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# $M^2$ -MedDialog: A Dataset and Benchmarks for Multi-domain Multi-service Medical Dialogues

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## Abstract

Medical dialogue systems (MDSs) aim to assist doctors and patients with a range of professional medical services, i.e., diagnosis, consultation, and treatment. However, one-stop MDS is still unexplored because: (1) no dataset has so large-scale dialogues contains both multiple medical services and fine-grained medical labels (i.e., intents, slots, values); (2) no model has addressed a MDS based on multiple-service conversations in a unified framework. In this work, we first build a Multiple-domain Multiple-service medical dialogue ( $M^2$ -MedDialog) dataset, which contains 1,557 conversations between doctors and patients, covering 276 types of diseases, 2,468 medical entities, and 3 specialties of medical services. To the best of our knowledge, it is the only medical dialogue dataset that includes both multiple medical services and fine-grained medical labels. Then, we formulate a one-stop MDS as a sequence-to-sequence generation problem. We unify a MDS with causal language modeling and conditional causal language modeling, respectively. Specifically, we employ several pretrained models (i.e., BERT-WWM, BERT-MED, GPT2, and MT5) and their variants to get benchmarks on  $M^2$ -MedDialog dataset. We also propose pseudo labeling and natural perturbation methods to expand  $M^2$ -MedDialog dataset and enhance the state-of-the-art pretrained models. We demonstrate the results achieved by the benchmarks so far through extensive experiments on  $M^2$ -MedDialog. We release the dataset, the code, as well as the evaluation scripts to facilitate future research in this important research direction<sup>1</sup>.

## Introduction

Medical researches with AI techniques are growing rapidly (Zhang et al. 2021; Kao, Tang, and Chang 2018; Chintagunta et al. 2021; Wang et al. 2020), as one of them, medical dialogue systems (MDSs) are promising in increasing access to healthcare services, reducing medical costs (Zeng et al. 2020; Yang et al. 2020; Zeng et al. 2020; Li et al. 2021b). Unlike common task-oriented dialogue systems (TDSs) for ticket or restaurant booking (Li et al. 2017; Peng et al. 2018; Wen et al. 2017), MDSs are more challenging in that they require a great deal of expertise. For example, there are much more professional terms which are often expressed in colloquial language (Shi et al. 2020).

Recently, an extensive effort has been made towards building data for MDS research (Liao et al. 2020; Yang et al. 2020; Shi et al. 2020). However, they all have some limitations: (1) There is a lack of a complete diagnosis and treatment procedure. A practical medical dialogue is usually a combination consultation, diagnosis and treatment, as shown in Figure 1. To our knowledge, none of previous studies considers all three services simultaneously (Wei et al. 2018; Xu et al. 2019; Liu et al. 2020; Yang et al. 2020). (2) Labels are not comprehensive enough. Most datasets only provide the slot-value pairs for each utterance, e.g., there is one utterance in (Zhang et al. 2020): “Patient: Doctor, could you please tell me is it premature beat?” The label is only “Symptom: Cardiopalmus”. But the intent labels and the medical knowledge triples related to each utterance are rarely provided in existing MDS datasets. (3) Labels are not fine-grained enough. We found that composite utterances, which contain more than one intent/action, are common in practice. For example, at the third utterance in Figure 1, the patient said “Ten days. Yes. What is the disease?”, there are three different kinds of intents: informing time, informing symptom status and inquiring diseases. Previous studies usually provide a single coarse-grained label for the whole composite utterance, which might mislead the training of models and/or lead to inaccurate evaluation. Besides, the involved medical entities are limited in scale. For example, the very recent dataset, MedDG (Zeng et al. 2020), only contains 12 diseases.

To this end, our first goal is to contribute a MDS dataset with the following new features: (1) We consider medical dialogues for consultation, diagnosis and treatment, as well as their mixture. (2) We provide more comprehensive and fine-grained labels, e.g., action-slot-value triples for sub-utterances. (3) We consider more than 276 diseases, 20 slots and 2,468 medical entities. Besides, We ground the dialogues with medical knowledge triples by mapping medical entities.

Most previous methods for MDSs including some recent ones (Yang et al. 2020) adopt similar techniques as those in open-ended dialogue systems (ODSs) (Liu et al. 2020; Yang et al. 2020; Zeng et al. 2020). These methods can hardly make accurate decision-making considerations as they do not track the patient’s state or model the doctor’s policy explicitly. Recently, more and more studies consider MDSs as a kind of TDS (Wei et al. 2018; Xu et al. 2019; Liao et al. 2020) by decomposing a MDS system into sub-tasks, e.g., natural lan-

<sup>1</sup>Under review  
<https://github.com/yanguojun123/Medical-Dialogue>



Figure 1: A practical medical dialogue involving consultation, diagnosis, and treatment. They are all dependent. Combined with the knowledge triple in the upper right corner, we can better infer the related diseases. The lower right part is our annotation example, including intention, slot and value.

guage understanding (NLU), dialogue policy learning (DPL), and natural language generation (NLG). However, they only focus on one of the sub-tasks. For example, Shi et al. (2020) study NLU, i.e., slot filling in medical consultation. Wei et al. (2018) investigate DPL in medical diagnosis. There is a lack of comprehensive analysis on the performance of all the above tasks when achieved and/or evaluated simultaneously.

