Research on Automatic Question Answering Systems Based on Medical Knowledge Graphs

Junzhe Deng*
School of International Education, Guangdong University of Technology, Guangzhou, China
**Corresponding author*

Abstract: In recent years, intelligent question answering systems have played an increasingly significant role in the healthcare domain. However, traditional retrieval-based and rule-based methods struggle to cope with the complexity and diversity of medical knowledge, resulting in significant shortcomings in the accuracy and reasoning capabilities of question answering systems. To address this issue, this paper proposes an automatic question answering system based on a medical knowledge graph. Firstly, a large-scale medical knowledge graph is constructed to represent medical entities (such as diseases, drugs, and symptoms) and their relationships. Secondly, a question answering model combining graph reasoning and natural language processing (NLP) is designed. Through modules such as entity recognition, relation extraction, and graph reasoning, semantic understanding and reasoning of complex medical questions are realized. Experimental results demonstrate that the proposed system achieves significant improvements in question answering accuracy and semantic reasoning ability compared to traditional methods, and can effectively answer diverse questions in the medical domain. This research provides a new perspective for the design and implementation of medical question answering systems and has high practical value.

Keywords: Medical Knowledge Graph; Intelligent Question Answering System; Natural Language Processing; Graph Reasoning

1. Introduction

With the advancement of internet technology and artificial intelligence, intelligent question answering systems have found widespread applications in various domains. Among them, medical question answering systems have gained increasing attention due to their potential to provide valuable assistance to patients and doctors in medical consultation, health management, and medical knowledge dissemination. However, traditional medical question answering systems primarily rely on rule-based or retrieval-based methods, which often struggle to handle complex medical semantics and fail to meet users' demands for accuracy and professionalism.

The medical domain is characterized by its complex and vast knowledge base, and medical terminology is highly specialized and ambiguous. Effectively understanding and processing this information within a question answering system presents a significant challenge. In recent years, knowledge graphs (KGs) have been widely adopted in various question answering systems. By representing entities and relationships in a graph structure, KGs offer a more intuitive way of expressing semantics. Graph-based question answering systems can model and reason about semantic relationships between medical entities through the complex connections of graph nodes and edges, thereby effectively addressing the information silos and semantic ambiguities inherent in traditional question answering systems[1].

This research aims to construct an automatic question answering system based on a medical knowledge graph to address the limitations of rule-based or retrieval-based methods in answering complex questions in the medical domain. Unlike traditional methods, our system combines deep learning techniques with knowledge graphs and introduces a multi-level entity relationship model to enhance the semantic understanding capabilities of the question answering system. The main contributions of this paper are as follows: First, we propose a graph-based framework for medical semantic understanding. Second, we design a question answering mechanism that

combines natural language processing (NLP) and graph reasoning. Finally, we experimentally validate the effectiveness of our system in the medical question answering domain and explore potential directions for future improvements[2].

This research not only enriches the theoretical and applied research of intelligent question answering systems but also provides new insights into the development of graph-based automated question answering systems in the healthcare domain. The results demonstrate that the medical question answering system based on knowledge graphs exhibits excellent performance in terms of answer accuracy, reasoning ability, and contextual understanding, making it applicable to scenarios such as medical diagnosis assistance, drug recommendation, and patient education.

2. Related Work

Question Answering (QA) systems are a significant research area within the fields of Natural Language Processing (NLP) and Information Retrieval (IR)[3]. Traditional QA systems can be categorized into rule-based, retrieval-based, and generative methods. However, when dealing with complex medical semantics, these traditional approaches often fall short. Therefore, knowledge graph-based QA systems have gained significant attention in recent years, particularly in the medical domain. Knowledge graphs can effectively integrate and manage complex medical knowledge, providing richer semantic information support for QA systems.

2.1 Current State of Traditional Question Answering Systems

Traditional question answering (QA) systems primarily rely on two main approaches: rule-based and retrieval-based methods[4]. Rule-based methods parse questions using predefined grammar rules and pattern matching, then return answers based on defined conditions. While these methods can provide accurate answers in specific scenarios, they often struggle with the vast and diverse knowledge in the medical domain due to the complexity and scalability of rule creation.

Retrieval-based methods, on the other hand, rely on text matching algorithms such as TF-IDF and BM25 to retrieve relevant text passages from large document collections and extract answers from them. These methods perform well for simpler factual questions but fall short when dealing with complex medical semantic relationships, such as drug-disease interactions.

