Prompt-based Generative Approach towards Multi-Hierarchical Medical Dialogue State Tracking

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Abstract

The medical dialogue system is a promising application that can provide great convenience for patients. The dialogue state tracking (DST) module in the medical dialogue system which interprets utterances into the machine-readable structure for downstream tasks is particularly challenging. Firstly, the states need to be able to represent compound entities such as symptoms with their body part or diseases with degrees of severity to provide enough information for decision support. Secondly, these named entities in the utterance might be discontinuous and scattered across sentences and speakers. These also make it difficult to annotate a large corpus which is essential for most methods. Therefore, we first define a multi-hierarchical state structure. We annotate and publish a medical dialogue dataset in Chinese. To the best of our knowledge, there are no publicly available ones before. Then we propose a Prompt-based Generative Approach which can generate slot values with multi-hierarchies incrementally using a top-down approach. A dialogue style prompt is also supplemented to utilize the large unlabeled dialogue corpus to alleviate the data scarcity problem. The experiments show that our approach outperforms other DST methods and is rather effective in the scenario with little data.

1 Introduction

The medical dialogue system that can simulate the actions of clinicians is a promising application. The systems acquire the patient’s information interactively through natural language and give diagnoses and suggestions of treatments. One of the major challenges in implementing such a system is how to understand the patient’s utterances and convert the utterances into a machine-friendly structure. In particular, the structure mainly consists of two parts, patient’s major intention and the detailed values of the intention, called intent and slot respectively. The task of defining, extracting, and maintaining such a structure is called Dialogue State Tracking (DST) in task-oriented dialogue systems.

Current task-oriented dialogue systems ([Lei et al., 2018], [Acharya et al., 2021]) mainly focus on simple personal assistant tasks such as buying movie tickets, booking restaurants. Though logically the research on medical dialogue systems ([Kao et al., 2018], [Wei et al., 2018], [Xu et al., 2019]) exist, the tasks are processed in the same way as simpler systems. However, after we began with a project on a dialogue-based medical decision support system one year before, we found the differences and challenges obvious.

Firstly, it requires more complex and accurate state information to make the correct diagnosis possible. Typical state structure of task-oriented systems is in the form of \{intent,(slot, value)+\}. A case in point in the restaurant reservation system may be \{book, (time, 5 pm), (day, Jan.13)\}. However, simple slot and slot-values pairs are not enough for medical systems. For example, the patient says “I do not have a headache”, it’s wrong to convert the utterance to (“symptom”, “headache”) and it is a disaster to neglect the negation in the medical domain. Furthermore, if another patient says “I have a severe headache after drinking”, both the severity and condition of the symptom should be extracted and represented. Besides, the number of the intention types of the patients and clinicians are much bigger. In real clinical practice, the patients are not only in need of diagnosis or treatment, but also acquire medical knowledge or look for the console. Typical samples for comparison can be found in Table 1.

Secondly, there are many discontinuous, overlapping, and nested entities in the utterances. These entities may even across sentences and speakers. For example, the patient says “我的头感到有点疼(My head feels painful)”. Most named entity recognition (NER) model will extract “疼(painful)”, however, the right answer should be "头疼(headache)", and “头疼” “疼” are separated in original sentences. Another example is “伤口又疼又痒(wound hurts and itches)”. Usually NER model will treat this as a whole entity, but to be accurate, we want “伤口疼(wound hurts)” and “伤口痒(wound itches)” so that it will be possible to be normalized into two symptoms.

Traditionally most existing DST methods are based on deep learning and require a large annotated dataset. For the medical dialogue application, both the complexity of state structure and diverse forms of named entities imply the requirement of a larger corpus. However, it is almost unrealistic due to the annotation cost.
2 Related Work

The two subtasks of dialogue state tracking, namely intent detection and slot filling, used to be handled separately. Typically, intent detection is treated as a classification problem and slot filling as a sequence labeling problem (Xu and Hu, 2020) so that the relationship between the two tasks can be fully exploited. While the two tasks take different forms traditionally, generation-based methods (Wu et al., 2019, Kim et al., 2021) take the advantage of unifying various types of NLP tasks. Feng et al., 2021 proposed the Seq2seq-DU method formalizing DST as a sequence to sequence problem using BERT (Devlin et al., 2019) and point generation, but its performance may be affected when facing utterances with multiple values. Another reason for the generation-based methods being popular is the publishing of large annotated DST datasets, such as MultiWOZ (Budzianowski et al., 2018), Ramadan et al., 2018, Eric et al., 2019, Zang et al., 2020), Schema-Guided Dialogue Dataset (Rastogi et al., 2019), etc. A large training dataset is necessary for the generation-based method due to its larger searching spaces.

