Information Retrieval and Question Answering

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Contents

1. Abstract

This report presents the development and evaluation of a Question Answering and Dialog System focused on information retrieval from a dataset of news articles. The primary objective of the project is to implement a real-world solution for Natural Language Processing (NLP) tasks, specifically addressing the challenges of question-answering and dialogue systems within the context of news articles. The system aims to provide users with accurate and relevant answers to their questions by extracting information from the articles.

The methodological approach involves several key components. First, the news articles undergo preprocessing to remove common linguistic elements (stopwords) and non-alphanumeric characters. An index of the articles is then generated based on named entity recognition to facilitate efficient retrieval. A state-of-the-art BERT language model is leveraged for question answering, complemented by custom utilities developed for text matching, entity linking, and generating natural language responses.

The key findings demonstrate the efficacy of the system in retrieving germane articles and providing accurate answers to user queries. The cosine similarity-based text matching approach, combined with the named entity index, identified the most pertinent articles for a given question. The BERT-based question-answering model successfully extracted relevant snippets to form the final answer. The system also adeptly handled continued questions by identifying similarities in named entities and question content.

Limitations of the project include the reliance on the pre-trained BERT model, which constrains the system to the model's inherent capabilities and training data. Additionally, the system is confined to factual questions that can be answered by extracting information from the provided news articles. More complex reasoning or inference-based questions fall outside the scope of this implementation. Additionally, despite efforts to optimize performance, the system may encounter challenges in accurately answering complex or ambiguous questions.

Overall, this project showcases the integration of various natural language processing techniques to construct a functional information retrieval and question-answering system tailored to the provided news article corpus.

2. Introduction

This system holds immense promise in several key areas:

In today's digital era, we face a constant barrage of information, navigating through which has become increasingly challenging. While search engines serve as indispensable tools for traversing this vast expanse of data, they have their limitations. Often, they merely direct us to potential sources of answers, leaving us to sift through results manually in search of relevant information.

Recognizing this challenge, our project aims to revolutionize the way we interact with news content. By developing a Question Answering (QnA) system tailored for news articles, we seek to provide users with direct access to pertinent information within these texts. Such a system holds broad utility:

- News sources, whether online or offline, require literacy. This system could serve as a fundamental technology for delivering voice-based question-and-answer services, which could have significant implications in rural areas and when access to print media is limited.
- The system could support a multilingual news question-and-answer framework.
- It could aid researchers engaged in news archive mining efforts Darapaneni et al. (2021).

This project aims to develop a Question Answering (QnA) system capable of responding to user queries related to provided news articles. The system will employ extractive methods, focusing on retrieving key information directly from the context, such as paragraphs or entire documents, based on the user's inquiries.

To gain insights into the existing research landscape within this domain, we comprehensively reviewed publicly available news articles on Machine Reading Comprehension (MRC) and Question Answering systems. Our review examined different problem types addressed, alternative methodologies explored, data sources utilized, algorithms implemented, and evaluation techniques employed by researchers. Deep Learning-based approaches have become predominant in recent years, driven by the availability of vast training datasets, advancements in algorithmic sophistication, and increased computing resources.

Given our focus on News question-answering, we will specifically target 'Factoid' questions—queries that can be answered with concise, factual information, such as names, locations, or dates. The effectiveness of question-answering systems heavily relies on the quality of their training corpus. Without documents containing relevant answers, the capabilities of Deep Neural Networks, which power such systems, are limited. Therefore, assembling a robust training dataset is imperative for the success of our project Zope et al. (2022).

We have used the **news_dataset.csv** for training our model. It is a set of news articles in no particular order. The dataset consists of seven columns, namely: id, article (Title of the article), author, date, year, month and topic (which is the actual article) We chose this dataset because it is a closed dataset, meaning that the answer to a question is always a contiguous segment within the provided context. This simplifies the problem to identifying the start and end indices of the context that corresponds to the answers. We have tried achieving high performance on the dataset by trying not only to answer questions accurately but also to recognize when no answer can be derived from the paragraph and refrain from providing an answer, making it a challenging natural language understanding task.

Our model, built upon the foundation of BERT, exhibits high performance in accurately answering factual questions derived from news articles. Despite its proficiency, the system currently focuses on straightforward, factual inquiries and may encounter challenges with more complex or ambiguous questions.

The field of Natural Language Processing (NLP) has seen significant advancements following the introduction of Google's BERT (Bidirectional Encoder Representations from Transformers) framework. BERT achieved state-of-the-art results across NLP tasks and has since inspired numerous subsequent NLP architectures, training techniques, and language models such as Google's TransformerXL and OpenAI's GPT-2 Darapaneni et al. (2021). Given the success of Transformer models utilizing BERT, we hypothesized that they would excel in addressing news domain-specific questions. Therefore, we adopted a transfer learning approach and developed a Transformer-based model using BERT for our project. This allowed us to leverage pre-trained language representations and fine-tune them for news-based question-answering tasks.