In recent years, with the rapid development of deep learning, generative models based on deep neural networks, such as BERT and GPT, have been gradually introduced into QA systems. These models, with their ability to deeply capture contextual information, significantly improve the fluency and accuracy of question answering. However, the medical domain is highly specialized, and traditional generative models often lack domain-specific knowledge and reasoning capabilities, making it difficult to handle complex medical questions.

2.2 Application of Deep Learning Models in Question Answering Systems

The widespread adoption of deep learning models in question answering systems is primarily due to their exceptional ability to capture context and complex language structures. When dealing with natural language, traditional rule-based or retrieval methods often struggle with semantic ambiguities and long-distance dependencies. In contrast, deep learning models, especially pre-trained models like BERT and GPT, can learn rich language patterns and implicit knowledge through pre-training on large-scale corpora.

Key reasons for choosing deep learning models in question answering systems include:

- **Strong Contextual Understanding:** Deep learning models effectively capture long-distance contextual dependencies using attention mechanisms, enabling them to excel in processing complex sentences. For instance, in a sentence involving multiple diseases, drugs, and symptoms, deep learning models can understand the relationships between each entity, ensuring accurate answers.
- **Ability to Handle Unstructured Data:** Many question answering systems deal with unstructured text data, particularly in the medical domain, where medical literature and clinical reports often lack a fixed format. Deep learning models can automatically learn language patterns and knowledge from unstructured text without requiring extensive manual rule annotation.
- **Understanding of Complex Semantic Relationships:** Compared to traditional retrieval methods, deep learning models can better understand complex semantic relationships.

Pre-trained models like BERT, having learned contextual information from vast amounts of data, can handle complex semantic reasoning tasks such as "drug side effects" or "disease comorbidities."

- **Scalability and Adaptability:** Deep learning models can be fine-tuned to adapt to different task scenarios. In particular, in the medical domain, fine-tuning pre-trained models with specialized medical corpora can further enhance their understanding and reasoning abilities for medical questions. Variants like ClinicalBERT are specifically optimized for the medical domain and have shown excellent performance in medical question answering systems.

Although deep learning models have significant advantages in semantic understanding, their application in the medical domain still faces challenges, particularly in knowledge reasoning and inference, which require support from more domain-specific knowledge.

2.3 Progress in Medical Knowledge Graphs

A knowledge graph is a semantic network that represents entities (such as diseases, drugs, symptoms) and their relationships through a graph structure. Knowledge graphs offer significant advantages in complex semantic modeling and reasoning. Typical medical knowledge graphs include UMLS (Unified Medical Language System), DrugBank, and OMIM (Online Mendelian Inheritance in Man). These graphs integrate rich clinical terminology, drug information, and genetic data, providing abundant semantic information for medical question answering systems.

The construction of medical knowledge graphs typically involves data preprocessing, entity recognition, relation extraction, and graph fusion. Entity recognition identifies medical terms using Named Entity Recognition (NER) techniques, while relation extraction extracts semantic relationships between entities using supervised learning or deep learning models (such as BERT+CRF). This provides a foundation for knowledge-graph-based question answering systems to support complex reasoning[5].

2.4 Knowledge Graph-Based Question Answering Systems

Knowledge graph-based question answering systems combine the reasoning capabilities of knowledge graphs with the semantic understanding abilities of deep learning models to handle complex questions. By reasoning over entities and relationships in the graph, the system can answer questions involving complex semantics and context. Graph path searching, semantic matching, and Graph Neural Networks (GNNs) are common implementation techniques.

For example, models like KG-BERT and GNNs can combine knowledge graph structure with textual information to achieve semantic understanding and relationship reasoning in question answering systems. For the question "What are the drugs for treating hypertension?", the system can find relevant drugs through the relationship between "hypertension" and "drug" in the graph, thus generating an accurate answer. Compared to traditional retrieval-based or generative models, knowledge graph-based question answering systems demonstrate unique advantages in medical reasoning, semantic disambiguation, and relation parsing.

3. Construction of Medical Knowledge Graph

Medical knowledge graphs, as structured representations of various entities and their relationships within the medical domain, have found widespread applications in medical knowledge management and information retrieval. Their construction typically involves multiple stages, including data source selection, entity recognition, relation extraction, graph fusion, data storage, and quality evaluation. This paper will delve into the construction methods of medical knowledge graphs, providing in-depth analyses of each step.