Therefore, our second goal is to propose a neural model that explicitly models the above three tasks to provide a complete medical procedure. We follow causal language modeling and adopt several pretrained language models (i.e., BERT-WWM, BERT-MED, MT5 and GPT2) and fine-tune them with the  $M^2$ -MedDialog dataset to get benchmark baselines. Last but not least, we propose a pseudo labeling algorithm and three natural perturbation methods to expand the proposed dataset and enhance the state-of-the-art pretrained models. We conduct extensive experiments on the proposed dataset and evaluate on three tasks. We found the unified framework beneficial to jointly learn all tasks simultaneously.

## Related Work

We survey related work in terms of datasets and models.

### Medical dialogue datasets

Most medical dialogue datasets contain only one domain (Wei et al. 2018; Xu et al. 2019; Shi et al. 2020; Zhang et al. 2020; Liu et al. 2020; Wang, Song, and Xia 2018; Lin et al. 2019) and/or one medical service (Wei et al. 2018; Xu et al. 2019; Liao et al. 2020; Shi et al. 2020; Lin et al. 2021, 2019). However, context information from other services and/or domains is often overlooked in a complete medical aid procedure. For example, in Figure 1, the symptom “sore throat” mentioned in the diagnosis service has the long-term effect on the suggestion “talk less” in the follow-up consultation service. To this end, we provide medical dialogues for consultation, diagnosis and treatment, as well as their mixture

in the  $M^2$ -MedDialog dataset. Although a few datasets (Zeng et al. 2020; Li et al. 2021b) contain multiple medical services in multiple domains, they target the NLG only without considering the NLU and DPL. Differently,  $M^2$ -MedDialog contains necessary labels for NLU, DPL and NLG. Another challenge of existing datasets is the medical label insufficiency problem. The majority of datasets only provide a spot of medical labels for slots or actions (Wei et al. 2018; Xu et al. 2019; Liao et al. 2020; Shi et al. 2020; Zhang et al. 2020; Liu et al. 2020; Lin et al. 2021). Moreover, their labels are too coarse to distinguish multiple intents or actions in one utterance. Unlike all datasets above, our dataset provides comprehensive and fine-grained intent/action labels for constituents of an utterance.

To sum up,  $M^2$ -MedDialog is the first multiple-domain multiple-service medical dialogue dataset with fine-grained medical labels and large-scale entities, which is more competitive compared with the datasets mentioned above in terms of 9 aspects (i.e., domain, service, task, intent, slot, action, entity, disease, dialogue). A summary can be found in Table 1.

### Medical dialogue models

Similar to TDSs (Chen et al. 2017), a MDS system can be divided into several sub-tasks, e.g., NLU, DPL, and NLG.

NLU aims to understand user utterances by intent detection (Wei et al. 2018) and slots filling (Weld et al. 2021; Chen and Yu 2019; Qin et al. 2019). Du et al. (2019, 2020) formulate NLU as a sequence labeling task and use Bi-LSTM to capture contextual representation for filling entities and their relations into slots. Lin et al. (2019) improve filling entities with global attention and symptom graph. Shi et al. (2020) propose the label-embedding attentive multi-label classifier and improve the model by weak supervision from responses. dialogue state tracking (DST) tracks the change of user intent (Mrkšić et al. 2017). Zhang et al. (2020) employ a deep matching network, which uses a matching-aggregate module to model turn-interaction among utterances encoded by Bi-LSTM. In this work, we integrate DST into vanilla NLU to generate intents and updated slot values simultaneously.

DPL decides system actions given a set of slot-value dialogue states and/or a dialogue context (Chen et al. 2017). Wei et al. (2018) first use reinforcement learning (RL) to extract symptoms as actions for disease diagnosis. Xu et al. (2019) apply deep Q-network based on a medical knowledge graph to track topic transitions. Xia et al. (2020) improve RL based DPL using generative adversarial learning with regularized mutual information. Liao et al. (2020) use a hierarchical RL model to alleviate the large action space problem. We generate system actions as general tokens to fully avoid action space exploration in these RL models.

