Efficient Symptom Inquiring and Diagnosis via Adaptive Alignment of Reinforcement Learning and Classification

Hongyi Yuan\textsuperscript{1, 2}, Sheng Yu\textsuperscript{1, 2*},
\textsuperscript{1}Center for Statistical Science, Tsinghua University, China
\textsuperscript{2}Department of Industrial Engineering, Tsinghua University, China
yuanhy20@mails.tsinghua.edu.cn, syu@tsinghua.edu.cn

Abstract
The medical automatic diagnosis system aims to imitate human doctors in the real diagnostic process. This task is formulated as a sequential decision-making problem with symptom inquiring and disease diagnosis. In recent years, many researchers have used reinforcement learning methods to handle this task. However, most recent works neglected to distinguish the symptom inquiring and disease diagnosing actions and mixed them into one action space. This results in the unsatisfactory performance of reinforcement learning methods on this task. Moreover, there is a lack of a public evaluation dataset that contains various diseases and corresponding information. To address these issues, we first propose a novel method for medical automatic diagnosis with symptom inquiring and disease diagnosing formulated as a reinforcement learning task and a classification task, respectively. We also propose a robust and adaptive method to align the two tasks using distribution entropies as media. Then, we create a new dataset extracted from the MedlinePlus knowledge base. The dataset contains more diseases and more complete symptom information. The simulated patients for experiments are more realistic. Experimental evaluation results show that our method outperforms three recent state-of-the-art methods on different datasets by achieving higher medical diagnosis accuracies with few inquiring turns.

1 Introduction
Medical automatic diagnosis (MAD) or dialogue systems for medical automatic diagnosis (DSMAD) is one of the main areas of research in the application of artificial intelligence in healthcare. An MAD system aims to imitate a human doctor and interact with the patients, collecting their symptom information and giving confident diagnoses. Currently, many people perform online searches for self-diagnosis; however, many results obtained in these searches may be inaccurate or irrelevant. Moreover, in the real clinical encounters, due to limited healthcare resources, diagnosis accuracy can be low in many rural areas. Therefore, a well-developed MAD system has great potential in supporting clinical diagnostic decisions, increasing diagnosis accuracies, and helping with the patients’ self-diagnosis.

The MAD process is formulated as a sequential decision-making problem, mainly including three steps \cite{Ledley and Lusted, 1991}: (1) A patient reports initial symptoms or discomforts, which are referred to as self-reports; (2) The system, in the role of the doctor, asks the symptom-related questions to the patients or assigns medical examinations for the patients such as laboratory tests or diagnostic procedures (e.g., X-ray); (3) When the system collects enough information, it gives a final diagnosis of the disease. With the promising capacity of reinforcement learning (RL) in solving sequential decision-making problems in various fields, researchers are increasingly interested in applying RL to MAD, formulating the whole diagnostic process as a Markov decision process (MDP) \cite{Yu et al., 2020}. For instance, many previous works developed such systems and focused on online self-diagnosis \cite{Tang et al., 2016; Peng et al., 2018; Kao et al., 2018; Liao et al., 2020}. These MAD systems were referred to as symptom checkers.

While more information is always beneficial for diagnosis accuracy, asking too many questions lowers the patients’ experience, and taking too many examinations raises the medical costs. The goal of MAD is not only to achieve high diagnosis accuracy but also to reduce the costs of collecting symptom information. The diagnostic procedure involves various diseases, symptoms and medical examinations, which results in large decision space. Moreover, each patient only has a few symptoms, and the available information is therefore sparse for diagnostic encounters. These features of MAD set obstacles to RL methods to learn the logic of diagnostic reasoning.

Many recent works combine symptom-inquiring and diagnosis actions into a common action space (e.g., \cite{Peng et al., 2018; Xu et al., 2019}). This combination neglects the difference between these two kinds of actions. Symptom-inquiring actions aim to obtain informative symptoms with as few steps (or other kinds of costs) as possible, while the diagnosis action is one-step and aims to obtain an accurate diagnosis at the end of each diagnostic process. The former actions may fall into the RL framework, while the latter is naturally a classification problem. Forcing diagnosis as part of MDP increases
the search space for the agent, limiting not only the diagnosis accuracy but also the symptom inquiring efficiency. There is few work that treat the two kinds of actions separately [Lin et al., 2020; Lin et al., 2021a]. They design different mechanisms to incorporate two actions. However, their methods are only tested on dataset containing few disease. Their methods have not been evaluated on more complicated situations with various diseases and symptoms.