3.1 Data Sources and Preprocessing

The foundational step in constructing a medical knowledge graph involves identifying suitable data sources and subjecting the data to rigorous preprocessing. In the medical domain, data sources exhibit considerable diversity, encompassing medical literature, clinical data, drug databases, disease databases, and electronic health records (EHRs). Common medical data sources include:

- **Medical Literature Databases:** Such as PubMed and Medline, these repositories house an extensive collection of medical research articles, clinical trials, and case reports, serving as invaluable resources for identifying diseases, drugs, and treatment modalities.

- **Drug Databases:** Databases like DrugBank, PharmGKB, and KEGG (Kyoto Encyclopedia of Genes and Genomes) provide comprehensive information on drugs, including their targets, chemical structures, and associations with diseases.
- **Disease Databases:** Databases such as OMIM (Online Mendelian Inheritance in Man), Disease Ontology (DO), and UMLS (Unified Medical Language System) offer detailed descriptions of diseases, encompassing etiology, symptoms, and associated genes.

Post data collection, preprocessing emerges as a pivotal stage in the construction of a high-quality knowledge graph. Data preprocessing primarily entails data cleaning, format conversion, deduplication, and standardization. Specifically, for unstructured textual data (e.g., medical literature), tasks such as sentence segmentation, tokenization, and the removal of extraneous characters (e.g., punctuation marks, HTML tags) are necessary. Structured data (e.g., drug information in DrugBank) necessitates field alignment, deduplication, and standardization.

Moreover, given the heterogeneity of data standards across various data sources (e.g., a single drug or disease may have multiple synonyms or spelling variants), the harmonization of naming conventions is imperative. Standard medical ontologies like UMLS or SNOMED CT (Systematized Nomenclature of Medicine—Clinical Terms) are commonly employed for entity standardization, thereby ensuring consistency and interoperability of medical terminology within the knowledge graph.

3.2 Entity Recognition

3.2.1 Entity Category Definition

When constructing a medical knowledge graph, it is imperative to define specific entity categories, as these categories directly influence the representational capacity of the graph. Common medical entity categories include:

- **Diseases:** Encompassing disease names, etiologies, symptoms, and associations with other diseases.
- **Drugs:** Including drug names, compositions, mechanisms of action, and therapeutic effects.
- **Symptoms:** Describing clinical manifestations associated with diseases, such as fever and headache.
- **Genes:** Representing genetic information related to diseases and drug targets.
- **Treatment Methods:** Such as surgery, drug therapy, and radiation therapy.

3.2.2 Entity Recognition Methods

Entity recognition methods can be broadly categorized into three types: rule-based methods, statistical methods, and deep learning-based methods.

- **Rule-Based Methods:** These methods rely on predefined medical term dictionaries, contextual rules, and regular expressions for matching. While effective for handling relatively fixed terms (e.g., drug names), they often fall short when dealing with novel terms and contextually flexible sentences.
- **Statistical Methods:** Traditional machine learning models like Hidden Markov Models (HMMs) and Conditional Random Fields (CRFs) are employed, trained on manually annotated corpora. These models require substantial amounts of annotated data and may exhibit lower accuracy in complex sentence structures.
- **Deep Learning-Based Methods:** In recent years, deep learning models such as BERT, BioBERT, and their variants have been extensively applied to medical entity recognition. These models can capture semantic information within the context, significantly enhancing recognition accuracy.

3.3 Relation Extraction

3.3.1 Rule-Based Relation Extraction

Rule-based methods typically employ manually crafted pattern matching rules to identify specific relational patterns within text (e.g., using dependency parsing to analyze subject-verb-object structures). While effective for handling simpler sentence structures, these methods exhibit limited scalability and struggle with diverse textual expressions.

3.3.2 Machine Learning-Based Relation Extraction

Machine learning-based methods treat relation extraction as a classification problem, learning relational patterns between entities through training on annotated datasets. Common models include Support Vector Machines (SVMs) and Maximum Entropy models. The advantage of these methods lies in their ability to leverage feature engineering to enhance model generalization, but they often rely on a large amount of annotated data.

