MedDG: A Large-scale Medical Consultation Dataset for Building Medical Dialogue System

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Abstract

Developing conversational agents to interact with patients and provide primary clinical advice has attracted increasing attention due to its huge application potential, especially in the time of COVID-19 Pandemic. However, the training of end-to-end neural-based medical dialogue system is restricted by an insufficient quantity of medical dialogue corpus. In this work, we make the first attempt to build and release a large-scale high-quality Medical Dialogue dataset related to 12 types of common Gastrointestinal diseases named MedDG, with more than 17K conversations collected from the online health consultation community. Five different categories of entities, including diseases, symptoms, attributes, tests, and medicines, are annotated in each conversation of MedDG as additional labels. To push forward the future research on building expert-sensitive medical dialogue system, we propose two kinds of medical dialogue tasks based on MedDG dataset. One is the next entity prediction and the other is the doctor response generation. To acquire a clear comprehension on these two medical dialogue tasks, we implement several state-of-the-art benchmarks, as well as design two dialogue models with a further consideration on the predicted entities. Experimental results show that the pre-train language models and other baselines struggle on both tasks with poor performance in our dataset, and the response quality can be enhanced with the help of auxiliary entity information. From human evaluation, the simple retrieval model outperforms several state-of-the-art generative models, indicating that there still remains a large room for improvement on generating medically meaningful responses.

Introduction

During the COVID-19 pandemic, millions of patients worldwide have been facing delays in diagnosis and treatment due to the diversion of medical resources. As a result, telemedicine is increasingly expected to play a role in relieving therapeutic stress. According to [McCall] (2020), telemedicine has substantially risen from around 10% of general medicine consultations before COVID-19 to approximately 75% in the UK during the peak of the pandemic.

Data and code in this paper are publicly available at [https://github.com/lwgkzl/MedDG](https://github.com/lwgkzl/MedDG)

Figure 1 demonstrates a typical medical consultation dialogue in the MedDG dataset between a patient (orange) and a doctor (blue) with the corresponding annotated entities.
Medical conversational agents pose a great tool to assist doctors in responding to easily-diagnosed common disease and pre-collecting patients’ medical information for the hard disease. In order to advance the development of medical conversational agents, several medical dialogue corpora have been released to facilitate the research of information extraction (Lin et al. 2019; Zhang et al. 2020a; Shi et al. 2020) and automatic diagnosis (Wei et al. 2018; Xu et al. 2019). However, these corpora fail to address the problem of dialogue generation due to the lack of full natural language-based dialogues and the limited dataset scale. Specifically, the quantity of dialogues in these corpora is around 500 to 2k, which is apparently insufficient to train the learning-based dialogue generation model.

To mitigate the dilemma of data scarcity, we collect MedDG, a large-scale Medical Dialogue dataset related to 12 Gastrointestinal diseases. As shown in Table 1, compared with previous datasets, our dataset has the following advantages. First, our MedDG contains more than 17K dialogues and 385k utterances, which is 10 times larger than previous datasets, thus more suitable for the training of generative models. Second, MedDG is informative and diverse, including 12 types of diseases and 160 types of entities, which is much closer to the realistic medical consultation scenario. Finally, the average and median number of the entity occurrence times are significantly higher than other corpora, indicating that the annotation labels are abundant and relatively balanced.

In addition to constructing MedDG, we propose two tasks based on the dataset. The first task is to predict next entities according to dialogue contexts, while the other aims to generate doctors’ responses. To get a clear understanding of these two tasks, we compare several state of the art models on MedDG, including both classic neural baselines and popular pre-train language models, such as BERT (Devlin et al. 2019) and GPT (Radford et al. 2019). Besides, we also design two entity-aware dialogue systems including both retrieval-based and generation-based models to utilize entity-level information. Experimental results demonstrate that the response quality can be enhanced by combining entity information with dialogue history in the generation phase, while there still remains a large room for improvement on designing specific dialogue modules to utilize entity annotation and generate medically meaningful responses.

