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The advance of dialogue system with neural network

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Abstract. With the rapid reform of artificial intelligence, the dialogue system as an important branch of artificial intelligence has also developed greatly in recent years. However, dialogue systems also face many challenges, and accurate and well-sampled training data in dialogue systems is often not readily available. How to use the relationship extraction model based on meta-learning from a small number of samples to improve the accuracy of the relationship prediction method on few-shot learning training data. In addition, this article also explores methods of data compression, summarizing previous compression methods in different ways and related work. At the same time, the application of data compression in the dialogue chat model is also studied. The comparison before and after data compression is carried out to make the dialogue chat model maintain the original answer quality when the data part is reduced, and how to use knowledge graph and reinforcement learning to improve the answer quality of the dialogue system after data compression.

Keywords: few shot learning, dialogue system, knowledge graph, relationship extraction, data compression.

1. Introduction

The dialogue system is an important research direction in artificial intelligence [1, 2]. In recent years, thanks to the development of deep learning technology and the improvement of hardware computing power, the research of dialogue systems is also advancing rapidly. The dialogue system has formed a relatively mature research and development program, and related industrial products, such as voice assistants, smart speakers, intelligent customer service, have entered people's lives. According to the usage scenarios, the dialogue system is divided into a task-based dialogue system, a question-and-answer dialogue system, and an open-domain dialogue system. Task-based dialog systems are designed to meet the specific needs of users with as few conversation rounds as possible. Therefore, task-based dialogue systems are also known as goal-driven dialogue systems, such as customer service robots, air ticket booking systems, which provide users with services in specific areas and are designed to help users complete tasks such as shopping and booking air tickets. This kind of human-computer dialogue system can greatly reduce labor costs, simplify the human-computer interaction process, and improve the intelligence of applications, so it has extensive research and application value. The question-and-

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answer dialogue system is mainly used to meet the user's information acquisition needs and answer the user's questions in concise language. The open-domain dialogue system differs from the first two types of dialogue systems. Its design purpose is generally to accompany or entertain. The main role is to communicate with the user in language, help users pass the time, and meet the user's emotional and social belonging needs. The more rounds of dialogue, the better.

The development process of the dialogue system can be summarized into three stages: 1) the dialogue system based on symbol rules and templates; 2) the dialogue system based on statistical machine learning; 3) the dialogue system based on data-driven deep learning. The first generation of dialogue systems is represented by the 1966 psychological counseling robot Eliza, which mainly relies on artificial grammar rules and ontology design developed by experts. The second-generation dialogue system does not require manual design rules and templates and reduces the manual complexity of the dialogue system through statistical machine-learning methods. They are based on statistical machine learning methods. This method has weak learning ability, but it needs to be better explained, and not easy to patch vulnerabilities. The third generation of the dialogue system is the mainstream of current research, using deep learning to replace shallow learning, making end-to-end learning feasible, represented by Baidu's PLATO (2.6B), Facebook (Meta) Blender (9.4B) and Google's Meena (2.6B), in terms of diversity and personalization to achieve specific results. Still, these model parameters are relatively large, and the generated responses are not controllable.

The ultimate goal of the dialogue system is to simulate a real person for a natural conversation. In reality, many internal or external factors influence people's dialogue behavior, such as personality, emotions, experience, memory, and knowledge. The ability of people to associate discourse context with these factors in conversation and respond differently leads to differences between people and dialogue systems.

This paper introduces the three directions of dialogue learning, few shot learning, knowledge graph-based question answering, and reinforcement learning reasoning based question answering system, including reinforcement learning, relationship extraction based on meta-learning, multi-round dialogue reinforcement learning, and discusses the critical challenges currently faced, model compression and data compression techniques, including counting word frequency and dialogue quality evaluation after removing specific word frequencies and stop words.