In our work, we handle two kinds of actions separately, performing the symptom inquiring part using RL and treating the diagnosis part as a classification task. We design a subtle approach to incorporate two models. In real diagnostic processes, a human doctor will arrive at a conclusion when the information collected provides enough confidence and rules out other possibilities. In information theory, entropy is a measurement of uncertainty. Therefore, in our work, we monitor the entropy given by a disease classifier. When the entropy is lower than a threshold, the symptom inquiring process will be terminated, and a diagnosis will be given. However, the entropy threshold is difficult to determine given different disease distributions, and a poor choice of the threshold will result in unsatisfactory performance of the MAD system. To address this problem, we propose an adaptive approach for selecting a proper threshold.

The training of RL methods has to explore the diverse actions given various patients’ known symptom statuses, and it is unavailable to train RL methods on real patients or medical histories in consideration of safety and privacy. Thus, the previous works evaluate their methods on synthetic patients simulated by medical knowledge bases or medical dialogue histories. However, the shortage of previous works is that the existing datasets either contain few diseases or have incomplete symptom information. Thus, the simulated patients result in unrealistic conditions. Pertaining to this problem, we explore the public online medical knowledge bases and propose a new dataset for simulating more realistic patients. The proposed dataset contains various diseases and more complete symptom information.

The main contributions of this work are as follows:

• We publish a new disease dataset with corresponding symptoms and medical examinations to simulate synthetic patients. Compared to other widely used datasets, the proposed dataset contains more comprehensive disease information.

• We propose a novel MAD method that incorporates an RL agent and a classifier. We design a composite reward incorporating disease classification entropies to incentivize informative symptom inquiries.

• Different from previous work [Xia et al., 2020] using fixed thresholds, we propose an efficient method to adaptively determine the appropriate entropy threshold. The threshold changes along with the training of the RL agent and the classifier dynamically.

Through extensive experiments, we show the efficiency and superior performance of the proposed method compared to other MAD methods. We also demonstrate the robustness of our threshold selection method and effectiveness of our reward design.

2 Related Works

Automatic medical diagnosis or clinical diagnosis inference has drawn much attention in healthcare research. Previous studies mostly utilized structured or unstructured medical data to develop a disease classification system. A large variety of machine learning or deep learning methods have been used to build such systems [Kononenko, 1993; Kononenko, 2001; Lin, 2009; Mullenbach et al., 2018]. For example, [Choi et al., 2016] and [Choi et al., 2017] developed recurrent neural network (RNN)-based methods to perform differential diagnosis given the patients’ medical histories and current conditions. [Hosseini et al., 2018] used graph neural networks for disease diagnosis based on medical histories and knowledge graphs. Some recent works were inspired by TREC-CDS tasks. They applied deep RL to retrieve medical disease concepts from clinical narratives with external knowledge bases (e.g., Wikipedia) [Ling et al., 2017a; Ling et al., 2017b]. However, these methods can only make diagnosis given rich medical histories. In real clinical settings, doctors may meet patients with no clinical history and very limited initial symptom information. These methods will fail in such scenarios.

Previous studies have also developed dialogue systems to interact with patients and give more personalized medical instructions [Li et al., 2021; Lin et al., 2021b]. However, these methods focused on natural language processing and could only provide an one-step dialogue interaction with the patients based on real dialogue histories. Our work does not aim to generate comprehensive dialogues or give instructions only once, but aims to deal with the inner decision-making logic of real diagnostic processes to achieve higher diagnosis accuracies with less symptom inquiring costs.

