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On Dialogue Systems Based on Deep Learning

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Abstract—Nowadays, dialogue systems increasingly become the way for humans to access many computer systems. So, humans can interact with computers in natural language. A dialogue system consists of three parts: understanding what humans say in natural language, managing dialogue, and generating responses in natural language. In this paper, we survey deep learning based methods for dialogue management, response generation and dialogue evaluation. Specifically, these methods are based on neural network, long short-term memory network, deep reinforcement learning, pre-training and generative adversarial network. We compare these methods and point out the further research directions.

Keywords—Dialogue management, response generation, reinforcement learning, deep learning, evaluation.

I. Introduction

WITH the rapid development of computer science, the way of human-computer interaction has undergone tremendous changes. From the traditional keyboard and mouse to the touch screen, voice, and other methods, the means of human-computer interaction become more and more convenient for humans [9], [35]. Interactions with others via a language is a necessary skill of human beings, so it is also the most straightforward way in which humans interact with computers. If humans can communicate with computer systems via natural languages, they can handily access various information and services that computer systems provide. Therefore, researchers have done much work on dialogue systems [9], [69], [15].

In the past decade, dialogue systems have been widely applied in entertainment, navigation, and communication in different forms, such as: 1) *Personal assistant systems* (*e.g.*, Google Now [16]). Their dialogue functions can effectively save users' considerable time and efforts when they access various services. For example, users can speak to a personal assistant system to check the weather, search movie, and book services, which users often need to click multiple times. 2) *Voice control systems*. In a smart home [51], a human user can voice-activate various operations of home appliances. For example, users can ask TV to play movies or news and operate the essential functions of electronic devices. Human drivers can use Apple's CarPlay system [20] to realise voice calls, SMS sending and receiving, and electronic equipment operation through natural language interaction at any time. 3) *Customer service robots*. Customer service robots based on human-computer dialogue systems can effectively reduce the pressure of customer service [44], [32]. They can significantly improve the efficiency of the customer service, save cost and human resources, and guarantee more effective services in shopping platforms.

A dialogue system consists of three parts: understanding what humans say in natural language, managing dialogue, and generating responses in natural language. The main task of dialogue management is to detect the state of the dialogue and take proper dialogue strategies to ensure that a conversation can be carried out efficiently towards the preset objectives. A proper dialogue management function can accurately grasp the progress of the dialogue, and continuously optimise the quality of communication in the process of multiple rounds of conversation with the user, thereby improving user satisfaction and bringing higher profits to the merchant. The natural language generation of the dialogue system is also an essential component of a dialogue system. A good generation model can reply to the user with accurate information by generating a sentence suitable for the new scene with a small amount of training corpus [36]. Besides, it is also crucial to evaluate the performance of a dialogue system because the result of evaluations can improve the system. So, researchers propose many methods for evaluating dialogue systems because different systems may be evaluated in different ways.

Natural language understanding is a branch of artificial intelligence. Mainly to enable computers to understand and use the natural language used by human society, such as Chinese and English, to achieve natural language communication between humans and computers. Like the currently successful smart home [51], users enter text or voice commands on the mobile terminal to remotely realise the operation of particular furniture in the smart home. It is how a typical computer understands the natural language entered by the user and converts it into an interactive way that the computer can execute relevant instructions.

In this paper, we survey deep learning [2] based methods for dialogue management, response generation, and system evaluation. In the era of big data, a large amount of dialogue data become available from a large corpus of user dialogue [48], so it is feasible to apply deep learning technology into dialogue systems. The significant advantage of using deep learning is that it eliminates complex processes such as language understanding, and uses powerful computing and abstraction capabilities to extract valuable knowledge and features from data. For example, the natural language generation based on deep learning does not rely on a specific answer library or template, but can generate answers according to the content of the question. So it can be regarded as a generation model for dialogue systems under certain conditions.