NLG generates system responses given the outputs from NLU and DPL (Pei, Ren, and de Rijke 2019). Yang et al. (2020) apply several pretrained language models (i.e., Transformer, GPT, and BERT-GPT) to generate doctors’ responses for COVID-19 medical services. Liu et al. (2020) provide several NLG baselines based on sequence-to-sequence models (i.e., Seq2Seq, HRED) and pretrained language models (i.e., GPT2 and DialoGPT). Li et al. (2021a) use pretrained language models to predict entities and generate responses. Re-

Dataset	(#)Domain	(#)Service	(#)Task	#Intent/Slot/Action	#Entity	#Disease	#Dialogue
CMDD(Lin et al. 2019)	Pediatrics	Diagnosis	NLU	- / 1 / -	162	4	2,067
SAT(Du et al. 2019)	14	3	NLU	- / 1 / -	186	-	2,950
MSL(Shi et al. 2020)	Pediatrics	Consultation	NLU	- / 1 / -	29	5	1,652
MIE(Zhang et al. 2020)	Cardiology	2	NLU	- / 4 / -	71	6	1,120
MZ(Wei et al. 2018)	Pediatrics	Diagnosis	DPL	- / 2 / 6	67	4	710
DX(Xu et al. 2019)	Pediatrics	Diagnosis	DPL	- / 2 / 5	41	5	527
RD(Liao et al. 2020)	Pediatrics	Diagnosis	DPL	- / 2 / 2	90	4	1,490
SD(Liao et al. 2020)	9	Diagnosis	DPL	- / 2 / 2	266	90	30,000
COVID-EN(Yang et al. 2020)	COVID-19	3	NLG	- / - / -	-	1	603
COVID-CN(Yang et al. 2020)	COVID-19	3	NLG	- / - / -	-	1	1,088
MedDG(Liu et al. 2020)	Gastroenterology	2	NLG	- / 5 / -	160	12	17,864
MedDialog-EN(Zeng et al. 2020)	51	3	NLG	- / - / -	-	96	257,332
MedDialog-CN(Zeng et al. 2020)	29	3	NLG	- / - / -	-	172	<b>3,407,494</b>
Chunyu(Lin et al. 2021)	-	Diagnosis	NLG	- / 2 / -	-	15	12,842
KaMed(Li et al. 2021b)	<b>100</b>	<b>3</b>	NLG	- / 4 / -	<b>5,682</b>	-	63,754
$M^2$ -MedDialog-base	30	3	3	<b>5/20/7</b>	2,468	276	1,557
$M^2$ -MedDialog-large	40	3	3	<b>5/20/7</b>	4,728	<b>843</b>	95,408

Table 1: Comparison between our corpus and other medical dialogue corpora. SD and MedDG are automatically labeled with rules. COVID-EN, COVID-CN, MedDialog-EN and MedDialog-CN are all original dialogues without human-labels.

cently, meta-learning (Lin et al. 2021) and semi-supervised variational Bayesian inference (Li et al. 2021b) are adopted for low-resource medical response generation.

### $M^2$ -MedDialog Dataset

Our  $M^2$ -MedDialog is built following the pipeline in Figure 2: (1) We collect raw medical dialogues and knowledge base from online websites; (2) We clean dialogues by a set of reasonable rules, and sample dialogues by considering the proportions of disease categories; (3) We define annotation guidelines and incrementally improve them by dry-run annotation feedbacks until standard annotation guidelines are agreed by annotators; (4) We conduct human annotation with standard annotation guidelines.

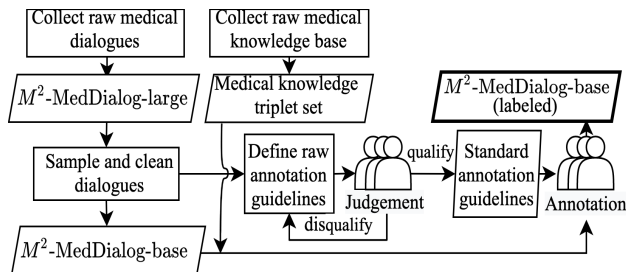


Figure 2: The process of dataset construction.

### Collecting raw dialogues and knowledge base

We collect 95,408 natural multiple-turn conversations between doctors and patients from ChunYuYiSheng<sup>2</sup>, a Chinese online medical community. These raw dialogues cover 40 domains (e.g., pediatrics), 3 services (i.e., diagnosis, consultation, and treatment), 51 disease categories (e.g., upper respiratory tract infection), 843 diseases (e.g., upper respiratory tract infection), and 4,728 medical entities.

<sup>2</sup><https://www.chunyuyisheng.com/>

We crawled 2.6M medical <entity1, relation, entity2> triplets from CMeKG2.0<sup>3</sup>, a Chinese medical knowledge base. For example, the triplet <paracetamol, indication, headache> denotes paracetamol can relieve headache. The entities involve about 901 diseases, 920 drugs, 688 symptoms, and 200 diagnosis and treatment technologies. The number of relations is about 125.

### Cleaning and sampling dialogues

We conduct the following steps to obtain a set of dialogues for human annotation: (1) Filtering out noise dialogues. First, we filter out short-turn dialogues with less than 8 utterances, because we found these short dialogues usually do not contain much information. Next, we filter out inaccurate dialogues with images or audios and keep dialogues with literal utterances only. Finally, we filter out dialogues in which too few medical entities emerged in the crawled knowledge triplet set. (2) Anonymizing sensitive information. We use special tokens to replace sensitive information in raw dialogues, e.g., "[HOSPITAL]" is used to anonymize the specific name of a hospital. (3) Sampling dialogues by disease categories. In order to balance the distribution of diseases, we extract the same proportion of dialogues from each disease to form  $M^2$ -MedDialog-base for annotation.