Our contribution can be summarized as follows:

- We collect MedDG, a large-scale medical dialogue dataset related to 12 types of common gastrointestinal diseases. MedDG contains more than 17K conversations and 385K utterances with the annotation of 5 types of medical entities, making it as a convincing benchmark to evaluate the medical consultation capability of dialogue systems.
- We provide various baselines for both the entity prediction task and the response generation task on the MedDG dataset, and propose two methods to make use of dialogue entity prediction results in the medical dialogue system.
- We conduct extensive experiments, including quantitative and human evaluations, to compare many state-of-the-art neural-based and pre-train based models, giving a comprehensive understanding of the new proposed medical dialogue generation task. Results show that utilizing predicted entities as auxiliary information could effectively improve the response quality by the input concatenation method.

### Related Work

#### Medical Dialogue Methods

Natural language understanding of medical dialogue has been investigated a lot recently, such as information extraction (Zhang et al. 2020a), relation prediction (Du et al. 2019; Lin et al. 2019) and slot filling (Shi et al. 2020). The adoption of reinforcement learning framework in dialogue systems (Dhingra et al. 2017; Li et al. 2017; Peng et al. 2018) has inspired dialogue management strategy learning in the medical domain. Wei et al. (2018) took the first step to address the issue of medical dialogue for automatic diagnosis using the Deep Q-Network. Furthermore, Xu et al. (2019) improved the rationality of decision-making for medical dialogue, which incorporates external probabilistic symptoms related to the framework of reinforcement learning. Liao et al. (2020) assigned different workers to conduct symptom acquisition and disease diagnosis hierarchically. However, these reinforcement learning approaches merely learn from tabular data containing the presence of symptoms, while ignoring the significance of other important information such as the attributes of the symptom, tests, and medicine.

Most of the previous work merely focuses on a single module of the medical dialogue system, e.g., natural language understanding or dialogue management, while the study of constructing a complete system are relatively few. The early attempts include Ferguson et al. (2009); Wong, Thangarajah, and Padgham (2011); Gatius and Namsrai (2012); Liu et al. (2016). A more recent work is Xu et al. (2019), which introduces a knowledge-routed dialogue system for automatic diagnosis. It uses pre-defined templates to simulate a doctor’s response based on the action predicted by the dialogue management module. However, the action pool is limited to symptoms and diseases, unable to handle other everyday situations like check requirements and medical recommendations. Beyond that, the ignorance of a more general response generation module leads to a huge gap in practical applications.

#### Medical Dialogue Datasets

Wei et al. (2018) first launched a dataset for medical diagnosis, but it only contains the structured user goal data instead of natural language dialogue. The DX dataset (Xu et al. 2019) contains 527 natural language dialogues, but the sentence patterns are simple. Lin et al. (2019) collected the CMDD dataset with 2067 dialogues on four pediatric diseases and Zhang et al. (2020a) releases MIE with 1120 dialogues on six cardiovascular diseases. However, CMDD and MIE are all proposed only for the purpose of NLU training, and not large enough to build a complete generative dialog system. Besides, Shi et al. (2020) is another medical dialogue corpus in the general domain with 2k labeled data and
| Dataset            | Domain    | # Diseases | # Dialogues | # Utterances | # Entities | Avg. | Med. |
|-------------------|-----------|------------|-------------|--------------|------------|------|------|
| MZ (Wei et al. 2018) | Pediatrics | 4          | 710         | -            | 70         | 67.06 | 33   |
| DX (Xu et al. 2019) | Pediatrics | 5          | 527         | 2,816        | 46         | 65.95 | 12   |
| CMDD (Lin et al. 2019) | Pediatrics | 4          | 2,067       | 87,005       | 161        | 194.39 | 18   |
| MIE (Zhang et al. 2020a) | Cardiology | 6          | 1,120       | 18,129       | 71         | 93.70 | 64   |
| MedDG (ours)      | Gastroenterology | 12       | 17,864      | 385,951      | 160        | 1357.64 | 428  |

Table 1: Comparison between our corpus and other human-labeled medical dialogue corpora. Statistics include the quantity of dialogues, disease types and entity types, the average (Avg.) and medium (Med.) occurrence times of entities, and the corpus diversity (Div.), respectively.