Some researchers survey dialogue systems, but our work

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is different from them. Deriu et al. [12] survey the methods for evaluating dialogue systems. The evaluation methods are based on deep learning, but not all the methods are so. Instead, our survey in this paper covers the applications of deep learning in all the aspects of dialogue systems. Baltrušaitis, Ahuja, and Morency [5] use a new classification method to understand the achievements of machine learning in the past to summarise the latest progress in multi-modal machine learning. It mainly talks about the latest development of machine learning classification. Our paper focuses on the application of deep learning methods in dialogue systems. Yan [65] surveys open-domain dialogue systems based on deep learning, so it does not cover task-oriented dialogue systems. However, in this paper, we are concerned not only open-domain dialogue systems but also task-oriented ones. Chen et al. [9] survey open-domain and task-oriented dialogue systems based on deep learning. However, they cover little about automatic system evaluation based on deep learning. Besides, all the above surveys do not cover the advances in 2019 and 2020, but we do in this paper.

The rest of this paper is organised as follows. Section II briefs some specific aspects in dialogue management. Sections III-V discuss natural language response generation methods based on several main methods of deep learning. Section VI discuss neural networks and generative adversarial network-based methods for evaluating open-domain dialogue systems. Finally, Section VII concludes this paper with future work.

II. Dialogue Management

This section briefs some deep learning based methods for dialogue management.

A. Data Collection

As shown in Table I, the publicly used dialogue data sets mainly come from multiple fields. Compared with the corpora available in Table I, conversation data on social networks is more comfortable to obtain, and there are many users to product data. For example, various dialogue corpora collected on Sina Weibo, Douban Forum or Twitter can integrate.

B. Dialogue Act Recognition

Kumar et al. [25] build a hierarchical Recurrent Neural Network (RNN), which uses a bidirectional LSTM as a base unit and the Conditional Random Field (CRF) as the top layer to classify each utterance into its corresponding dialogue act. The input of the CRF layer is all previous utterances and their dialogue acts (thus reflecting the dependency among semantic labels and utterances). On two benchmark data sets, Switchboard and Meeting Recorder Dialogue Act, their experiments show that their method outperforms are better.

Wu et al. [63] use a Convolutional Neural Networks (CNN) to match each utterance in the context with the response at multiple levels, further improving the role between the utterance relationship and the context information. By accumulating the vectors in time sequence through RNN, that can establish relationships between chat in response.

C. Conversation State Tracking

The state tracking component of a dialogue system interprets the users utterances during a dialogue and accordingly updates the systems belief state: a probability distribution over all possible states of the dialogue. Then during a dialogue, according to its current belief state, the system to decide how to respond. Mrkšić et al. [41] develop a multi-domain RNN dialogue state tracking model. First, a very general belief tracking model is established on all available data, and then a general model is specialised for each domain to learn the behaviour of a specific domain. Mrkšić et al. [42] propose a neural belief tracker to detect time slot value pairs. The system first communicates with a user and then iterates over all possible time slot values to determine the users representation status. Wang et al. [60] propose a new state-tracking network model that uses a displayed gate-to-slot state update mechanism. When dealing with the current number of rounds of conversations, it can extract all dialogue boxes to consider historical data. In order to achieve accurate dialogue state tracking in multi-domain, Kumar et al. [24] propose a multi-attention dialogue state tracking network, which uses a variety of granular attention mechanisms to more robustly encode conversation history and slot semantics to capture the semantic relationship, followed by the self-attention layer, to help resolve references to earlier slots mentioned in the dialogue. In future work, it is worth discussing that multi-attention dialogue state tracking network can adapt to new fields without providing any training data in this new field, and can predict the status of the previous topic in the case of changing topics.