3.3.3 Deep Learning-Based Relation Extraction

Deep learning models (e.g., CNNs, RNNs,

BERT) extract relations by learning features autonomously, without relying on manually designed features or rules. The introduction of pre-trained language models like BERT enables relation extraction to capture long-distance dependencies and complex contextual semantics, significantly improving extraction performance. In the medical domain, models specifically optimized for biomedical text, such as BioBERT and SciBERT, can be employed to further enhance relation extraction accuracy[6].

3.4 Graph Integration and Construction

3.4.1 Entity Alignment and Disambiguation

Entity Alignment refers to the process of merging identical entities from disparate data sources. For instance, "Aspirin" in UMLS and "Acetylsalicylic Acid" in DrugBank should be mapped to the same entity. **Entity Disambiguation** is employed to differentiate between homonyms (e.g., "flu" can refer to a disease or a virus).

Common alignment methods include string-based matching, context-based similarity, and embedding-based methods. **Embedding-based methods** represent entities as low-dimensional vectors and calculate vector similarity to effectively address synonymy and polysemy.

3.4.2 Graph Construction and Storage

Medical knowledge graphs are typically stored and managed using graph databases such as Neo4j and JanusGraph. Graph databases offer a visual representation of entities and their relationships, and provide efficient graph query capabilities (e.g., using Cypher or SPARQL query languages). During graph construction, a graph schema must be defined, specifying entity types, relationship types, and their attributes to ensure the graph's structure and standardization.

3.5 Quality Evaluation and Optimization

To ensure the utility and accuracy of a knowledge graph, systematic quality evaluation and optimization are essential. Common evaluation metrics for knowledge graphs include entity coverage, relationship accuracy, semantic consistency, and knowledge completeness. The following strategies can be employed to enhance graph quality:

- **Expert-Annotated Validation:** Inviting medical domain experts to evaluate the entities and relationships within the graph ensures data accuracy.
- **Rule-Based Automated Checks:** By defining rules (such as entity relationship constraints and logical consistency checks), errors and anomalies within the graph can be automatically detected.
- **Comparison with External Data Sources:** Cross-validation with other authoritative data sources (e.g., medical literature databases) can identify redundant or missing knowledge within the graph.

4. QA System Design Based on Knowledge Graph

4.1 System Architecture Design

A knowledge graph-based question answering system typically consists of several core modules: user input module, natural language processing module, knowledge graph query module, answer generation module, and result evaluation module.

4.1.1 User Input Module

Users input their questions through text boxes or voice input. This module is responsible for standardizing user queries and performing basic preprocessing (e.g., tokenization, stop word removal).

4.1.2 Natural Language Processing Module

This module analyzes natural language questions from users, including entity recognition, intent classification, and relation extraction to identify core entities and relationship types within the query.

4.1.3 Knowledge Graph Query Module

This module conducts graph queries using entities and relationships within the knowledge graph to obtain potential answer sets. Query methods include graph traversal, path search, and semantic reasoning.

4.1.4 Answer Generation Module

Based on the query results, this module generates natural language answers that are understandable to users and optimizes the fluency and semantic coherence using language models.

4.1.5 Result Evaluation Module

This module evaluates and optimizes the system's output. Evaluation metrics such as accuracy, recall, and F1-score are used to measure the performance of the question answering system.

4.2 Design of Natural Language Processing Module

The natural language processing module is the first processing stage in a knowledge graph-based question answering system. It comprehends and transforms user-provided natural language inputs into structured queries that can be executed on the knowledge graph. This module primarily consists of three submodules: question parsing, entity recognition and linking, and question type identification.

4.2.1 Question Parsing

The primary objective of question parsing is to analyze the semantic structure of a user's natural language query and determine its question type (e.g., lookup, inference, comparison). Typical question types include:

- **Lookup Questions:** For instance, "What are the common causes of headaches?" The system should retrieve diseases or symptoms related to "headache" from the graph.
- **Inference Questions:** For example, "Which drugs can alleviate headaches caused by hypertension?" The system needs to infer the relationship between "hypertension" and "headache" and find treatment options.
- **Comparison Questions:** For example, "What are the differences between ibuprofen and aspirin?" The system needs to find the attributes and mechanisms of action of both drugs in the graph and conduct a comparative analysis. Using pre-trained language models (such as BERT, BioBERT) for question parsing can better capture contextual information and deep semantic relationships within the query, thereby improving parsing accuracy.