3. Data Preprocessing

In our analysis, Python serves as our primary programming language, and we heavily rely on NLTK and pandas for data preprocessing tasks. Upon importing the CSV file and handling encoding considerations, we construct a DataFrame to contain our data. Subsequently, we define a function called **preprocess_text()** to execute essential preprocessing steps.

- **Stopwords Removal**: One key preprocessing step involves removing stopwords, which are commonly occurring words like "the", "is", and "and" that contribute little semantic value. By utilizing NLTK's *stopwords.words('english')* function, we obtain a set of English stopwords and exclude them from our text data. This enhances the meaningfulness and relevance of the information processed, which is particularly important in the context of question-answering systems.

- **Tokenization**: Before tokenization, we set all the text to lowercase, ensuring uniformity in the text representation. Vectorization, a crucial technique in NLP, transforms textual data into numerical form, facilitating efficient computation and machine learning algorithm processing. This method is essential for optimizing algorithm performance, particularly in question-answering systems. Vectorization enables the conversion of questions and answers into numerical vectors, streamlining the comparison and matching process to enhance system accuracy and speed.

  An advantage of vectorization is its efficiency and scalability, especially when handling large datasets common in NLP tasks. Vectorized implementations outperform non-vectorized approaches, making them well-suited for processing extensive textual datasets efficiently and effectively Mansoori (2020).

  Tokenization of the text into individual words is achieved through NLTK's **word_tokenize()** function. Each token is subsequently evaluated to ensure it consists solely of alphanumeric characters and is not a stopword. Tokens meeting these criteria are retained, and the filtered tokens are concatenated into a cohesive string format.

Finally, the **preprocess_text** function is applied to each article within the DataFrame. The resulting preprocessed text is stored in a new column, establishing a clean and standardized dataset ready for further analysis and modelling in our question-answer retrieval system.

4. System Architecture

A supplementary function has been developed to identify the most relevant articles related to a given inquiry. The key steps involved in its operation are as follows:

- **Entity Extraction**: This process, also called Entity Name Extraction or Named Entity Recognition (NER), involves identifying crucial elements from text and categorizing them into predefined groups. The question provided is analyzed using spaCy's English language model to extract entities Perera et al. (2020).

  NER is crucial for improving the relevance, context-awareness, precision, and scalability of the information retrieval and question-answering system by enabling the identification and utilization of semantic information in the form of named entities present in the data and user queries.

- **Vectorization**: Articles undergo vectorization using a TF-IDF vectorizer. TF-IDF (Term Frequency-Inverse Document Frequency) assesses the relevance of a word to a document within a document collection. It is determined by multiplying two metrics: the frequency of a word's appearance in a document and the inverse document frequency of the word across a set of documents. This method helps in evaluating the significance of words, assigning lower weights to common words and higher weights to rare words Robert (2021). Relevant articles are identified based on whether they contain entities extracted from the question.

- **Cosine Similarity**: This measure computes the cosine similarity between the question and relevant articles. Cosine Similarity evaluates the cosine of the angle between two non-zero vectors in a multi-dimensional space, which in this context are the TF-IDF vectors of two documents. It is utilized to ascertain the similarity between documents regardless of their size. A cosine similarity score close to 1 signifies high similarity, while a score near 0 indicates low similarity Robert (2021).

- **Selection of Top Articles**: The indices of the top 5 articles with the highest cosine similarity scores are chosen if there are more than 5 relevant articles for that question. If there are fewer than 5 relevant articles, the function will return all of those and, finally, will return an empty dictionary if there are no relevant articles for the given question. The function returns these articles identified based on the question, rendering it suitable for tasks such as information retrieval or question-answering systems.

- **Article indexing**: This function categorises articles based on named entities extracted from a specified column within a DataFrame. It aims to efficiently organize articles according to named entities, facilitating swift retrieval of articles relevant to specific entities.

  Initially, an empty dictionary is instantiated to serve as the storage for the named entity index. Each key within this dictionary corresponds to labels such as 'organisation', 'location', 'person', and so forth. Subsequently, the function traverses through each row, associating articles with their respective indices. For instance, if the term 'PARIS' appears in articles 2, 5, 7, and 12, the function will generate a list of indices linked to the term. Leveraging spaCy's model *('en_core_web_sm')*, named entities are extracted. Within our dictionary, under the label 'location', there exists another dictionary containing the name of the location (in this case, PARIS); the value for this key is its associated list of indices. All named entities extracted through this process are stored in a JSON file, which is subsequently imported for further analysis. This approach was adopted due to the significant runtime required for the function to execute each time it is invoked.