### Incremental definition of annotation guidelines

We hire 15 annotators with the relevant medical background to work with the annotation process. We define 5 intents, 7 actions and 20 slots and design a set of primer annotation guidelines. First, each annotator is asked to annotate 5 dialogues and then to report unreasonable, confusing and ambiguous guidelines with corresponding utterances. Second, we summarize the confusing issues and improve the guidelines by a high agreement among annotators. We repeat the

<sup>3</sup><http://cmekg.pcl.ac.cn/>

above two steps by three rounds and obtain a set of standard annotation guidelines.

### Human annotation and quality assurance

We build a web-based labeling system similar to (Ren et al. 2021) to make the annotation more convenient<sup>4</sup>. In the system, each annotator is assigned with 5 dialogues each round and is asked to label all utterances following the standard annotation guidelines. To assure annotation quality, we provide: (1) Detailed guidelines. For each data sample, we introduce the format of the data, the specific labeling task, the examples of various types of labeling, and detailed system operations. (2) A real-time feedback paradigm. We maintain a shared file to track problems and solutions in real time. (3) A semi-automatic quality judgement paradigm. We adopt a rule-based quality judgement model to assist annotators to re-label the untrusted annotations. (4) An entity standardization paradigm. We use Levenshtein distance ratio (Levenshtein et al. 1966) to compute the similarity between an annotation and an entity in medical knowledge triplet. If a max similarity score is in [0.9,1], we ask the annotator to replace the annotation with a standard entity from the medical knowledge triplet.

### Dataset statistics

Table 2 shows the data statistics.  $M^2$ -MedDialog-base contains 1,557 dialogues with sub-utterance-level semantic labels in the format of intent-slot-value or action-slot-value. It is randomly divided into 657/100/800 dialogues for training, validation, testing, respectively. It has 30 domains and 3 services, and 70% of the dialogues involve multiple services. The average number of utterances and characters distribute approximately the same in all sets.

	Train	Dev	Test	Total
#Dialogue	657	100	800	1,557
#Utterance	10,642	1,718	13,086	25,446
#Utterance/dialogue	16.50	17.18	16.36	16.34
#Char./dialogue	311.80	332.63	318.35	316.50
#Char./utterance	19.25	19.36	19.46	19.37
#SL/dialogue	29.85	31.01	29.85	29.93
#SL/utterance	1.84	1.81	1.82	1.83

Table 2: Statistics of  $M^2$ -MedDialog-base dataset.

Figure 3 shows the number of utterances distributed over different types of intents/actions and slots. In the left chart, there are 5 patient intents (i.e., “Informing”, “Inquiring”, “Chitchat”, “QA” and “Others”) and 7 doctor actions (including 5 intent types plus “Recommendation” and “Diagnosis”). These cover 42,081 utterances in total, and an utterance might contain multiple intents/actions. “Informing” and “Inquiring” account for the largest proportion (62%), while “Diagnosis” takes up the minimal proportion (1%). It shows that patients have a huge demand of online medical consultations, while doctors are very cautious to make online diagnosis. In the

right chart, it contains 20 types of slots covering 2,468 entities in total. “Symptom” (23%) has the largest proportion of entities, followed by “Treatment” (16%), “Disease” (11%) and “Medicine” (11%).

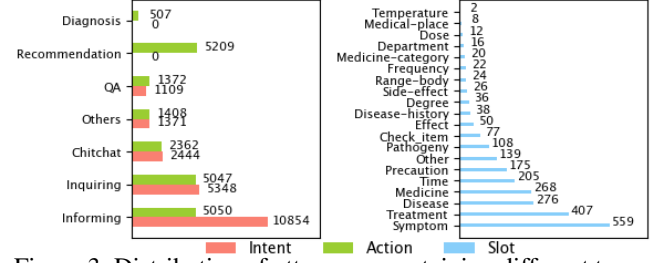


Figure 3: Distribution of utterances containing different types of intents/actions (left) and slots (right), respectively.

## Methodology

### Unified MDS framework

We tackle a MDS as a context-to-text generation problem (Hosseini-Asl et al. 2020; Pei et al. 2020) and deploy a unified framework called SeqMDS. Formally, given a sequence of dialogue context  $X$ , a MDS aims to generate a system response  $Y$  which maximizes the generation probability  $P(Y|X)$ . Specifically, all sub-tasks are defined by the following formation.

The NLU part of SeqMDS aims to generate a list of intent-slot-value triplets  $I_t$ :

$$I_t = \text{SeqMDS}(U_t), \quad (1)$$

where dialogue history  $U_t = [U_1^{(u)}, U_1^{(s)}, \dots, U_t^{(u)}]$  consists of all previous utterances. And  $I_t$  can be used to retrieve a set of related knowledge triplets  $K_t$  from the knowledge base..

