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The advance of multi-round dialogue system with deep learning

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Abstract. Multi-turn dialog systems have seen significant advances in recent years, driven by various approaches. The Multi-layer Semantic Method, Reinforcement Learning Method, Knowledge Graph Method, and Medicine Knowledge Graph Method have all shown promising results in advancing the state-of-the-art in this field. However, challenges remain in developing models that can handle complex and diverse user inputs and generate responses that are not only informative but also engaging and natural. Further research is needed to address these challenges and advance state of art in multi-turn dialogue systems. This paper reviews four critical methods for improving the quality of multi-turn dialogue systems: Multi-layer Semantic Method, Reinforcement Learning Method, Knowledge Graph Method, and Medicine Knowledge Graph Method. The Multi-layer Semantic Method utilizes multi-layer neural networks to model dialogue context and generate responses with improved coherence and relevance. The reinforcement Learning Method employs a reward-based approach to optimize response generation by training models to maximize long-term dialogue success. The knowledge Graph Method incorporates external knowledge sources, such as knowledge graphs, to enrich the dialogue context and improve response quality. The Medicine Knowledge Graph Method focuses on integrating medical knowledge into dialogue systems for healthcare applications. Each of these methods has demonstrated promising results in enhancing the quality of multi-turn dialogue systems.

Keywords: multi-turn dialogue, natural language processing, deep learning, knowledge graph, reinforcement learning.

1. Introduction

In recent years, the widespread application of dialogue systems in scenarios such as intelligent customer service, virtual assistants, and speech recognition has become a hot topic of increasing interest [1-3]. A dialogue system is a computer system based on natural language processing technology that can

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understand and respond to the natural language used by humans, thereby achieving seamless human-machine interaction. Nowadays, dialogue systems are playing an increasingly important role. Firstly, dialogue system technology can promote the development of human-machine interaction technology. Its research can improve human-machine interaction's naturalness, fluency, and efficiency, thus better serving human society. Secondly, dialogue systems can improve artificial intelligence technology's user experience and application value. For example, in intelligent customer service, dialogue systems can replace human customer service to answer user questions, improving the efficiency of customer service and user satisfaction. Research on dialogue systems can promote human language understanding and cognitive science development, providing valuable experimental data and theoretical references for human language understanding and cognitive science.

Multi-turn dialogue systems are AI technologies that enable natural conversations with users, gradually understanding their intentions and providing relevant responses based on user input and context [4, 5]. The three mainstream methods used in multi-turn dialogue system design are rule-based, statistical-based, and deep learning-based approaches. Rule-based methods involve defining a series of rules in advance to judge user intent and make responses accordingly. While this approach is highly interpretable and controllable, it may require many rules and can become difficult to maintain for complex dialogue tasks. Statistical-based methods build probabilistic models to represent the multi-turn dialogue process. These models use algorithms like Bayesian networks or Conditional Random Fields (CRF) to model and predict user intentions. Statistical-based approaches require significant data to train models but can handle a certain degree of semantic complexity, making them suitable for intelligent customer service and assistance scenarios. Deep learning methods use Recurrent Neural Networks (RNNs) or variants such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) to process context information. Generative Adversarial Networks (GAN) or Sequence-to-Sequence (Seq2Seq) models are commonly used for learning in this approach.

While deep learning methods require significant data and computational resources for training, they have excellent performance and scalability for handling semantically complex and context-sensitive multi-turn dialogue tasks [6, 7]. In addition to these three mainstream methods, there are other approaches like knowledge graph-based and memory-based methods, each with advantages and disadvantages. Designing multi-turn dialogue systems involves considering user intent understanding, dialogue context maintenance, and response generation. Dialogue systems must also address issues such as speech input and multiple languages. A knowledge graph-based dialogue system is an AI-powered conversational system that utilizes a knowledge graph's structure and representation methods to understand user queries or questions and provide meaningful responses or recommendations. The two primary components of a knowledge graph-based dialogue system are typically natural language understanding and natural language generation. Natural language understanding involves converting user natural language queries into structured queries to match and retrieve entities, attributes, and relationships in the knowledge graph. Natural language generation involves converting the system's structured response into the natural language to provide users with meaningful responses. A knowledge graph-based dialogue system can be applied in various fields, such as intelligent customer service, Q&A, and intelligent assistants. It can enhance user experience, reduce the workload of human customer service, and provide users with more personalized and efficient services.

