A Knowledge-Base based approach to Implement a Question-Answering System

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Abstract - This research paper presents a knowledge-base-based approach to implement a question-answering system, using extractive summarization techniques. The objective of this study is to leverage a knowledge base to enhance the accuracy and efficiency of question-answering systems. By integrating extractive summarization, the relevant information is extracted from the knowledge base to generate concise and accurate answers. The approach is evaluated using a dataset, and the results demonstrate the system's effectiveness in providing accurate answers. The findings contribute to the field of question-answering systems, and highlight the significance of incorporating a knowledge base and Extractive text Summarization.

1 Introduction

Question-Answering Systems have emerged as valuable tools in natural language processing, aiming to bridge the gap between human language and computational understanding. These systems allow users to input questions in natural language and receive accurate and meaningful answers. However, developing effective question-answering systems poses challenges in accessing and summarizing huge amounts of information. This research paper proposes a knowledge-base-based approach that leverages a pre-existing knowledge base and utilizes extractive summarization techniques to generate accurate answers.

The primary objective of this study is to enhance the accuracy and efficiency of question-answering systems by integrating a knowledge base. By utilizing a knowledge base, the system gains access to a vast repository of information, enabling it to provide more accurate and comprehensive answers. Extractive summarization techniques are employed to identify and extract key information from the knowledge base that directly addresses the user's query.

2 Literature Review

Question-answering (QA) systems have garnered significant attention in the field of natural language processing (NLP) and information retrieval. Over the past decade, numerous research efforts have been dedicated to advancing QA systems by leveraging techniques such as knowledge bases, extractive summarization, and deep learning approaches. In this section, we provide an overview of relevant literature that explores the use of knowledge bases and extractive summarization in QA systems.

A comprehensive survey conducted by Agichtein and Savenkov [1] summarizes the advancements made in QA systems over the last decade. The authors discuss various approaches, including knowledge-based techniques, for improving QA performance. They highlight the importance of incorporating external knowledge sources into QA systems, which can be achieved through methods like knowledge graph-based reasoning [6] and utilizing pre-trained language models [7].

Bordes et al. [2] propose a knowledge-based approach to QA systems that incorporates external knowledge sources. Their work demonstrates the effectiveness of integrating structured knowledge bases, such as Freebase, to enhance QA performance. Similarly, Min et al. [14] propose an open-domain QA system that combines knowledge bases and text information for improved question answering.

Extractive summarization techniques play a crucial role in distilling relevant information from large text documents. Chen et al. [4] thoroughly examine the CNN/Daily Mail reading comprehension task and discuss the importance of extractive summarization for generating informative answers. They analyze the effectiveness of various extractive summarization methods, including the utilization of global and local contexts [15].

Cao et al. [3] introduce the SWAP-NET framework, which leverages extractive summarization using alternating pointer networks. Their approach demonstrates the effectiveness of extractive summarization in generating concise and accurate summaries. Liu and Lapata [13] propose a text summarization method using pre-trained encoders, which has shown promising results in generating high-quality summaries.

Furthermore, the application of deep learning techniques has significantly contributed to the advancement of QA systems. Chen et al. [5] present a neural network-based approach for open-domain QA, highlighting the importance of attention mechanisms for capturing relevant information. Rocktäschel et al. [21] explore the use of neural attention for reasoning about entailment, which is relevant in QA systems. Seo et al. [22] propose a bidirectional attention flow model for machine comprehension, which has been successful in answering questions based on given contexts.

The adoption of sequence-to-sequence learning with neural networks has also gained prominence in QA systems. Sutskever et al. [23] introduce sequence-to-sequence learning, widely applied in various NLP tasks. Vaswani et al. [24] propose the transformer model, emphasizing the role of attention mechanisms in capturing contextual information. These advancements in sequence-to-sequence learning and attention mechanisms have significantly influenced the development of QA systems.

In the domain of extractive summarization, Wang et al. [25] explore the use of deep learning for table extraction. Their work demonstrates the efficacy of deep learning techniques in extracting information from structured data sources, which can be valuable for QA systems. The integration of external knowledge sources and the use of extractive summarization methods have shown promising results in improving QA performance. Additionally, advancements in deep learning, attention mechanisms, and sequence-to-sequence learning have greatly influenced the development of QA systems, enabling more accurate and comprehensive question-answering. However, the integration of a knowledge base and extractive summarization in question-answering systems has received limited attention in the literature.