4.2.2 Entity Recognition and Linking

Entity recognition and linking is one of the most critical steps in knowledge graph-based question answering systems. It aims to identify core medical entities (such as diseases, symptoms, drugs) from user-provided questions and map them to specific nodes in the knowledge graph.

- **Entity Recognition:** Named Entity Recognition (NER) models such as BERT+CRF are used to label medical terms within the query with specific categories (e.g., disease, drug, symptom). BERT's bidirectional encoding mechanism enables it to better capture contextual semantic information, making it particularly suitable for handling complex medical texts. By precisely identifying and labeling medical terms (e.g., diseases, drugs, symptoms) within queries as specific categories, our approach can effectively distinguish and annotate entities, even in the presence of long-distance dependencies and fuzzy boundaries. This method demonstrates exceptional performance when dealing with large amounts of heterogeneous data and polysemous words frequently encountered in medical texts.
- **Entity Linking:** Entity linking maps the recognized medical entities to standard entity nodes in the knowledge graph. Semantic similarity calculations (e.g., embedding-based similarity) are used to resolve synonymy and polysemy issues. For example, "headache" could refer to the symptom "Headache" or the disease "Chronic Headache"; therefore, context-based reasoning is required for accurate linking.

4.2.3 Question Type Identification

Question type identification involves analyzing the semantic structure of a query to determine its intent and answer type (e.g., whether inference is required, or if a comparison between multiple entities is needed). Common methods include:

- **Rule-based Method:** Manually crafted rules are used to classify questions based on specific keywords (e.g., "what are," "related to").
- **Deep Learning-based Method:** Models such as BERT and BiLSTM are used to perform deep semantic analysis of the query context to determine the question type.

By accurately identifying the question type, the query can be transformed into a specific graph query task, and subsequent query strategies can be determined.

4.3 Graph Query and Reasoning Mechanism

The graph query and reasoning mechanism is the most crucial component of a knowledge graph-based question answering system. It determines the system's ability to reason and its efficiency in handling complex medical questions. This module primarily involves three types of query and reasoning methods: semantic query based on graph structure, path-based reasoning, and rule-based reasoning.

4.3.1 Semantic Query Based on Graph Structure

The goal of semantic query is to find answers that meet specific conditions by traversing the nodes and edges in the graph structure. Common query methods include:

- **SPARQL Queries:** SPARQL (SPARQL Protocol and RDF Query Language) is a widely used query language for RDF (Resource Description Framework) graphs, capable of performing complex graph query operations. SPARQL statements can be used to find entities

and their relationships that meet specific criteria.

- **Cypher Queries:** Cypher is a query language specifically designed for the Neo4j graph database. It supports pattern matching of nodes and edges in graph structures and can perform complex path searches and pattern reasoning.

4.3.2 Path-based Reasoning

Path-based reasoning involves finding the shortest path or specific path patterns between two entity nodes in the graph to answer complex questions. For example, for the question "Is aspirin effective in relieving migraines?", the system needs to find the path between "aspirin" and "migraine" in the graph and determine if there is a "treats" or "alleviates" relationship within the path. Common methods include:

- **Graph Traversal Algorithms:** Algorithms such as depth-first search (DFS) and breadth-first search (BFS) can be used to find all possible paths between entities.
- **Probabilistic Graphical Models:** By introducing probabilistic graphical models (e.g., Bayesian networks, Markov logic networks), probabilities can be assigned to nodes and edges in the graph, allowing for the calculation of path probabilities.

4.3.3 Rule-based Reasoning

Rule-based reasoning involves performing complex reasoning within the graph using predefined logical rules (e.g., if-then rules). For example, for the question "Which drugs can be used to treat coughs caused by childhood colds?", the system can reason using the following rule:

IF | disease A | can cause | symptom B | AND | drug C | can treat | symptom B
THEN | drug C | can be used to treat | symptom B | caused by | disease A

Such rules are typically used with ontology reasoning engines (e.g., OWL2) to perform semantic reasoning and complex reasoning based on relationships within the knowledge graph.

4.4 Answer Generation and Optimization

After graph query and reasoning, the system needs to convert the results into natural language answers for user comprehension. Answer generation primarily involves two steps: answer extraction and natural language generation.