100k unlabeled data, but in the form of separate utterance instead of the whole dialogue. Table 1 summarizes the public human-labeled Chinese medical dialogue corpora. Compared with these corpora, our proposed MedDG involves more diseases, entities, dialogues and utterances to alleviate the issue of data scarcity.

**MedDG Dataset**

To further advance the research in medical dialogue system, we constructed a natural language dialogue dataset that includes the conversation between doctors and patients in the medical consultation scenario with the annotation of important entities. In this section, we introduce our proposed dataset from the perspective of construction details and dataset statistics.

**Construction Details**

In the following, we describe our pipeline to construct and annotate the dataset. As shown in Figure 2, to control costs within a reasonable range, we design a semi-automated annotation method. First, a part of the dataset is manually annotated, and then an automatic program is designed to label the rest of the dataset.

The source doctor-patient dialogues are collected from the Gastroenterology department of a Chinese online health community, Chunyu-Doctor, where patients can submit posts about their relative gastrointestinal problems and then consult with qualified doctors for professional diagnosis advice. We select consultations related to Gastroenterology because it is common, diverse, and has more inquiries, while other departments may depend more on tests. Dialogues containing personal information, images, or audios are all filtered before annotation. Dialogues without enough turns are also ignored. After discussing with domain experts, we choose five main categories of entity for annotation: diseases, symptoms, attributes, tests, and medicine. We further define items of each category based on the terminology lists in the Chinese medical knowledge graph CMeKG and the frequency in our corpus. Figure 3 lists the common items of each entity category.

Similar to Zhang et al. (2020a); Shi et al. (2020), we use an utterance-to-information annotation method instead of sequential labeling because entities are not always explicitly or consecutively expressed. As shown in Figure 1, each utterance of the conversation is labeled separately. Eight annotators with the relevant medical background were involved in the annotation process. They first discuss to determine a primer annotation guide. Then each one annotates a small part of data and reports the confusing utterance according to the guide. We summarize the found issues, improve the guide, and launch the formal annotation process. Each conversation is randomly assigned to three annotators, and a total of 1,000 conversations are manually annotated. The Cohen’s kappa coefficient among annotators is between 94.81% and 97.59%, indicating a strong agreement between annotators.

We then develop a program to label the rest conversation automatically. The program consists of regex rules for each item to cover all human-labeled data, and apply these rules to label other dialogues. We randomly pick 400 auto-labeled utterances and show them to three experts to evaluate the annotation quality of the program. Experts are required to find errors and omissions from these utterances. We modify the program to correct these errors, select 400
Table 2: Data statistics of MedDG. The last four rows are the average number of characters in each utterance and dialogue, and the average number of entities in each utterance and dialogue, respectively.

|                 | Train | Dev  | Test  | Total |
|-----------------|-------|------|-------|-------|
| # Dialogues     | 14,864| 2,000| 1,000 | 17,864|
| # Utterances    | 321,666| 42,850| 21,435| 385,951|
| # Char. per U   | 17.70 | 17.77| 17.64 | 17.70 |
| # Char. per D   | 382.99| 380.67| 378.06| 382.45|
| # Entities per U| 0.56  | 0.57 | 0.61  | 0.56  |
| # Entities per D| 12.09 | 12.24| 13.02 | 12.16 |

The frequency of symptoms is the highest, accounting for 55% of the total.