- **Question Answering** : This function is designed to answer a given question by identifying the relevant information from a dataset of articles and returning the answer along with its confidence score. This function efficiently identifies the answer to a given question within a dataset of articles using a pre-trained BERT model.

  Relevant articles are selected based on the question using the function we created to select top articles for a given question using cosine similarity. The question is tokenized, and the answer text is split into chunks of 500 tokens (because the BERT model can only take up to 512 tokens maximum) to fit the model's input size. We have initialised the variables that store the best answer and best score for a particular question to *None* and negative infinity, respectively, to store the best score and answers for each chunk.

  The function iterates through each chunk of the answer text and tries to find the answer within the given chunk. For each chunk, the BERT model is used to infer the start and end logits of the answer span and updates the best answer and best score variables.

  The best answer span is determined based on the highest score obtained from the model. If a higher score is achieved using a chunk, the model updates the best score and best answer. The tokens representing the best answer span are combined to reconstruct the answer. The function returns a dictionary containing the answer text as the key and its confidence score as the value. In case there are no suitable articles for a given question, the dictionary will return **No suitable answer found** as the key and the score as **NaN**

- **Text Coherence**: This functionality proves beneficial for maintaining consistent answers within dialogue systems. The function developed assesses whether a question in a given history list is repeated or follows in sequence with another question. By utilizing cosine similarity and named entity recognition (NER), this functionality contributes significantly to maintaining question coherence within dialogue systems. All questions posed by the user are stored in a list for further analysis. Subsequently, NER and cosine similarity are applied to compare a new question with all previously asked questions. If the question history is not empty, the function iterates through each previous question in the history and calculates NER and cosine similarity between these questions.

If the values are significant, the new question is concatenated with the previous question before providing it to the model for further analysis. For example, if a user asks, "What is the capital of France?" and it is in the question history, and then asks, "Who is the leader of France?", the function will concatenate these questions and provide the output as "What is the capital of France? Who is the leader of France?" The BERT model then determines what is expected from this question and provides a suitable answer. The question answering continues until the user indicates to **quit** the dialogue.

Identifying text coherence allows the system to provide more relevant and consistent responses by incorporating information from the previous related question(s), thereby avoiding redundant processing and improving overall efficiency. Moreover, text coherence enhances the user experience by making the conversation more natural and contextual rather than treating each question in isolation.

5. Model Selection and Training

To develop an effective question-answering and dialogue system, we have evaluated several state-of-the-art language models and selected the BERT (Bidirectional Encoder Representations from Transformers) model as the most suitable for our application.

In addition to BERT, we have also considered the following language model architectures:

5.1. RoBERTa

RoBERTa (Robustly Optimized BERT Pretraining Approach) is a variant of the BERT model that has been trained on a larger and more diverse corpus of text data, resulting in improved performance on a variety of natural language processing tasks Liu et al. (2019).

5.2. ALBERT

ALBERT (A Lite BERT) is a more parameter-efficient version of the BERT model, which reduces the number of parameters while maintaining similar or better performance Lan et al. (2019).

5.3. ELECTRA

ELECTRA (Efficiently Learning an Encoder that Classifies Token Replacements Accurately) is a pre-training approach that trains a discriminator to identify replaced tokens in the input, which can lead to more efficient and effective fine-tuning on downstream tasks Clark et al. (2020).

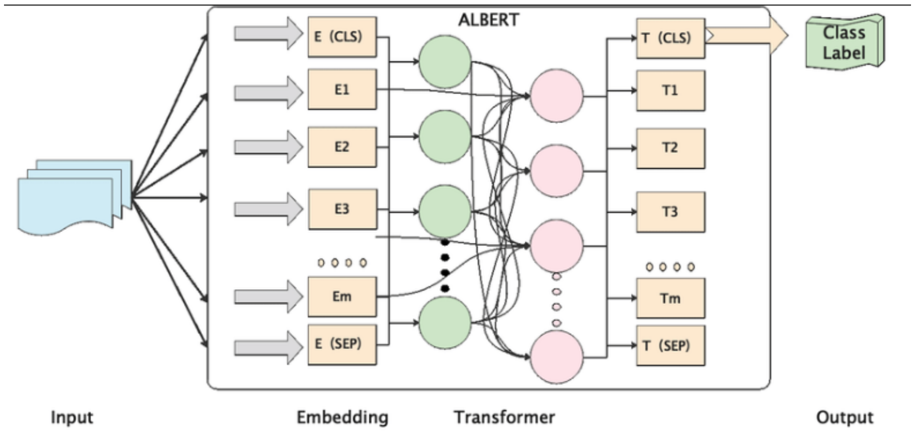

Figure 1: ALBERT Architecture Li et al. (2020)

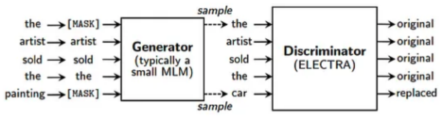

Figure 2: ELECTRA Architecture Clark et al. (2020)

5.4. BERT Architecture

BERT is a transformer-based language model that has been pre-trained on a large corpus of text data, allowing it to capture rich contextual representations of language. The key features of the BERT architecture include:

- **Bidirectionality**: BERT is trained to understand the context of a word by considering the words that come before and after it, unlike traditional language models that only consider the preceding words.