4.4.1 Answer Extraction

Answer extraction involves selecting the optimal answer set from all possible query results through filtering and ranking. Common strategies include:

- **Confidence-based Answer Ranking:** By calculating the confidence of each answer based on features such as occurrence frequency, node weight, and path length, answers can be ranked.
- **Context-based Answer Selection:** By considering the semantic match between the context and the answer, as well as the similarity between the answer and the question, the most semantically suitable answer can be selected using semantic matching models (such as BERT).

4.4.2 Natural Language Generation (NLG)

When converting answers into natural language expressions, template matching or generation model-based methods are commonly used:

- **Template Matching:** Predefined answer templates (e.g., "X can be used to treat Y") are used to generate concise answer expressions.
- **Generation-based Method:** Generative models such as GPT are used to generate complete answer sentences that adhere to grammatical rules based on the question context.

By combining contextual information and language models, more fluent and understandable answers can be generated, enhancing the user experience.

4.5 Performance Optimization and Evaluation

To improve the efficiency and accuracy of the question answering system, performance optimization and system evaluation are necessary. The following strategies can be adopted:

- **Index Optimization:** Creating index structures for frequently used entities and relationships in the knowledge graph can significantly enhance query efficiency.
- **Distributed Storage and Querying:** Utilizing distributed graph databases (such as JanusGraph) to store large-scale graph data can improve the system's parallel query capabilities.
- **Multi-turn Interaction and Contextual Understanding:** Introducing a multi-turn dialogue mechanism supports deep reasoning and complex problem discussions in multi-turn interactions.

System evaluation employs metrics such as accuracy, recall, F1-score, and response time to measure the system's performance on different types of questions. By continuously optimizing and debugging, the practicality and user experience of the question answering system can

be improved.

4.6 Multi-turn Interaction and Contextual Understanding

In knowledge graph-based question answering systems, multi-turn interaction is a crucial feature to enhance user experience and improve answer accuracy. Through multi-turn interactions, the system can maintain consistency across consecutive questions and contexts, and gradually deepen its understanding of the query. Particularly in complex medical queries, users often require multiple sequential questions to obtain more detailed answers or information.

4.6.1 Context Tracking and State Maintenance

In multi-turn dialogues, systems require the ability to track context, which involves remembering previously asked questions and their corresponding answers. This capability is crucial for maintaining conversational coherence, especially in multi-hop reasoning tasks. For instance, a user might initially ask, "What are the common causes of headaches?" and then follow up with, "So, which medications can treat migraines among them?" The system needs to understand the context of the second question and recognize that "migraines" refers to one of the "common causes of headaches" mentioned in the previous question.

To achieve this, systems typically maintain a dialogue state tracking (DST) module. This module can:

- Record key information such as entities, relations, and intents in each turn of the dialogue.
- Perform contextual reasoning and information augmentation to enable subsequent questions to be reasoned based on the answers to previous questions.
- Manage ambiguities and uncertainties in multi-turn dialogues, and clarify user needs through multiple rounds of clarification.

4.6.2 Question Decomposition and Elaboration

Medical questions often involve multiple layers of semantic complexity, and users may initially pose overly broad or complex queries. Knowledge graph-based question answering systems can decompose these complex questions into more specific sub-questions and provide answers through a gradual, multi-turn interaction.

For example, for the question "What are the symptoms and treatment options for hypertension?", the system can first decompose it into multiple sub-questions through a multi-turn dialogue:

- What are the common symptoms of hypertension?
- What are the common treatments for these symptoms?
- What are the differences between these treatments?

Through this stepwise questioning, the system can provide a more detailed answer to complex questions, allowing users to gradually obtain the complete information they need.

4.6.3 Clarification and User Feedback Loop

In multi-turn interactions, systems must possess the ability to clarify user queries, especially when users pose vague or ambiguous questions. Systems can obtain more information by asking follow-up questions or seeking clarification to ensure accurate understanding of the query. For example, if a user asks, "What are the treatments for migraines?", but the knowledge graph contains multiple types of migraines (e.g., tension headaches, chronic migraines), the system could ask, "Which type of migraine are you referring to?"

This clarification mechanism can be implemented through a dynamic dialogue management module. This module is responsible for:

- Dynamically adjusting strategies for query parsing and response generation.
- Acquiring more information through multiple rounds of follow-up questions in uncertain situations.
- Revising and optimizing system responses based on user feedback.

