Mental Health Question and Answering System Based on Bert Model and Knowledge Graph Technology

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ABSTRACT

With the development and progress of society, people are facing increasing pressure. The emergence of this phenomenon has led to a rapid increase in the incidence of mental illness. In order to deal with this phenomenon, this paper proposes a system of question and answering on the basic knowledge of mental health (MHQ&A) by using deep learning retrieval technology and knowledge graph technology. The system MHQ&A is designed mainly for the general public, to answer the basic knowledge of mental health, especially the field of depression. First of all, the basic and the professional question and answer data about mental health were respectively obtained by the reptilian bot from the "IASK" website knowledge and the "Dr. Dingxiang" website. Then, the questions and answers obtained through the crawler are made into a Question and Answering Knowledge Graph of Basic Health Knowledge in the mental health field, which is combined with semantic data of antidepressants and the semantic data of depression papers. Finally, a set of template matching rules is designed to determine the type of problem of users. If the questions are about the professional knowledge of medicine or thesis, the reasoning template will be used to reason and search the answer in the "Question and Answering Knowledge Graph of Basic Health Knowledge in the Mental Health Field". If the questions are about other basic knowledge in the field of mental health, the BERT model is used to vectorize the questions of users, and the matching questions and corresponding answers in the MHQ&A are found through cosine similarity calculation. Through the test of system accuracy, it is proved that the system can effectively combine deep learning technology and knowledge.

CCS CONCEPTS

• Real-time operating systems • Natural language processing • Semantic networks

KEYWORDS

Knowledge Graph, Deep learning, Question and answering system, Mental illness

1. Introduction

Depression and anxiety are very common all over the world. One in four people suffer from depression or have received treatment [1]. It has become the world's second-largest disease which seriously threatens human health [2]. It is necessary to pay attention to the adverse effects of depression on the health of patients and its related economic burden [3]. For individuals experiencing pessimism, it is difficult to talk other people their feelings [4] due to their shame of illness [5]. With the rapid development of social media, people with mental illness prefer to seek help from strangers through social media, such as the "tree hole" in social media. Therefore, correct guidance is very necessary for the treatment of patients with mental illness, especially depression. As a community of knowledge sharing and communication with social attributes, the public-oriented question and answer website provides a personalized platform for users to express their health needs. It not only meets the needs of users to search for relevant information, but also provides users with social support [6] and meets their emotional needs [7].

The emergence of knowledge graph provides the possibility for the development of knowledge question answering system. Knowledge map is a structured data set that is compatible with

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RDF data model and uses ontology as schema layer. An ontology is an explicit formal specification of a conceptual system. Generally speaking, an ontology describes a domain of discourse. A typical ontology consists of a limited number of terms and the relationships between them. RDF (Resource Description Framework) is essentially semantic data. It provides a uniform standard for describing entities or resources.

With the development of artificial intelligence technology, the research of knowledge graph technology and deep learning technology has been intensified. Knowledge graph technology has been applied in intelligent semantic search, question answering system, public security, medical, military and many other industries [8-10]. Bordes et al. [11] pioneered the use of vector embedding methods to encode questions and answers, and calculate based on the similarity between the method encoding questions and answers. Later, some people proposed methods such as subgraph vector [12] and memory network [13]. Convolutional neural networks and recurrent neural networks are also often used to encode sentences [14-15]. These methods only need to simply query the knowledge base to complete the searching and sorting functions of candidate answers.

We believe that the structured knowledge stored in the knowledge graph is mostly professional knowledge, which is not effective for non-professional question and answer in the field of mental illness. Therefore, this research combines deep learning model and knowledge graph technology to construct a system MHQ&A to solve the doubts of patients with suspected mental illness, especially those with suspected depression.

2. Models and Algorithms

2.1. Bert model

The sentence vector is generally obtained through word vector superposition, averaging, or weighted average. But the above methods cannot understand the meaning of the context. For example, the same word may have different meanings in different contexts, but it will be represented as the same word vector. The vectors of the same word in different contexts should be different. Polysemous words generate different vectors due to different contexts. In this way, the sentence vectors generated by BERT can be truly used in semantic calculations. In addition, BERT's method of generating sentence vectors also eliminates the error caused by the weighting of word vectors.

