MedConQA: Medical Conversational Question Answering System based on Knowledge Graphs

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Abstract

The medical conversational system can relieve doctors’ burden and improve healthcare efficiency, especially during the COVID-19 pandemic. However, the existing medical dialogue systems have the problems of weak scalability, insufficient knowledge, and poor controllability. Thus, we propose a medical conversational question-answering (CQA) system based on the knowledge graph, namely MedConQA, which is designed as a pipeline framework to maintain high flexibility. Our system utilizes automated medical procedures, including medical triage, consultation, image-text drug recommendation, and record. Each module has been open-sourced as a tool\textsuperscript{1}, which can be used alone or in combination, with robust scalability. Besides, to conduct knowledge-grounded dialogues with users, we first construct a Chinese Medical Knowledge Graph (CMKG) and collect a large-scale Chinese Medical CQA (CMCQA) dataset, and we design a series of methods for reasoning more intellectually. Finally, we use several state-of-the-art (SOTA) techniques to keep the final generated response more controllable, which is further assured by hospital and professional evaluations. We have open-sourced related code, datasets, web pages, and tools, hoping to advance future research.

1 Introduction

Conversational question answering (CQA) systems are emerging research topics, and they are the natural evolution of the traditional question answering (QA) paradigm (Gao et al., 2018; Ghazarian et al., 2021), allowing more natural conversational interactions between users and the systems (Zaib et al., 2021). CQA can improve the users’ experience by providing conversational interaction (Zhou et al., 2021). It can be applied to many scenarios such as electricity business (Meng et al., 2021), medical healthcare

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\textsuperscript{\dagger} https://github.com/WENGSYX/DrugRec

Figure 1: Main processes of the MedConQA.

(Liu et al., 2021b; Li et al., 2022), and personal assistants (Uğurlu et al., 2020), etc.

With the pandemic of the COVID-19, it is significant for building the medical CQA system, which is advantageous to improving the efficiency of medical services and reducing the burden on doctors with broad application prospects (Palanca et al., 2019). Recently, related medical service applications have become more and more popular, such as identifying symptoms (Zheng et al., 2017), automatic diagnosis (Moreira et al., 2019; Wang et al., 2021b) and medical recommendations (Wu et al., 2021), etc. However, there are three problems with existing applications: a) Most applications only have a single reply function and are difficult to scale. b) Many rule-based medical QA systems (Weizenbaum, 1966) are monotonous and lack sufficient expertise. Although products (Zhang et al., 2017b; Cui et al., 2017; Levy et al., 2021) have responded based on knowledge in recent years, there is still much room for improvement in the full use of knowledge and the quality of generated responses. c) Due to the medical industry’s high safety requirements, ensuring a safe and controllable response is also a significant challenge.

In this paper, we present a medical conversational question answering system with knowledge graphs, namely MedConQA, which is designed in a pipeline manner for high flexibility. As shown in Figure 1, it presents three main processes in our system: before diagnosis, during the consultation, and after diagnosis. The before diagnosis phase consists of the symptom consultation and
medical triage. The consultation phase includes disease confirmation and dialogue generation. The after-diagnosis phase focuses on image-text recommendation and medical record summary. In summary, MedConQA provides users with natural conversational QA services, which is relatively rare (Wang et al., 2021b) but more meaningful (Liu et al., 2020a).

MedConQA has the following highlights:

1. MedConQA implements a pipelined manner for automating medical procedures, alleviating the problems of weak scalability, insufficient knowledge, and poor controllability of the current medical dialogue system.

2. Multiple modules such as medical triage, consultation, image-text drug recommendation, and record are integrated into MedConQA, where each module is open-sourced as the auxiliary tool for further study.

3. MedConQA integrates several advanced technologies such as medical entity disambiguation and response generation, where the effect of each technology is reported. It is competitive compared with other state-of-the-art (SOTA) medical dialogue systems on both automated and human evaluations.