Multi-turn dialogue systems are complex AI technologies that require a combination of various methods and techniques to achieve high-quality dialogue performance. As natural language processing and deep learning technologies advance, multi-turn dialogue systems will become more widely used and developed. However, the shortcomings of the dialog system show up after a few rounds of conversation. It has become an important research direction on how to use the stable and continuous personalized model to assist the dialog system and enhance the interactive effect of the dialog system. Importing a Knowledge Graph as an external Knowledge base which is used to store relevant information and connect the inner and external data into the dialog system can greatly enhance the fluency and accuracy of the dialog system efficiently, but how to effectively combine Knowledge Graph and dialog system remains to be explored. The systematic evaluation and labeling of dialogue are still under exploration at present. Using appropriate standards to complete automated dialogue quality assessment helps measure the model's effectiveness accurately and can effectively guide the further development of the dialogue system.

This paper introduces four methods and discusses the research progress in multi-round dialogue systems. The first method, Multi-layer Semantic Method, combines the semantic information of different levels to improve the quality of responses. The second method, Reinforcement Learning Method, uses reinforcement learning to optimize the dialogue policy and enhance the performance of the dialogue system by rising the e accuracy and stability through optimize the models and experiments. The third method, Knowledge Graph Method, integrates the knowledge graph into the dialogue system to enrich the content of the conversation and provide more accurate responses. The fourth method, Medicine Knowledge Graph Method, applies the knowledge graph to the medical domain and effectively offers medical advice and support to users.

In conclusion, the development of multi-round dialogue systems has made great progress in the recent past in both algorithms and applications, and various methods have been proposed to improve the quality of dialogue systems. However, many challenges remain to be addressed, such as fully introducing non-semantic natural interactive information such as emotions into the dialogue system, interactive adaptation and evolution, and the development of large-scale real-world cognitive dialogue systems. The development of multi-round dialogue systems is of great significance for improving the quality of human-machine interaction and promoting the development of artificial intelligence.

2. Methods

2.1. Multi-layer semantic method

High-quality multiple rounds of dialogue need to consider the semantic information of different granularity. Multi-layer Semantic Method combines the word sequence model, sentence sequence model, and keyword model. The multi-layer semantic model scheme is composed of three sub-models [8]. The final scoring formula of the mixed model is defined as:

$$p_h(y = 1|c, r) = \sigma(w_1 Score_w + w_2 Score_u + w_3 Score_k + b). \tag{1}$$

Where $\sigma(x)$ is the sigmoid activation function, w_1, w_2, w_3 and b is the network parameters, that need to learn in training, three score is the scores result of three stages respectively, according to the formula design of three points score function are:

$$Score_w = h_c^T W_1 h_r + b_1. \tag{2}$$

$$Score_u = \hat{Z} W_2 + b_2. \tag{3}$$

$$Score_k = P_3. \tag{4}$$

Use cross entropy to describe the global loss function of the statement model:

$$L_{global} = -\sum_{i=1}^{N} \left[y_i \log\left(P_h(c, r_i)\right) + (1 - y_i) \log\left(1 - P_h(c_i, r_i)\right) \right] + \lambda |w|^2 \tag{5}$$

To make the parameter training more targeted, the two loss function formulas designed define the local loss function as:

$$L_{local} = L_1 + L_2 \tag{6}$$

The final definition of the loss function is as follows:

$$L = L_{global} + L_{local} \tag{7}$$

In the process of actual training, the primary aim is to minimize the loss value L. The training data is given in context, response, and label. In the prediction, when the actual probability p is more

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significant than 0.5, it is an accurate response; otherwise, it is not. When faced with multiple possible responses, the selected answer is determined by choosing the candidate with the highest probability of being the true response. Experimental results have shown that the multilayer semantic approach is superior to traditional methods, indicating that it is a more effective approach for predicting accurate responses. Overall, the multi-level is ahead of the benchmark method in several experimental indexes. This indicates that the multi-layer semantic model is suitable for the multi-round dialogue system and superior to other benchmark methods.

