A Graph Based and Patient Demographics Aware Dialogue System for Disease Diagnosis

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Abstract

A dialogue system for disease diagnosis aims at making a diagnosis by conversing with patients. Existing disease diagnosis dialogue systems highly rely on data-driven methods and statistical features, lacking profound comprehension of medical knowledge, such as symptom-disease relations. In addition, previous work pays less attention to demographic attributes of a patient, which are important factors in clinical diagnoses. To tackle these issues, this work presents a graph based and demographic attributes aware dialogue system for disease diagnosis. Specifically, we first build a weighted bidirectional graph based on clinical dialogues to depict the relationship between symptoms and diseases and then present a bidirectional graph based deep Q-network (BG-DQN) for dialogue management. By extending Graph Convolutional Network (GCN) to learn the embeddings of diseases and symptoms from both the structural and attribute information in the graph, BG-DQN could capture the relations between diseases and symptoms better. Moreover, BG-DQN also encodes the demographic attributes of a patient to assist the disease diagnosis process. Experimental results show that the proposed dialogue system outperforms several competitive methods in terms of diagnostic accuracy. More importantly, our method can complete the task with less dialogue turns and possesses better distinguishing capability on diseases with similar symptoms.

Introduction

Dialogue systems that aim to complete specific task by interacting with users have attracted increasing research interest in diverse applications (Ghazvininejad et al., 2018; Wu et al., 2019; Zhao et al., 2020). In the medical domain, dialogue systems could be used to find symptoms and make a diagnosis by conversing with patients (see Table 1 for an example). This type of dialogue system have substantial potential to improve the efficiency of collecting information from patients (Kao, Tang, and Chang, 2018) and assist general practitioners in clinical diagnosis.

Current dialogue systems have made significant successes in disease diagnosis, but they still suffer from some limitations. First, previous work makes decisions based on
**Self-report**
My child is 5 years old. Lately, he began to cough and have a fever of 39 degrees.

**Dialogue**
Doctor: Does your child have a rash?
Patient: Yes!
Doctor: Is your child anorexic?
Patient: Yes!
Doctor: Your child may have hand foot mouth disease.

Table 1: An example of the disease diagnosis dialogue system. Underlined phrases are demographic attribute and symptoms.

This paper proposes a novel graph based and demographic attributes aware dialogue system for disease diagnosis. In response to the first limitation, we construct a weighted bidirectional disease-symptom relation graph based on the conditional probabilities between diseases and symptoms, and propose a bidirectional graph based deep...
Q-network (BG-DQN) for dialogue management\footnote{1} BG-DQN extends Graph Convolutional Network (GCN) (Kipf and Welling \citeyear{kipf2017}) to learn the embedding of a disease or symptom in a bidirectional graph. By integrating information about neighborhoods and edges of a disease or symptom node, the learnt embeddings could capture the relationships between diseases and symptoms. Moreover, to tackle the second limitation, demographic attributes of patients are incorporated into BG-DQN to assist the disease diagnosis process. The ideas of this work are inspired by the way of human doctor thinking. On one hand, the reasoning process in human brain is almost based on the graph extracted from experiences \cite{zhou2018}. On the other hand, demographic attributes of a patient are usually knowable for doctors and taken into account when diagnosing diseases.

Two public disease diagnosis dialogue datasets are used to evaluate the proposed dialogue system. Experimental results demonstrate that the proposed dialogue system outperforms the existing state-of-the-art methods by modelling the constructed disease-symptom relation graph and demographic attributes of patients. Besides, our method can complete the diagnosis task with less dialogue turns and possesses better distinguishing capability on diseases with similar symptoms, which means better user experience and higher competitiveness in real-world applications.

In summary, this paper makes the following contributions:

\begin{itemize}
\item A novel graph based dialogue system training via reinforcement Learning (RL) is proposed. To the best of our knowledge, this is the first study to integrate the Graph Neural Network\footnote{GNNs are a family of neural networks designed to deal graph-structured data. The GCN used in this work is a type of GNN.} with RL based dialogue systems.
\item This work depicts the disease-symptom relation in the form of a graph and incorporates it into the disease diagnosis process by extending GCN to model the bidirectional graph. In this way, our method could better capture the symptom-disease relation and thus requires less turns to complete tasks.
\item The proposed dialogue system can be aware of demographic features of a patient. Experimental results reveal that demographic features play an important role in the disease diagnosis.
\end{itemize}