The second section of this paper introduces the idea and development of few shot learning and evaluation indicators, the application of knowledge graph in question-answering systems, and the concept of reinforcement learning, which only requires weak signals for training which can be regarded as an intermediate link between supervised learning and unsupervised learning. The third section explains how to use meta-learning-based methods to perform relationship extraction on small sample data, introduces the meta-learning process, and how to effectively find answers in the knowledge graph. Finally, the question-answering system of reinforcement learning is introduced, which relies on intelligent agents and environment interaction to generate training samples to help intelligent agents adjust strategies, elaborates the dialogue agents in multi-round dialogue scenarios, and introduces the reinforcement model.

2. Preliminaries

2.1. Few-shot learning

The goal of few-shot learning is to learn how to solve a problem from a small number of samples. Another concept related to few-shot learning is zero-shot learning [3]. Zero-shot learning means that without training data, the model is trained by using information, such as attributes of categories, to identify new categories. The concept of few-shot learning first emerged from computer vision and has attracted wide attention in recent years. There are many excellent algorithms in the image classification task. However, in natural language processing, the development is relatively slow because the image and language characteristics are different. When the number of samples is small, image feature extraction is easier than text.

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According to the number of training samples, the existing few-shot learning can be divided into three categories: 1) there is only one training sample, which is called single-shot learning; 2) There is no target training sample, which is called zero-sample learning; 3) When the target training samples are dozens of orders of magnitude, it is called few-shot learning. Many kinds of literature refer to these three categories as few-shot learning. There are two main research areas of few-shot learning: conceptual learning and experiential learning. Concept learning is the process of making machines mimic the human brain as much as possible, that is, the process of understanding the essential concept of things through a small number of samples, while another idea of experiential learning is to transform the problem of small samples into a general big data paradigm. The classification results of small sample data will be measured from the overall and single-category evaluation indexes. 1) Single-category evaluation index: Single-category evaluation index measures the classification results of each category in more detail. 2) Overall evaluation index: Overall evaluation index can measure the classification results on the whole data set.

2.2. Knowledge graph

With the advent of the era of big data, it has become an urgent need for people to accurately and quickly obtain information from massive data [4]. Intelligent question-answering can solve such problems. Intelligent question-answering can obtain information through unstructured or structured data to answer questions. Each of these two types of data has its advantages. Unstructured data has a wide range of knowledge coverage, while structured data is more combinatorial and can be used to handle complex reasoning problems. Nowadays, there are many methods to combine unstructured data and structured data to complete question-answering tasks. A knowledge graph (KG) belongs to structured data, which usually stores facts as triples. Due to its intuitive and rich knowledge, it is widely used in natural language processing (NLP) tasks, such as knowledge question answering, dialogue systems, recommendation systems, information retrieval, and so on. Knowledge Graph Question Answering (KGQA) is the most widely used, aiming to use existing knowledge graphs to answer natural language questions. However, most of the existing large-scale knowledge maps still need to be completed, making it difficult to answer some questions. Knowledge map inference technology can mine or infer missing entities and the implicit relationships between entities in the knowledge map. Therefore, applying knowledge map inference technology to KGQA can effectively solve the problem of incomplete knowledge graph and further improve the accuracy of answer prediction.

2.3. Reinforcement learning

Reinforcement learning aims to train an agent to perform appropriate actions when interacting with a specific environment, as shown in Figure 1 [5]. Reinforcement learning is an intermediate link between supervised and unsupervised learning, as it only requires weak signals for training. Reinforcement learning includes an intelligent agent and environment. The interaction process between the two can be modeled using Markov models. Represented by a quintuple M=<S, A, P, R, Y>, S is a collection of all environmental states an agent can detect. A is a collection of all possible continuous or discrete actions that an intelligent agent can perform in an environmental state. Intelligent agents interact with the environment by executing actions. P is a transition matrix that stores the probability that the current state of the environment will change to another state after the agent makes an action. R represents a collection of rewards that can be obtained during the interaction between an agent and the environment. Each time an agent performs an action and causes a change in the state of the environment, it will receive immediate feedback from the environment. The interaction process between the agent and the environment (as shown in Figure 1): a cycle of two steps: the agent first observes the current environment state s and selects action a based on its strategy; Then, according to the transition probability matrix P, the environmental state is transferred to s, and an instant reward r is provided to the agent. Intelligent agents aim to maximize cumulative discount rewards and adjust and optimize their execution strategies through continuous trial and error in the environment.