2.2. Reinforcement learning method

Applying Reinforcement Learning in the dialog system is the action decision of learning dialogues [9]. The action in the reinforcement learning corresponds to the next steps in the dialogues. After the dialogue understanding module processes the user's input text, it obtains structured concession intention information. Based on the Q learning algorithm of reinforcement learning, the system Dynamically selects reasonable negotiation strategies according to the price changes users give in different rounds. Time belief function:

$$b_b^s(t) = 1 - \exp\left(1 - \frac{\min\{t, \bar{t}\}}{\bar{t}}\right)^{\beta \ln K_s} \tag{8}$$

Where t represents the negotiation time between the current system and the user, that is, the number of price negotiation rounds, $\bar{t}$ represents the longest negotiation time for the system design, and K_s represents the negotiation coefficient,", β Is a real number with a value range between [0, 1.5]. The calculation method of negotiation strategy based on Q learning is as follows:

$$P_s^{(t)} = P_s + \bar{Q}_s\left(s(t), P_s^{(t)}\right) \tag{9}$$

The time belief of the system should not be a fixed subtraction function or a certain probability value but can be dynamically adjusted based on the user's behavior modeling results. Based on the concession information of the dialogue understanding module, the user can be modeled, and then the system's belief knowledge can be changed based on the modeling results, thereby achieving dynamic changes in negotiation strategies.

2.3. Knowledge graph method

Currently, there are many challenges and issues in the multi-turn dialogue capability of conversational systems. For example, in complex multi-turn scenarios, the system is quickly interrupted by the user's speech or introduced to new topics, making it difficult for the system to keep up with the user's intent and reducing the effectiveness and user experience of the conversational system. Therefore, improving the multi-turn dialogue capability of conversational systems through a knowledge graph-based approach can better achieve natural, coherent, and effective interaction between the system and users, meet users' diverse and personalized needs, and has high practical application value and research significance.

A knowledge graph is a type of representation that captures knowledge as a graph consisting of nodes (entities) and edges (relationships). It is a structured and organized way of representing knowledge, with nodes representing entities (such as people, places, and things) and edges representing their relationships. Knowledge graphs can represent complex knowledge domains and enable more sophisticated reasoning and knowledge discovery. A graph node represents an entity, an edge represents the relationship between nodes, and the basic composition unit is the triple (SPO) composed of entities and relationships.

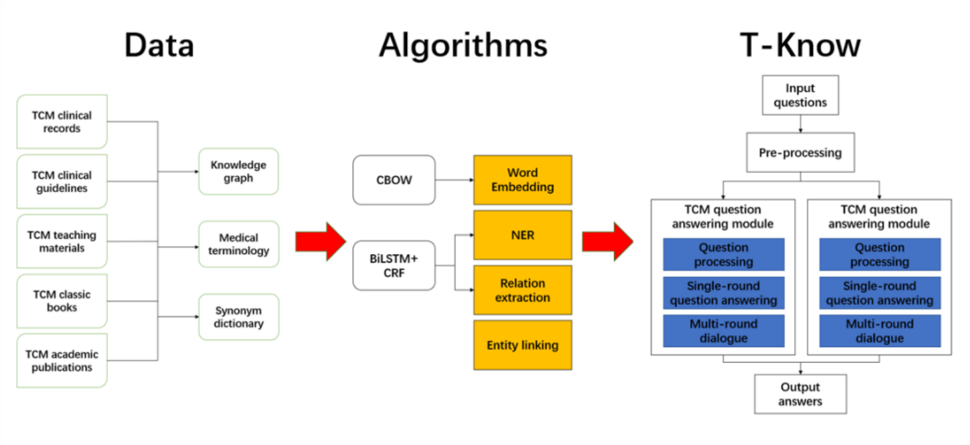

Figure 1. the overview of traditional Chinese medicine knowledge graph [10].

To construct the Traditional Chinese Medicine (TCM) knowledge graph, Liu et al. utilized a diverse range of data resources such as authorized and anonymous clinical records, clinical guidelines, teaching materials, classical medical books, and academic publications, as illustrated in Figure 1 [10]. The authors implemented several preprocessing steps on the unstructured text, including Chinese word segmentation, stop word removal, and semantic annotation. Building on these preprocessing steps, the authors leveraged the Bi-LSTM+CRF algorithm to extract and recognize medical named entities and relations, resulting in the generation of entity-relation-entity-relation (the triplet of the constructed knowledge map). Finally, the extracted triplets were subjected to knowledge graph verification and automatic construction.The TCM knowledge map created by the authors consists of five primary nodes: disease, symptom, syndrome, prescription, and TCM. There are several logical relationships between these nodes. Additionally, the authors integrated a logical reasoning function based on the TCM knowledge graph, which enables the deduction of entity or relationship by reasoning the logical relationship between entity nodes.