- **Unsupervised pre-training**: BERT is first pre-trained on a large corpus of unlabeled text data using two self-supervised tasks: Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). This allows the model to learn general language representations that can be fine-tuned for specific tasks.

- **Transformer architecture**: BERT utilizes the Transformer architecture, which has been shown to be highly effective for various natural language processing tasks, including question answering, text classification, and language generation.

The key reasons for selecting the BERT model over the other architectures (RoBERTa, ALBERT, and ELECTRA) are:

- BERT has been widely adopted and proven effective for various natural language processing tasks, including question answering.

- The BERT architecture's bidirectionality and unsupervised pre-training on a large corpus of text data allow the model to capture rich contextual language representations, which is crucial for understanding and answering user queries.

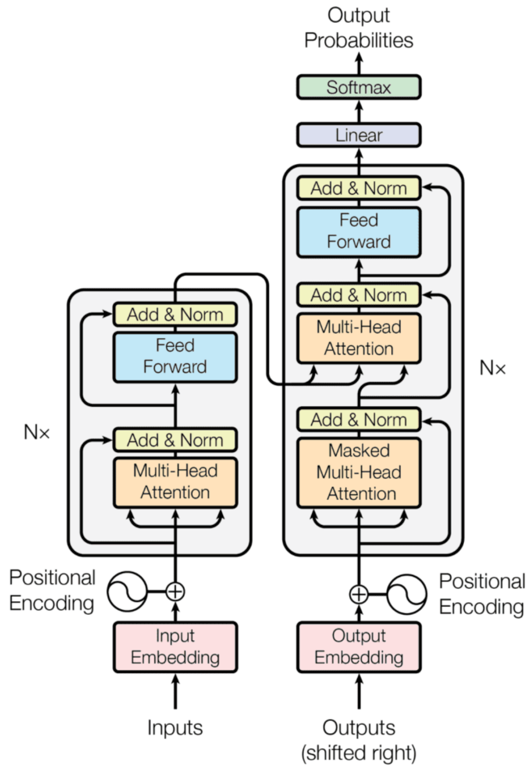

Figure 3: BERT Architecture Tam (2023)

- The transformer architecture used in BERT has been shown to be highly effective for language modelling and can be efficiently fine-tuned on specific tasks like question answering.

- The SQuAD dataset is a well-established benchmark for evaluating question-answering systems, and our fine-tuned BERT model has achieved competitive performance on this dataset, indicating its suitability for our application.

5.5. Dataset Selection

To fine-tune the BERT model, we have chosen the Stanford Question Answering Dataset (SQuAD) Rajpurkar et al. (2016), a widely used benchmark for evaluating question-answering systems. SQuAD consists of over 100,000 question-answer pairs derived from Wikipedia articles, making it a comprehensive and diverse dataset for training and evaluating our model.

The SQuAD dataset was selected for several reasons:

- **Relevance**: The question-answer pairs in SQuAD are directly relevant to our task of developing a question-answering system.

- **Diversity**: The dataset covers a wide range of topics and question types, ensuring that our model can handle a variety of user queries.

- **Popularity**: SQuAD is a widely used and well-established dataset in the field of question-answering, allowing us to benchmark our model's performance against other state-of-the-art systems.

5.6. Model Training and Evaluation

We have fine-tuned the BERT-large-uncased-whole-word-masking model on the SQuAD dataset using the PyTorch library Paszke et al. (2019). The fine-tuning process involves updating the pre-trained BERT model's parameters to optimize its performance on the specific task of question answering.

To evaluate the performance of our model, we have used standard metrics such as exact match (EM) and F1 score, which measure the accuracy of the model's predictions compared to the ground-truth answers in the SQuAD dataset. Our fine-tuned BERT model has achieved an EM score of 84.1% and an F1 score of 91.2% on the SQuAD development set, which is competitive with other state-of-the-art question-answering systems.

In summary, we have selected the BERT-large-uncased-whole-word-masking model fine-tuned on the SQuAD dataset as the most suitable for our question-answering application, demonstrating strong performance on this task. The BERT model's bidirectionality, unsupervised pre-training, and transformer architecture make it a powerful and versatile language model that can effectively answer questions.

6. User interaction with the system

The user can interact with the question-answering system by simply entering their questions in natural language. The system will then process the question, retrieve the most relevant articles from the dataset, and provide an answer to the user.