4.6.4 Graph-based Reasoning in Multi-turn Interaction

In multi-turn interactions, systems must not only process continuous natural language inputs but also perform incremental reasoning within knowledge graphs. Each round of question-answering may involve new entities and relations, requiring the system to update query conditions in real-time and find the best answer in the graph that matches the current question. For example, in medical question answering, if a user first asks "What is the relationship between hypertension and headaches?" and then asks "Which medications can treat both?", the system needs to further reason about the dual therapeutic effects of medications based on the previous results.

To support complex reasoning in multi-turn interactions, systems can employ:

- **Path-based sequential reasoning:** This involves expanding existing path searches in each round of dialogue to find new relevant entities and relations.
- **Context-aware semantic queries:** By using the results of previous rounds of dialogue as constraints, more precise graph queries can be performed.

4.6.5 User Intent Adjustment and Dialogue Strategy Optimization

In multi-turn interactions, users' initial questions or intents may change over time. The system should be able to dynamically adjust its strategies based on the progress of the conversation. For example, a user may initially focus on disease symptoms, but after several rounds of interaction, they may shift their attention to treatment options or side effects. Therefore, the system should have a flexible intent recognition mechanism that can adjust the direction of the conversation in real-time.

This can be achieved by optimizing dialogue strategies using reinforcement learning. Reinforcement learning enables the system to select the optimal response strategy in each round of interaction, improving the relevance of the Q&A and user satisfaction.

5. Experiments and Results Analysis

To validate the effectiveness of the medical knowledge graph-based question answering system in the medical domain, a series of experiments were designed and the results were analyzed in depth. The experiments aimed to evaluate the system's performance in terms of question answering accuracy, reasoning ability, and system efficiency. During the experiments, we compared retrieval-based, deep learning-based, and knowledge graph-based question answering methods and analyzed the performance of each module under different experimental scenarios.

5.1 Experimental Environment and Dataset Selection

Experiments were conducted under the following environment:

Hardware: NVIDIA RTX 3080 Laptop GPU, Intel i7-11800H CPU, 32GB RAM

Software: Python 3.8, TensorFlow 2.4, Neo4j 4.0 (for graph database), Scikit-learn, Spacy (NLP toolkit)

Graph Database: Neo4j was used to store and manage the medical knowledge graph, supporting graph queries and reasoning based on the Cypher language.

5.1.1 Dataset Selection

To ensure the comprehensiveness and professionalism of the experimental data, multiple datasets were used to construct the medical knowledge graph, and specific question-answering datasets were selected for model training and testing:

Knowledge Graph Construction Datasets:

- **DrugBank:** Contains drug names, chemical structures, targets, mechanisms of action, and relationships with diseases.
- **UMLS (Unified Medical Language System):** Used to standardize medical terminology and provide cross-domain entity mapping.
- **OMIM (Online Mendelian Inheritance in Man):** Describes the genetic background and gene relationships of diseases.
- **PubMed Abstracts:** Through natural language processing techniques, relationships between diseases, symptoms, and drugs were extracted from large-scale medical literature.

Question-Answering Datasets:

- **MedQA:** Contains nearly 50,000 medical questions and answers, covering topics such as diseases, symptoms, and drugs.
- **COVID-QA:** Specifically designed to test the system's ability to answer questions related to COVID-19, including disease transmission, symptoms, and treatment options.

5.2 Experimental Design and Methodology

The experiments are designed to provide a comprehensive evaluation of the system's question-answering performance and reasoning capabilities.

5.2.1 Comparison Experiments

The purpose of comparison experiments is to compare the graph-based question-answering system with other methods, focusing on its performance on different types of questions. The specific design is as follows:

- **BM25-based QA Model:** A traditional BM25 retrieval algorithm is used to retrieve the most relevant answer segments from documents based on keyword matching. BM25, as a classic text retrieval algorithm, serves as a benchmark model for most question-answering systems.
- **BERT-based QA Model:** A pre-trained

BERT model is used for the question-answering task to evaluate its performance in medical question answering.

- **KG-QA Model:** The constructed medical knowledge graph is used, combined with graph reasoning and path searching, to answer complex questions.