Dataset Statistics
Table 2 summarizes the data statistics of MedDG. The training/test set is divided into 14864/2000/1000 conversations, respectively. The average length of utterances and dialogues are approximately the same in three sets, as well as the average number of entities in each utterance and dialogue, which means that the distribution of the data in the three sets is relatively consistent among three sets. There are 160 entity items in total, consisting of 12 disease items, 62 symptom items, 4 attribute items, 20 test items, and 62 medicine items. The complete name list of 160 entity items and the regex table are presented in the supplementary material. As shown in Figure 3, the frequency of symptoms is the highest, accounting for 55% of the total.

Models
Task Definition
Medical dialogue system aims to generate context consistent and medically meaningful responses conditioned on the conversation histories. In this paper, we mainly focus on two tasks, entity prediction and response generation. Formally, given the conversation history between doctors and patients $X = \{ X_1, X_2, ..., X_t, ..., X_K \}$, $K$ is the current turn of the dialogue history. $X_t$ is a sentence from doctors or patients. The next doctor’s response $Y = \{ y_1, y_2, ..., y_T \}$ corresponds to an entity set $e_y = \{ e^y_1, ..., e^y_T \}$. The entity prediction task is to predict the entity set $e_y$ and we only consider the samples with a non-empty set, while the response generation task is to generate $Y$ directly.

Entity Prediction Model
The entity prediction model is made up of a neural dialogue encoder in conjunction with a single-layer multi-label classifier. Concretely, the encoder input is the concatenation of utterances again, and repeat this process until the accuracy rate is higher than a given threshold. Eventually, the accuracy rate achieves 96.75%, which means the utterance-level annotation accuracy is higher than 95% by the binomial test with a significance value $p < 0.01$, validating the effectiveness of the annotation program. Finally, we put all the manually annotated data in the test set and randomly divide the automatically labeled data into the training set and the development set.

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![Figure 3: Entity distribution in the MedDG dataset. The pie chart in the upper left corner shows the proportion of entities in the five categories, and other five charts demonstrate the entities statistics of each category.](https://code.ihub.org.cn/projects/1775)
Response Generation Model

We adopt multiple widely used text generation models as follows:

- **Seq2Seq** (Sutskever, Vinyals, and Le 2014) is a classical attention-based sequence to sequence model with vanilla RNN encoder and decoder.

- **HRED** (Serban et al. 2016) extends the traditional RNN encoder by stacking two RNNs in a hierarchical way: one at word level and one at the utterance level, which is frequently used as a dialogue encoder.

- **GPT2** (Radford et al. 2019) is a language model based on Transformer. We use the parameter pre-trained on chitchat dialogue.

- **DialoGPT** (Zhang et al. 2020b) is a variant of GPT-2 model using a maximum mutual information scoring function to penalize bland responses.

For each model, the generation loss is the average of negative log likelihood of the target sequence \( \{y^*_t\} (1 \leq t \leq T) \):

\[
\mathcal{L}_g = \frac{1}{T} \sum_{t=1}^{T} \log P(y^*_t).
\] (1)

Entity-aware Dialogue Model

Since the generative models mentioned above are irrelevant to the annotated entity labels in our dataset, we further propose two entity-aware dialogue models to make use of the auxiliary entity information.

**Entity concatenation** This method is to directly concatenate the entity information after the dialogue history as new input text. We first train a BERT classifier to predict possible medical entities in the next utterance based on the dialogue history. These predicted entities are then concatenated to the end of dialogue history as additional learning signals, encouraging models to generate responses relevant to these entities. We use the **-Entity** suffix to distinguish generative models trained on new entity-concatenated data.

**Entity retrieval** We also built a retrieval-based dialogue system that uses predicted entities as key information to retrieve the most relevant response. Firstly, we collect an entity-utterance dict from the training set, where dict key is a combination of entities and value is a set of utterance containing such entity combination. Then we also use the BERT classifier to predict possible entities from dialogue history. Finally, we retrieve a key from the dict which has smallest entity combination while covering all predicted entities. The response is randomly picked from the utterance set corresponding to such key. This baseline is named as **Retrieval**.