Liu et al. developed the TCM Question Answering module, which employs the Bi-LSTM+CRF model for named entity recognition in various TCM texts. The model comprises three layers. The search layer represents each word in the problem sentence as a vector using a pre-trained or randomly initialized word embedding matrix. The bidirectional LSTM in the second layer automatically extracts sentence-level features. The embedding word sequence for each word in the sentence serves as input to the bidirectional LSTM, with the implicit state sequence output by the forward LSTM spliced by position to obtain a complete implicit state sequence. The third layer, the CRF layer, marks sentence-level sequences. For relation extraction, a multi-channel convolutional neural network (CNN) was used to determine the relationship between a pair of entities in a free problem. The CNN has two channels, one for capturing syntactic information and the other for contextual information. The convolution layer of each channel accepts a variable-length input and returns a fixed-length vector using the maximum sampling method. These fixed-length vectors are combined to form the input to the final softmax classifier, whose output vector dimension equals the total number of relational categories. Each dimension's value equals the confidence mapped into the corresponding predicate in the knowledge graph.

In the Single-round Question Answering scenario, Liu et al. utilized the S-MART entity linking tool to retrieve associated entities from the TCM knowledge map. Normally, named entity recognition and entity relationship extraction are predicted separately, which can result in errors during the process. Therefore, the authors applied a joint optimization model to select the globally optimal "entity-relationship" configuration from the candidate results extracted from entity links and relationships. The process of global configuration optimization is essentially a sorting problem. To identify a "reasonable" entity-relationship configuration, the authors incorporated TCM knowledge to sort the entity relationships. This means that the "reasonable" entity-relationship configuration should be more

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commonly found in the TCM knowledge graph. By utilizing the TCM knowledge graph, the authors were able to effectively locate the answer to the user's question.

2.1. Medicine Knowledge Graph Method

Structured information from the knowledge graph is applied to the dialog system, and an end-to-end dialog system is proposed by integrating medical knowledge graph bidirectional encoder representations from transformers, Bidirectional encoder representations from transformers, BERT) + bidirectional gated recurrent unit (BiGRU) + conditional random fields (CRF) method to identify keywords [11]. After matching the identified keywords with the entity database to find the corresponding information, it will serve as the common knowledge information of the input vector of the GPT2 model, thus affecting the output of the end-to-end generated model and finally getting the corresponding reply. This model includes two modules:

Keyword extraction module. The function of this module is to extract the keywords in the current round information and search the relevant knowledge information from the knowledge graph's common sense database. The module uses BERT + BiGRU + CRF model structure to carry out sequence annotation on the whole round information to identify the keywords in the current question. Then, according to the pre-established synonym lexicon, the method of perfect matching is preferred. Suppose the corresponding entity cannot be found through perfect matching. In that case, the bm25 classical retrieval algorithm is used to find the corresponding entity in the knowledge graph common sense database, the related attributes of the entity, and the relationship between the entity and other entities. The input of BERT model triples is classified as a word vector, sentence vector, and position vector, and the beginning and end are labeled with [CLS] and [SEP], respectively. In this method, the task of keyword extraction is converted into word dichotomy. That is, the information of the input model is labeled with 0 and 1, and the one marked with 1 is the keyword. The bm25 algorithm is derived from the independent binary model, but the independent binary model only considers the occurrence of word items in the text without considering the weight of words. bm25 algorithm is improved to match similarity using word frequency, inverse document frequency, and field length normalization information.

End-to-end module. This module uses GPT2 as a pre-training model for conversation generation and fine-tunes it. The structure of the GPT model is shown in the figure. GPT uses Transformer's coding layer but simplifies the model structure in the model, removing the second self-attention structure of the coding layer. GPT2 is the development and extension of the GPT model. It mainly has several innovations in design. First, it puts the Layer norm (layer normalization) before each sub-block. Second, the parameter initialization of the residual layer can be self-regulated according to the defined network depth. The third is to expand the size and length of the dictionary and input order, as well as the batch size of the training test.