MedConQA aims at providing automated medical services for the majority of users. Preliminary experiments have been performed in the Xiangya Hospital of Central South University (Changsha, China), which demonstrates the research prospects and practical applications of the proposed system.

2 System Description

The Figure 2 overviews the main framework of our proposed system, and the whole process includes: 1) Symptom consultation and triage: MedConQA conducts medical triage for users by consulting and collecting symptoms, in which entity recognition and disambiguation further improve triage accuracy. 2) Disease confirmation: MedConQA confirms disease through the dynamic symptom selection algorithm and CRM and further derives the corresponding entities that need to be used later. 3) Dialogue generation: MedConQA combines the previously obtained entities as the prompt for the generation module to get the generated response. 4) Others: MedConQA also contains other functional modules, including image-text recommendation and medical record modules, which can be flexibly expanded and combined.

2.1 Entity Disambiguation Module

Figure 3: Contrastive pre-training in medical entity disambiguation.

In this section, we introduce the entity disambiguation module, which is consisted of technolo-
gies of the named entity recognition and contrastive pre-training. As for the named entity recognition, we implement the method (Sarker et al., 2019) for recognizing the medical entities in the utterance. We achieve the accuracy of 91.07% in the simple medical entity recognition dataset of the IFLYTK\(^3\), which ranks top-3 of the competition. After obtaining the entities, the entity disambiguation with contrastive learning is performed, which is shown in Figure 3. We introduce the contrastive pre-training framework with Smedbert (Zhang et al., 2021a) for medical entity disambiguation, which is our champion scheme in SDU@ AAAI-22-Shared Task2 Acronym Disambiguation\(^4\). Specifically, we design a contrastive pre-training method that enhances the model’s generalization ability by learning the medical phrase-level contrastive distributions between true meaning and ambiguous phrases (Li et al., 2021; Weng et al., 2021). During the pre-training, we cover up the student model’s medical entities, then make the student model output closer to the meaning of the teacher model, and away from other unrelated medical entities. Both models initialize the same parameters, where the parameters of the teacher model are frozen. For the masking of these medical entities, we adopt the expert medical dictionary THUOCL (Han et al., 2016) for experiments. After entities are obtained, we adopt the pre-trained model for matching the recognized entities and medical entities in the knowledge graph. Finally, we map the ambiguous phrases into the entities in the knowledge graph.

2.2 Medical Triage

We implement the triage function with the Smedbert (Zhang et al., 2021a) model, which is fine-tuned in medical entity triage data provided by IFlytek\(^5\). The final results can achieve the F1 values of 90.37% for medical triage classification (See Experimental Details in Section B.1). Finally, we apply this method to our medical triage module.

2.3 Central Records Memory

Central Record Memory (CRM) has storage and reasoning functions, and it is mainly composed of data formats in the form of a dictionary of entity triples. First, the CRM maps the medical entities obtained in the disambiguation module to specific attributes on the knowledge graph, and stores the past entities into the dictionary. In the next round of dialogue conversation, CRM will not only map the entities of the current round on the graph but also update the current state. The information of the entities on the current round is appended into the new dictionary again. After that, the CRM will send the entities obtained by the knowledge graph inference into the generation module for further sentence generation.

2.4 Symptoms Selection Algorithm

In order to reduce the redundant asking rounds as much as possible and ensure the accurate diagnosis of the disease, we designed a symptom selection algorithm based on dynamic programming to solve the optimization problem without recursively solving all sub-problems in turn and avoiding unnecessary calculations. As shown in the Algorithm 1, we regard each round of consultation as a sub-question to be judged, that is, we only need to select the symptom in the current state that can rule out the most diseases at one time. We traverse all the diseases in the knowledge graph, and if the intersection of the symptoms of the disease and the symptoms of the user is not an empty set, it will be added to the list of suspected diseases. Once

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Algorithm 1 Dynamic Symptom Selection

Require: A known user symptoms KS; A Chinese medical knowledge graph KG, The attributes in KG contain KG.symptoms and KG.diseases.