Experiments

Implementation Details

For RNN-based models, the single-layer LSTM (Hochreiter and Schmidhuber 1997) is used as RNN encoders and decoders. Both the word embedding and hidden dimensions of LSTM are set to 300. We use Adam optimizer with a minibatch size of 16 and set the initial learning rate to 0.001. For BERT-based and GPT-based models, we follow the configurations in the origin paper. Each model is trained up to 30 epochs. The overall training time is less than one day on a machine with four NVIDIA RTX2080 Ti graphic cards. The patience argument is set to 5 for early stopping. The models are saved according to the best \( F_1 \) score for the entity prediction task and the best **BLEU-4** score for the response generation task in the validation set of MedDG. All experiments are implemented by Pytorch.

Automatic Evaluation

**Metrics** For the entity prediction task, the metrics \( P_e, R_e \) and \( F_1e \) refer to the precision, recall and F1 measures of all categories of predicted entities. We also calculate the F1 score of each entity category and donate them as \( F_1D \) (Diseases), \( F_1S \) (Symptoms), \( F_1A \) (Attributes), \( F_1T \) (Test) and \( F_1M \) (Medicine), respectively. \( P_f \) is the future prediction precision by considering all entities occurred in the following conversation as target entities with the ignorance of order.

For the response generation task, the smoothed sentence-level **BLEU-1** and **BLEU-4** (Chen and Cherry 2014) are used as the uni-gram and four-gram lexical similarity metric. **Entity-P/R/F1** is the precision/recall/F1 score between predicted entities in generated response and gold entities to measure the correctness of entity usage. Distinct-1/2 (Li et al. 2016) is also provided to evaluates the uni-gram and bi-gram diversity of generated responses.

**Results** The results of the entity prediction task are shown in Table 3. Compare with classic RNN and CNN encoder, the BERT-based encoders reach better performance in terms of all metrics, which validates the effectiveness of pre-training. Moreover, PCL-MedBERT outperforms BERT in most of the metrics, proving that conducting further pre-training on domain-specific data can improve the model performance. Thus PCL-MedBERT is chosen as the backbone of all entity-aware dialogue models. However, the predicted entity F1 metric \( F_1e \) is still lower than 30%, which remains a large room for improvement.

The performance of both retrieval-based and generation-based dialogue models are summarized in Table 4. We analyze the results from the following perspectives:

**The influence of entity concatenation** All the generative models obtain more than 4% absolute improvement in terms of the Entity-F1 metric after adding predicted entities to enhance the generation, and the BLEU scores are also improved, proving that the entity concatenation method can effectively improve the generation quality. Meanwhile, the diversity metrics (Distinct-1/2) decrease in most cases. This is because the guidance of the entity enforces the model to generate more fixed patterns, such as asking symptoms or informing disease.

**Retrieval vs. Generation** Since we only implement a relatively simple retrieval model based on merely the predicted entities without contextual information, the BLEU score is much lower than generative modes. In contrast, the diversity and entity correctness metrics are relatively high. The entity recall is higher than all generation models because our re-
| Model          | $F_{1_D}$ | $F_{1_S}$ | $F_{1_A}$ | $F_{1_T}$ | $F_{1_M}$ | $P_e$  | $R_e$  | $F_{1_c}$ | $P_f$  |
|---------------|-----------|-----------|-----------|-----------|-----------|--------|--------|-----------|--------|
| LSTM          | 31.18     | 21.72     | 48.95     | 25.05     | 15.66     | 25.34  | 27.75  | 26.49     | 45.74  |
| TextCNN       | 29.54     | 20.55     | 50.33     | 23.58     | 19.01     | 22.37  | 30.12  | 25.67     | 42.75  |
| BERT          | 31.66     | 24.27     | **52.44** | 26.03     | 19.82     | 26.05  | 31.09  | 28.35     | **47.33** |
| PCL-MedBERT   | **33.72** | **25.62** | 46.85     | **27.49** | **20.78** | **26.46** | **33.07** | **29.40** | 46.82  |