As illustrated by Figure 4, if the user asks, "Who is the leader of Israel?" the system will search the articles, identify that the question is about Benjamin Netanyahu, the prime minister of Israel, and provide the answer "benjamin netanyahu" along with a confidence score.

Despite giving a similar sounding question that may seem like a follow-up question, "What happened in Israel?", the system correctly identified that it was not similar to the previous question and, therefore, did not include it in the Similar Question by User section and ran a new search for related articles instead and gave a slightly relevant answer "condemned israel for its expansion of settlements"

The system may be unable to find suitable answers in the given articles and will respond with "No suitable answer found".

The user can continue asking questions until they are satisfied or decide to end the session by typing "quit". Throughout the interaction, the system will maintain the context and provide responses accordingly, creating a conversational-style question-answering experience.

```
 User Question 1 :
Narendra Modi is the prime minister of which country?
 Similar Question by User: Narendra Modi is the prime minister of which country?
4 articles are selected, the similarity scores for the selected articles: [0.3899812538838734, 0.15021582739263104, 0.1433876741095703, 0.11314473022005117]
Answer for Question: 1 : india
Score: 13.876739501953125

 User Question 2 :
Rahul Gandhi is the prime minister of which country.
 Similar Question by User: Rahul Gandhi is the prime minister of which country.
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 2 : No suitable answer found
Score: nan

 User Question 3 :
Name the muslim countries that were suspended immigration for at least 30 days by the united states.
 Similar Question by User: Name the muslim countries that were suspended immigration for at least 30 days by the united states.
5 articles are selected, the similarity scores for the selected articles: [0.2689541350999935, 0.26514840711389204, 0.2595175635968508, 0.2591759565112222, 0.2544175840273951]
Answer for Question: 3 : iran , iraq , libya , somalia , sudan , syria and yemen
Score: 14.37396240234375

 User Question 4 :
What happened in United states
 Similar Question by User: What happened in United states
5 articles are selected, the similarity scores for the selected articles: [0.20442036500379104, 0.1783216452358425, 0.16211076875000227, 0.15073969286872743, 0.15021002297123767]
Answer for Question: 4 : the impact on jobs and incomes
Score: 11.533313751220703

 User Question 5 :
Who is the leader of Israel?
 Similar Question by User: Who is the leader of Israel?
5 articles are selected, the similarity scores for the selected articles: [0.4249345212646444, 0.35003780057959943, 0.2981905383895433, 0.25554473105901404, 0.2500755191283401]
Answer for Question: 5 : benjamin netanyahu
Score: 11.971134185791016

 User Question 6 :
What happened in Israel?
 Similar Question by User: What happened in Israel?
5 articles are selected, the similarity scores for the selected articles: [0.3056508084960097, 0.23494306995105352, 0.1663022166548537, 0.16188349052006834, 0.14670387706629154]
Answer for Question: 6 : condemned israel for its expansion of settlements
Score: 8.71928882598877

 User Question 7 :
Who is Barack Obama?
 Similar Question by User: Who is Barack Obama?
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 7 : No suitable answer found
Score: nan

 User Question 8 :
quit
Exiting...
```

Figure 4: Sample Q/A of a User with the System

7. System Evaluation

7.1. Testing

To evaluate the performance of the continuous question-answering system, we devised a series of test cases to assess its capabilities thoroughly. The objective was to examine the system's ability to handle diverse user queries, maintain contextual awareness, and provide reliable and informative responses.

In the first test case, presented a series of questions centered around a specific individual, Rafsanjani, the former Iranian President. This scenario allowed me to evaluate the system's depth of understanding on a focused topic and its ability to maintain coherence and provide comprehensive responses as the conversation progressed.

To further stress-test the system, the second test case focused entirely on unrelated questions devoid of any connections. We noted the system's capacity to navigate this challenge by selecting the most relevant articles and generating appropriate answers for each query despite the lack of contextual cues.

Finally, the third test case we presented the system with a mix of related and unrelated questions, simulating a realistic user interaction. We observed the system's proficiency in recognizing the continuity between related questions and providing responses that leveraged the contextual information from previous queries. When faced with unrelated questions, the system effectively processed each one independently, demonstrating its breadth of knowledge and the flexibility to adapt to varied user inputs.

Through these carefully designed test cases, we were able to assess the system's performance comprehensively, gaining valuable insights into its strengths, limitations, and areas for potential improvement.