**Related Work**

Three works are much related to this paper, in which Deep Q-network (DQN) is applied for automatic diagnosis. \citet{kao2018} regarded the symptom checking as sequential decision problem and utilized hierarchical DQN to solve it. \citet{wei2018} proposed a disease diagnosis dialogue dataset and applied the DQN for disease diagnosis. The two works are mainly based on data-driven methods. \citet{wu2019} raised a Knowledge-routed Deep Q-network (KR-DQN) with constraints for diseases and symptoms relation which can reduce the inquiries of illogical or repeated

\footnote{1} Dialogue management is the central controller of a dialogue system, and it decides which action to take in response to the user.
symptoms. But KR-DQN highly rely on statistical features and may be still insufficient in the utilization of medical knowledge. Besides, previous work pays less attention on demographic attributes of patients. Unlike the above models, we construct a symptom-disease relation graph based on clinical dialogues, and propose BG-DQN that can learn the embeddings of symptoms and diseases in the graph and utilizes the demographic attributes of patients.

There has been a lot of works that apply reinforcement learning (RL) to dialogue systems. Cuayahuitl, Keizer, and Lemon (2015) applied deep RL to strategic dialogue management, experimental results demonstrate this approach outperformed several baselines, including random, rule-based, and supervised-based approaches. To reduce the accumulated errors, Li et al. (2017) constructed an end-to-end learning framework for task-oriented dialogue systems, they trained all portions of the dialogue system by DRL in an end-to-end manner. In addition, domain knowledge is important for dialogue systems to achieve specific goals. Eric et al. (2017) regarded the smooth docking between the system and the knowledge base as a key issue and they addressed this issue by putting forward an end-to-end model with a key-value retrieval mechanism. Madotto, Wu, and Fung (2018) raised the memory-to-sequence (Mem2Seq) which is an end-to-end neural generative model. They introduced the multi-hop attention mechanism to copy words directly from dialogue history or knowledge base. Considering the powerful expression ability of graph structure, we describe the medical knowledge in the form graph, and introduce the GCN to make the symptom-disease relation graph collaborate with the Deep Q-network (DQN) (Mnih et al., 2015).

Method

Overview

The overview of the proposed graph based and patient demographic attributes aware dialogue system is illustrated in Figure 1. The proposed dialogue system consists of three components: natural language understanding component (NLU), dialogue manager (DM) and natural language generation component (NLG). Given an utterance from a user, NLU detects the user intent and fills slots to represent the user intent. DM is the brain of a dialogue system, it decides which symptom to inquiry or makes a diagnosis. NLG converts system actions into natural language. The focus of this work is the DM. Inspired by the way of human doctor thinking, we construct a disease-symptom relation graph and present a new bidirectional graph based deep Q-network (BG-DQN) which could also incorporate demographic attributes of a patient for DM. NLU and NLG components are implemented with template-based methods. The following subsections will describe the construction of the symptom-disease relation graph and the BG-DQN for DM in detail.

Construction of Symptom-Disease Relation Graph

Given a disease diagnosis dialogue corpus, diseases and symptoms in the corpus are taken as nodes in the graph. There are two types of edges in our symptom-disease rela-
Figure 2: A small example of the symptom-disease relation graph, which is a weighted bidirectional graph. Blue nodes represent diseases and orange nodes represent symptoms. Edges only exist between diseases and symptoms. The number above an edge represent the edge weight.

The decision making processes in the DM is often cast as a Markov Decision Process (MDP) (Young et al., 2013) and can be trained via reinforcement learning (RL). Deep Q-network (DQN) (Mnih et al., 2015) is a classical RL methods, which combines RL with deep learning. This subsection introduces a novel DQN that can model the graph data and a patient’s demographic attributes to obtain more reasonable actions (see the right part in Figure 1 for an illustration).

In this work, the dialogue system action space size $n = \text{num\_greeting} + M + N$, where $\text{num\_greeting}$ denotes the number of greeting action, $M$ is the number of optional diseases and $N$ is the number of optional symptoms. The BG-DQN takes dialogue state $s$, patient demographic attributes $p$ and the symptom-disease relation graph.
graph $G$ as inputs and outputs the $a_r \in \mathbb{R}^n$ that contains the Q-values (also known as action-value) of optional actions:

$$a_r = Q(s, p, G|\theta),$$

where $\theta$ is the parameter of the proposed BG-DQN. The Q-value of an action means the expected accumulated reward from that state. The dialogue state $s$ contains the one-hot representation of the previous action of both dialogue system and user, known symptoms and the current turn count. The patient demographic attributes $p$ contains the one-hot representation of each attribute. Multi-Layer Perceptron (MLP) is employed to obtain a hidden representation $s_h$ by taking the concatenation of the representations of state $s$ and patient demographic attributes as input. The structure of the MLP is a neural network with three layers.