The BERT model is a two-stage NLP (Natural Language Processing) model. The first stage is called "Pre-training", when unlabeled corpus to train a language model is used. The second stage is called "Fine-tuning". A pre-trained language model to complete specific NLP downstream tasks is used in this stage.

The BERT model is composed of an N-layer Transformer model. The output value of each layer of Transformer can be used as a sentence vector. However, the value of the last layer of the Bert model is very close to the target value of the training task, and the first few layers of the Bert model may not have fully learned the semantic features. Therefore, this experiment chooses the penultimate layer of Bert as the sentence vector.

2.2. Cosine similarity algorithm

The degree of similarity compares the similarity of two things. Generally, the distance between the features of things is calculated to measure the index of similarity. If the distance is small, the similarity is large; on the opposite, if the distance is large, that similarity is small. We use the cosine value of the angle between two vectors in the vector space as a measure of the difference between two individuals. The closer the value is to 1, the closer the angle is to 0°, that is, the more similarity the two vectors are, which is called cosine similar. Assuming that A and B are two n-dimensional vectors, A is [A1, A2, ..., An] and B is [B1, B2, ..., Bn], then the cosine of the angle θ between A and B as shown in formula (1):

$$\cos\theta = \frac{\sum_{i=1}^{m}(A_i \times B_i)}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \times \sqrt{\sum_{i=1}^{n}(B_i)^2}} \tag{1}$$

3. Question and Answering Knowledge Graph

The question answering system includes 5 modules: crawler module, knowledge graph module, question judgment module, query module, and user interaction module. In order to balance the response speed of the system and the accuracy of the answers to the questions, we considered dividing the knowledge graph module of the question answering system into two sub-modules, and dividing the query module into two different functional sub-modules. When asking the system professional medical questions and essay questions, the query sub-module 1 will be used to match the best answer in the knowledge graph sub-module 1. When asking the system about daily non-professional knowledge, the query sub-module 2 will be used to infer the best answer in the knowledge graph sub-module 2. The structure of the question answering system is shown in Figure 1:

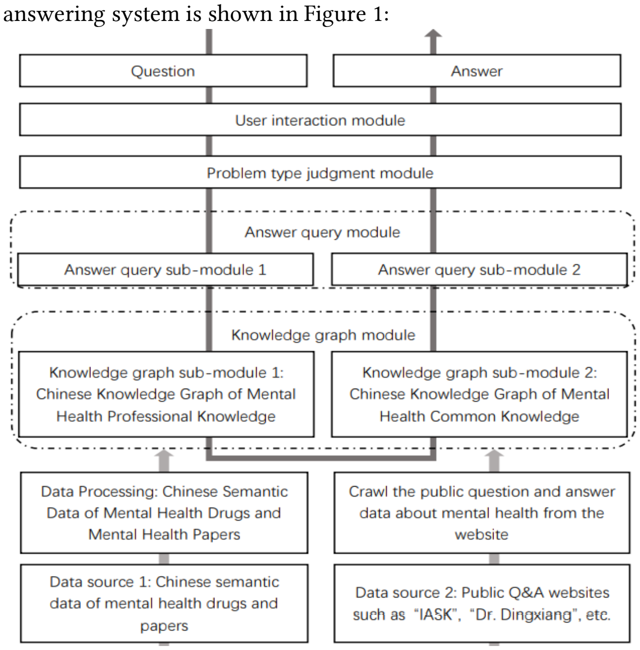

Figure 1: Architecture diagram of question answering system

3.1. Web crawler and data processing

The data sources of this paper consist of two parts. The first part of the data comes from the “Chinese semantic data of Mental Health Drugs” and the “Chinese semantic data of Mental Health Papers” that our team has. In this experiment, the above-mentioned two knowledge graph data were sorted and collected to form a “Chinese Knowledge Graph of Mental Health Professional Knowledge”. The second part of the data comes from the mental health question-and-answer data published on the websites of “Ask Knowledge” and “Dr. Dingxiang”.