Similar to our task, some works developed symptom checkers for online healthcare services by RL. [Tang et al., 2016] divided the diseases and related symptoms into 11 anatomical parts and applied deep Q-learning (DQN) methods on each part to inquire about symptoms. [Wei et al., 2018] also used DQN methods to inference diagnosis. [Kao et al., 2018] and [Liao et al., 2020] used hierarchical RL: a master agent is assigned to decide which anatomical part agent of the lower hierarchy to inquire about symptoms and when to give the diagnosis. [Kao et al., 2018] also added contextual information of a patient (e.g., sex and age) to enhance the diagnosis accuracy through a Bayesian approach. Splitting diseases into several anatomical parts can reduce the task complexity. With appropriate joint policy training, the above works outperform naive DQN methods. [Xu et al., 2019] proposed a method called KR-DQN that embedded entity relations into a DQN agent. A trainable correlation matrix was added to the agent outputs to help inquire about related symptoms and give diagnoses. [Peng et al., 2018] proposed a method based on the policy gradient method, called REFUEL. They designed auxiliary rewards and used a dual neural network architecture rebuilding the sparse features of the patients to help discover the positive symptoms more quickly. All of the above works combined symptom inquiring and disease diagnosis into the same action space. In addition, they ignored the fact that negative symptoms
also contain rich information and are critical in real clinical decision-making. [Xia et al., 2020] and [Lin et al., 2020; Lin et al., 2021a] separated the two kinds of actions. They used RL methods to inquire about symptoms and employed another neural network to give diagnoses given the current symptom information. [Xia et al., 2020] used a generative adversarial network [Goodfellow et al., 2014] framework to balance symptom inquiring and disease diagnosis, and also designed entropy-based rewards to guide the agent to inquire informative and rational questions. Their method gives the diagnosis when the maximum inquiring step length is reached or the entropy of the disease distribution is smaller than a fixed threshold; however, it may be difficult to choose such a threshold for different disease sets. [Lin et al., 2021a] proposed a method called INS-DS comprising two cooperative modules: a symptom inquiry module and an introspective module. The introspective module intervenes in the potential responses of the inquiry and decides to give the diagnosis if the diagnoses of these interventions remain unchanged. [Lin et al., 2020] designed a criterion that the model gives the diagnosis when the probability of the preferred disease is beyond the upper bound of the 6σ confidence interval of the other diseases’ probabilities. The confidence interval is estimated by bootstrapping the classifiers. However, the above three works only tested their method on datasets with few diseases, while there are various diseases and symptoms in real clinical settings.

Pertaining to this diagnostic decision-making task, a more recent work proposed a non-RL competitive bipartite framework, called FIT, using a multi-modal variational autoencoder model and a two-step sampling strategy for disease prediction [He et al., 2021]. They reported state-of-the-art results on different datasets.

3 Method

Generally, a DSMAD or MAD system refers to a system that includes two parts: 1) the natural language generation (NLG) part that parses and analyses the input language of a patient and outputs the inquiry question to the patient; 2) the dialogue management (DM) part that decides which symptoms to ask about and when to give the diagnosis according to the current information of the patient. Our work focuses on DM because extracting symptoms from the patient’s responses and generating questions are handled by natural language processing or templates and are not part of clinical decision-making.

Figure 1 illustrates the architecture overview of our proposed model, and the pseudo-code is shown in Algorithm 1. The model consists of a symptom-inquiring agent, a disease-diagnosing module and a stopping criterion. The symptom-inquiring agent is a policy network inquiring about the patient’s symptoms already known by the model; the disease-diagnosing module is a neural network classifier that outputs a disease classification given the currently known symptoms; and the stopping criterion is used to decide when to stop inquiring about symptoms and to give a diagnosis. At each dialogue turn, the disease-diagnosing module receives the current patient’s symptom information vector and predicts the current disease distribution. Then, the entropy of the distribution is calculated to determine whether to give the diagnosis. When the entropy is below a dynamic threshold, which means we already have enough information for accurate diagnosis, then the symptom-inquiring agent stops asking for more symptoms and a diagnosis will be given by the classifier. If a correct diagnosis is given, the dynamic threshold is updated by the entropy of the final disease distribution.

3.1 Notations

We denote the number of all symptoms as $N$ and the number of all diseases as $M$. We design our symptom-inquiring agent based on an RL framework. The symptom-inquiring part is a finite-horizon MDP with a state space $S$, an action space $A$, and a policy $\pi$. Each state $s \in S$ is a sparse vector of length $N$, and each entry of the vector indicates the status of the corresponding symptom. The status of a symptom can be positive, negative, or unknown, represented by 1, −1, and 0, respectively. Each action $a \in A$ is an integer that represents the symptom to inquire about. The size of the action space is $N$. The disease-diagnosing part is formulated as a classification task. The neural network classifier $f_\psi$ receives the current patient’s state $s$ as input and outputs a disease distribution denoted as $p_\psi(d|s)$ and $p_\psi(d|s) = f_\psi(s)$, where $d$ denotes the diseases. Then, the entropy $H_\psi(s)$ of $p_\psi(d|s)$ is calculated to check the stopping criterion, formulate the reward for the symptom-inquiring agent and update the dynamic threshold.