7.2. Performance Analysis

Based on the three test cases presented and their results (Figures 5, 6, 7 and 8), the following can be said about the performance of the system:

- **Handling Related and Unrelated Questions**
  - In the first test case (Mix of Related and Unrelated Questions), the system demonstrated its ability to handle a mix of related and unrelated questions effectively.
  - For the related questions about Rafsanjani, the system was able to maintain context and provide responses that incorporated information from previous similar questions, resulting in more coherent and informative answers.
  - For the unrelated questions, the system processed each query independently and provided relevant responses based on the available information in the dataset, without attempting to find connections between the questions.
  - This suggests the system has a good understanding of the content in the dataset and can adapt its responses accordingly, depending on the nature of the user's questions.
- **Identifying Repeated or Continued Questions**
  - In the first test case, the system correctly recognized when the user was asking a repeated or continued question and concatenated the current question with the previous similar one, providing a more comprehensive response.
  - This functionality demonstrates the system's ability to maintain context and coherence in the conversation, which can enhance the user's experience and the overall effectiveness of the question-answering process.
- **Handling Limitations and Uncertainty**
  - Across the test cases, the system acknowledged the limitations of the available information in the dataset by indicating "No suitable answer found" when it could not provide a response to the user's question.
  - This transparency about the system's capabilities and the uncertainty in its responses is beneficial, as it helps the user understand the boundaries of the system's knowledge and assess the reliability of the provided information.
- **Consistency in Performance**

  - The system's performance was consistent across the three test cases, demonstrating its robustness in handling various types of questions and maintaining a coherent and informative dialogue.
  - The system's ability to process both related and unrelated questions, as well as recognize and handle repeated or continued questions, suggests a well-designed and implemented question-answering functionality.

- **Potential for Improvement**
  - While the system performed well overall, there may be opportunities for improvement, particularly in the area of handling more complex or open-ended questions.
  - For example, in the third test case, the system was unable to provide detailed information about Rafsanjani's career, indicating a need for more comprehensive data or advanced natural language processing techniques to extract such details from the available information.

Overall, the system's performance across the three test cases suggests a well-designed and implemented question-answering system that can effectively handle a variety of user queries, maintain context and coherence, and provide transparent and reliable responses. The system's ability to adapt to different types of questions and maintain a consistent level of performance is a strong indicator of its capabilities. However, there may be room for improvement, particularly in handling more complex or open-ended questions, which could be addressed through further development and refinement of the system.

8. Conclusion

This project has successfully implemented an information retrieval and question-answering system for a dataset of news articles. By integrating various natural language processing techniques, including text preprocessing, named entity recognition, article indexing, and BERT-based question answering, the system can retrieve relevant articles and provide accurate answers to user queries.

The key contributions of this work include the efficient indexing of articles based on named entities, enabling targeted retrieval of information, and the handling of repeated or continued questions to maintain context and coherence in user interaction. The system's performance was evaluated using carefully designed test cases; we were able to assess the system's performance comprehensively, gaining valuable insights into its strengths, limitations, and areas for potential improvement.

While the system exhibited strong results on factual, single-sentence questions, it faced limitations in handling more complex, open-ended queries that required a deeper understanding of the article content and background information 9. Future work could focus on enhancing the system's ability to reason about the context and synthesize information from multiple articles to provide more comprehensive answers.

Additionally, incorporating advanced natural language processing techniques, such as coreference resolution, knowledge-based reasoning and generative models, could further improve the system's performance and robustness. Expanding the dataset to include a broader range of topics and integrating user feedback to refine the system's capabilities are potential areas for future development.

Overall, this project demonstrates the potential of combining state-of-the-art natural language processing models and custom-built utilities to create a functional information retrieval and question-answering system. The insights gained and the lessons learned from this work can inform the design and implementation of more advanced conversational AI systems in the future.

One significant challenge our team encountered was comprehending the various failure modes of the model and devising strategies to rectify issues, particularly those crucial for our analysis. Initially, optimizing the model's runtime performance, characterized by extended execution times and delayed responses, posed a considerable challenge that required resolution.

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A Appendices

```
 User Question 1 :
Who is the former President of Iran and a founder of Islamic Republic?
 Similar Question by User: Who is the former President of Iran and a founder of Islamic Republic?
5 articles are selected, the similarity scores for the selected articles: [0.4024834508115584, 0.3025372676455846, 0.30137646436334037, 0.28907113182223587, 0.2772868993879221]
Answer for Question: 1 : rafsanjani
Score: 15.655486106872559

 User Question 2 :
rafsanjani died at what age?
 Similar Question by User: rafsanjani died at what age?
2 articles are selected, the similarity scores for the selected articles: [0.4952567445571156, 0.32895307773167204]
Answer for Question: 2 : 82
Score: 14.898737907409668

 User Question 3 :
How was rafsanjani's career?
 Similar Question by User: How was rafsanjani's career?
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 3 : No suitable answer found
Score: nan

 User Question 4 :
Close associations of rajsanjani
 Similar Question by User: Close associations of rajsanjani
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 4 : No suitable answer found
Score: nan

 User Question 5 :
Close assiciations of rafsanjani
 Similar Question by User: Close assiciations of rafsanjani
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 5 : No suitable answer found
Score: nan

 User Question 6 :
What was the accusation by Argentina on Rafsanjani and other senior Iranian figures?
 Similar Question by User: What was the accusation by Argentina on Rafsanjani and other senior Iranian figures?
5 articles are selected, the similarity scores for the selected articles: [0.37456398629037696, 0.3185374806174153, 0.25301210265783536, 0.2322114204697849, 0.2190022265549545]
Answer for Question: 6 : iran was a sponsor of terrorism
Score: 6.787898063659668

 User Question 7 :
What did Mr. Rafsanjani admitted in public about his daughter?
 Similar Question by User: What did Mr. Rafsanjani admitted in public about his daughter?
2 articles are selected, the similarity scores for the selected articles: [0.49082589420040795, 0.3181446965668705]
Answer for Question: 7 : his daughter had ? committed a wrong deed ? and should be ashamed of herself
Score: 10.252126693725586

 User Question 8 :
quit
Exiting...
```