3. Prospects and challenge

Table 1. the paper number of the multi-round dialogue system in Annual Meeting of the Association for Computational Linguistics.

Year	Submissions	Accepted	%Accepted
2019	183	52	28.4
2020	250	62	24.8
2021	275	58	21.1
2022	232	47	20.3

As shown in Table 1, the multi-round dialogue system has attracted wide attention in recent years. However, there are still many problems with dialogue systems, and this paper hopes they can be solved.

1) An important direction is how to fully introduce non-semantic natural interactive information such as emotions into the dialogue system. The one-question-and-answer dialogue of human-computer interaction differs from the gradual thinking of human beings. Taking the whole sentence as the processing unit will make the entire human-computer dialogue longer and unnatural. It can also affect

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users so that make them less interested in the target. The concentration goes down, especially in large-scale and real-world dialogue systems, it is usually not because the machine needs to understand the user or know how to give feedback that cause the dialogue fails. However, the failure usually comes from the fact that the machine needs to know when to provide feedback to the user or the user needs to know when to respond. Talk to the machine means that the current dialogue system research only focuses on "what to feedback," but another important topic of interactive research is still missing: "when to give feedback." Therefore, the dialogue system based on natural reincarnation is another future research of cognitive technology important topic.

2) Interactive adaptation and evolution. The process of learning and adapting to the environment and the interaction is an important manifestation of the intelligence of the cognitive subject. The dialogue strategy mentioned in the previous section can also be broadly viewed as the machine's adaptive answer to the user's feedback during the interaction. The main purpose of language model adaptation is to make the search space of speech recognition more skewed towards the domains and vocabulary the user mentions. This kind of self-adaptation often selects a series of specific grammar for recognition through the dialogue state in the grammar-based recognition system. The advantages are simple and easy, and the recognition rate is high when the correct choice is made. The rate is high and difficult to recover.

3) Large-scale real-world cognitive dialogue system. Although many dialogue systems involve more data and larger tasks, the operation of related systems is still based on recruited testers rather than real users, which affects the training of dialogue strategies and the evaluation of dialogue systems. Cognitive technology still needs to be under the real conditions of big data are fully practice verification. Therefore, building and running a complete cognitive dialogue system for large-scale tasks based on existing research in the real world and comparing it with traditional mechanical dialogue systems is the experimental direction of cognitive technology. It is also a way to deal with the abovementioned problems—the necessary test platform for the challenge.

4. Conclusion

The multi-round dialogue system has made significant progress in recent years, and this paper has presented several approaches to improving its performance. One of the critical areas of focus is the introduction of non-semantic natural interactive information, such as emotions, into the dialogue system. This is an important direction for future research, as it can significantly improve the quality of human-machine interaction. There are already some promising developments in this area, such as using sentiment analysis techniques to identify user emotions and adapt the dialogue accordingly. However, there is still a lot of work to be done in fully integrating emotional information into the dialogue system, and this presents an exciting opportunity for future research. Another area of future research is interactive adaptation and evolution. The ability of a dialogue system to learn and adapt to user preferences and needs is crucial for its long-term success. Some promising approaches in this area include reinforcement learning, which allows the dialogue system to learn from its interactions with users, and active learning, which enables the system to seek out new information to improve its performance actively. In addition, evolving the dialogue system over time, using techniques such as genetic algorithms, is an exciting direction for future research. Finally, a major goal for the future of multi-round dialogue systems is to create large-scale real-world cognitive dialogue systems that can be deployed in various settings. These systems must handle a wide range of user needs and preferences and be capable of learning and adapting over time. Achieving this goal will require significant advances in natural language understanding, knowledge representation, and machine learning and will likely require collaboration between researchers in multiple fields. In conclusion, the multi-round dialogue system has come a long way in recent years, but there is still much work to be done to achieve the full potential of these systems. By focusing on introducing non-semantic natural interactive information, interactive adaptation and evolution, and large-scale real-world cognitive dialogue systems, we can continue to make progress and build systems that are truly capable of supporting natural, human-like interaction.

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