Table 3: Results of the entity prediction task on the MedDG dataset. Note that all metrics are normalized to $[0, 100]$ and the best results are in **bold**.

| Model           | BLEU-1 | BLEU-4 | Distinct-1 | Distinct-2 | Entity-P | Entity-R | Entity-F1 |
|-----------------|--------|--------|------------|------------|----------|----------|-----------|
| Retrieval       | 23.08  | 12.58  | 0.62       | 9.98       | 11.44    | 33.11    | 17.00     |
| Seq2Seq         | 26.12  | 14.21  | 0.88       | 4.77       | 14.07    | 11.45    | 12.63     |
| Seq2Seq-Entity  | 35.24  | 19.20  | 0.75       | 5.32       | 12.41    | 25.65    | 16.73     |
| HRED            | 31.56  | 17.28  | 1.07       | 8.43       | 13.29    | 11.25    | 12.18     |
| HRED-Entity     | **38.66** | **21.19** | 0.75 | 7.06       | 12.01    | 26.78    | 16.58     |
| GPT2            | 29.35  | 14.47  | **1.26**   | **13.53**  | 7.33     | 12.22    | 9.17      |
| GPT2-Entity     | 30.87  | 16.56  | 0.87       | 11.20      | 20.76    | 14.51    | **17.08** |
| DialoGPT        | 34.57  | 18.09  | 0.50       | 9.92       | 11.30    | 9.99     | 10.61     |
| DialoGPT-Entity | 34.90  | 18.61  | 0.77       | 9.87       | **21.16** | 13.53    | 16.51     |

Table 4: Performance of all comparison dialogue systems on the MedDG dataset in terms of response quality, diversity and entity correctness. Note that all metrics are normalized to $[0, 100]$ and the best results are in **bold**.

| Model | Sentence Smoothness | Knowledge Correctness | Entire Quality |
|-------|---------------------|-----------------------|---------------|
| Retrieval | 4.23 | 4.29 | **4.18** |
| HRED      | 3.46 | 3.12 | 3.16 |
| HRED-Entity | 3.93 | 4.05 | 4.05 |
| GPT2      | 2.84 | 2.70 | 2.73 |
| GPT2-Entity | 3.27 | 2.69 | 2.83 |
| $\kappa$ | 0.41 | 0.59 | 0.52 |

Table 5: Results of human rating on the MedDG datasets. $\kappa$ is the average pairwise Cohen’s kappa score between annotators.

RNN-based Models vs. GPT-based Models Although the GPT2-Entity model generates more correct entities, the BLEU scores of HRED-Entity are higher than all GPT-based methods. The possible reason is that the parameters of GPT2 and DialoGPT are pre-trained by the chit-chat corpus, so they tend to generate responses irrelevant to the medical domain. We also observe this phenomenon in human evaluation. Besides, the Entity-F1 scores of all dialogue models are all lower than 20%, meaning that there still remains a large room for improvement on generating meaningful responses with correct entities.

Manual Evaluation

We also perform human evaluation for a more thorough comparison of five selected dialogue models (Retrieval/HRED/HRED-Entity/GPT2/GPT2-Entity). We randomly picked 100 test cases in each dataset. Three annotators with a medical background are invited to rate the response of these models independently in three aspects: sentence smoothness, knowledge correctness, and the entire quality. The scores range from 1 (strongly bad) to 5 (strongly good).

The evaluation result is summarized in Table 5. To our surprise, the Retrieval model is significantly higher than the other generative models on all metrics, especially in terms of sentence fluency, which is inconsistent with the automatic evaluation. A possible explanation is that the BLEU metric only measures the similarity between predicted response and the gold sentence, while neglecting other reasonable responses in the corpus. From the results of four generation models, we can observe that HRED-based models outperform GPT2-based models by a large margin. Corresponding to the automatic evaluation, incorporating entities helps to further improve the generation quality. In addition, the average pairwise Cohen’s kappa scores between annotators exceed 0.4 for all metrics, which indicates a moderate annotator agreement.