Motived by the convincing performance of the Graph Convolutional Network (GCN) on the graph data (Hamaguchi et al., 2017; Hamilton, Ying, and Leskovec, 2017), we introduce it to learn the embeddings of diseases and symptoms in the relation graph. Formally, let $G = (V, E)$ denote our symptom-disease relation graph, with $V$ (|V| = $n$, the greeting actions serve as separate nodes) and $E$ being the sets of nodes and edges, respectively. $X \in \mathbb{R}^{n \times d}$ is the feature matrix, each row $x_v \in \mathbb{R}^d$ is the feature vector for the node $v$, where $d$ is the dimension of feature vectors. $X$ is simply set as an identity matrix which means every disease or symptom is represented by a one-hot vector.

Let $A \in \mathbb{R}^{n \times n}$ be the adjacency matrix of $G$, where $A_{ij}$ equals the edge weight of the edge going from node $i$ to node $j$. If there is no edge between node $i$ and node $j$, then $A_{ij}$ is zero. $D \in \mathbb{R}^{n \times n}$ is used to denote the degree matrix of $G$, where $D_{ii} = \sum_j A_{ij}$. For extending GCN to model a bidirectional graph, we divide the symptom-disease relation graph into two undirected graph $G_1$ and $G_2$. The two graphs have the same attributes except the adjacency matrix. The edge weights of $G_1$ are $P(dis|sym)$, and the edge weights of $G_2$ are $P(sym|dis)$. This work utilizes a one-layer GCN, the k-dimensional node feature is computed as

$$H = \sigma(\tilde{A}_1 X W_1) + \sigma(\tilde{A}_2 X W_2),$$

where $\tilde{A}_1 = D_1^{-\frac{1}{2}} A_1 D_1^{-\frac{1}{2}}, \tilde{A}_2 = D_2^{-\frac{1}{2}} A_2 D_2^{-\frac{1}{2}}, W_1 \in \mathbb{R}^{d \times k}, W_2 \in \mathbb{R}^{d \times k}$ are trainable weight matrices and $\sigma$ is a nonlinear function (e.g., ReLU). $H \in \mathbb{R}^{n \times k}$ consists of embeddings of $n$ optional actions.

Then we obtain Q-values of candidate actions by computing the inner product between $H$ and $s_h$:

$$a_r = H \cdot s_h^\top.$$

Finally, the DM will select the action with the largest Q-value as the next action.

Following Mnih et al. (2015), two important tricks for training DQN, target network and experience replay are applied in this work. The DM’s experience $e_t(s_t, a_t, r_t, s_{t+1})$ at each time-step $t$ is stored in an experience replay buffer. Let $y$ denote the expected Q-value of taking an action $a$ under state $s$, according to the Bellman equation (Bellman and Dreyfus, 2015):

$$y = r + \gamma \max_{a'} Q(s', a'|\theta_{\text{target}}),$$
where $r$ denotes the reward after taking action $a$, the state $s$ transfers to $s'$ after taking the action $a$. $\theta'$ denotes the parameters of the target network, which are updated merely every $C \in \mathbb{N}$ iterations with the assignment $\theta' = \theta$ and $\gamma$ is a discount rate. This work uses the Huber loss function [Huber [1964]]:

$$L = \begin{cases} 
\frac{1}{2} (y - Q(s, a|\theta))^2, & |y - Q(s, a|\theta)| \leq \alpha \\
\alpha(|y - Q(s, a|\theta)| - \frac{1}{2}\alpha), & |y - Q(s, a|\theta)| > \alpha 
\end{cases}$$

(5)

where $\alpha \in \mathbb{R}^+$ controls the transition between two functions. Besides, we use $\epsilon$-greedy exploration policy in training phase. It chooses an action randomly with probability $\epsilon$ and takes the action given by $\text{argmax}_a Q(s, a|\theta)$ with probability $1 - \epsilon$.

