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Question Answering in the Context of Artificial Intelligence

Abstract

The present research project examines approaches to improving question-answering systems (QA) based on artificial intelligence (AI). With AI Improvements QA systems will be important in enhancing knowledge retrieval and human-computer interactions. This project investigates current approaches for solving context challenges, focusing on the combined use of deep learning, machine learning, and natural language processing. Examining related work sheds light on alternative approaches, such as Arabic question-answering approaches and template-based convolutional recurrent neural networks for complex question answering. In the proposed research, the effectiveness of these strategies was evaluated with a focus on their effects on accuracy and relevance.

1 .Introduction

This research project investigates Question Answering (QA), a rapidly developing area of artificial intelligence that is important for current information retrieval and human-computer interaction. With a focus on combining deep learning, machine learning, and natural language processing, the research explores current approaches to improve the accuracy and efficiency of question Answering models. Using Arabic QA systems and a Template-based Convolutional Recurrent Neural Network for complex question answering as examples of related works, the project aims to investigate and compare various approaches for satisfying the evolving needs of accurate and context-aware QA.

2 .Related work

A method for enhancing question answering systems through two primary stages—passage retrieval and passage re-ranking—is presented in the paper "**Question Answering Passage Retrieval and Re-ranking Using N-grams and SVM**" by Nouha Othman and Rim Faiz.The system uses the dependence degree of the n-gram terms in the query to determine which passages to recover correctly during the passage retrieval phase. An SVM-based model including lexical, syntactic, and semantic similarity metrics is used in the passage re-ranking stage.The efficacy of the technique is demonstrated through experimental assessment with the CLEF dataset, outperforming the performance of previously presented systems, such as context classification models [1].

With its consideration of aspects such as space editing, named entity nesting, syntactic dependencies, and WordNet-based conceptual similarity, the suggested solution improves system performance (accuracy of 0.76 and c1 score of 0.85). The goal of this study is to simplify the system while maintaining accurate and relevant segment retrieval, highlighting the importance of question responses in information retrieval, natural language processing, and online searching. Superior performance was revealed through comparisons with similar systems, highlighting the effectiveness of the SVM and n-gram models in tasks such as semantic text similarity. This methodology enhances the accuracy of responses by integrating many selection criteria and establishing a threshold value for the ultimate score [1].

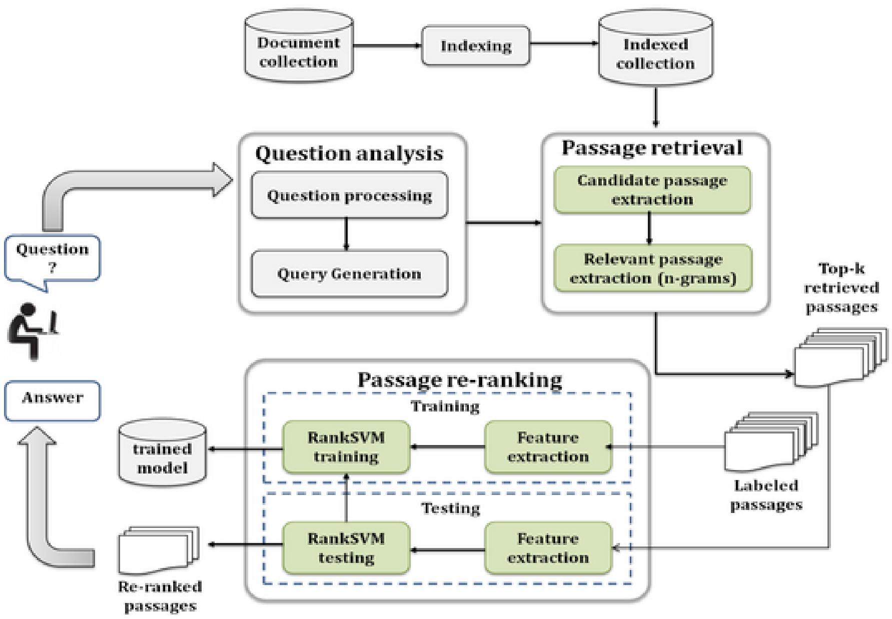

Fig.1 Architecture of the PreRankQA approach[1].