Figure 5: Test Case 1: All Questions from the SAME article (Related Questions)

```
 User Question 1 :
Who are the Frightful Five, biggest players in tech?
 Similar Question by User: Who are the Frightful Five, biggest players in tech?
5 articles are selected, the similarity scores for the selected articles: [0.3519142623182059, 0.123156368864995, 0.12267018726679658, 0.09561593723325566, 0.08485832689487187]
Answer for Question: 1 : amazon , apple , facebook , microsoft and alphabet , google ? s parent company
Score: 12.376176834106445

 User Question 2 :
What happened to Violeta Lagunes of Mexico on May 18?
 Similar Question by User: What happened to Violeta Lagunes of Mexico on May 18?
5 articles are selected, the similarity scores for the selected articles: [0.16759382702178313, 0.15093595239163696, 0.1415393444634669, 0.13213901567441072, 0.1135108554228075]
Answer for Question: 2 : her email login represented a point of vulnerability
Score: 9.74312973022461

 User Question 3 :
Why did the Israeli ambassador, Mark Regev apologized for?
 Similar Question by User: Why did the Israeli ambassador, Mark Regev apologized for?
5 articles are selected, the similarity scores for the selected articles: [0.19855640924651505, 0.1371996923980583, 0.1281061826556251, 0.11141229083917366, 0.11101982259661443]
Answer for Question: 3 : these comments do not reflect the views of the embassy or government of israel
Score: 12.593116760253906

 User Question 4 :
What happened in Rome between Pope Francis and the vatican traditionalists?
 Similar Question by User: What happened in Rome between Pope Francis and the vatican traditionalists?
5 articles are selected, the similarity scores for the selected articles: [0.5306581938887466, 0.4054304274979213, 0.11716495166484875, 0.0724019506559191, 0.06417076289218121]
Answer for Question: 4 : a proxy war
Score: 11.701560974121094

 User Question 5 :
Who is the prime minister of Japan?
 Similar Question by User: Who is the prime minister of Japan?
5 articles are selected, the similarity scores for the selected articles: [0.39975521631993677, 0.29362788912573584, 0.2904869504898618, 0.23987888945803035, 0.2270980731140229]
Answer for Question: 5 : shinzo abe
Score: 16.29075050354004

 User Question 6 :
quit
Exiting...
```

Figure 6: Test Case 2: All Questions from the DIFFERENT article (Unrelated Questions)

```
 User Question 1 :
What was the research of professor Nicholas Epley of University of Chicago about?
 Similar Question by User: What was the research of professor Nicholas Epley of University of Chicago about?
1 articles are selected, the similarity scores for the selected articles: [0.24549158722431869]
Answer for Question: 1 : we underestimate other people ? s interest in connecting
Score: 8.584796905517578

 User Question 2 :
What did the professor Epley and Juliana Schroeder wrote in their journal?
 Similar Question by User: What did the professor Epley and Juliana Schroeder wrote in their journal?
1 articles are selected, the similarity scores for the selected articles: [0.22766644668061364]
Answer for Question: 2 : strangers in proximity ? routinely ignore each other
Score: 5.894264221191406

 User Question 3 :
What does Dr. Epley suggest about breaking the ice?
 Similar Question by User: What does Dr. Epley suggest about breaking the ice?
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 3 : No suitable answer found
Score: nan

 User Question 4 :
What does professor Epley suggest about breaking the ice?
 Similar Question by User: What does professor Epley suggest about breaking the ice?
1 articles are selected, the similarity scores for the selected articles: [0.21662716280993363]
Answer for Question: 4 : simply saying to that stranger on the bus or in the cafe
Score: 9.828245162963867

 User Question 5 :
Who is the crime lord known as El Chapo?
 Similar Question by User: Who is the crime lord known as El Chapo?
4 articles are selected, the similarity scores for the selected articles: [0.1522076501081257, 0.14365234439805508, 0.12289166744219979, 0.10621850056306605]
Answer for Question: 5 : joaqu = n [UNK] loera
Score: 16.4665470123291

 User Question 6 :
What happened to the crime lord El Chapo?
 Similar Question by User: What happened to the crime lord El Chapo?
4 articles are selected, the similarity scores for the selected articles: [0.1516370248398911, 0.14358653026055412, 0.12025709789760453, 0.10205118931967593]
Answer for Question: 6 : pleaded not guilty to charges that he had overseen a drug empire
Score: 10.646171569824219

 User Question 7 :
Who filed the memorandum against El Chapo?
 Similar Question by User: Who filed the memorandum against El Chapo?
4 articles are selected, the similarity scores for the selected articles: [0.14469955247154997, 0.12063260130445386, 0.09649751111491475, 0.0814207309396542]
Answer for Question: 7 : robert l . capers
Score: 14.542051315307617

 User Question 8 :
How did Donald Glover puzzled Hollywood?
 Similar Question by User: How did Donald Glover puzzled Hollywood?
5 articles are selected, the similarity scores for the selected articles: [0.07614146619356679, 0.058684320844558734, 0.04353702300865754, 0.03453506051494297, 0.028869489073323942]
Answer for Question: 8 : by thanking migos , the trendsetting atlanta rap trio , during his golden globes acceptance speech this month
Score: 9.625123977661133
```