But annotating a DST dataset is rather expensive, some studies try to avoid this problem. Lin et al., 2021 uses multiple machine reading comprehension datasets to train a generative model and achieves zero-shot cross-task transferring to the DST field. Du et al., 2021 uses a weakly supervised method to pretrain a span-based QA model for zero-shot slot filling. But these methods still need large annotated datasets of other tasks which are not always available.

As for the medical field, several dialogue systems (Kao et al., 2019, Wei et al., 2018, Xu et al., 2019) have been proposed to provide automatic diagnosis. The setup is similar to the general one except that its contents relate to the medical domain. Liu et al., 2020b published a medical consultation dataset on the dialogue system without annotation. Shi et
al., 2020] created a dataset for the medical slot filling task but only consider one symptom slot type with definite slot values.

However, making a diagnosis is more complex than making a decision in the general field like booking a restaurant. In this paper, we fully exploit the difficulties for the DST tasks in the medical dialogue system, providing solutions as well as publishing annotated datasets.

3 Task Definition

A dialogue $D$ consists of a list of utterances $U_1, R_1, ..., U_T, R_T$, where $U$ is the user’s input and $R$ is the response of the system. $T$ is the total turns of the dialogue. The input of the $t_{th}$ turn is denoted as $D_t = \{U_1, R_1, ..., R_{t-1}, U_t\}$. Notice that $R_t$ is not in $D_t$ because it will be the output of this turn for the system.

A schema must be predefined to represent the structure of the state. The schema involves a set $I$ indicating the intents of the user, and a hierarchical structure $S$. An example can be found in Table 1. $I$ contains all possible intents, like \{describe, ask, ...\} for patient’s intents and \{diagnose, recommend, ...\} for doctor’s intents. There are multiple hierarchies in $S$. The first hierarchy of $S$ contains all the fields $f$ needed for the system, like symptom. The second hierarchy of $S$ is a set of the slot types required by the corresponding field, like the name of the symptom. The value of each field $V_f$ is a compound structure including all the slots in $S[f]$.

Given a dialogue history $(D_t)$ and a schema $(I, S)$, the task is to first identify the intent $I_t$ of the input utterance $U_t$ and then identify all values $V_f$ for each field $f$ in $S$. The structure of $V_f$ is same with $S[f]$.

4 Approach

In this work, we treat the DST task as a Seq2seq task using a generative model. As shown in Figure 1, we use prompt token $P$ to transform the target (intent or slot type) and their value into a series of dialogue-style question-answer pair $(Q,A)$. By using $Q$ to generate $A$, we convert the DST task into a response generation task. This makes it possible to pretrain the model with unlabeled dialogue datasets. The result of the DST task is acquired by parsing the generated output utterance. An extra decoding algorithm is used to guarantee the utterance is well-formed.

4.1 Dialogue-style Prompt

There have been two common ways to construct the QA pair. As shown in Table 2, the easiest way is to simply use the slot type name with its description (Lee et al., 2021). Another way is to construct a question (Lin et al., 2021, Du et al., 2021, Liu et al., 2020a). However, it is easy to find that the dialogue itself is in the form of question and answer. If we construct the QA pair in the medical dialogue form, namely the question looks like an inquiry from a physician, and the answer is an ordinary utterance from a patient, we may fully utilize the large unlabeled medical dialogue corpus. Based on the above intuition, we propose a dialogue-style Prompt, as shown in the last row of Table 2.

For example, if the target is symptom “headache” with extent “bad”, we can construct a series of question and answers. For the first turn, the question is “Doctor: what symptoms do you have”, and let the model generate “Patient: I have a headache”. The prefix indicates the role of the speaker, “headache” is the value of the target slot, and “I have” is also a prompt indicating the model to output the expected result. For the next turn, we want to further get the extent of the headache symptom. We put the former output value of the last turn namely “headache” into the question, “Doctor: How is your headache”. The answer is “Patient: I feel bad”. We choose to use multi-turn QA instead of one like Seq2seq-DU [Feng et al., 2021], because we think that it would be difficult for the model to generate long sequences with a specified format accurately.