**Empirical study**

**Dataset**

**MZ dataset**

The MZ dataset [Wei et al., 2018] was collected from the Baidu Muzhi Doctor website. This dataset contains 710 dialogue goals that involve 4 types of diseases (infantile diarrhea, children functional dyspepsia, upper respiratory infection and children’s bronchitis) and 66 types of symptoms. Each dialogue goal contains the actual result of diagnosis, the symptoms in the patient’s self-report, and the symptoms obtained by conversing with the patient. The sizes of the training set and test set are 568 and 142, respectively. For the MZ dataset, the demographic attribute is the age of patients, which has two types of values: child and adult.

**DX dataset**

The DX dataset [Xu et al., 2019] was collected from an online health-care website (dxy.com). It contains 527 real medical diagnosis dialogues. The DX dataset covers five diseases (pneumonia, allergic rhinitis, upper respiratory infection, diarrhea, and hand-foot-mouth disease) and 41 symptoms. As [Xu et al., 2019], 423 dialogues are selected for training models, and the remaining 104 dialogues are regarded as the test set. The demographic attribute in this dataset is the age of patients, which has two types of values: child and adult.

**Experimental Configuration**

**Deployment Details**

This work employs the proposed dialogue system with PyTorch and PyTorch Geometric [Fey and Lenssen, 2019]. Parameter settings are as follows: the discount rate $\gamma$ in Equation 4 is set to 0.9 and the $\epsilon$ of the $\epsilon$-greedy exploration policy is 0.1. $\alpha$ in Equation 3

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3In reinforcement learning setting, the agent will obtains an immediate reward $r \in \mathbb{R}$ after taking the action $a$. The setting of reward value is introduced in the Deployment Details section.
is set to 5. The maximum number of dialogue turns is set to 22, the rewards for successful and failed diagnoses are set to +44 and -22, respectively. The size of experience replay buffer is set to 10000, the batch size is set to 32 and the learning rate is 0.01. The stochastic gradient descent (SGD) algorithm is used as the optimizer. The model is trained for 800 epochs.

A user simulator that mimics human behaviors is required to train the proposed dialogue system. The user simulator extracts a user goal from the dataset to start the diagnostic process. The user simulator has two types of action: request and notification. The request action is to request the system for diagnosis. The notification action is to answer the inquiry of a certain symptom, which consists of three answers, True, False, and Not sure. The dialogue will be terminated and judged as a successful diagnosis if the dialogue system informs a correct disease, and when the system informs a wrong disease or the current dialogue reaches the maximum number of turns, it will be judged as a failed diagnosis.

Baseline Methods

Several methods were selected as baseline methods to validate the performance of the proposed dialogue system. “SVM-em” means the method using Support Vector Machine (SVM) (Cortes and Vapnik, 1995) to predict diseases by taking explicit symptoms as inputs. “SVM-em&im” means the SVM trained with both explicit and implicit symptoms. “Basic DQN” means the method employing DQN for disease diagnosis dialogue systems, which is proposed in (Wei et al., 2018). Sequicity (Lei et al., 2018) is an outstanding end-to-end task-oriented dialogue system framework. KR-DS (Xu et al., 2019) considers conditional probabilities between symptoms and diseases, and conditional probabilities between actions to reach reasonable decisions. “SVM-em” and “SVM-em&im” are only trained for MZ dataset and Sequicity is only trained for DX dataset. This is because MZ dataset only contains user-goals and thus can not be trained with an end-to-end dialogue system; DX dataset that reserves original conversation data can train an end-to-end dialogue system.

Overall Results

| Method         | Accuracy | Ave turns |
|----------------|----------|-----------|
| SVM-ex         | 0.59     | -         |
| SVM-ex&im      | 0.71     | -         |
| Basic DQN      | 0.65     | 5.11      |
| KR-DS          | 0.73     | 3.18      |
| Our method     | 0.79     | 2.86      |

Table 2: Performance comparison on the MZ dataset.