5.2.2 Ablation Studies

Ablation studies are used to evaluate the impact of each module (such as entity disambiguation, relation extraction, and reasoning mechanism) on the overall system performance. The specific ablation experiments are designed as follows:

- **Without Entity Disambiguation:** Tests the change in question-answering accuracy when entity disambiguation is not performed.
- **Without Relation Reasoning:** Only simple graph queries are performed without complex reasoning.
- **Without Answer Generation Optimization:** Directly returns the query results without fluency optimization based on NLG (Natural Language Generation).

5.2.3 Performance Testing Experiments

When the system scale is large, the efficiency of graph queries significantly affects the response speed of the question-answering system. We designed performance tests with different scales of graph data (10,000, 100,000, and 1,000,000 triples), focusing on the system's response time, memory usage, and query efficiency.

5.3 Performance Metrics and Evaluation Methods

To comprehensively evaluate the performance of the graph-based question-answering system, we adopted the following evaluation metrics:

- **Accuracy:** Represents the proportion of correct answers returned by the system.
- **Recall:** Represents the proportion of correct answers that the system will be able to retrieve from all possible answers.
- **F1-Score:** A combined metric of precision and recall, calculated as:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

- **Mean Reciprocal Rank (MRR):** Represents the average reciprocal rank of the first correct answer in all returned answers. A higher MRR indicates that the system is more likely to return the correct answer in the top-ranked results.
- **Response Time:** Evaluates the time (in milliseconds) from user input to result return.

5.4 Experimental Results Analysis

5.4.1 Comparison Experiment Results

Table 1 presents the experimental results of three different types of question-answering models on the MedQA dataset. The knowledge graph-based question-answering system significantly outperforms other models in terms of accuracy and F1-score.

Table 1. Comparison Experiment Results

Model	Accuracy (%)	Recall (%)	F1-Score (%)	MRR	Average Response Time (ms)
BM25-based QA Model	67.5	65.2	66.3	0.51	50
BERT-based QA Model	75.8	73.9	74.8	0.68	150
KG-QA Model	82.6	80.4	81.5	0.73	120

The experimental results demonstrate that the knowledge graph-based question-answering model can leverage complex semantic information and relationship reasoning within the graph to achieve excellent performance in terms of accuracy and answer ranking. Additionally, the response time for graph queries is more efficient compared to the BERT model.

5.4.2 Ablation Study Results

Table 2 shows the performance of the question-answering system on the MedQA dataset under different module ablation conditions. It can be seen that entity disambiguation and relation reasoning have a significant impact on the overall system performance.

Table 2. Ablation Study Results

Experimental Setup	Accuracy (%)	Recall (%)	F1-Score (%)
Full Model	82.6	80.4	81.5
w/o Entity Disambiguation	75.3	73.8	74.5
w/o Relation Reasoning	70.8	68.7	69.7
w/o Answer Generation	79.5	77.6	78.5

After removing the entity disambiguation module, the system's accuracy decreased by 7.3%, indicating that entity disambiguation has a significant effect on handling polysemy. After removing the relation reasoning module, the system's accuracy decreased by 11.8%, indicating that relation reasoning plays a key role in answering complex questions.

5.4.3 Performance Testing Results

Table 3 shows the response time and memory usage of the system under different scales of graph datasets.

Table 3. Performance Testing Results

Graph Scale	Node Count	Edge Count	Average Response Time (ms)	Memory Usage (GB)
10,000	5,000	10,000	100	2.1
100,000	50,000	100,000	250	4.5
1,000,000	500,000	1,000,000	800	10.7

As the graph scale increases, the system's response time grows exponentially. However, by optimizing the graph index structure (such as multi-level indexing based on node types and relationship types), memory usage can be effectively controlled, and good query efficiency can be maintained on large-scale datasets.

6. Conclusion

An automatic question answering system based on a medical knowledge graph is proposed in this paper to overcome the limitations of traditional methods in handling complex semantics and reasoning in the medical domain. A large-scale medical knowledge graph is constructed and integrated with natural language processing and graph reasoning techniques to enable accurate understanding and answering of medical queries. Experimental results show that our system surpasses traditional methods in terms of answer accuracy, semantic understanding, and the ability to reason over complex questions.

Future work will concentrate on the following aspects: expanding the knowledge graph to include multimodal data such as images and genetic information; improving the system's real-time performance and stability for complex reasoning tasks; and exploring the integration of knowledge graphs with large-scale language models to address more complex medical scenarios and enhance the system's practical applicability.

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