Case Study

We take a close look at the model performance by studying the examples of the response from five different models in the MedDG dataset. As shown in Table 6, the responses of retrieval model included all the predicted entities, but they
### Utterance & Gold Response Model Response

| Utterance & Gold Response | Model Response |
|---------------------------|----------------|
| **P1:** I have a dull pain and grunting in the upper right corner of my belly button. (Female, 44 years old) | Retrieval: Hello, how long has this situation been? How many times a day do you poop?  
          GPT2: Hello, how long has this been happening?  
          You feel this situation for a long time?  
          GPT2-Entity: Hello, how long has this been happening?  
          You feel this situation for a long time?  
          HRED: Hello, how long has this been happening?  
          You feel this situation for a long time?  
          HRED-Entity: Hello, how long has this been happening?  
          You feel this situation for a long time?  |
| **D1:** Hello, how long has this been happening?  
          就是这种情况多长时间了? | **Predicted Label:** Duration (时长)  
          **Golden Label:** Duration (时长) |
| **P2:** For more than a week, I took a B-ultrasound yesterday and said nothing was found, but I felt full after eating. | Retrieval: Are there nausea, vomiting, acid reflux, abdominal pain and diarrhea?  
          GPT2: Is this normal?  
          GPT2-Entity: Any nausea, acid reflux and belching?  
          HRED: Do you have cholecystitis?  
          HRED-Entity: Is there any heartburn, acid reflux, bloating, greasy heartburn?  |
| **D2:** Are there nausea, vomiting, acid reflux, abdominal pain and diarrhea?  
          有恶心呕吐反酸, 腹痛腹泻吗？ | **Predicted Label:** Reflux, Hiccups, Nausea, Heartburn (反流, 打嗝, 恶心, 烧心)  
          **Golden Label:** Diarrhea, Abdominal pain, Nausea, Vomiting, Reflux (腹泻, 腹痛, 恶心, 呕吐, 反流) |
| **P6:** May I ask what kind of disease I have?  
          请问您我这个大概是哪里的问题。 | Retrieval: This may be caused by gastritis. It is recommended that you have a gastroscopy to rule out digestive ulcers.  
          GPT2: Sorry, I was a bit busy just now.  
          GPT2-Entity: This situation is considered to be caused by gastritis with gastric mucosa. You can consider taking medicine for a period of time to adjust.  
          HRED: Consider gastrointestinal?  
          HRED-Entity: Considering the possibility of gastritis, it is recommended to have a gastroscopy to see.  |
| **D6:** Consider you this may be caused by enteritis, gastritis or gastrointestinal dysfunction.  
          考虑你这有可能是胃肠炎, 胃肠功能紊乱引起的。 | **Predicted Label:** Gastritis, Gastroscope (胃炎, 胃镜)  
          **Golden Label:** Gastrointestinal dysfunction, Gastritis, Enteritis (胃肠功能紊乱, 胃炎, 肠炎) |

Table 6: Examples of the generated response. **P** represents the \( i \)th utterance of the patient and **D** donates the doctor’s \( i \)th gold response. Due to the space limitation, we only demonstrates the retrieval baseline and four generative models (GPT/GPT-Entity/HRED/HRED-Entity) in the first two turns (**D**1, **D**2) and the last turn (**D**6). All correct entities in the predicted response are underlined.

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**Conclusion and Future Work**

In this paper, we proposed MedDG, a large-scale Chinese medical dialogue consultation dataset with the annotation of rich medical entities. We implement several state-of-the-art models for entity prediction and dialogue generation tasks and design two entity-aware dialogue models. Experimental results show that response quality can be enhanced with the help of predicted entities. Since the entity list in MedDG is obtain from a medical knowledge graph, in the future, we plan to introduce the domain knowledge into the medical dialogue to model the relationship between different medical entities.
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