The performance comparisons of different methods on MZ and DX datasets are shown in Tables 2 and 3, respectively. Two phenomena can be observed from Tables 2 and 3.
Table 3: Performance comparison on the DX dataset.

| Method                    | Accuracy | Ave turns |
|---------------------------|----------|-----------|
| Sequicity (Lei et al., 2018) | 0.285    | 3.40      |
| Basic DQN (Wei et al., 2018) | 0.731    | 3.92      |
| KR-DS (Xu et al., 2019)   | 0.740    | 3.36      |
| **Our method**            | **0.769**| **2.88**  |

Figure 3: (a) depicts the graph-based reasoning process. (b) shows conversations from different methods. Conversations from our method are annotated and grounded with a part in (a). Specifically, except dyspepsia and diarrhea, bronchitis might cause the symptom of vomiting. Therefore, our method first rules out the possibility of bronchitis by asking if the patient has a fever (left part in (a)). Then, to discriminate between dyspepsia and diarrhea, our method inquires the urine volume of the patient since decreased urine volume is not a typical symptom of dyspepsia but a typical symptom of diarrhea (right part in (a)).
First, our method achieves the highest diagnostic accuracy. It is worthy of note that our method beats state-of-the-art methods by more than 6% in MZ dataset. These results confirm the effectiveness of the proposed dialogue system for disease diagnosis. We can also observe that the performance improvement for DX dataset is comparatively slight. This may because the size of DX dataset is relatively small, which may restrict the performance of GCN. Second, our method completes the task with less turns. In fact, baseline methods tend to ask symptoms having low degree of distinction, and thus increase dialogue turns. Figure 3 presents examples from the basic DQN, KR-DS and our method. One can observe that DQN asks some irrelevant symptoms. KR-DS performs better but the symptoms it asked have poor discrimination. Our method can inquire the discriminative symptoms for diseases with similar symptoms and completes the task with less turns. This phenomenon demonstrates our method could capture the relation between symptom and disease better. We attribute this advantage to the utilization of the symptom-disease relation graph.

### Ablation Study

| Method                        | Accuracy | Ave turns |
|-------------------------------|----------|-----------|
| Basic DQN (Wei et al., 2018)  | 0.65     | 5.11      |
| DQN + knowledge branch (Xu et al., 2019) | 0.68 | 3.26 |
| Our method                    | 0.792    | 2.86      |
| w/o demographic               | 0.691    | 2.52      |
| undirected RG $G_1$           | 0.683    | 2.65      |
| undirected RG $G_2$           | 0.667    | 2.94      |
| w/o RG                        | 0.733    | 3.21      |

Table 4: Ablation study on the MZ dataset. The second blocks in two subtables are the results of degraded versions of the proposed dialogue system.

The results of ablation study are shown in Tables 4 and 5. “DQN+knowledge branch” is a degraded version of KR-DS that only considers the knowledge-routed graph branch. “w/o demographic” is the proposed dialogue system without encoding demographic attributes of patients. “undirected RG $G_1$” and “undirected RG $G_2$” are degraded versions of “w/o demographic”, they use undirected graphs $G_1$ and $G_2$ as the symptom-disease relation graph, respectively. “w/o RG” is our dialogue system without encoding the symptom-disease relation graph. From Tables 4 and 5 we have the following observations.  

First, the effectiveness of modelling the disease-symptom relation graph, because removing the modelling of the symptom-disease relation graph decreases the diagnostic accuracies consistently. In addition, “w/o demographic” outperforms the “DQN + knowledge branch”, which implies that the features about medical knowledge learnt by our method is more powerful than the statistical features. More importantly, we can find that the modelling of the symptom-disease relation graph contributes to the re-
| Method                                  | Accuracy | Ave turns |
|----------------------------------------|----------|----------|
| Basic DQN (Wei et al., 2018)           | 0.731    | 3.92     |
| DQN + knowledge branch                 | 0.731    | 3.56     |
| Our method                             | **0.769**| **2.88** |
| w/o demographic                        | 0.752    | 2.91     |
| undirected RG G_1                      | 0.741    | 3.04     |
| undirected RG G_2                      | 0.734    | 2.97     |
| w/o RG                                 | 0.745    | 3.24     |

Table 5: Ablation study on the DX dataset. The second blocks in two subtables are the results of degraded versions of the proposed dialogue system.

duction of dialogue turns. If we assume that the comprehension of symptom-disease relation could help the dialogue system to complete disease diagnosis with less turns, this result could demonstrate that incorporating the relation graph is key to promote the comprehension of symptom-disease relation.

Second, bidirectional symptom-disease graph can bring more information than undirected graphs. As mentioned above, the edge weights of G_1 are P(dis|sym), and the edge weights of G_2 are P(sym|dis). The performance of “undirected RG G_1” is slightly better than “undirected RG G_2”. It indicates that the P(dis|sym) may provide more information in disease diagnoses.