The DPL part of SeqMDS generates the action-slot-value pairs  $A_t$  given  $U_t$ ,  $I_t$ , and  $K_t$  as an input:

$$A_t = \text{SeqMDS}([U_t, I_t, K_t]). \quad (2)$$

The NLG part of SeqMDS generates a response based on all previous information:

$$U_t^{(s)} = \text{SeqMDS}([U_t, I_t, K_t, A_t]). \quad (3)$$

SeqMDS in the above equations can be implemented by either a causal language model or a conditional causal language model, which are described in the next two subsections.

### Causal language model

We consider the concatenation  $[U_t; I_t; K_t; A_t; U_t^{(s)}]$  as a sequence of tokens  $X_{1:n} = (x_1, x_2, \dots, x_n)$ . The  $j$ -th element  $x_j^i$  can be an intent token (in intent-slot-value pairs), an action token (in action-slot-value pairs), or a general token (in utterances from patients or doctors). For the  $i$ -th sequence  $X_{1:n}^i$ , the goal is to learn the joint probability  $p_\theta(X_{1:n}^i)$  as:

$$p_\theta(X_{1:n}^i) = \prod_{j=1}^n (x_j^i | X_{0:j-1}^i). \quad (4)$$

<sup>4</sup><https://github.com/yanguojun123/Medical-Dialogue>



The cross-entropy loss is employed to learn parameters  $\theta$ :

$$\mathcal{L}(\mathcal{D}) = - \sum_{i=1}^{|\mathcal{D}|} \sum_{j=1}^{n_i} x_j^i \log p_\theta(x_j^i | X_{1:j-1}^i), \quad (5)$$

where  $\mathcal{D} = \{X^1, X^2, \dots, X^{|\mathcal{D}|}\}$  is the training set. In this work, we implement the above causal language model using the GPT2 model (Radford et al. 2019).

### Conditional casual language model

We consider the concatenation  $[U_t], [U_t; I_t; K_t], [U_t; I_t; K_t; A_t]$  as the input sequence  $X_{1:n}$  and  $I_t, A_t, U_t^{(S)}$  as the generated sequence  $Y_{1:m}$  in NLU, DPL and NLG, respectively.

For each input sequence, a Transformer encoder is used to convert  $X_{1:n}^i = (x_1^i, x_2^i, \dots, x_n^i)$  to the corresponding hidden states  $H_{0:n}^i = (h_0^i, h_1^i, \dots, h_n^i)$ ,

together with the current decoded tokens  $Y_{1:j-1}^i$ , a Transformer decoder is used to learn the probability  $p_\theta(Y_{1:m}^i | H_{1:n}^i)$  over the vocabulary  $V$  at the  $j$ -th timestamp by:

$$p_\theta(Y_{1:m}^i | H_{1:n}^i) = \prod_{j=1}^m p_\theta(y_j^i | Y_{1:j-1}^i, H_{1:n}^i). \quad (6)$$

Similarly, the model can be learned by minimizing the cross entropy loss as follows:

$$\mathcal{L}(\mathcal{D}) = - \sum_{i=1}^{|\mathcal{D}|} \sum_{j=1}^{n_i} y_j^i \log p_\theta(y_j^i | Y_{0:j-1}^i, H_{1:n}^i). \quad (7)$$

In this work, we implement the above conditional causal language model using the MT5 model (Xue et al. 2021).

### Pseudo labeling

We propose a pseudo labeling algorithm to extend the unlabeled dialogues. As shown in Algorithm 1, we denote the

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#### Algorithm 1: Pseudo labeling.

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**Input** :  $D_L, D_P, R; U_L = \{(U_L^i, A_L^i)\}_{i=1}^{|U_L|}$

**Output** :  $U_P = \{(U_P^i, A_P^i)\}_{i=1}^{|U_P|}$

```

1 foreach  $D_P^j \in D_P$  do
2   foreach  $U_P^{ij} \in D_P^j$  do
3      $\eta, a = \text{MaxSimilarity}(U_P^{ij}, U_L)$ 
4     if  $\eta > \delta$  then
5        $A_P^i \leftarrow a$ ;
6     else
7       foreach  $R^i \in R$  do Update  $A_P^i$ ;
8 Function  $\text{MaxSimilarity}(U_P^{ij}, U_L)$  :
9    $\eta = 0; a = \text{null}; x = \text{len}(U_P^{ij}); y = \text{len}(U_L^k)$ ;
10  foreach  $U_L^k \in U_L$  do
11     $\hat{\eta} = 1 - \text{LevenshteinDistance}(x, y) / (x + y)$ ;
12    if  $\hat{\eta} > \delta$  then
13       $\eta \leftarrow \hat{\eta}; a \leftarrow A_L^k$ 
14  return  $\eta, a$ ;
```