Ensure: Symptoms of this round of inquiry

Cand ← {} for diseases ∈ KG.diseases do
  if KS = disease.symptoms then
    return diseases
  end if
  if KS ⊂ disease.symptoms then
    Cand append symptoms
  end if
end for

for s ∈ Cand do
  if len(s) ≤ len(\(\overline{\text{Cand}}\)) then
    break
  end if
end for

Symptoms ← s.symptoms - KS
return Symptoms
<table>
<thead>
<tr>
<th>Dataset</th>
<th>Domain</th>
<th>Entity</th>
<th>Symptom</th>
<th>Dialogue</th>
</tr>
</thead>
<tbody>
<tr>
<td>COVID-19-CN (Yang et al., 2020)</td>
<td>COVID-19</td>
<td>/</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>MedDG (Liu et al., 2020b)</td>
<td>Gastroenterology</td>
<td>160</td>
<td>12</td>
<td>17864</td>
</tr>
<tr>
<td>Chunyu (Lin et al., 2020)</td>
<td></td>
<td>5682</td>
<td>15</td>
<td>12842</td>
</tr>
<tr>
<td>MedDialog-CN (Zeng et al., 2020)</td>
<td></td>
<td>29 Departments</td>
<td>/</td>
<td>172</td>
</tr>
<tr>
<td>M² MedDialog (Wang et al., 2021a)</td>
<td></td>
<td>40 Departments</td>
<td>4728</td>
<td>843</td>
</tr>
<tr>
<td>CMCQA(Ours)</td>
<td></td>
<td>45 Departments</td>
<td>33615</td>
<td>8808</td>
</tr>
</tbody>
</table>

Table 1: Statistics of the CMCQA compared with other datasets.

<table>
<thead>
<tr>
<th>Name</th>
<th>Symptom</th>
<th>Check</th>
<th>Drug</th>
<th>Food</th>
<th>Img</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num</td>
<td>8808</td>
<td>3353</td>
<td>17318</td>
<td>366</td>
<td>3770</td>
</tr>
</tbody>
</table>

Table 2: Statistics of entities in CMKG

the symptoms of all suspected diseases are counted, the symptom with the most frequent occurrences will be found and the symptom can be judged as the output symptom. When disease reasoning is required, the CRM will perform this algorithm until the final state of the user’s disease is confirmed.

2.5 Entity Knowledge Reasoning
As for the entity knowledge reasoning, MedConQA will strictly abide by the actual consultation process (Ha and Longnecker, 2010). The first stage is symptom reasoning, the second stage is examination reasoning, and the third stage is drug reasoning. Our system will initially conduct repeated symptom consultations with users to ensure that the system sends complete user symptom entities to the CRM. After this, MedConQA will synthesize all symptoms entities from the CRM, reasoning on the basis of related entities in our CMKG to get the user’s medical examination. Finally, if the user continues to consult with the drug for the treatment of the disease, MedConQA will perform drug recommendations with the corresponding images based on CMKG which is shown in Table 2, so that the user can obtain convenient and right suggestions. In order to avoid misdiagnosis, in the symptom reasoning stage, the MedConQA system will ask the user about the symptoms in a “diagnosed” style until the user’s disease is confirmed.

2.6 Generating Module
We adopt the method of entity prompt learning for training and prediction (Liu et al., 2021a). More precisely, we append the reasoned entity input with the conversational QA history, forming a prompt for response generation. Moreover, we design the prefix template for auto-regressive decoding.