3 Methodology

The proposed methodology consists of three major sections including a description of the dataset used, followed by the preprocessing steps and model training. The sections can be divided into finer steps like:

3.1 Dataset Selection:

The dataset widely used as an academic benchmark for extractive question answering is SQuAD (Stanford Question Answering Dataset). For our research, we utilize the SQuAD dataset as it provides a suitable foundation for evaluating our approach. Additionally, SQuAD v2, a harder benchmark that includes questions without answers, can also be utilized. As long as the dataset contains columns for contexts, questions, and answers, the steps described below can be adapted accordingly.

3.2 Preprocessing Steps:

We begin by examining the dataset to ensure the presence of the required columns: contexts, questions, and answers. For the first element in our training set, we print these fields to verify their correctness. The context and question fields are straightforward to use, while the answers field requires additional handling. The answers field consists of a dictionary with two lists. Although this format is expected by the SQuAD metric during evaluation, it can be customized for your own dataset. The "text" field contains the answer text, and the "answer_start" field indicates the starting character index of each answer in the context.

3.3 Model Selection:
For our question-answering system, we choose to fine-tune a BERT model, a popular transformer-based architecture. However, any model with a fast tokenizer implementation can be used. It is important to ensure that the tokenizer used is backed by 🤗 Tokenizers and supports the required model architecture.

3.4 Label Generation:
During training, we generate labels for the model to predict the start and end positions of the answer in the input tokens. The labels are the indices of the tokens indicating the answer's start and end positions. The training objective is to predict one start and end logit per token in the input.

3.5 Handling Long Contexts:
Some examples in the dataset may have very long contexts, exceeding the maximum length set for the model. To address this, we employ a sliding window approach. The long context is divided into multiple training features, with a specified maximum length and stride. This ensures that the model can process the information effectively.

3.6 Preprocessing Validation Data:
Preprocessing the validation data involves storing the offset mappings and associating each created feature with its original example using the provided ID column. It is important to clean up the offset mappings, setting offsets corresponding to the question to None.

3.7 Model Training:
The model training process is similar to previous sections, but special attention is required for computing metrics. As padding is applied to samples during training, the post-processing step involves interpreting the model predictions into spans of the original context. The computed metric from the 🤗 Datasets library helps evaluate the model's performance.

3.8 Post-processing Predictions:
The model outputs logits for the start and end positions of the answer in the input IDs. Post-processing involves masking the logits corresponding to tokens outside the context, converting them into probabilities, and determining the best answer span based on the highest logits. This process is adapted slightly to skip the softmax step and consider only the highest logits.

3.9 Metric Evaluation:
The metric used to evaluate the predicted answers is the same as mentioned above. The predicted answers are expected in a specific format, a list of dictionaries with keys for the example ID and predicted text. The theoretical answers are also provided in a list of dictionaries with keys for the example ID and possible answers.

By following these steps, we can effectively implement our knowledge-base-based question-answering system using extractive summarization. The subsequent sections will present the results and analysis of our approach.

4 Results and Discussion

The SQuAD (Stanford Question Answering Dataset) comprising various user queries and corresponding correct answers is used to evaluate the proposed approach's effectiveness. Evaluation metrics, including exact match, and F1 score, are employed to assess the system's performance. The experiments demonstrate the system's ability to retrieve relevant information from the knowledge base and generate accurate and concise answers.

The experimental results show promising performance of the knowledge-base-based question-answering system using extractive summarization. The exact match, and F1 score indicate the system's ability to retrieve relevant information and generate accurate answers. However, limitations such as dependency on the quality and completeness of the knowledge base, as well as the reliance on extractive summarization, are present.

Model	*F1 score*	*Exact Match score*
Our model in	*88.2500000000*	*83.0*

Training	*0004*	
Our model during Evaluation	*85.9722710003 5236*	*77.549668874 17218*
Bert-finetuned-squad	*88.5*	*80.8*
DistilBERT fine-tuned on SQuAD	*86.9*	*79.1*

Table 4.1: Metrics comparison of various models

5 Conclusion

This research paper proposed a knowledge-base-based approach to implement a question-answering system using extractive summarization techniques. The integration of a knowledge base enhances the system's accuracy and efficiency by providing access to a vast repository of information. Extractive summarization enables the system to generate concise and accurate answers. The experimental evaluation demonstrates the effectiveness of the proposed approach. Future research could focus on addressing limitations and exploring the integration of other techniques such as abstractive summarization and deep learning models.

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