---

whole dialogue set as  $D$ , the labeled set as  $D_L$ , and the unlabeled set as  $D_P$ . Then we decompose  $D, D_L$ , and  $D_P$

into utterance data sets, i.e.,  $U, U_L$  and  $U_P$ , respectively. Each element of  $U_L$  contains a raw utterance data and its corresponding label.  $R$  is a set of predefined rules, e.g., ‘‘the action is ‘Recommendation’ and the slot is ‘Medicine’, if ‘take orally’ is mentioned in some utterance.’’ The output is  $U_P$  with pseudo labels. The main procedure is as follows. For each utterance in  $U_P$ , we calculate the similarities between the current utterance  $U_P^{ij}$  and all labeled utterances in  $U_L$  to get the maximum similarity  $\eta$  and the corresponding label  $a$ . If  $\eta$  is larger than the threshold  $\delta = 0.8$ ,  $a$  is assigned as the pseudo label of  $U_P^{ij}$ . Otherwise, each rule in  $R$  is applied to  $U_P^{ij}$  to update  $A_P^i$  gradually. The similarity is deployed based on Levenshtein distance (Levenshtein et al. 1966), as it considers both the overlap rate and the order of characters.

### Natural perturbation

We use three natural perturbation strategies to extend the labeled dialogues: (1) Alias substitution. If an utterance contains a drug with an alias, then the drug will be replaced with its alias to obtain a new data. For example, people from different regions may have different names for the same drug. (2) Back-translation. Chinese utterances are first translated into English and then back into Chinese to form new data. Patients often use colloquial expressions, which motivates us to adopt back-translation to produce formal utterances from the informal ones. (3) Random modification. We randomly add, delete and replace a character of several medical entities in utterances. This simulates the common situation - typographical errors in online medical communities.

## Experimental Setups

### Benchmark models

We employ several pretrained models as benchmarks: (1) **BERT-WWM** (Cui et al. 2019) is a BERT (Devlin et al. 2019), pre-trained on Chinese Wikipedia corpus. (2) **BERT-MED**<sup>5</sup> is a BERT pre-trained on Chinese medical corpus. (3) **GPT2** (Radford et al. 2019) is used as a Transformer decoder for causal language modeling. We use the one pre-trained on Chinese chitchat dialogues<sup>6</sup>. (4) **MT5** (Xue et al. 2021) is used as a Transformer encoder-decoder model for conditional causality modeling. We use the one pre-trained on multilingual C4 dataset<sup>7</sup>.

Please refer to the original papers for the detailed settings of the above models. We finetune the models on three training datasets produced by pseudo labeling, natural perturbation, and human annotation, respectively. We use AdamW (Kingma and Ba 2015) as the optimization algorithm. The maximum training epochs is set to 30.

### Automatic evaluation

We use 4 metrics to evaluate the NLU and DPL tasks: (1) **Micro-F1** is the intent/action/slot F1 regardless of categories.

<sup>5</sup><https://code.iHub.org.cn/projects/1775>

<sup>6</sup><https://github.com/yangjianxin1/GPT2-chitchat>

<sup>7</sup><https://github.com/google-research/multilingual-t5>

(2) **Macro-F1** denotes the weighted average of F1 scores of all categories. In this work, we use the proportion of data in each category as the weight. (3) **BLEU** (Chen and Cherry 2014) indicates how similar the generated values of intent/action slots are to the golden ones. (4) **Combination** is defined as  $0.5 * \text{Micro-F1} + 0.5 * \text{BLEU}$ . This measures the overall performance in terms of both intent/action/slot and the generated response. We use 4 metrics to evaluate the NLG task: (1) **BLEU1** and **BLEU4** (Chen and Cherry 2014) denotes the uni-gram and 4-gram precision, indicating the fraction of the overlapping n-grams out of all n-grams for the responses. (2) **ROUGE1** (Banerjee and Lavie 2005) refers to the uni-grams recall, indicating the fraction of the overlapping uni-grams out of all uni-grams for the responses. (3) **METEOR** (Lin 2004) measures the overall performance, i.e., harmonic mean of the uni-gram precision and recall.

## Human evaluation

For the NLG task, we sample 300 context-response pairs to conduct human evaluation. We ask annotators to evaluate each response by choosing a score from 0, 1, 2, which denotes bad, neutral, good, respectively. Each data sample is labeled by 3 annotators. We define 2 human evaluation metrics: (1) **Fluency** measures to what extent the evaluated responses are fluent. (2) **Specialty** measures to what extent the evaluated responses provide complete and accurate entities compared with the reference responses.

## Results and Analyses

### Natural language understanding

Table 3 shows the performance of all models, and the ablation study of MT5 (oracle), on the NLU task. First, for

	Micro-F1/Macro-F1(%)		BLEU(%) Combi.	
	Intent	Intent-Slot	Value	
BERT-WWM	71.76/71.79	57.38/58.21	-	-
BERT-MED	71.47/71.79	<b>57.64/58.72</b>	-	-
GPT2	73.32/69.23	49.23/46.27	8.17	28.70
MT5	<b>75.32/72.67</b>	55.63/53.07	18.44	<b>37.03</b>
-Pseudo labeling	74.33/71.12	54.84/52.01	18.21	36.53
-Natural perturbation	73.90/70.77	53.97/50.99	<b>18.85</b>	36.41
-Historical utterances	74.43/71.62	54.10/51.19	18.04	36.07