### Algorithm 1 Our proposed method

**Input**: Disease knowledge base $\mathcal{D}$, Initial threshold $K_{\text{init}}$  
**Output**: Optimal policy $\pi_{\phi^*,\psi}$, classifier $f_{\phi^*}$, threshold $K^*$

1. Initialize $\pi_{\phi^*}$ and $f_\psi$ with random weights $\phi$ and $\psi$.
2. Initialize the stopping threshold $K = K_{\text{init}}$.  
3. Generate synthetic patients using $D$.
4. repeat
5. Sample a patient and generate initial state vector $s_0$.
6. Calculate the initial entropy $H_\psi(s_0)$.
7. while $H_\psi(s_t) > K$ and $t \leq T$ do
8. Inquire a symptom $a_t \sim \pi_{\phi}(s_{t-1})$.
9. Interact with the patient and obtain the next state $s_t$ and reward $r_1^t$.
10. Calculate the disease distribution entropy $H_\psi(s_t)$.
11. Calculate the entropy difference reward $r_2^t_H$.
12. Calculate the overall reward $r_t = \mu r_1^t + \nu r_2^t_H$.
13. Store a training sample $(s_{t-1}, a_t, r_t, d_t)$.
14. end while
15. Update the policy network parameter by Equation (1).
16. Update the classifier parameter by cross-entropy loss.
17. if give the correct diagnosis then
18. Update threshold by Equation (2).
19. end if
20. until End of epochs


3.2 Disease-Diagnosing Model

The disease-diagnosing model is an MLP classifier. Given the patient’s state $s_t$ at time step $t$, the state vector is fed to the classifier to generate the disease distribution. Then, the entropy of the disease distribution is calculated as follows:

$$H_\psi(s_t) = -\sum_{i=1}^M p_\psi(d_i|s_t) \log (p_\psi(d_i|s_t)).$$

If the entropy $H_\psi(s_t)$ is smaller than the threshold, then the model returns a diagnosis that has the highest probability. Otherwise, the symptom-inquiring agent inquires about symptoms to gather more information.

The MLP classifier is trained together with the RL agent in a supervised fashion. At each inquiry turn, the current state vector is paired with the true disease label to form a training sample $(s_t, d_t)$. Then, we train the classifier using these collected samples with cross-entropy loss. Thus, the classifier is accustomed to predicting the disease with partial symptom information.

3.3 Symptom-Inquiring Agent

The symptom-inquiring agent $\pi_\phi$ uses an MLP policy network. At time step $t$, the agent generates a symptom-inquiring action $a_t$ given the current patient’s state $s_t$. The objective of RL is to maximize the expected accumulated rewards $E_{\pi_\phi}[\sum_{t=0}^T \gamma^t r_t]$, where $\gamma$ is the discount factor. The agent is expected to inquire about the most valuable symptoms for obtaining an accurate diagnosis. We adopt the policy gradient method to optimize the network parameter $\phi$.

The symptom-inquiring agent ought to discover the patient’s symptoms and pose as few as possible queries because in real clinical encounters, asking about too many negative symptoms is a waste of time, and taking too many medical examinations is a waste of medical resources and brings additional cost and even physical harm to the patient. To address this issue, when the agent inquires about a symptom, a negative reward is assigned to the agent. If the inquired symptom is positive, then a positive reward is additionally added, while if it is negative, a smaller positive reward is given. In reality, a doctor will not ask about a known symptom, but without restrictions, the agent may inquire about the same symptom repeatedly. To avoid this phenomenon, no additional positive rewards are given if the agent inquires about a known symptom. The goal of collecting symptom information is to give confidence diagnoses. Thus, when our method gives a correct diagnosis, another additional positive reward is provided, while when the method gives an incorrect diagnosis or fails to diagnose within the maximum step length $T$, an additional negative reward is added. This part of the reward, denoted as $r_p$, is designed to incentivize the agent to inquire about positive symptoms, avoid repeated enquiries, and give correct diagnoses.

Inspired by [Xia et al., 2020], our work also introduces mutual information to improve the agents’ performance. In real-world diagnostic processes, doctors often inquire about informative and discriminative symptoms in order to identify the disease. These symptoms are not necessarily positive for a patient. Such a symptom can help rule out some candidate diseases. In information theory, entropy measures the level of information or uncertainty of a distribution. Ideally, the entropy given by the classifier will decrease with more symptoms known in the patient’s state vector. A more informative symptom is one that leads a larger decrease in the disease distribution entropy. To make the symptom-inquiring agent learn to inquire about more informative symptoms, we add the entropy difference as part of the training reward. The entropy difference reward is formulated as:

$$r_H = \max(\Delta H_\psi/H_\psi(s_0), 0).$$

$\Delta H_\psi$ is the entropy difference between two successive time steps to measure the information gain from the inquired symptom. The entropy difference is calculated as:

$$\Delta H_\psi = H_\psi(s_t) - H_\psi(s_{t+1}),$$

where $s_t$ is the current state vector and $s_{t+1}$ denotes the next state vector. $H_\psi(s_0)$ is the disease distribution entropy based on the patient’s initial self-reports. It serves as a normalizing term to make the entropy difference reward consistent across different patients because the entropy difference can vary from very large to small given different patients’ self-reports. As the diagnostic process progresses, the symptom information gradually becomes complete. The entropy should decrease monotonically, and the entropy difference should be uniformly greater than 0. While in practice, negative entropy
differences exist because the classifier is imperfect, particularly in the early training stage. Therefore, the reward takes the maximum value between the normalized entropy difference and 0.