This experiment uses the Selenium tool to obtain the second part of the data. We use this tool to automatically search for 15 keywords such as “mental health”, “depression”, “anxiety”, and “irritability” in web pages, as shown in Table 1. After standardized processing of the obtained data, it is converted into RDF format and stored in the “Chinese Knowledge Graph of Mental Health Common Sense”. The structure is shown in Table 2.

Table 1: Keywords included in the crawler

Website	Keyword Search
IASK	depression, depression medicine, mental health, mental illness
Dr. Dingxiang	depression, depression medication, depression treatment, depression symptoms, depression judgment, depression classification, depression degree, depression performance, mental health, mental illness, anxiety

Table 2: Key predicates in the knowledge graph

Knowledge Graph Named Graph	Key Predicate	Remarks
http://www.qa.com/drug/	http://wasp.cs.vu.nl/medicine#hasID	Drug ID
	http://wasp.cs.vu.nl/medicine#hasName	Drug name
	http://wasp.cs.vu.nl/medicine#hasDosageAndAdministration	Drug usage and dosage
	http://wasp.cs.vu.nl/medicine#hasAdverseReactions	Adverse drug reactions
	http://wasp.cs.vu.nl/medicine#hasCautions	Drug precautions
	http://wasp.cs.vu.nl/medicine#hasIndications	Drug indications
	http://wasp.cs.vu.nl/medicine#hasProducer	Drug producer
http://www.qa.com/pubmed/	http://www.ztonebv.nl/KG#hasChineseTitle	Chinese title of the paper
	http://www.ztonebv.nl/KG#hasChineseAbstractText	Chinese abstract
	http://www.ztonebv.nl/KG#hasChineseJournalName	Chinese Journal of papers

We use the mental health question-and-answer data obtained by crawlers to construct a “Chinese Knowledge Graph of Mental Health Common Sense”. In addition, we use the BERT Chinese model after the pre-training process, and the sentence vector of the question in the “Chinese Knowledge Graph of Mental Health Common Sense” is calculated. And the calculated question sentence vector will be stored in the knowledge graph in the form of semantic data, as shown in Table 3.

Table 3: Key predicates in the knowledge graph

Knowledge Graph Named Graph	Key Predicate	Remarks
http://www.qa.com/qa/	http://www.ztonebv.nl/KG#Question	The question of crawler acquisition
	http://www.ztonebv.nl/KG#Answer	Answer to question obtained by crawler
	http://www.ztonebv.nl/KG#URL	Question URL obtained by the crawler
	http://www.ztonebv.nl/KG#Embedding	Sentence vector of BERT model calculation question

4. Methods of question analysis and answer retrieval

4.1. Question type judgment method

In order to make the query more accurate and faster, the system introduces the problem judgment module. After the user asks a question, the question sentence first passes through the question judgment module. This module includes 6 dictionaries, namely “disease/symptom dictionary”, “mental health drug name dictionary”, “drug attribute dictionary”, “paper attribute dictionary”, “drug problem keyword dictionary” and “paper problem keyword dictionary”, as shown in Table 4.

Table 4: Dictionary in problem judgment module

Dictionary	Dictionary content
Disease/symptom dictionary	Alzheimer's disease, Alzheimer's disease, β-amino

	aciduria, Aspirin allergy, Headache, etc.
Dictionary of Mental Health Drugs	Lorazepam tablets, Gapura, Fluoxetine hydrochloride enteric-coated tablets, Jin Kai Ke, etc.
Dictionary of Drug Properties	Symptoms, Effects, Production, Adverse reactions, Indications, Drug names, Trade names, etc.
Thesis attribute dictionary	Title, Astract, Journal, etc.
Keyword Dictionary of Drug problem	What kind of medicine, What kind of medicine, What kind of medicine, The name of the medicine, What kind of medicine, etc.
Keyword Dictionary of Thesis Questions	Papers, Articles, Which articles, How many articles, etc.