Finally, as shown in Tables 4 and 5, “w/o RG” obviously outperforms “basic DQN”. This proves that the demographic attribute of a patient plays a significant role in disease diagnosis and this information is effectively used by our model.

**Qualitative Analysis**

Figures 4-7 visualize detail results of KR-DS and our method by confusion matrices. From these figures, one can see that KR-DS is difficult to distinguish diseases with similar symptoms. For example, KR-DS misdiagnose many dyspepsia cases as diarrhea, upper respiratory infection cases as bronchitis. However, the proposed dialogue system could better distinguish between diseases with similar symptoms. Therefore, our method may have a higher clinical value.
| Predicted label | True label |
|----------------|------------|
| **Upper respiratory infection** | 0.50 0.47 0.00 0.03 |
| Bronchitis | 0.03 0.97 0.00 0.00 |
| Dyspepsia | 0.00 0.00 0.48 0.52 |
| Infantile diarrhea | 0.00 0.04 0.04 0.91 |

Figure 4: Normalized confusion matrix for the result of KR-DS on the MZ dataset.

| Predicted label | True label |
|----------------|------------|
| **Upper respiratory infection** | 1.00 0.00 0.00 0.00 |
| Bronchitis | 0.00 0.91 0.09 0.00 |
| Dyspepsia | 0.00 0.06 0.65 0.29 |
| Infantile diarrhea | 0.00 0.00 0.28 0.72 |

Figure 5: Normalized confusion matrix for the result of our method on the MZ dataset.
**Figure 6:** Normalized confusion matrix for the result of KR-DS on the DX dataset.

| True label                  | Upper respiratory infection | Children hand-foot-mouth disease | Pediatric diarrhea | Pneumonia | Allergic rhinitis |
|-----------------------------|----------------------------|----------------------------------|--------------------|-----------|------------------|
| Upper respiratory infection | 0.46                       | 0.00                             | 0.00               | 0.21      | 0.33             |
| Children hand-foot-mouth disease | 0.05                      | 0.90                             | 0.00               | 0.00      | 0.05             |
| Pediatric diarrhea          | 0.00                       | 0.00                             | 0.55               | 0.00      | 0.05             |
| Pneumonia                   | 0.25                       | 0.05                             | 0.00               | 0.50      | 0.20             |
| Allergic rhinitis           | 0.05                       | 0.00                             | 0.00               | 0.05      | 0.90             |

**Figure 7:** Normalized confusion matrix for the result of our method on the DX dataset.

| True label                  | Upper respiratory infection | Children hand-foot-mouth disease | Pediatric diarrhea | Pneumonia | Allergic rhinitis |
|-----------------------------|----------------------------|----------------------------------|--------------------|-----------|------------------|
| Upper respiratory infection | 0.75                       | 0.00                             | 0.00               | 0.17      | 0.08             |
| Children hand-foot-mouth disease | 0.00                      | 0.95                             | 0.05               | 0.00      | 0.00             |
| Pediatric diarrhea          | 0.00                       | 0.05                             | 0.55               | 0.00      | 0.00             |
| Pneumonia                   | 0.45                       | 0.00                             | 0.00               | 0.50      | 0.05             |
| Allergic rhinitis           | 0.20                       | 0.00                             | 0.00               | 0.10      | 0.70             |
Conclusion

This paper presents a novel graph based and demographic attributes aware dialogue system for disease diagnosis. Instead of relying on statistical features, we build a weighted bidirectional graph to describe the symptom-disease relation, and a bidirectional graph based deep Q-network (BG-DQN) is proposed for dialogue management. To the best of our knowledge, this work is the first investigation to incorporate the GNN into RL based dialogue systems. In addition, the proposed dialogue system takes into consideration the demographic attributes of patients when inquiring symptoms and making a diagnosis. Experiments conducted on two datasets confirm the effectiveness of the proposed dialogue system by utilizing the symptom-disease relation and demographic attributes. Besides, experiments demonstrate that the proposed dialogue system can complete the diagnosis task with less dialogue turns and achieve better distinguishing capability on diseases with similar symptoms, which means our method may be more competitive in clinical applications. In the future, we would like further explore the potential of GNNs in the research of medical diagnosis. We would also like to incorporate more information of patients into disease diagnosis agents, such as the heredity and medical history of patients.

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