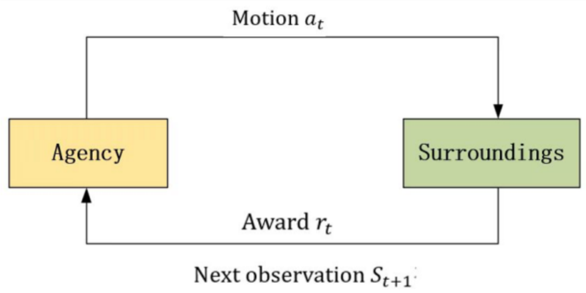

Figure 1. Reinforcement learning framework methods.

3. Methods

3.1. Relation extraction from knowledge base entities based on meta-learning

Entity relation extraction is a critical step in knowledge base question answering. Meta-learning problem is one of the hot issues in machine learning. Similar to the idea of transfer learning, meta-learning also learns prior knowledge from related tasks and then uses prior external knowledge to help learn new tasks. Typically, meta-learning assumes that some task distribution can be obtained in advance, sampled in an external data space. Assuming that multiple tasks can be sampled from this task distribution, a task consists of a training set and a validation set, also referred to as the support set and the query set in meta-learning. A task can be thought of as a data point in the training data of a traditional machine-learning process. Learning meta-knowledge from the external data space is called the meta-training process. Traditional relationship prediction methods rely heavily on training data with high accuracy and sufficient sample size. However, in practice, small sample-size training data are often obtained. To improve the accuracy of relationship prediction methods on small sample size training data.

The meta-learning relationship prediction method, which can learn a large class of relationship model optimization algorithms from the external data space. The Dbase dataset is a basic class obtained in the given external data space, in which many samples are under each relation category. The Dnovel dataset is a few-shot relation prediction dataset in which a few samples are under each relation category. This paper learns a series of relation classification tasks, summarize the learned relation classification experience, and learns a general knowledge of the classification performance of the Dnovel dataset. N-way k-shot is a common experimental setup in meta-learning, where the support set is similar to a regular training set containing N categories and K samples in each category, and the query set is similar to a regular validation set containing the same N categories as the support set and Q samples in each category. In meta-learning, a task consists of a support and query set.

The meta-learning process consists of two training phases. The first stage is the classification baseline stage. It first trains a classifier using all the data on the Dbase dataset and removes its last FC layer to obtain the feature extraction function F. The second phase is the meta-baseline phase, which aims at meta-knowledge acquisition. Given the feature extraction function F obtained in the previous stage, this method sample N-way K-shot tasks from the Dbase dataset, extract the semantic features of the support set using F to obtain the feature vector set corresponding to each class, and then calculate the prototype vector corresponding to each class using Equation (1). The prototype vector represents the essential semantic features of each class:

$$w_c = \frac{1}{|S_c|} \sum_{x \in S} f_\theta(x) \tag{1}$$

where given a meta-learning task with a support set s, let s_c denote the samples in class c, and the average features of these samples wc is computed as the prototype vector of class c. Then use Equation (2) and the prototype vector corresponding to each class to calculate the predicted probability distribution for each sample in the query set.

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$$P(y = c|x) = \frac{exp(<f_\theta(x), w_c>)}{\sum_{c'} exp(<f_\theta(x), w_{c'}>)} \tag{2}$$

3.2. *Question answering system based on knowledge graph*

The core issue in question-answering systems is clearly understanding the user's questions. How to effectively find answers in the knowledge map is one of the key issues in intelligent question-answering systems. One common way is to use the vectorized representation model of the knowledge map to vectorize the knowledge map while also using the vectorized representation of analytical questions. Finally, similarity comparison determines the corresponding answers for the user in the knowledge map.