Thus, the overall reward for training the symptom-inquiring agent is a weighted combination of \( r_p \) and \( r_H \):

\[
r = \mu r_p + \nu r_H,
\]

where \( \mu \) and \( \nu \) are the weights of the two kinds of rewards.

We also introduce an entropy regularization term

\[
H(\pi_\phi(a|s)) = -\sum_{i=1}^N \pi_\phi(a_i|s) \log(\pi_\phi(a_i|s))
\]

to the objective function to help the symptom-inquiring agent explore high-reward actions and escape from local optima at the beginning of the training stage. The parameter updating rule under the new objective is:

\[
\phi' = \phi + \alpha \left[ \frac{R(s, a)\nabla_\phi \pi_\phi(a|s)}{\pi_\phi(a|s)} + \beta \nabla_\phi H(\pi_\phi(a|s)) \right]
\]

where \( \alpha \) is the learning rate, \( \beta \) is a weight parameter and \( R(s, a) \) is the accumulated reward under state \( s \) and action \( a \).

### 3.4 Stopping Criterion

Intuitively, inquiring about symptoms should stop when the disease distribution entropy is lower than a threshold; however, the required threshold varies across different disease symptom datasets and is difficult to choose manually. To this end, our method proposes an adaptive approach to automatically find a proper threshold.

At the beginning of training, we randomly initialize a reasonable threshold. During each training episode, our method gives a diagnosis if the entropy is lower than the threshold or the preset max step \( T \) is reached. If a correct diagnosis is given, the disease distribution entropy is used to adjust the threshold according to the following equation:

\[
K' = K + (1 - \lambda)H_\phi(s_{\text{fin}}),
\]

where \( K \) is the dynamic threshold, \( s_{\text{fin}} \) denotes the final patients’ state vector, and \( \lambda \) is a Polyak parameter controlling the speed of updating the threshold. As the training progresses, the classifier becomes more accurate, and the output entropy will properly reflect the diagnosis confidence. With the above updating scheme, a proper threshold is automatically found to achieve the early stop of the symptom inquiring stage.

## 4 Experiments

### 4.1 Datasets

Due to the highly sensitive nature of medical data and strict laws on their use, it is difficult to access real-world datasets on patients’ symptoms, examinations, and diagnoses. Therefore, we evaluate our method using two medical knowledge sources, SymCat\(^1\) and MedlinePlus\(^2\), to generate synthetic patients. A simulated synthetic patient contains a disease and a set of relevant symptoms or medical examinations. We note that there are several early works (e.g., [Xia et al., 2020; Xu et al., 2019; Lin et al., 2021a]) that have evaluated their methods on two public medical dialogue datasets, namely the MuZhi Medical Dialogue Dataset [Wei et al., 2018] and the Dxy Medical Dialogue Dataset [Xu et al., 2019]. However, these two datasets only contain a small number of diseases (Dxy contains 5 diseases and MuZhi contains 4 diseases) and are not appropriate benchmarks for realistic patients simulations because the real clinical encounters are more complicated.

### 4.2 SymCat

We follow [Kao et al., 2018] and [Peng et al., 2018] in using the SymCat dataset to simulate patients. SymCat contains 801 diseases and 474 symptoms. For each disease in SymCat, there are corresponding symptoms, context information (e.g., gender, age) and their occurrence probability. The patient simulation procedure first uniformly samples a disease. Then, the symptoms are generated by performing a Bernoulli trial on each corresponding symptom using their individual probability, and one of the sampled symptoms is assigned to be the patient’s self-report. We also generate each patient’s context information, including sex and age. Ages are encoded into several binary values, each representing a non-overlapping range of ages. The sex and age ranges are generated using the probabilities in SymCat. The encoded context information is concatenated to the state vectors. To compare our method with other baselines, we randomly sample 200, 300, and 400 diseases to form 3 different disease sets. Furthermore, SymCat also provides disease categories. We extract the diseases belonging to the ‘Common Disease’ category to form another disease set. For each disease set, we sample \( 10^6 \), \( 10^5 \) and \( 10^5 \) synthetic patients for training, developing and testing. Under the above simulation settings, each synthetic patient has approximately 3 symptoms on average.