D. Dialogue Policy

Dialogue policy decides how to respond to users, so plays a vital role in dialogue systems. Chen et al. [10] propose a framework of integrating graph neural network (GNN) and deep reinforcement learning. Under the framework, they further propose dual GNN-based dialogue policy, which decomposes the decision in each turn into a high-level global decision and a low-level local decision. Their experiments show that their model significantly outperforms traditional reinforcement learning methods for dialogue policy. Papangelis and Stylianou [43] use the deep Q-network to train a single domain-independent policy network in dialogue management for multiple domains. They evaluate their method by a simulated and paid human. The results show that their more practical and scalable method outperforms some previous approaches.

III. Encoder-Decoder Model for Response Generation

Most dialogue systems based on learning use the encoder-decoder model. The encoder encodes the input sentence, convert the input sentence represented by semantic into a non-linear transformation. Each time step decoder is a time step generating the net word according to the corresponding dialogue history information, and then perform combinations to generate responses. In real conversations, encoder and decoder are not fixed, and some options are

TABLE I
OPEN HUMAN-MACHINE DIALOGUE SYSTEM DATA SETS

Data Set	Description	Access
JDDC Corpus	Multi-round Chinese dialogue for electronic customer service	http://jddc.jd.com/
Taskmaster-1	Conversational corpus facing reality and diversification in six fields	https://g.co/dataset/taskmaster-1
MedDialog	Large-scale dialogue datasets in the medical field	https://github.com/ UCSD-AI4H/
MANtIS	Multi-domain information search dialogue dataset	https://guzpenha.github.io/MANtIS/
KdConv	Multi-round knowledge-driven Chinese multi-domain dialogue data set	https://github.com/thu-coai/KdConv
SAMsum	Manually completed user utterances and annotated semantic role tags	https://arxiv.org/abs/1911.12237
MultiWOZ 2.1	Multi-domain dialogue data set status correction and status tracking benchmarks across seven different domains	https://arxiv.org/abs/1907.01669

Recurrent Neural Network (RNN) [4], Long Short Term Memory (LSTM) [54], and Gated Recurrent Unit (GRU) [1].

Due to the form of question and answer (Q&A), the lengths of input and output are not fixed. The processing method of Seq2Seq is to use an RNN (encoder) to map the input sequence to a fixed-dimensional vector for another RNN (decoder) to use. The vector is mapped to the target sequence. Since long-term dependence is weakened in RNN, RNN is unsuitable for dealing with the relationship between distant information. To the end, a common way is to add a LSTM or a GRU. In the completion of multiple rounds of dialogue, a layered coded dialogue model is proposed, which is extended based on the Seq2Seq dialogue model. Zhao and Xiang [72] add a layer in the middle of the coder RNN and the decoder RNN, and the middle layer RNN is hidden. The layered state contains information about the current "statement vectors" such that the decoder RNN generates a word that will accept the state output of the final hidden layer of the intermediate layer RNN. The middle layer RNN is equivalent to establishing the same background knowledge in the dialogue between a user and the system, such as topic knowledge or concept knowledge, to generate a useful reply for the dialogue system. Similarly, Wen and Young [61] present the RNN-based statistical natural language generator that can learn to generate responses directly from pairs of dialogue act and utterance without any predefined syntaxes or semantic alignments. However, the dialogue model based on Seq2Seq still has several defects. (1) *Universal answer*. The Seq2Seq dialogue model tends to produce universal answers in an open domain. For example, when answering the question What do you think about this product? the system may reply, I do not know about this product. Zhou et al. [74] introduce a memory network into the conversation model to generate the corresponding emotional responses based on user input and specified emotion categories. (2) *Consistent answer*. Because the data-driven approach to training the model is not based on logical reasoning and knowledge representation, when the same problem appears in different expressions, the dialogue system may have inconsistent answers. To address this issue, Ilievski et al. [21] use a migration model to generate a consistent answer. (3) *Long-term dialogue*. At the same time, the model still tends to achieve short-term goals. That is, in training, it focuses on generating the next word only, regardless of whether or not the word affects future generated words, the problem of gradient disappearance will happen. The impact of short-term goals is even more significant. To address the issue, Serban et al. [49] propose Seq2Seq layered model to encode the conversation history into a model.