There also have been many ways to output the answer, like indicating the start and end position (Du et al., 2021), tagging the input sequence (Du et al., 2021), or generating the answer. We choose the generative model because it is better in tackling different kinds of output, no matter extractive or categorical. It would be hard for other models to be able to deal with both two tasks. Besides, the generated output must follow a predefined pattern to be easily parsed to a structure. For example, “I have a, b, c”. The comma can only appear in
Two-stage training process. The first stage is pretraining. The data for pretraining is filtered by the classifier. The training target is to generate the response according to the dialogue history. The second stage is fine-tuning which follows the same idea. We convert the slot and value into a pair of dialogue-style question and answer. The training target is still to generate the answer using the dialogue history including the constructed question.

| Input Dialogue | Query Type | Constructed Query Sample | Output result |
|----------------|------------|--------------------------|---------------|
| Patient: I have a bad headache. | Type name | symptom | headache |
| Question | What symptoms does the patient have? | Doctor: What symptoms do you have? | Patient: I have headache. |

We mix the descriptive utterance and random one in a ratio of 4:1.

**Fine-Tune** During the fine-tuning process, we transform the labeled data into the dialogue style and let the model generate the constructed answer.

### 4.3 Decoding Strategy

The major problem of the generative model is that the output is unpredictable and may be invalid. Furthermore, putting the history of dialogue into the input can help the model better understand the conversation but may introduce more noises [Yang et al., 2021] as well. Most generative-based DST methods simply discard invalid values. [Lin et al., 2021] uses canonicalization technique [Gao et al., ] to replace the predicted value with the closest value in the ontology. However, ontology is not always available.

To prevent the situation from happening, we use a constrained decoding algorithm during inference. Since the model generates the result in an autoregressive way, it is easy to control the decoding progress. In each step of decoding, we only focus on a limited range of tokens instead of the whole vocabulary. In this way, we can ensure the output is in the expected pattern.

For the extractive result, the output range will be limited to the tokens in the latest utterance, since the state change can only come from the newest input. For the categorical target, a trie-tree is constructed according to the candidates and we use it to guide the output range.
5 Experiments

5.1 Dataset

MDST is the dataset annotated in this paper. The original corpus comes from one of the biggest online medical consultation service providers in China, who hired clinicians to give suggestions to patients on the Internet. We collect 183,386 dialogues and annotate 89 of them. Detailed statistics are shown in Table 3. Compared to the two commonly used DST datasets, the dataset is much smaller. However, it costs a lot of effort to define the annotation specification with the help of clinicians. It also takes about six persons more than 2 months of effort to define the annotation specification with the help of clinicians. The dataset is divided into training, test, and validation sets in a ratio of 8:1:1.

MSL is proposed by [Shi et al., 2020] which is a dataset for medical slot filling task. It only focuses on symptom slot with finite values. It contains 1152 labeled utterances for training, 500 for validation, and 1000 for the test. We keep the same setup in our experiments.

5.2 Baseline

We set baselines of the intent detection and the slot filling tasks separately since few researchers process the two tasks in one unified model as we are.

BERT [Devlin et al., 2019] is easy to fine-tune on the intent detection task if we treat the task as a multi-label classification task. The input is one utterance instead of the whole dialogue history and the output is the intent of that utterance.

QA We follow the method proposed by [Lin et al., 2021] as the baseline. It treats the slot filling task as a Seq2Seq task in the form of question answering. We use the two methods in Table 2. One is to simply use the target slot type name, and the other is to convert the type name into a question with a template.

5.3 Metrics

Intent Detection could be defined as a multi-label classification task, so we use precision, recall, and F1 as the metrics.

Slot Filling is a bit complicated. We first transform the hierarchical state into a flat structure like ("symptom", "headache") and ("symptom", "headache", "extent", "serious"). In this way, it would be convenient to calculate the precision, recall, and F1 between the predicted tuple list and answer tuple list. With the approach, only when the slot value is completely the same as the answer is regarded as correct.