<table>
<thead>
<tr>
<th>Method</th>
<th>Pre.</th>
<th>Rec.</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>RoBERTa (Liu et al., 2019)</td>
<td>83.14</td>
<td>74.77</td>
<td>78.32</td>
</tr>
<tr>
<td>hBERT (Zhong et al., 2021)</td>
<td>88.21</td>
<td>85.44</td>
<td>86.23</td>
</tr>
<tr>
<td>BERT-MT (Pan et al., 2021)</td>
<td>90.11</td>
<td>87.04</td>
<td>89.07</td>
</tr>
<tr>
<td>Ours</td>
<td>92.03</td>
<td>90.21</td>
<td>91.07</td>
</tr>
</tbody>
</table>

Table 3: F1 performance in entity disambiguation (%).

Specifically, we manually design templates of different reasoning processes described in the section 2.5 to further increase the controllability of the generated responses. In this way, we use the prompt and prefix method to fuse the context information with the reasoned entities from CRM. As a result, the generated response will be the condition on the prompt and prefix, so as to improve the factual accuracy and controllability of the model.

2.7 Other Function Modules
2.7.1 Image-text Drug Recommendation
We utilize the CMKG dataset and implement medical knowledge entity reasoning, linking drug entities to corresponding images to achieve image-text drug recommendations. It will be helpful for users to find drug information more easily.

2.7.2 Medical Record
The last module is the medical record. In order to make it easier for users to conduct secondary treatment more conveniently and quickly, MedConQA will write a medical record from the whole conversation after users finish the consultation. Specifically, we process the unstructured conversations history information based on the CPT (Shao et al., 2021) model to generate the key summarization of the user’s condition from this consultation. At the same time, this module will also process structured information stored in central records memory, such as department, examinations, drugs, and other information. Finally, two kinds of information are integrated through post-processing splicing to generate the user’s medical record (Experimental Results Shown in Section B.2).
Table 4: Performance of different methods in both CCKS-A and CCKS-B test sets (%).

<table>
<thead>
<tr>
<th>Model</th>
<th>CCKS A</th>
<th></th>
<th>CCKS B</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Avg</td>
<td>F1</td>
<td>BLEU</td>
<td>Dist.</td>
</tr>
<tr>
<td>GPT2-Entity (Liu et al., 2020b)</td>
<td>13.43</td>
<td>25.75</td>
<td>7.30</td>
<td>7.23</td>
</tr>
<tr>
<td>HERD-Entity (Liu et al., 2020b)</td>
<td>13.85</td>
<td>26.42</td>
<td>7.37</td>
<td>7.75</td>
</tr>
<tr>
<td>BertGPT-Entity (Lewis et al., 2019)</td>
<td>13.79</td>
<td>26.57</td>
<td>7.03</td>
<td>7.78</td>
</tr>
<tr>
<td>CPM2-prompt (Zhang et al., 2021b)</td>
<td>15.21</td>
<td>26.38</td>
<td>10.04</td>
<td>9.21</td>
</tr>
<tr>
<td>Ours</td>
<td>17.73</td>
<td>30.24</td>
<td>12.55</td>
<td>10.42</td>
</tr>
</tbody>
</table>

Table 5: Results of human evaluation, where $\kappa$ is the average pairwise Cohen’s kappa score between annotators.

<table>
<thead>
<tr>
<th>Model</th>
<th>Sentence Fluency</th>
<th>Knowledge Correctness</th>
<th>Entire Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPT2-Entity (Liu et al., 2020b)</td>
<td>3.22</td>
<td>3.12</td>
<td>3.17</td>
</tr>
<tr>
<td>HERD-Entity (Liu et al., 2020b)</td>
<td>3.83</td>
<td>3.77</td>
<td>3.74</td>
</tr>
<tr>
<td>BertGPT-Entity (Lewis et al., 2019)</td>
<td>3.71</td>
<td>3.78</td>
<td>3.82</td>
</tr>
<tr>
<td>CPM2-prompt (Zhang et al., 2021b)</td>
<td>4.10</td>
<td>4.17</td>
<td>4.15</td>
</tr>
<tr>
<td>Ours</td>
<td>4.14</td>
<td>4.20</td>
<td>4.19</td>
</tr>
<tr>
<td>Golden Response</td>
<td>4.77</td>
<td>4.83</td>
<td>4.81</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>0.54</td>
<td>0.57</td>
<td>0.58</td>
</tr>
</tbody>
</table>