Although Seq2Seq approach is widely used for dialogue generation, most existing Seq2Seq based models tend to generate responses that lack specific meanings needed. Zhang et al. [67] find that the main reason for this problem is that Seq2Seq does not penalise the case whose generated probability is high, but the real likelihood is low. Intuitively, the actual probability of a response is proportional to the coherence degree between the post and the response. Therefore, the coherent score can be used as a reward function in the reinforcement learning framework to improve the situation described above.

The small number of language data sets results in low quality of sequence generation, so pre-training of language knowledge is required. In order to alleviate this limitation, many scholars have proposed pre-training methods [45], [37], [38], and use pre-training weights in the word embedding representation in the Seq2Seq model. Bidirectional Encoder Representations from Transformers (BERT) [13] consists of several levels of self-attention [58], and learning common sense from a large corpus such as Wikipedia, the performance of natural language understanding (NLU) is rapidly improving. Although it can only perform classification tasks, the current BERT-based research has been extended to sequence generation tasks in UNILM [14], T5 [47]. GPT3 [6] and Transformer models [64] have also achieved better results in sequence generation tasks. We believe that these pre-training models will play a more significant role in the dialogue response generation module. However, they have relatively high requirements for hardware capacity and also have limitations on the length of input tokens.

Zhou et al. [75] use an encoder-decoder structure based on LSTM, which considers the user's question information, semantic time slot values, and the type of dialogue behaviour in the interaction when generating the correct answer. Use the attention mechanism to focus on the critical information conditional on the current decoder state, encode the conversation type embedding, and the neural network-based model can generate different answers in response to different behaviour types. Li et al. [28] propose a hierarchical annotation scheme and an end-to-end neural response generation model, using intent and semantic slots as intermediate sentence representations, and also designed a filter based on whether these intermediate representations are suitable for the design task and dialogue constraints. The appropriate choice of response can guide the user to complete the task while maintaining user participation. Targeted response generation is the focus of future research. Combining the attention mechanism and knowledge reasoning related content can effectively solve the problem of inconsistent responses generated with remote conversation history records and avoid generating unreasonable responses.

Although the encoder-decoder model performs well in dialogue systems dealing with complex domains, the generated responses are not very interpretable. Zhao et al. [70] propose an unsupervised discrete sentence representation learning method to generate interpretable responses. This method discovers interpretable semantics through automatic encoding or context prediction. In order to take advantage of the number of universal RNNs, to help achieve more flexible latent variable allocation to enhance the expressive of generative models, Shen et al. [50] propose a new framework, which consists of Conditional Variational Auto-Encoders (CVAE) module and Automatic Encoder (AE) module. The CVAE module learns to generate latent variables, and the AE module establishes a real dialogue between these latent variables. The training consists of two stages: first, learn to encode discrete text into continuous embeddings, and then learn to generalize the latent representation by reconstructing the coded embeddings. The framework effectively integrates these two structures in dialogue generation to improve the flexibility of the dialogue. In future work, researchers can consider applying this framework to any dialogue generation task based on the Seq2Seq model, using the characteristics of latent variables to generate more diverse responses to meet user needs.

For a given post, the conventional encoder-decoder models can learn high-frequency but trivial responses, yet it is difficult to determine which speaking styles are suitable to generate responses during a dialogue. To this end, Zhou et al. [73] propose the Elastic Responding Machine (ERM) based on a proposed encoder-diverter-filter-decoder framework. ERM uses multiple responding mechanisms to generate acceptable responses differently for different posts. Their experiments show how the learned model controls the response mechanism and reveal some underlying relationship between mechanism and language style.

The current research on the encoder-decoder model for generating responses mainly uses some embedded potential variables to enhance the diversity of responses. The quality of the responses to the problems is still lacking, and it is combined on the end-to-end model. The search information of the knowledge base and the information of the dialogue context may have a good effect in the dialogue generation, which can be considered in future work.