Implement question parsing based on knowledge map representation learning. Question parsing is the primary task of a question-answering system. Its main purpose is to decompose the semantic information in a user's question through syntax analysis and identify key entities. Firstly, the entity naming recognition model BiLSTM-CNN-CRF is used to identify a question's entity, clarifying the question's core part in the knowledge map. Secondly, use tools such as speech tagging and syntax analysis to decompose a question's structure because only the question's core word and the predicate relationship of the question can be determined in the question, and the missing object part is the answer required by the user. Therefore, question parsing extracts the subject-predicate structure in the question and converts it into a triple form. The transH model can not only introduce rich semantic information from the knowledge map, but moreover, it is also possible to learn the correct representation of entities and relationships between them and use the TransH vectorization method to vectorize the triple structure of questions, thereby using the TransH model to predict the correctness of the triple structure of questions in the knowledge map [6].

Implement answer generation based on knowledge map representation. The TransH model represents and learns the structural features of relationships and entities. Firstly, the entities parsed from the question are linked to entities in the knowledge map using SPARQL. Then all the triplets of the knowledge subgraph with the entity as the core are taken out as alternative answers.

3.3. *Question answering system based on reinforcement learning*

In a multi-round conversation scenario, an intelligent agent is a conversation system or a conversation generation model that requires training, also known as a conversation agent. When the interaction object of a conversation agent is a real user, it is not widely used due to its high labor cost. Another method is for two conversation agents to conduct a conversation, with both parties providing input to each other, and the rewards are obtained through manual scoring criteria. Reinforcement learning was first applied to dialog generation tasks. It will pose a huge challenge when applying reinforcement learning to reply generation tasks due to the large action space and the inability to provide immediate rewards.

In question answering system based on reinforcement learning, two dialogue agents are used to generate dialogue data, and reinforcement learning is applied to knowledge selection strategy learning in multiple rounds of dialogue. Two conversation agents choose strategies based on their respective knowledge and give each other appropriate responses based on background knowledge. Then, the response generated by the conversation agent and its background knowledge is input into the strategy evaluation module, which evaluates the rationality of the knowledge selected by the conversation agent and feeds back the reward signal to the conversation agent. There are two types of rewards: direct rewards: are given directly after the conversation agent makes a knowledge selection, mainly considering whether the current knowledge is conducive to improving the amount of reply to information. Indirect reward: Obtained by evaluating the response statement, consider whether the selected knowledge positively impacts the contextual relevance and knowledge consistency of the final generated response statement. The dialogue simulation process is shown in Figure 2.