### 4.3 MedlinePlus

The symptom information in the SymCat dataset is incomplete. Some diseases in SymCat do not have enough symptom information. For example, ‘esophageal cancer’ only has superficial and ambiguous symptom descriptions such as ‘fatigue’ and ‘vomiting’, and the marginal probability of the symptoms is very low. This will result in an abnormal situation in which a synthetic patient with ‘esophageal cancer’ only has 1 or 2 uninformative symptoms. Moreover, the dataset has no disease-related medical examination information. Thus the patients simulated using SymCat are not sufficiently realistic for testing clinical MAD systems.

To generate more realistic patients, we propose a new dataset extracted from MedlinePlus. MedlinePlus is a public medical knowledge base that contains many disease-related articles. Each article contains subsections about symptoms and medical examinations. We used MedType [Vashishth et al., 2021] to identify symptom and medical examination entities from the articles, and manually checked the extracted entities. The resulting dataset has 618 diseases, 614 symptoms and 514 medical examinations. Each disease has approximately 12 related symptoms and 5 related medical examination sources.
We compare our method with three baselines, namely REFUEL, FIT [He et al., 2021a] and INS-DS [Lin et al., 2021a]. REFUEL is a state-of-the-art RL method on SymCat. FIT achieves state-of-the-art accuracies on synthetic patients simulated by different datasets. INS-DS is a recently proposed method that also splits the symptom-inquiring and disease-diagnosing actions and uses a different stopping criterion. INS-DS showed best performance on the Dxy and MuZhi datasets. However, these three previous works did not provide open source code. Thus, we implemented REFUEL and INS-DS according to the details described in their papers. FIT did not provide enough details for re-implementation. Therefore, we use the results reported in their paper for its performance.

A good MAD system should achieve high diagnosis accuracy and pose as few symptom inquiries as possible. Thus, we use diagnosis accuracy and inquiring turns to evaluate our method. We also report the match rate that was used by previous works as another evaluation metric. The match rate is the average inquired positive symptoms per turn and measures the ability of the method to hit a positive symptom. However, as explained previously, a high positive symptom match rate is a biased metric because negative symptoms may also be helpful by ruling out other potential diseases.

The results on the three metrics are shown in Tables 1, 2, 3. On different disease sets from SymCat, our method achieves the best accuracies, significantly outperforming other methods. Although the randomly selected 200, 300 and 400 disease sets are not exactly the same as those used in the FIT paper, our method surpasses FIT’s reported results by a large margin. REFUEL achieves the best match rate results, showing excellent capability in inquiring about positive symptoms because of its feature rebuilding trick. REFUEL collects more patients’ positive symptom information, but the method still faces obstacles in increasing the accuracies. As previously mentioned, combining symptom-inquiring and disease-diagnosing actions will enhance the difficulty in learning good behaviors of both action spaces. The agent may not learn the connection between two actions solely by maximizing pre-designed rewards, and the inquired positive symptoms may contain limited information for diagnosis. INS-DS achieves the minimum inquiring turns, but the method actually inquires neither positive nor informative symptoms, and its accuracies are mainly determined by the patients’ self-reports. The failure of INS-DS is most likely due to the inappropriate reward design that places too much emphasis on the importance of diagnosis actions and gives no penalty for repeated inquiries. This reward design may be only good for small disease sets. Another drawback of INS-DS lying in its stopping criterion is that the agent may inquire about an irrelevant symptom, and given the positive or negative state of the symptom, the classifier results in the same diagnosis. This circumstance may mislead the method to make a false diagnostic action; thus, IND-DS fails to complete the diagnostic process.

On MedlinePlus dataset, our method outperforms all baselines in diagnosis accuracy and match rates. INS-DS also achieves minimum inquiring turns but fails to acquire discriminative symptoms and only gives diagnoses based on the patients’ self-reports. Although REFUEL finds several positive symptoms, it fails to give diagnosis actions and keep inquiring symptoms until the maximum step. Because a patient
has many possible symptoms while possesses only one disease in the large combined action space of MedlinePlus, the agent can more easily gain positive rewards from inquiries than diagnosis. The penalty against reaching the maximum step is relatively small. Through this inappropriate reward design, REFUEL does not learn to give diagnosis based on symptom information. It takes a conservative policy to obtain rewards by only acquiring symptoms until the step limits.

Another advantage of our method is that our method converges quite rapidly. With the same number of simulated patients in each epoch, REFUEL requires 1000 epochs of training in the original REFUEL paper and our re-implementation, while our method only needs 100 epochs of training on SymCat and 200 epochs on MedlinePlus. Our method shows a higher training efficiency.