IV. DRL based Model for Response Generation

Deep learning has a strong perceptual ability but lacks specific decision-making ability, while reinforcement learning has a decision-making ability but is not very helpful in perceiving problems. Therefore, it is necessary to integrate the two to complement each other for providing a solution to the problem of perceived decision-making in complex systems. That is Deep Reinforcement Learning (DRL) [40], [3], an end-to-end sensing and control system with strong versatility. Zhao et al. [71] propose a novel latent action framework that regards the action space of the end-to-end dialogue agent as a latent variable and develops an unsupervised method to derive the action space from a specific corpus. Compared with the word-level strategy gradient method, this framework has better improvements on the MultiWoz corpus [8].

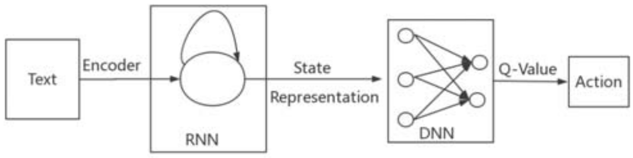

Fig. 1 The basic framework of DQN

The integration of encoder and decoder RNN and reinforcement learning can be used for dialogue generation. It is also an active research topic nowadays, taking the advantages of the two methods to achieve better results. Through the research on the development of DRL in recent years, value-based DRL not only approximates the value function in Q-learning with deep neural networks but also makes other improvements. For example, DeepMind [39] proposed the DQN (Deep Q-Network) algorithm in 2013. The key idea behind the DQN algorithm is empirical feedback, storing the data obtained from its system exploration environment, and then using random sampling samples to update the parameters of the deep neural network. There are two motivations for experience feedback. The first one is a deep neural network as a supervised learning model, which requires data to satisfy independent and identical distribution. The second is empirical feedback that breaks the correlation between sample data using storage-sampling, which is an essential difference from the Q-learning algorithm.

Fig. 1 shows the general construction idea of the current DRL-based DQN model. The idea behind this basic framework is to encode the input image through CNN, or to encode the input text through RNN, to obtain a representation of the state according to the calculation; and then use DNN (Dynamic Neural Network) to input the obtained state representation as an input and output the Q value of the action. The selection of optimal action is further performed based on the calculated result. The overall framework uses a variety of multi-layered deep neural networks to complete the fitting process of Q functions in reinforcement learning, replacing the traditional form Q-learning method.

Although using a neural network-based dialogue generation model, a multi-round dialogue system in the open domain quickly falls into an infinite loop of universal replies. So some researchers [26], [66], [11] apply DRL to task-based dialogue management and use the depth value network to evaluate each round of sentence candidates and then choose the most probable future non-probability sentence as multiple rounds of reply. Song et al. [52] use the depth value network in DRL to evaluate each round of candidate sentences, and then select the sentence with the most considerable future benefit instead of the largest probability to learn the multi-round dialogue strategy. Their experiments show that the proposed method improves the number of dialogue rounds compared to the Seq2Seq method. Cuayáhuitl et al. [11] present a DRL based dialogue system with finite action sets as a form of meaning representation. Their approach derives responses from sentence clustering. The training datasets for learning to interact with human users in a particular style are from dialogue clustering, where dialogue data without any manually-labelled data. Their experiments show that DRL is promising for building trainable chatbots that exhibit fluent and human-like conversations, but its successful application remains an open question.

Regarding the deep reinforcement learning model to complete the construction of the dialogue system, the initial idea was to combine the advantages of deep learning and reinforcement learning. However, in the process of finding strategies, the model training has not only a long period but also the method of finding strategies is severe, and the model parameters are hard to train. The quality of the action-state space of reinforcement learning is the decisive factor that determines the training period and effect of the model. Therefore, the use of deep reinforcement learning models in the dialogue system, how to build a useful action-state space, and finding the best dialogue strategy are future research work.