3 Experimental Details

3.1 Data Description

CMCQA is a huge conversational question-and-answer data set for the Chinese medical field, where the statistics of medical conversation datasets is shown in Table 1. It is collected from the Chinese medical conversational question answering website ChunYu, and has medical conversational materials in 45 departments, such as andrology, stomatology, gynaecology, and obstetrics. Specifically, CMCQA has 1.3 million complete sessions or 19.83 million statements or 0.65 billion tokens. At the same time, we further open source all data to promote the development of related fields of conversational question answering in the medical field.

CMKG is collected from open-sourced knowledge graphs. We have processed the data crawled from the website, and then sorted it into the form of tables. For example, for the symptom of stomachache, the “disease” attributes include “gastritis”, “gastric cancer”, “gastric ulcer” and other diseases. The “examination” attributes include “gastroscopy” and “pathological biopsy of gastric mucosa”, etc. After that, we search and link the entities in the knowledge graphs in Bing image database. After the completion of the construction, the authors manually correct it again, eliminate about 20% of the obvious error information, and then submit it to the expert doctors for final verification to ensure the accuracy of the knowledge graphs.

3.2 Implementation

We train the model based on the Pytorch (Paszke et al., 2019) and use the hugging-face (Wolf et al., 2020) framework. All the finetuned models are implemented in the collected medical corpus. During training, we employ the AdamW optimizer (Loshchilov and Hutter, 2017). The learning rate is set to 1e-5 with the warm-up (He et al., 2016). Four 3090 GPUs are used for all experiments.

3.3 Evaluation Setting

To ensure correct medical entity information and fluent responses, we provide automatic and human evaluations accordingly. As for the effects of other modules and the total system, we also present detailed results (See Appendix B). Specifically, we conduct experiments entity disambiguation dataset of SDU@AAAI 2021 and medical dialogue generation dataset of the CCKS. We adopt the evaluation metrics, including the F1, BLEU (Papineni et al., 2002), and Dist. (Li et al., 2016) scores. The F1 score reflects the correctness of medical entity knowledge. The BLEU score reflects the reliability of the generated responses. The Dist. score represents the diversity of the generated sentences. We further prepare the human evaluation for randomly picking 100 cases from the test dataset. Each generated sentence is scored by three independent...
persons with a medical background. We adopt the same human evaluation metrics as the work (Liu et al., 2020b). The rating scale for each metric ranges from 1 to 5, where 1 represents the worst and 5 the best.

3.4 Results

The experimental results of medical entity disambiguation are shown in Table 3. It can be seen that our results achieve the best results compared to other SOTA methods. Meanwhile, we also conducted related evaluations on the test dataset, which is shown in Table 4. As is shown from the table, our method achieves the best results against recent strong baselines and leads in accuracy, relevance and diversity. We provide a human evaluation to further judge the performance between different methods. As shown in Table 5, our method achieves competitiveness in human evaluation compared to other SOTA methods. It is noted that there is still a long way from the generated responses to the real responses of people. Moreover, the average pairwise Cohen’s kappa (Randolph, 2005) scores between annotators range between 0.4 and 0.6 for all metrics, which represents a moderate annotator agreement.