4.6 Ablation Studies of The Reward Design

In our method, we propose a composite reward for guiding our MAD model. To further demonstrate the effectiveness of our reward design, we conduct ablation studies to show the importance of two parts of the reward. We train our method with only reward \( r_p \) or \( r_H \) on three different disease sets: our proposed MedlinePlus disease set, 400 SymCat disease set and common SymCat disease set. We use the same training setting as above. The results are shown in Table 4. From the table, we can see that the performance of training with the composite reward is the best. This reward design guides the model to inquire both positive and informative symptoms and achieve high diagnosis accuracies.

4.7 Robustness of Adaptive Entropy Threshold

To further illustrate the robustness of our adaptive entropy threshold updating scheme, we conduct more experiments on the MedlinePlus dataset. A robust entropy threshold updating scheme is expected to maintain similar final values and diagnosis accuracies of the method with different starting values. In this experiment, we select different starting values of the entropy thresholds and repeat the experiment on the MedlinePlus dataset, keeping other training settings the same. We select 6 different starting values 0.3, 0.8, 1, 2, 3 and 4 and train each with the same training steps. In Figure 2 and 3, we present the entropy threshold and accuracy changing curves of the initial 10000 training steps. As shown in the figures, the entropy thresholds first increase and then gradually converge to the same value. The thresholds increase at the early training stage because the classifiers are not good enough and produce a relatively smooth disease distribution, resulting in high entropy. The dynamic threshold and accuracy changing curves of different starting values have basically the same trajectories. This shows that our threshold updating scheme is not sensitive to the selection of starting values and robustly finds the proper entropy threshold.

5 Conclusion

In this work, we propose a new MAD method that achieves higher accuracies with more efficient symptom inquiring. Our method treats the symptom-inquiring and disease-diagnosing actions separately and devises a robust mechanism to cooperate two actions adaptively through the entropies of disease distributions. Our reward design helps the model learn to inquire informative and discriminative symptoms to get high diagnosis accuracies. We also proposed a new dataset for simulating realistic patients. Our proposed dataset can serve as a better evaluating dataset, because it contains more comprehensive and complete information of diseases. Experimental evaluations on different datasets with multiple baseline methods confirm the superiority and validity of our proposed method that achieves accurate and efficient automatic medical diagnosis, requiring less training time.
References

[Choi et al., 2016] Edward Choi, Mohammad Taha Bahadori, Andy Schuetz, Walter F. Stewart, and Jimeng Sun. Doctor ai: Predicting clinical events via recurrent neural networks. In Machine learning for healthcare conference, pages 301–318. PMLR, 2016.

[Choi et al., 2017] Edward Choi, Mohammad Taha Bahadori, Joshua A. Kulas, Andy Schuetz, Walter F. Stewart, and Jimeng Sun. RETAIN: An Interpretable Predictive Model for Healthcare using Reverse Time Attention Mechanism. arXiv:1608.05745 [cs], February 2017. arXiv: 1608.05745.

[Goodfellow et al., 2014] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. Advances in neural information processing systems, 27, 2014.

[He et al., 2021] Weijie He, Xiaohao Mao, Chao Ma, Yu Huang, Jose Miguel Hernandez-Lobato, and Ting Chen. Fit: a fast and accurate framework for solving medical inquiring and diagnosing tasks, 2021.

[Hosseini et al., 2018] Anahita Hosseini, Ting Chen, Wenjun Wu, Yizhou Sun, and Majid Sarrafzadeh. HeteroMed: Heterogeneous Information Network for Medical Diagnosis. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management, pages 763–772, Toronto, Italy, October 2018. ACM.

[Kao et al., 2018] Hao-Cheng Kao, Kai-Fu Tang, and Edward Y. Chang. Context-aware symptom checking for disease diagnosis using hierarchical reinforcement learning. In AAAI, 2018.

[Kingma and Ba, 2017] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2017.

[Kononenko, 1993] Igor Kononenko. Inductive and Bayesian learning in medical diagnosis. Applied Artificial Intelligence an International Journal, 7(4):317–337, 1993. Publisher: Taylor & Francis.

[Kononenko, 2001] Igor Kononenko. Machine learning for medical diagnosis: history, state of the art and perspective. Artificial Intelligence in Medicine, 23(1):89–109, August 2001.

[Ledley and Lusted, 1991] R. S. Ledley and L. B. Lusted. Reasoning foundations of medical diagnosis. M.D. Computing: Computers in Medical Practice, 8(5):300–315, October 1991.

[Li et al., 2021] Dongdong Li, Zhaochun Ren, Pengjie Ren, Zhumin Chen, Miao Fan, Jun Ma, and Maarten de Rijke. Semi-Supervised Variational Reasoning for Medical Dialogue Generation. Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 544–554, July 2021. arXiv: 2105.06071.