V. GAN Based Method for Response Generation

In dialogue systems, deep learning can be used to make decisions based on dialogue scenarios and to select the reasonable response, which can train personalised intelligent dialogue. The performance of the adversarial dialogue generation model depends on the discriminator. Reward signals with poor discriminators may appear sparse and unstable, which may cause the dialogue system to fall into an optimal local state or produce nonsense responses.

Su et al. [53] use a Generative Adversarial Network (GAN) to simulate the generation of multiple rounds of dialogue, training potential recursive encoder-decoder and discriminator for distinguishing real responses from generated responses.

This model has achieved well. However, for open-domain dialogue, it is difficult to determine the reward function. If the same question is entered according to the same context, and there are multiple reasonable responses, the entropy of the generated target response will be high.

Li et al. [27] locate the task of generating an open-domain dialogues as RL problems, uses adversarial training for dialogue generation, and jointly trains two system models to generate response sequences and distinguish human dialogues from machine-generated dialogues. The feedback from the discriminator is used as a reward to push the generator to produce authentic responses. The ultimate goal of such responses is no different from human responses.

Li et al. [29] study two methods of confrontation training an open-domain dialogue system. First, the adversarial dialogue generation method is extended to the adversarial imitation learning model. The goal is to train a dialogue system to imitate humans speak to observe real human dialogue. In the framework of adversarial and inverse reinforcement learning, a new reward model generated by the dialogue is proposed, which can provide a more accurate and accurate information reward signal for the dialogue training to help the generator update the parameters and output a more reasonable dialogue.

Feng et al. [18] use the query-response-future turn triples to generate a response in a given context and linking to future conversations. To model these triples, they propose a novel encoder-decoder based generative adversarial learning framework, called Posterior Generative Adversarial Network. It consists of a forward generative discriminator and a backward one. The two discriminators cooperatively make the generated response informative and coherent. Their automatic and human evaluation experiments show that their method can effectively generate informative and coherent responses.

Kim et al. [23] present a method for generating responses during a dialogue with a human user using Self-Attention Generative Adversarial Network. The response generated by GAN is similar to the response generated by humans. At the same time, the self-attention network maintains the context generated by single-track and multi-track responses.

Adversarial learning uses a discriminator to distinguish the generated response from the actual response. The smaller the degree of discrimination, the closer the response generated by the generator is to the human response. Adversarial learning can generate new dialogue data as a basis for training other models. Scholars have not studied this work. The combination of the GAN model and the deep learning will be a trend for further research.

The current end-to-end technical research is a hot topic, and researchers also combine the relevant knowledge base to help the dialogue system complete better dialogue. For the fusion knowledge base or other informations is also a way to explana the end-to-end technology. We summarise the advantages and difficulties of the existing technology and model combination in Table II, and point out the future work direction. We can know from Table II that each model based on deep learning has its advantages. With the development of language models, reinforcement learning and knowledge map, based on deep learning, combining different methods to strengthen the training process of the dialogue system will significantly improve the performance of the dialogue system. How to train multi-model ensemble learning is a direction worth studying in future dialogue systems.

With the development of technology, more and more deep learning has been studied in dialogue system. The task-based dialogue system considers the problems of the domain, and the dialogue system based on the open domain has become a current research hotspot. In a real dialogue scenario, both parties may be the leader of the dialogue. In future research, deep learning technology can be used to control the guidance and rhythm of the dialogue content. Firstly, the multi-step wizard makes the conversation rhythm more natural. Secondly, under the guidance of the content, the interaction between the two parties of the dialogue is considered. By predicting the dialogue trend, we can effectively grasp the dialogue rhythm.