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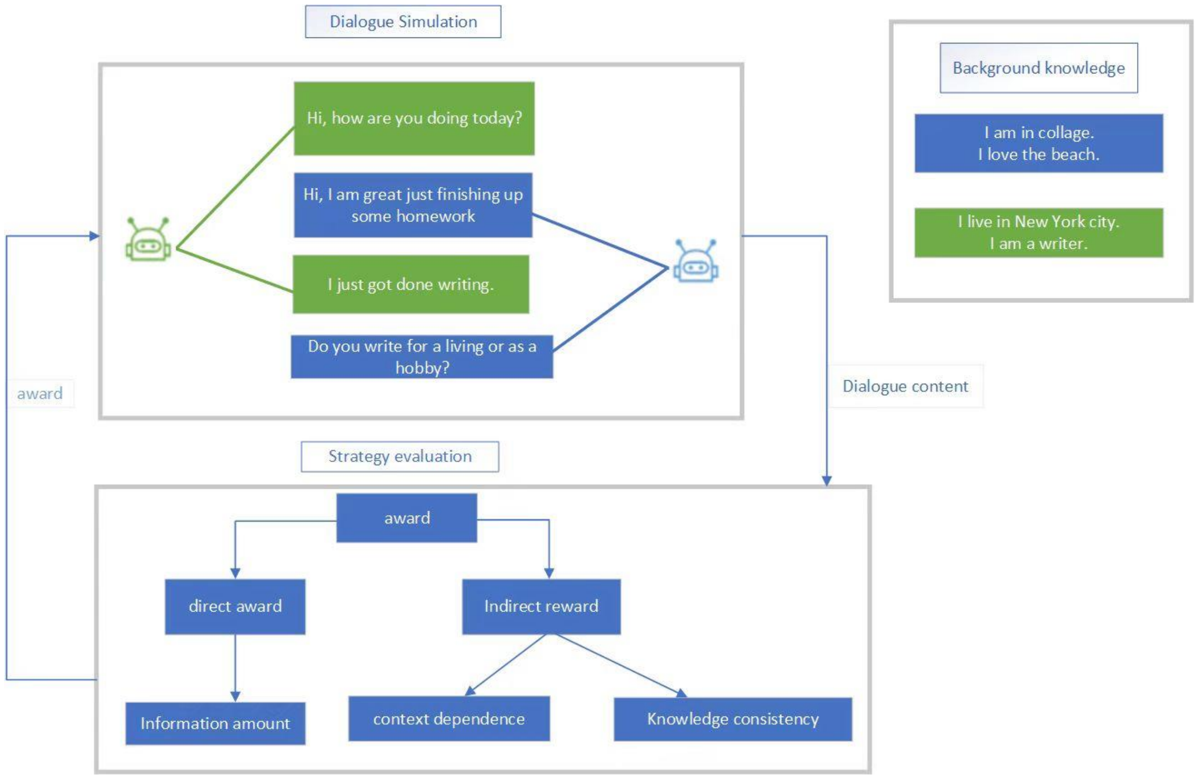

Figure 2. Multi-round dialogue based on reinforcement learning.

4. Discussion

Existing models are all good, but they are too large to train and, at the same time, rely on data highly. Although there is a small learning sample, the effect could be better. Therefore, it makes sense to study model compression and data compression. J. Rissanen et al. described a general-purpose data compression algorithm capable of compressing long strings generated by "finitely generated" sources with near-optimal per-symbol lengths without prior knowledge of the source [7]. Philip GageA proposed a simple general-purpose data compression algorithm called byte-pair encoding (BPE), which provides nearly identical functionality for compression as the popular Lempel, Ziv, and Welch (LZW) methods [8]. J. Ziv et al. proposed a general algorithm for sequential data compression [9]. Its performance is relative to the non-probabilistic model of the constraint source. The proposed generic code implements compression ratios that are consistently close to the lower limit of the achievable compression ratios for block-to-variable and variable-to-block codes, designed to match fully specified sources. Antonio Polino et al. proposed two novel compression methods that combine gravimetric quantification and distillation of more extensive teacher networks into smaller student networks [10]. Their results enable DNNs in resource-constrained environments to utilize architectural and precision advances developed on more powerful devices. M Haroush et al. proposed three ways to generate synthetic samples from training models, opening the way for true data-free model compression, and alleviating the need for training data during model deployment [11].

5. Conclusion

This paper discusses how few-shot learning, knowledge mapping, and reinforcement learning can be applied in conversation systems. It proposes a relationship prediction method based on meta-learning, which can learn from external data spaces to optimize algorithms in a large class of relational models. In addition, we also discussed how to apply reinforcement learning to knowledge selection strategy learning in multiple rounds of conversation and how to effectively find answers in the knowledge map and determine corresponding answers for users in the knowledge map through similarity comparison.

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Data and model compression methods that can improve model efficiency are also discussed. This article's work can maintain the model's functionality while reducing the amount of data. At the same time, a relatively reliable method is established to enable the conversation system to have a certain response quality when the training data is insufficient. This method reduces the time required to obtain reliable data sets and can efficiently train the model in a certain amount of time.

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