[Liao et al., 2020] Kangenbei Liao, Qianlong Liu, Zhongyu Wei, Baolin Peng, Qin Chen, Weijian Sun, and Xuanjing Huang. Task-oriented dialogue system for automatic disease diagnosis via hierarchical reinforcement learning, 2020.

[Lin et al., 2020] Junfan Lin, Ziliang Chen, Xiaodan Liang, Keze Wang, and Liang Lin. Learning Reinforced Agents with Counterfactual Simulation for Medical Automatic Diagnosis. arXiv:2003.06534 [cs], August 2020. arXiv: 2003.06534.

[Lin et al., 2021a] Junfan Lin, Lin Xu, Ziliang Chen, and Liang Lin. Towards a reliable and robust dialogue system for medical automatic diagnosis, 2021.

[Lin et al., 2021b] Shuai Lin, Pan Zhou, Xiaodan Liang, Jianheng Tang, Ruihui Zhao, Ziliang Chen, and Liang Lin. Graph-Evolving Meta-Learning for Low-Resource Medical Dialogue Generation. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, pages 13362–13370, 2021. Issue: 15.

[Lin, 2009] Rong-Ho Lin. An intelligent model for liver disease diagnosis. Artificial Intelligence in Medicine, 47(1):53–62, September 2009.

[Ling et al., 2017a] Yuan Ling, Sadid A. Hasan, Vivek Datla, Ashequl Qadir, Kathy Lee, Joey Liu, and Oladimeji Farri. Diagnostic Inferencing via Improving Clinical Concept Extraction with Deep Reinforcement Learning: A Preliminary Study. In Finale Doshi-Velez, Jim Fackler, David Kale, Rajesh Ranganath, Byron Wallace, and Jenna Wiens, editors, Proceedings of the 2nd Machine Learning for Healthcare Conference, volume 68 of Proceedings of Machine Learning Research, pages 271–285, Boston, Massachusetts, August 2017. PMLR.

[Ling et al., 2017b] Yuan Ling, Sadid A. Hasan, Vivek Datla, Ashequl Qadir, Kathy Lee, Joey Liu, and Oladimeji Farri. Learning to Diagnose: Assimilating Clinical Narratives using Deep Reinforcement Learning. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 895–905, Taipei, Taiwan, 2017. Asian Federation of Natural Language Processing.

[Mullenbach et al., 2018] James Mullenbach, Sarah Wiegrefe, Jon Duke, Jimeng Sun, and Jacob Eisenstein. Explainable prediction of medical codes from clinical text. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1101–1111, New Orleans, Louisiana, June 2018. Association for Computational Linguistics.

[Peng et al., 2018] Yu-Shao Peng, Kai-Fu Tang, Hsuan-Tien Lin, and Edward Chang. Refuel: Exploring sparse features in deep reinforcement learning for fast disease diagnosis. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, Advances in Neural Information Processing Systems, volume 31. Curran Associates, Inc., 2018.

[Tang et al., 2016] Kai-Fu Tang, Hao-Cheng Kao, Chun-Nan Chou, and Edward Y Chang. Inquire and diagnose: Neural symptom checking ensemble using deep reinforce-
ment learning. In NIPS Workshop on Deep Reinforcement Learning, 2016.

[Vashishth et al., 2021] Shikhar Vashishth, Denis Newman-Griffis, Rishabh Joshi, Ritam Dutt, and Carolyn Rose. Improving broad-coverage medical entity linking with semantic type prediction and large-scale datasets, 2021.

[Wei et al., 2018] Zhongyu Wei, Qianlong Liu, Baolin Peng, Huaxiao Tou, Ting Chen, Xuanjing Huang, Kam-fai Wong, and Xiangying Dai. Task-oriented dialogue system for automatic diagnosis. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 201–207, Melbourne, Australia, July 2018. Association for Computational Linguistics.

[Xia et al., 2020] Yuan Xia, Jingbo Zhou, Zhenhui Shi, Chao Lu, and Haifeng Huang. Generative adversarial regularized mutual information policy gradient framework for automatic diagnosis. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 1062–1069, 2020. Issue: 01.

[Xu et al., 2019] Lin Xu, Qixian Zhou, Ke Gong, Xiaodan Liang, Jianheng Tang, and Liang Lin. End-to-end knowledge-routed relational dialogue system for automatic diagnosis. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 7346–7353, 2019. Issue: 01.

[Yu et al., 2020] Chao Yu, Jiming Liu, and Shamim Nemati. Reinforcement learning in healthcare: A survey, 2020.