Table 3: Performance on the NLU task.

intent label identification, MT5 achieves the best Micro-F1 of 75.32%, followed by GPT2 of 73.32%. MT5 outperforms BERT-WWM/BERT-MED by 3.56%/3.85% and GPT2 wins by 1.56%/1.85%. So, MT5 and GPT2 can generate more accurate intent labels compared with BERT models. Second, for intent-slot label identification, BERT models outperform others by large margins in terms of both Micro-F1 and Macro-F1. BERT-MED achieves 2.01%/8.41% higher Micro-F1 and 5.65%/12.45% higher Macro-F1 than MT5 and GPT2. We believe one of the reasons is that BERT predicts over the label space rather than the whole vocabulary (like GPT2 and MT5), which makes the task easier. But BERT models are not able to predict the slot-values for the same reason. Another reason

is that unlike intent identification, the training samples of intent-slot identification are inefficient and imbalanced (See Figure 3), so the generation models (e.g., MT5 and GPT2) can hardly beat the classification models (e.g., BERT-WWM and BERT-MED). Third, for value generation, MT5 significantly outperforms GT2 by 10.27% in terms of BLEU and BERT models are unable to generate values. It shows that conditional casual language model is more conducive for value generation. Fourth, MT5 outperforms others in terms of overall performance, i.e., Combination. We conducted an ablation study, and found that pseudo labeling, natural perturbation, and historical utterances all have positive effect on the overall performance. Specifically, historical utterances have the largest influence (-1.04%), followed by natural perturbation (-0.62%) and pseudo labeling (-0.52%). All scores decrease except the BLEU score of MT5 without natural perturbation. This is because that the meaning of entities might be ambiguous after modification, e.g., “azithromycin” is replaced by its common name as “泰力特(tylett)”, which is hard to be distinguished from “力比泰(alimta)” in Chinese.

### Dialogue policy learning

Table 4 shows the performance of all models, and the ablation study of MT5 (oracle), on the DPL task.

	Micro/Macro-F1(%)		BLEU(%)	Combi.
	Action	Action-Slot		
BERT-WWM	52.48/51.98	37.23/35.12	-	-
BERT-MED	49.83/49.60	35.76/34.19	-	-
GPT2	43.79/38.80	22.37/19.55	2.87	12.62
GPT2 (oracle)	45.79/41.63	27.22/24.35	3.69	15.45
MT5	46.78/41.37	26.49/22.58	3.33	14.91
MT5 (oracle)	<b>53.07/52.07</b>	<b>38.58/36.51</b>	9.07	<b>23.82</b>
-Pseudo labeling	52.04/50.53	38.00/36.24	9.11	23.56
-Natural perturbation	52.40/49.82	37.64/35.63	<b>9.24</b>	23.44
-Historical utterances	50.73/47.97	35.98/33.63	7.38	21.68
-External knowledge	51.06/48.20	31.86/28.74	8.67	20.26

Table 4: Performance on the DPL task. The remark “oracle” indicates that the ground truth from NLU is used instead of the prediction.

First, MT5 (oracle) outperforms all the other models on all metrics. Specifically, it outperforms BERT-WWM by 0.59% and 1.35% on Micro-F1 for action and action-slot label identification, respectively. This reveals that MT5 can beat BERT models when more given more information in the input, especially the result from NLU. Besides, it achieves 5.38% higher BLEU and 8.37% higher Combination compared with GPT2 (oracle), which indicates that conditional casual language modeling is more effective in this case. Second, we explore the joint learning performance for MT5 and GPT2, where the prediction from NLU is used as an input of DPL. MT5 still outperforms GPT2 by 2.29% for the overall performance, specifically 2.99% for the action label identification, 4.12% for the action-slot label identification, and 0.46% for the value generation. Third, we conducted an ablation study on MT5 and found that pseudo labeling, natural perturbation,

historical utterances, and external knowledge are still helpful. Specifically, external knowledge has the largest influence (-3.56%), followed by historical utterances (-2.14%), natural perturbation (-0.38%), and pseudo labeling (-0.26%). All scores decrease generally. One exception is that BLEU increases by 0.17% without natural perturbation. Similar to the case in NLU, some modified entities may cause ambiguity.

## Natural language generation

	Word-in-Utterance (%)			
	BLEU1	BLEU4	ROUGE1	METEOR
GPT2	14.12	1.95	66.43	16.34
GPT2 (oracle)	25.98	5.73	<b>72.71</b>	29.41
MT5	11.47	1.43	63.74	12.91
MT5 (oracle)	<b>26.54</b>	6.76	71.77	<b>29.90</b>
-Pseudo labeling	25.20	6.43	71.08	28.86
-Natural perturbation	25.97	6.51	71.48	29.57
-Historical utterances	24.93	6.42	71.01	28.76
-External knowledge	26.27	<b>6.81</b>	71.58	29.85

Table 5: Automatic evaluation on the NLG task. The remark “oracle” indicates that the ground truth from NLU and DPL is used instead of the prediction.