4 Application

We present the application of MedConQA at the website, where the snapshot are shown in Figure 4. Figure 4 shows that if the user says that he is sick in his stomach, the system will get the entity “gastralgia” from the entity disambiguation module. Afterward, it will obtain the entity “gastritis” from the knowledge graphs through entity knowledge reasoning. The reasoned entity is sent to the generating module for further recommending the user to do a diagnosis in the hospital. Finally, if a user needs an urgent drug, the system will recommend the proper drug through the knowledge graphs. A medical record will be generated after the consultation, which will significantly facilitate the user’s secondary treatment.13

5 Conclusion

In this paper, we have analyzed three existing medical dialogue systems’ problems: weak scalability, insufficient knowledge, and poor controllability. Therefore, we proposed MedConQA, a medical conversational question answering system based on knowledge graphs. Our system integrated and open-sourced multiple modules for everyone to use freely, including medical triage, consultation, image-text drug recommendation, and record. Many of these technologies have achieved SOTA performance. Besides, for the professionalism and knowledge of the system, we have open-sourced and leveraged the CMKG and CMCQA datasets. Finally, we adopted several advanced techniques for the more controllable generated responses, which are further assured by hospital and professional evaluations.

13Medical conversational QA demo: https://www.youtube.com/watch?v=fsFnbim5hWc
Acknowledgements

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A Ethical Considerations

The constructed system aims to generate professional, fluent, and consistent medical responses. We have also realized that due to the adapt of pre-trained models that learn with the medical data from the Internet, the proposed approach may produce inappropriate text such as offensive, racially, or gender-sensitive responses. Meanwhile, although the proposed method can cover the stages of before, during, and after the medical treatment, it may also be maliciously exploited, for example, using forged medical reports to fabricate false medical reports.

We have carefully considered the above issues and provided the following detailed explanations: (1) All used medical data is collected from the Internet, and it is inevitable to contain offensive, racially or gender-sensitive doctor-user conversations. Due to the limited space, we briefly describe the characteristics and cleaning rules of the datasets and delete the utterances of doctor-user dialogue that are offensive, racially, or gender-sensitive. The detailed process can be found in the README file on the website https://github.com/Wengsyx/MedConQA. (2) The quality of the processed datasets will affect the credibility of the robustness evaluation. Compared with previous works, we adopt four types of criteria to evaluate the credibility of our system; they are: offline index evaluation (BLEU, Distinct, and F1), online users evaluation, dialogue rounds testing, and professional doctor evaluation. We hope to maximize the reliability and implement ability of the system based on such evaluation benchmarks. (3) MedConQA is a medical system with a suggestion nature, which uses knowledge graphs to provide multi-modal medical feedback. Our system may produce incorrect medical results. Therefore, the responses of the system are only for reference. Normal users should not seek medical treatment indiscriminately. (4) Our work does not contain identity information, the doctor only responds to the user’s condition, it will not harm anyone, and doesn’t invade people’s privacy. (5) The medicines recommended by MedConQA are over-the-counter medicines. Users need to consult their doctor for further confirmation when purchasing the drugs for prescription drugs. (6) Our system supports applications on different terminals.
In the future, we will adopt federated learning to capture the user’s condition and provide comprehensive protection more accurately, such as federated learning is able to provide privatized and personalized learning services for each user. Finally, since the proposed method uses external knowledge graphs, the information sources of these knowledge graphs also suffer from several issues such as risk and bias. Reducing these potential risks requires ongoing research.

B Effects of Other Modules

B.1 Medical Triage

<table>
<thead>
<tr>
<th>Model</th>
<th>cMedQA</th>
<th>cMedQA2</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT-open</td>
<td>73.82</td>
<td>79.97</td>
<td>76.77</td>
</tr>
<tr>
<td>BERT-wwm-open</td>
<td>72.96</td>
<td>79.68</td>
<td>76.32</td>
</tr>
<tr>
<td>RoBERT-open</td>
<td>73.18</td>
<td>79.57</td>
<td>76.38</td>
</tr>
<tr>
<td>BioBERT-zh</td>
<td>75.12</td>
<td>80.45</td>
<td>77.79</td>
</tr>
<tr>
<td>MC-BERT</td>
<td>74.46</td>
<td>80.54</td>
<td>77.50</td>
</tr>
<tr>
<td>KnowBERT-med</td>
<td>75.25</td>
<td>80.67</td>
<td>77.96</td>
</tr>
<tr>
<td>ERNIE-med</td>
<td>75.22</td>
<td>80.56</td>
<td>77.89</td>
</tr>
<tr>
<td>Ours</td>
<td>76.04</td>
<td>81.68</td>
<td>78.86</td>
</tr>
</tbody>
</table>

Table 6: F1 performance on different datasets in medical triage (%).