The problem judgment module combines the above-mentioned dictionaries into a template to judge the type of user's problem. For example, if the words in the "disease/symptom dictionary" and the "drug problem keyword dictionary" appear in the question at the same time, it can be inferred that the question is asking the symptomatic drug by describing the symptoms. If the question is related to a mental health professional drug or thesis, then the question will be handed over to the answer query sub-module 1 for processing. Otherwise, it will be handed over to the answer query sub-module 2 for processing.

4.2. Knowledge graph reasoning

The main method of answer query sub-module 1 is knowledge graph reasoning. The knowledge graph of this system is stored in RDF format, so SPARQL language can be used for knowledge reasoning. If the question judging module determines that the question is a medical or essay professional knowledge question in the field of mental health, the question will be further classified, as shown in Table 5:

Table 5: Dictionary in problem judgment module

Known information	Question target
Drug name	Attribute of the drug
Symptom description	Drug name
Paper topic	Paper abstract
Paper topic	Paper journal
Key words of the paper	Paper title
Key words of the paper	Number of papers

According to the classification of the question sentence, the corresponding dictionary will be selected to extract the key words in the question sentence, and the general SPARQL sentence which has been written before will be combined to do inference and query in the knowledge graph to obtain the answer.

4.3. Sentence vector similarity matching

The main method of the answer query sub-module 2 is to match the sentence vector similarity of the question sentence. If the problem judgment module concludes that the question is not a drug or essay professional knowledge problem in the field of mental health, then the question sentence will be handed over to the answer query sub-module 2 for processing.

The answer query sub-module 2 uses the BERT model to convert the user's question into a sentence vector of (1,768) dimensions, and calculates the cosine similarity of the sentence vector of each question in the Chinese Knowledge Graph of Mental Health Common Sense, as shown in Formula 1. The sentence vector of the user's question and of the existing question in the knowledge map will be calculated by using the cosine similarity formula, and the question that is most similar to the user's question in the knowledge map will be found. Then the SPARQL sentence is used to query the answer corresponding to the question in the knowledge graph.

5. Interaction between system and user

5.1. System implementation

This system uses the FLASK framework to encapsulate the various modules of the system into interfaces, and provides services to the WEB framework through interface calls, as shown in Figure 2.

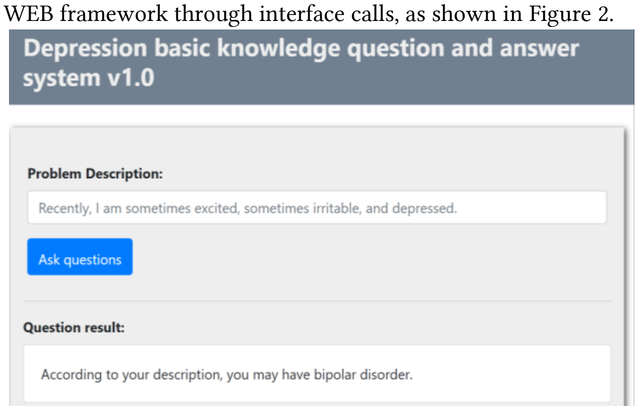

Figure 2: Interactive interface of question answering system

5.2. Functional test and verification

This study divides the test data into four parts. In the first part of the data, experts in the field of mental diseases put forward five professional problems of mental diseases. In the second part of the data, suspected patients with depression asked five questions about their own situation. In the third part, five questions about depression were raised by friends of patients with depression. The fourth part of the data asked five questions by people who had not been exposed to depression. Input these questions into the question answering system in turn and count the number of correct answers, as shown in Table 6:

Table 6: Number of test questions and questioners

People asking questions	Number of questions	Number of correct answers
Experts	5	2
Patients	5	5
Friends of the patient	5	3
Other people	5	4

6. Conclusion

The system combines the logical reasoning technology of the knowledge graph and the probability calculation technology of deep learning to improve the accuracy, flexibility and scalability of the system answer. The category of question is obtained by preprocessing the user's question, which further improves the efficiency of the question answering system in obtaining answers. However, the system still has shortcomings. We will solve the following issues in the next step: 1) Expand the scale of the knowledge graph; 2) Introduce the knowledge graph reasoning multi-hop algorithm; 3) We will use deep learning technology instead of dictionary to find keywords in questions.

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