5.4 Setup

To ensure the comparison is fair, our approach and all baseline models use BERT-base and chinese_roberta_www_ext from [Cui et al., 2019] as the pre-trained weights. We use cross-entropy as the loss function and Adam as the optimizer with the learning rate of 1e-5. The batch size is 16 and each epoch has 1000 steps, 30 epochs in total. All the experiments are done on one NVIDIA GeForce RTX 3090 with 24GB VRAM.

5.5 Experiment Results

According to the first two rows of Table 4, we can see the generation-based methods outperform the simple classification model. This shows that generation-based methods are suitable for the intent detection task. However, the performance of our approach is 2.54% worse than QA, only 0.18% on precision but 4.73% on recall. But from the first two rows in one unified model as we are.

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part of Table 5, our approach is 6.51% superior to the baseline on slot filling task. This result proves that our approach is more suitable for the more complicated task with larger state spaces.

From Table 6 we can see that our method is much better than the result reported by [Shi et al., 2020] in the MSL dataset. Although it’s possible to treat this slot filling dataset as a multi-label classification problem like [Shi et al., 2020], our approach is still suitable for this task, and pretraining can almost always improve the performance.

### 5.6 Ablation Study

**Dialogue-style Prompt** QA method uses pairs of questions and answers without the dialogue-style prompt. From Table 4 we can find that the performance of our approach is 2.54% worse than QA on intent detection task. But in the slot filling task, our approach outperforms 6.51% to the QA method. This may suggest that the dialogue-style prompt could make the model focus on the semantic information so that it can help improve the performance on complex slot filling tasks. For the simple task like intent detection, the help is minimal. Another possible reason is that the definition of intent does not completely conform to the normal speech habits which makes the prompt confuse the model.

**Pretraining** To find out whether the pretraining can help the model understand the dialogue, we trained the model with the same setup but loaded the parameters of BERT instead of the pre-trained weights. From Table 4 and 5, we can see that pretraining has slight help in intent detection but large help in slot filling. The result is consistent with the expectation that pretraining is able to make the model find out the relationship between the utterances. This is more helpful for the difficult task. The result on the MSL dataset in Table 6 also supports our conclusion.

We find that loss decreases faster during the fine-tuning process with pretraining. One of the main reasons is that the pretraining has made the model learn to generate utterances while the original BERT cannot. This implies pretraining might be helpful in low-resource scenarios which are common in the medical field.

To prove the conjecture above, we reduce the training dataset to 20%, 50%, and 80% and repeat the training process. From Table 4 and 5, we can see that the size of training data has a great impact on the performance, and the model with pretraining performs better than the one without pretraining in most scenarios. This proves that our pretraining approach is helpful in low-resource scenarios. For the simple task like intent detection, when the data is sufficient, the impact of pretraining becomes smaller like the result between 80% and 100% data in Table 4.

### 5.7 Error Analysis

We further look into the error produced by the model and compare the result with the BERT+CRF which is a common but effective NER model. Notice that since NER cannot handle discontinuous and multi-hierarchies structures, we only compare the performance on the first-level slots. According to Table 7, we notice that the performance of our approach is a bit lower than BERT+CRF and the main gap is the recall rate.

We find two typical scenarios to explain the reason. For example, the output of the utterance 我肚子感觉难受(My stomach feels uncomfortable) is (symptom, 肚子感觉难受("stomach feels uncomfortable")) which is correct for the NER model. But our approach outputs (symptom, 肚子难受("stomach uncomfortable")) which extracts a discontinuous entity. The answer is also correct. However, it is hard for us to find all possible correct answers and put them in the annotated corpus. This example may partly explain why the recall performance is not that ideal. Another example is the symptom 皮肤过敏(skin allergy) whose body_part is 皮肤(skin). Our approach extracts 过敏(allergy) as a symptom whose body_part is 皮肤(skin). It is also hard to decide whether the two should be split.

### 6 Conclusion

In this work, we first redefine the state with multiple hierarchies and annotate a dataset called MDST extending existing DST tasks. We propose a dialogue-style prompt with UniLM to solve the new problem. The proposed prompt also makes it possible to pretrain the model with the unlabeled medical dialogue corpus. The experiments show that our method outperforms baseline up to 6.51%, and in low-resource scenarios, the pretraining can improve the performance up to 4.29%.

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