TABLE II
DEEP LEARNING METHOD FOR DIALOGUE RESPONSE GENERATION

Research	Technology	Highlight	Difficulty	Further Work
[55]	Autoregressive Model Adversarial Model	Contours generated by adversarial models to approximate sentence distribution	Difficult to adjust the training model	Generate high-quality responses based on a small amount of corpus
[34]	Attention Mechanism RNN	Contextual elements combined with sentiment classification	Emotion Detection	Multi-round interactive scene to accurately detect the user's emotions
[57]	RNN Encoding LSTM Decoding	Select the semantic elements of aggregation coding	Decoder's selectivity quality of corpus	Learning and adaptability in new fields
[46]	Dynamic Fusion Network	Mining the correlation between the target domain and the source domain	Construction of shared-dedicated models	Migrating in areas with low similarity
[17]	Key-value Retrieval Network Knowledge Base	Tracking link of fuzzy dialogue state	Construction and applicability of knowledge base	Use of time or common sense reasoning in knowledge base
[33]	Memory to sequence	Multi-hop attention mechanism fusion knowledge base information	Implementation of multi-hop attention mechanism	Combine with more knowledge base
[62]	CNN Latent Dirichlet Allocation(LDA)	Integration of text and theme	Correlation of resopnse	Multi-information fusion
[59]	Knowledge Base Attention Mechanism encoder-decoder model	Knowledgeable and meaningful response	The knowledge base is not scalable	Build a bridge between the knowledge base and knowledge graph
[19]	Knowledge Base Memory Network	Generate replies with strong contextual relevance	Same as above	Get more knowledge representation with minimal context
[21]	Transfer learning DRL	Improved the lack of data	What the source and target areas have in common	Transfer learning in multiple source areas, applied in target areas
[18]	Triad GAN	Effectively produce a coherent response	Modeling triples	Expansion of triples using knowledge graph

This is a significant research for the dialogue system.

The reply logic of the dialogue system is the difficulty in the current research, especially for the open-domain. First, human dialogue usually includes common sense reasoning and deduction. It has not been fully realised. Second, based on the data-driven end-to-end model, there is a high probability of safe answers, and the consistency of the reply logic cannot be guaranteed. In future research, we can try to use deep learning methods to model the logical reasoning and deduction process of the dialogue, combine related knowledge bases and retrieval models, and integrate all the content into the generated response.

VI. Automatic Evaluation

With the rapid development of various kinds of deep learning, researchers have made significant progress in dialogue generation. Thus, it becomes more important to study how to evaluate a dialogue system because different dialogue tasks may need different evaluation methods [12]. Deep learning can more flexibly realise automatic evaluation of dialogue systems in open domains. This section briefs some deep learning based method for evaluating open domain dialogue systems.

A. Evaluation Criterion

The traditional criteria have apparent problems in evaluating the quality of the response of an open domain dialogue system. They can distinguish responses through a proper classification form, but there is still a gap between system response and human response. For an open domain dialogue system, there is no standard answer. Even if a reply has nothing to do with the standard answer, it cannot be directly judged: good or nonsense. It just means that the evaluation method can distinguish responses generated by a generation model from standard human replies. If the response generated by a dialogue system is highly similar to the human reply, it is reasonable to say the dialogue system is active.

Even with real conversations, it is difficult to determine the correctness of the answer. It is entirely subjective and is affected by many other indicators, which are currently difficult to model with computer systems accurately. Therefore, the evaluation of open-domain dialogue systems can only be based on user experience to check the relationship between system and human response. Specifically, an evaluation method based deep learning compares a response generated by the generator with a human. The lower the discrimination between the original and the generated reply, the better the generator is trained.

B. GAN Based Method

The adversarial loss can be used to evaluate the dialogue response generated by the dialogue system. Therefore, it can reduce human work in evaluating the dialogue system. Thus, Kannan and Vinyals [22] propose an automatic evaluation method by training an RNN to discriminate a dialogue model's samples from human-generated samples.

Bruni and Fernández [7] propose an adversarial evaluation method for evaluating open-domain dialogue systems. They use a binary classifier (modelled as an attention-based bidirectional LSTM) which takes a sequence of dialogue utterances as input and predicts whether the dialogue is real or fake. If a generated dialogue is coherent with the real dialogue, the classifier regards it as a positive example; otherwise, the classifier regards it as a negative example. By comparing the performance of their method with that of humans on the same task, they find that the job is hard, both for automated models and humans, but that their method can learn patterns so that it has an above-chance performance.