A approach for Arabic question answering (QA) systems is described in the paper "**Question Analysis for Arabic Question Answering Systems**" (by Waheeb Ahmed1 , Dr. Babu Anto P2). Several approaches have been used to improve response extraction and information retrieval accuracy, including named entity recognition, tokenization, stop-word removal, question expansion, categorization, and focus extraction. The questions were analyzed using the Mean Reciprocal Rank (MRR) to determine their usefulness [2].

A thorough Question Analysis Module is part of the technique for natural language questions, with an emphasis on extracting important components such as focus, question extension, question classification, and Q terms extraction. Examining the system's performance in attention detection and Question Classification tasks, the dataset of 250 questions showed an average accuracy of 65% across the five question categories. The system does a great job responding to "HUMAN" questions, but it has trouble handling more difficult "DESCRIPTION" questions. All things considered, this method works well for answering open-domain questions and produces excellent results [2].

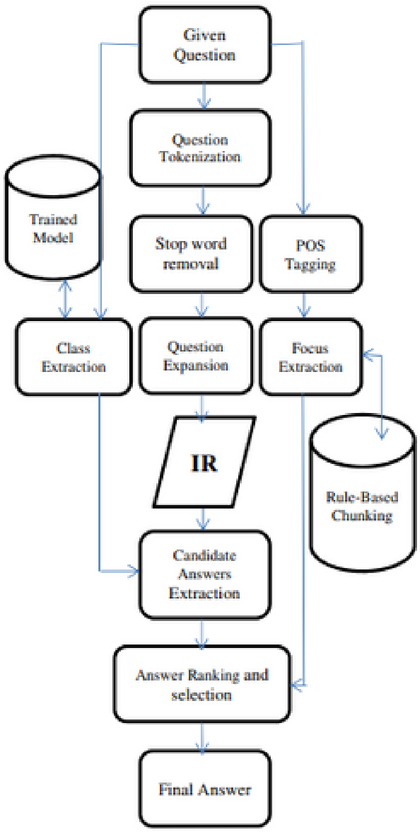

Fig.2 Question Analysis Module [2].

The study titled "**Convolutional recurrent neural network with template based representation for complex question answering**" and the authors are A. Chandra Obula Reddy and K. Madhavi proposes a Template representation based Convolutional Recurrent Neural Network (T-CRNN) for complex question answering (CQA) systems. The proposed approach involves transforming language questions into an internal representation using templates and mapping them to relevant queries against a knowledge base [3].

The methodology of this research involves a Question Representation. Using templates, inquiries in plain language are converted into internal representations. Through this method, the questions' structure and semantics are captured, making it possible to match them with queries in a knowledge base efficiently.Decomposition of Complex Question: The input question is divided using a "divide and conquer" strategy into Binary Factoid Questions (BFQs). Each BFQ is then addressed independently, and the replies are combined to provide the original question's solution. Application of Recurrent and Convolutional Neural Networks: To learn the semantic connection patterns between question and answer pairs, the proposed method uses two Convolutional Neural Networks (CNNs) operating in parallel. Recurrent Neural Networks (RNNs) have also been utilized to extract important contexts from response sequences. Rating and Choice of Response: The replies are scored, and the best answer to the question is chosen using a softmax classifier and multi-layer perceptron. Evaluation: Using metrics such as accuracy, f-measure, precision, and recall, the performance of the suggested T-CRNN technique was assessed. This assessment evaluates how well the method provides precise answers to challenging issues [3].