Table 5 shows the automatic evaluation of GPT2 and MT5, and the ablation study of MT5 (oracle), on NLG. First, MT5 (oracle) outperforms GPT2 (oracle) on METEOR. Specifically, MT5 (oracle) is 0.56% and 1.03% superior on BLEU1 and BLEU4 but 0.93% inferior on ROUGE1.

It shows that although GPT2 can generate relevant tokens, the generation of MT5 is more precise. Second, we explore the joint learning performance, where the prediction of NLU and DPL is used as the input of NLG. We found that MT5 is inferior to GPT2 as METEOR, BLEU1, BLEU4 and ROUGE1 drop by 3.43%, 2.65%, 0.52% and 2.69%. It is because that the predictive quality of upstream tasks have more influence on MT5 than GPT2. Third, we conduct an ablation study for MT5 (oracle). We found that pseudo labeling, natural perturbation, historical utterances, and external knowledge are still helpful. Historical utterances (-1.14%) is the most influential, followed by pseudo labeling (-1.04%), natural perturbation (-0.33%) and external knowledge (-0.05%).

	Fluency	Specialty
GPT2 (oracle)	1.72	1.04
MT5 (oracle)	1.82	1.22
Ground truth	1.91	2.00
$\kappa$	0.64	0.62

Table 6: Human evaluation on the NLG task.  $\kappa$  is the average pairwise Cohen’s kappa coefficient between annotators.

Table 6 shows the human evaluation on the NLG task. We did not consider the joint-learned GPT2 and MT5, as they contain the accumulated error from the upstream tasks, which will influence the evaluation of NLG. First, MT5 (oracle) performs better than GPT2 (oracle) on Fluency and Specialty. This indicates that MT5 can generate more fluent responses

that provide more accurate medical knowledge compared with GPT2. This is consistent with the results of automatic evaluation. Second, the Fluency score is higher than Specialty for both GPT2 and MT5. This is because Specialty is more difficult, as generating responses with massive and accurate expertise is more challenging. Third, the average pairwise Cohen’s kappa coefficient is larger than 0.6 for all metrics, which indicates a good annotator agreement.

## Case study

Table 7 gives an instance of the medical dialogue generated by GPT2 (oracle) and MT5 (oracle) given the same dialogue context. MT5 (oracle) performs better than GPT2 (oracle) in terms of both Fluency and Specialty. Specifically, the response generated by GPT2 (oracle) is less fluent, as the concrete object X after “eat less” is missing. MT5 (oracle) generates correct entities while the entity of “diarrhea” is missing in GPT2 (oracle). The joint-learned GPT2 and MT5 are inferior to their corresponding oracle models due to error accumulation from the upstream tasks.

**Dialogue context:** (historical utterances...)

$P_1$ : 查了, 没什么就是消化不良(We’ve checked. He gets indigestion.)

$D_1$ : 可以试试布拉氏酵母菌(You can try yeast boulardii.)

$P_2$ : 吃了思密达没用(He ate Smecta, but it didn’t work.)

**Ground truth:**

Intent-Slot-Value: Inform medicine 思密达无效(Smecta ineffectiveness)

Action-Slot-Value: Recommend precaution 少吃母乳(eat less breast milk)

Response: 最好母乳少吃, 吃腹泻奶粉. (He had better to eat less breast milk and replace it with diarrhea milk powder.)

**GPT2:**

Intent-Slot-Value: Inform medicine 思密达(Smecta)

Action-Slot-Value: Inform medicine 妈咪爱(mammie)

Response: 可以吃点妈咪爱. (You can take some mammie.)

**GPT2(oracle):**

Response: 可以吃点调理肠胃的奶粉, 少吃点[X] (He can eat some milk powder to regulate intestines and stomach and eat less [X].)

**MT5:**

Intent-Slot-Value: Inform medicine 思密达(Smecta)

Action-Slot-Value: Recommend medicine 妈咪爱(mammie)

Response: 可以吃妈咪爱. (He can take some mammie.)

**MT5(oracle):**

Response: 可以吃腹泻奶粉. (He can eat diarrhea milk powder.)

Table 7: Case study.  $P_i$  and  $D_i$  denote the  $t$ -th utterance from the patient and the doctor. The green and red tokens indicate the correct and incomplete entity, respectively.

## Conclusion and Future Work

In this paper, we create a multiple-domain multiple-service dataset with fine-grained medical labels for one-stop medical dialogue systems. We fit NLU, DPL and NLG into a unified SeqMDS framework, based on which, we deploy several cutting-edge pretrained language models as benchmarks. Besides, we have introduced two data argumentation methods, i.e., pseudo labeling and natural perturbation, to generate synthetic data to enhance the model performance. Extensive experiments have demonstrated that SeqMDS can achieve



good performance with different pretrained models as backends. As to future work, we call for studies to improve the benchmark performance, as well as underexplored research, e.g., dialogue context modeling among multiple services, out-of-domain NLU, DPL, etc.

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