C. RNN Based Method

Lowe et al. [30] develop an automated model based on RNN plus Encoder structure. The bottom layer of RNN change the words into word vectors, and the upper layer generates a vector of the entire context according to the word vector. It participates in the training by referring to the reply as a variable. In the process of training, the results generated by the model are compared with the reference response, which significantly reduces the difficulty of comparing the two answers. They also proposed a dialogue system evaluation index based on the neural network, which can predict the score of the generated response based on the question posed by a given user or previous answers and real answers. Using this method requires adding manual annotation to train the network, So the network scalability is terrible.

To reduce the manual labelling, Zhang et al. [68] use a pre-training method to learn the parameters of the Encoder. The Encoder generates result in the original model, which is used as an input to an independent RNN. Then the trained RNN generate a response to a specific text under certain conditions. The data can be used as the training data of the original RNN so that the same sentence can generate different responses.

D. Other Methods

A significant problem open-domain dialogue systems face is the lack of training data. Hence, the difficulty of data processing and the enormous current situation of data labelling needs to be solved. Lowe et al. [31] use classification reply as the training dialogue text data from the beginning. The training phase uses DE (Dual Encoder). It consists of an RNN with an LSTM that turns the text, candidate responses into a vector form, and enters all the words in a sentence. After LSTM, the state of the last hidden layer can be seen as a vector representation of the entire sentence. To confirm the probability that a reply is an actual reply of the text, a weighted product can be used, and the cross-entropy is minimised (text, reply) to obtain an accurate model. The recall rate can be used as an evaluation criterion, and the proportion of the correct answers to the top K results after sorting can be selected and compared with the manual score results to reflect the quality of the response.

Tong et al. [56] propose an adversarial multi-task neural metric to evaluate multilingual conversations, and shared feature extraction across languages. Their experiments show that the adversarial multi-task neural metric implements automatic labelling and its performance are better than single sentence labelling and existing multilingual indicators. Some commonalities between language knowledge can help the evaluation system to give different evaluation indexes. The ability to evaluate indicators to transfer knowledge from one language to another may be the direction of future research.

People have rules when classifying responses. The emotions expressed by a reply can be divided into several categories. The same type of emotions also has the problem of depth. They can also be divided into several categories. The proportion is tiny, and people in different fields and levels of knowledge may have different results, but this is also a rule. Regarding the quality evaluation of the dialogue systems, the current experimental stage is very similar to the results of a human child's reply, and it is still unable to reach the expert level of response. Therefore, there is still a long way to go in evaluating dialogue systems.

VII. Conclusions

Natural language dialogue systems provide humans with the most convenient way to access many services offered by computers. Therefore, many researchers are interested in developing such systems and propose various methods to address various problems in developing different dialogue systems. In this paper, we survey deep learning based methods for dialogue act recognition, conversation state tracking, dialogue policy, response generation, and system evaluation. Specifically, these methods are based on main deep learning methods: convolutional neural network, long short-term memory network, deep reinforcement learning, generative adversarial network and pre-training model.

In particular, many issues need to be addressed in the future. For example, it is significant to study the deep learning-based evaluation methods of dialogue systems. Such studies need to consider that deep reinforcement learning has evolved from the initial strategy search and value function to meta-learning, hierarchical reinforcement learning, imitation learning, transfer learning and lifelong learning. Regarding the prejudice and ethics in the dialogue system, it is still an issue that needs to be considered in the future dialogue system. In future work, we can consider incorporating different linguistic knowledge and human common sense to enhance the affinity and naturalness of interaction between the dialogue system and users. Besides, since the quality of data in which deep learning extract features must be high, one of the significant challenges in dialogue systems is how to extract as many features as possible from a limited quality data set.

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