As shown in Table 6, we use Smedbert (Zhang et al., 2021a) in the medical triage module, where the cMedQA (Zhang et al., 2017a) and cMedQA2 (Zhang et al., 2018) datasets are used for evaluation. By injecting knowledge to enhance language understanding, the performance of pre-trained language models (PLMs) has been significantly improved. Experiments show that Smedbert significantly outperforms strong baselines in various knowledge-intensive medical tasks.

B.2 Medical Record

As shown in Table 7, we present the performance in the medical record, where the evaluated metrics are followed by ROUGE-1/2/L (Lin and Hovy, 2002) scores. The medical record module generates user records by combining key summaries of user conditions from the CPT model with structured information in the central records memory. The experimental results show the effectiveness of our method, where the evaluated datasets contains parts: chief complaint, history of present illness, auxiliary examination, past history, diagnosis, and recommendation.

B.3 System Overall Evaluation

The quality evaluation of the total system for the demonstration is crucial in the medical field. Therefore, we invited three medical doctors to evaluate our system in many aspects. Specifically, we asked them to deliver one hundred different questions to our system in ten different medical departments. Then, the results of our system are evaluated from the four dimensions: i.e., fluency, bias, correction, and technology. We have counted these experimental results in Figure 5. From the results, we can find that most of our dialogue processes are highly reliable.

In addition, we require the medical doctors to record the main reasons once the quality of the generated response is poor. We found that a large number of wrong texts are due to the understanding error caused by the phenomenon of “polysemy”. When the system encounters such problems, it will be understood as a more popular meaning due to the bias of training data, and will not further ask users for more detailed information. Figure 6 is a screenshot of our Chinese version of the system. In the Chinese version, the alias of our system is “lingYi”.

<table>
<thead>
<tr>
<th>Model</th>
<th>ROUGE-1</th>
<th>ROUGE-2</th>
<th>ROUGE-L</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seq2Seq</td>
<td>58.50</td>
<td>43.46</td>
<td>56.39</td>
<td>52.72</td>
</tr>
<tr>
<td>Pointer-Generator</td>
<td>62.13</td>
<td>47.01</td>
<td>59.05</td>
<td>56.06</td>
</tr>
<tr>
<td>TS-MED</td>
<td>65.30</td>
<td>49.71</td>
<td>60.84</td>
<td>58.62</td>
</tr>
<tr>
<td>Ours</td>
<td>66.93</td>
<td>52.31</td>
<td>62.78</td>
<td>60.67</td>
</tr>
</tbody>
</table>

Table 7: Performance in the medical record.

14http://fudan-disc.com/sharedtask/lmes21/index.html
Figure 5: Quality evaluation of the total system, where the evaluation questionnaire is also presented.

<table>
<thead>
<tr>
<th>Q1: Fluency</th>
<th>Q2: Bias</th>
<th>Q3: Correctness</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Yes, just like I usually do.</td>
<td>A: No, I didn't find it.</td>
<td>A: Yes, it's impossible to have such symptoms.</td>
</tr>
<tr>
<td>B: The dialogue process is just so so.</td>
<td>B: Yes, it does exist.</td>
<td>B: Not necessarily, may also have other symptoms.</td>
</tr>
<tr>
<td>C: The semantics are very incoherent and stiff.</td>
<td>C: No, I didn't find it.</td>
<td>C: No, it didn't find it.</td>
</tr>
</tbody>
</table>

Figure 6: Snapshot of the proposed MedConQA system (Chinese Version).