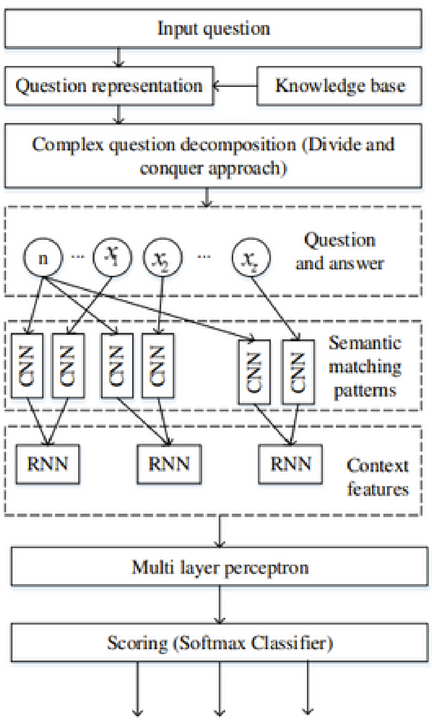

fig.3 Proposed approach of complex question answering [3].

The task of developing difficult distractions for multiple-choice visual question answering (VQA) is presented in this research titled “**Good, Better, Best: Textual Distractors Generation for Multiple-Choice Visual Question Answering via Reinforcement Learning**” (by Jiaying Lu, Xin Ye , Yi Ren , Yezhou Yang) as DG-VQA. The G OBBET model uses pre-trained VQA models as a knowledge source and policy gradient-based methodology. The model was created specifically for the DG-VQA task [4].

An analysis of the effect of data augmentation on the model performance is part of the training process. Tests investigated whether VQA models can be trained with simply generated distractors or with a mix of produced and original distractors. The enhanced durability of the VQA models was achieved by the improved G-OBBET model, which effectively generated a superior DG-VQA model [4].

The results show that DG-VQA helps train better-performing VQA models, outperforming baselines in terms of accuracy, and reducing the performance of previously trained VQA models. OBBET serves as an example of how AI approaches can be used to improve VQA model resilience by generating distractors[4].

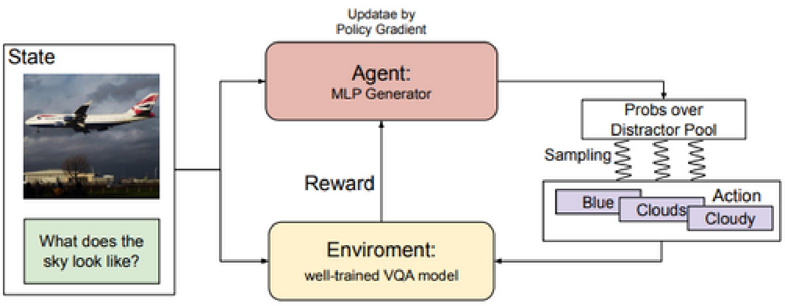

fig.4 The proposed GOBBET Framework [4].

The research conducted by Shervin Minaee and Zhu Liu is titled "**Automatic Question-Answering Using A Deep Similarity Neural Network.**"This study suggests a strong deep learning model for autonomous question answering in NLP. Questions and answers were included in the model using neural probabilistic modeling, and the similarity score between the answer-question pairings was calculated by training a deep similarity neural network [5].

The model performed well and achieved an amazing accuracy rate of 83.4% on the test set by utilizing a large-scale public question-answering database. This research highlights the role of word and document embedding approaches and shows that when training samples are increased, doc2vec outperforms bag-of-words in question classification. Furthermore, by contrasting deep learning models with the conventional multistage approach, this study highlights the use of deep learning models in question-answering systems [5].

Furthermore, the study highlights the transition to deep learning models in Q&A systems, in contrast to conventional multi-stage classic methods. Related works that have been mentioned include long short-term memory models (LSTM), convolutional neural networks (CNN), memory network models, and recursive neural network design. This study advances question-answering systems by using deep learning techniques and thoroughly investigating a variety of methods in the area [5].

3 .Conclusion

In conclusion, this research project explored the rapidly changing field of question answering with artificial intelligence (QA) and considered innovative ways to deal with contextual difficulties. Related works highlight the importance of combining machine learning, deep learning, and natural language processing to improve question-answering systems. Effective strategies are better understood due to the diversity of approaches, some of which are specifically designed to ensure quality in Arabic and answer complex questions.

This research project explains the changing requirements for accuracy and context awareness in quality assurance as the discipline evolves. By expanding on these findings, the proposed research project hopes to improve quality assurance systems and shed light on their critical functions in information retrieval and human-computer interactions.

4 .References

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