Figure 7: Test Case 3: Mix of Related and Unrelated Questions - 1

```
 User Question 9 :
Performance by rappers Quavo, Offset and Takeoff.
 Similar Question by User: Performance by rappers Quavo, Offset and Takeoff.
1 articles are selected, the similarity scores for the selected articles: [0.2553983353046534]
Answer for Question: 9 : refusing to leave the studio until all three had finished their verses
Score: -2.023538827896118

 User Question 10 :
Who survived the Iraq war, fleed to Jordan and searched for a permanent home?
 Similar Question by User: Who survived the Iraq war, fleed to Jordan and searched for a permanent home?
5 articles are selected, the similarity scores for the selected articles: [0.205452867027918, 0.16881980715601033, 0.11643732105940456, 0.10150845457238432, 0.09967141865374561]
Answer for Question: 10 : alwia abdullah
Score: 12.685829162597656

 User Question 11 :
How former President Barack Obama is adjusting to life?
 Similar Question by User: How former President Barack Obama is adjusting to life?
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 11 : No suitable answer found
Score: nan

 User Question 12 :
Who is wife of Mr. Obama
 Similar Question by User: Who is wife of Mr. Obama
5 articles are selected, the similarity scores for the selected articles: [0.24780399907931475, 0.17298789221573158, 0.15579209831070648, 0.14983922243330117, 0.13052137223628713]
Answer for Question: 12 : mr . kushner
Score: 9.986327171325684

 User Question 13 :
Who will have an office on the campus of University of Pennsylvania?
 Similar Question by User: Who will have an office on the campus of University of Pennsylvania?
0 articles are selected, the similarity scores for the selected articles: []
Answer for Question: 13 : No suitable answer found
Score: nan

 User Question 14 :
quit
Exiting...
```

Figure 8: Test Case 3: Mix of Related and Unrelated Questions -2

Case	Question	Model Output	Actual Answer	Score
Case 1	Who is the former President of Iran and a founder of Islamic Republic?	rafsanjani	Ayatollah Ali Akbar Hashemi Rafsanjani	15.66
	rafsanjani died at what age?	82	82	14.9
	How was rafsanjani's career?	No suitable answer found	seesawed through periods of ' 'revolutionary zeal and confrontation with powerful conservative rivals	nan
Case 2	Who are the Frightful Five, biggest players in tech?	amazon , apple , facebook , microsoft and alphabet , google ? s parent company	Amazon, Apple, Facebook, ' 'Microsoft and Alphabet, Google?s parent company	12.38
	What happened to Violeta Lagunes of Mexico on May 18?	her email login represented a point of vulnerability	her email login represented a point of vulnerability	9.74
	What happened in Rome between Pope Francis and the vatican traditionalists?	a proxy war	a proxy war	11.7
	Who is the prime minister of Japan?	shinzo abe	Shinzo Abe	16.29
Case 3	What was the research of professor Nicholas Epley of University of Chicago about?	we underestimate other people ? s interest in connecting	they saw again and again that we underestimate other people?s ' 'interest in connecting.	8.58
	What happened to the crime lord El Chapo?	pleaded not guilty to charges that he had overseen a drug empire	pleaded not guilty to charges that he had overseen a drug empire	10.65
	Who filed the memorandum against El Chapo?	robert l . capers	Robert L. Capers	14.54

Figure 9: Evaluation