) | 1.0 |
|  | Dr. Ajita Tiwari | 0.0 |
|  | 1994 | 0.666666 |
|  | 2006 | 1.0 |
|  | 40 years | 1.0 |
|  | 23 five per cent | 1.0 |
|  | Department of Information Technology | 1.0 |
|  | Diphu | 0.0 |
|  | Dept. of Comp. Sc. & Engg | 1.0 |

**Chapter 5**

**Conclusion and Future Work**

We introduced a question-answering system which is designed for Triguna Sen School of Technology at Assam University, Silchar, represents a significant advancement in user-friendly, conversational AI. It enables users to obtain accurate and relevant answers to their queries from vast amounts of textual data. The question-answering system’s ability to efficiently provide essential university details revolutionizes access to information, benefiting students, educators, and parents alike. To ensure its continued success, regular updates and continuous improvement are crucial in maintaining accuracy and relevance. Overall, the question-answering system revolutionizes access to essential university details, providing convenience and efficiency to individuals navigating the complex world of higher education.

In our future work, we would like to expand the dataset and also work on the pre-processing of extracted data. We aim to improve the accuracy of our question-answering system.

# Bibliography

|  |  |
| --- | --- |
| [1] | C. Lalithnarayan, “Section,” 30 December 2020. [Online]. Available: https://www.section.io/engineering-education/question-answering/. [Accessed 3 July 2023]. |
| [2] | E. Riloff and M. Thelen, “A rule-based question answering system for reading comprehension tests,” in *ANLP-NAACL 2000 workshop: reading comprehension tests as evaluation for computer-based language understanding systems*, Salt Lake City, 2000. |
| [3] | S. Quarteroni and S. Manandhar, “Designing an interactive open-domain question answering system,” *Natural Language Engineering,* vol. 15, no. 1, pp. 73-95, 2009. |
| [4] | S. Sarker, S. T. A. Monisha and M. M. H. Nahid, “Bengali question answering system for factoid questions: A statistical approach,” *International Conference on Bangla Speech and Language Processing (ICBSLP). IEEE,* pp. 1-5, 2019. |
| [5] | J. Weizenbaum, “ELIZA—a computer program for the study of natural language communication between man and machine,” *Communications of the ACM,* vol. 9, no. 1, pp. 36-45, January 1966. |
| [6] | J. Green, F. Bert, A. K. Wolf, C. Chomsky and K. Laughery, “Baseball: an automatic question-answerer,” *western joint IRE-AIEE-ACM computer conference,* pp. 219-224, 9 May 1961. |
| [7] | M. Mitra and B. B. Chaudhuri, “Information retrieval from documents: A survey,” *Information retrieval ,* vol. 2, pp. 141-163, May 2000. |
| [8] | T. Tahsin Mayeesha, A. M. Sarwar and R. M. Rahman, “Deep learning based question answering system in Bengali,” *Journal of Information and Telecommunication,* vol. 5, no. 2, pp. 145-178, 2021. |
| [9] | A. Mishra and S. K. Jain, “A survey on question answering systems with classification,” *Journal of King Saud University-Computer and Information Sciences,* vol. 28, no. 3, pp. 345-361, 2016. |
| [10] | O. Kolomiyets and M. F. Moens, “A survey on question answering technology from an information retrieval perspective,” *Information Sciences,* vol. 181, no. 24, pp. 5412-5434, 2011. |
| [11] | B. Ojokoh and E. Adebisi, “A review of question answering systems,” *Journal of Web Engineering,* vol. 17, no. 8, pp. 717-758, 2018. |
| [12] | H. A. Pandya and B. S. Bhatt, “Question answering survey: Directions, challenges, datasets, evaluation matrices,” *arXiv preprint arXiv:2112.03572,* vol. 1, pp. 1-17, 2021. |
| [13] | A. M. Pundge, S. A. Khillare and C. N. Mahender, “Question answering system, approaches and techniques: a review,” *International Journal of Computer Applications,* vol. 141, no. 3, pp. 34-39, May, 2016. |
| [14] | S. K. Dwivedia and V. Singh, “Research and reviews in question answering system,” *Procedia Technology,* vol. 10, pp. 417-424, 2013. |
| [15] | B. C. Das, “A Survey on Question Answering System,” *Department of Computer Science and Engineering, Indian Institute of Technology, Bombay, India,* pp. 1-161, 2014. |