SF-DST: Few-Shot Self-Feeding Reading Comprehension Dialogue State Tracking with Auxiliary Task

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Abstract

Few-shot dialogue state tracking (DST) model tracks user requests in dialogue with reliable accuracy even with a small amount of data. In this paper, we introduce an ontology-free few-shot DST model with self-feeding belief state input. The self-feeding belief state input increases the accuracy of multi-turn dialogue by summarizing previous dialogue. Also, we newly developed a slot-gate auxiliary task. This new auxiliary task helps classify whether a slot is mentioned in the dialogue. Our model achieved the best score in a few-shot setting for four domains on multiWOZ 2.0.

Index Terms: multi-domain dialogue systems, dialogue state tracking, belief tracking, reading comprehension, self-feeding

1. Introduction

Task-Oriented Dialogue (TOD) system conducts a conversation with a specific purpose and is increasingly necessary due to the emergence of artificial-intelligence speakers and virtual personal assistants. In general, a TOD system is composed of three main sections: a dialogue state tracking (DST) module to track the user’s purpose, a dialogue policy module (POL) to choose system actions like API calling or ending conversation, and a natural-language generation (NLG) module to produce a response to the user [1]. The DST system is a key component of these three parts since it generates a belief state that contains information about the user’s purpose. The belief state is often represented as slot value pairs. For example, in Figure 1, the belief state has hotel information, which is needed to achieve user’s purpose for hotel reservation.

Although DST is essential in a TOD system, labeling the DST dataset is costly. Some authors have tried to train DST using only limited data (few/zero-shot DST) to solve this problem. One promising way is to adopt reading comprehension (RC) in DST [2, 3]. The RC task aims to answer the question by understanding the passage. RC and DST have a similar goal: DST aims to find the value (answer) of slot (question) by understanding the dialogue (passage). In this approach, researchers design questions (e.g., Where is hotel area that the user wants?) for slots (e.g., hotel.area) in advance, and at each turn of dialogue, the model reads the dialogue and answers the questions. These predicted answers become belief state. The first research [2] that adopted RC in a DST divided slots into multiple-choice and span-prediction types and showed knowledge transfer ability of natural language questions. However, their model requires an ontology data that contains pre-defined values for each slots. This has low scalability to new domain and values. To overcome the limitation, [3] proposed an ontology-free model by answering questions generatively and could flexibly predict the unseen domain and values. However, both [2] and [3] require additional external data for pre-training their models. Also, their models have difficulty in classifying whether a slot is mentioned in the dialogue and this problem was the main reason for the accuracy drop.

The use of an auxiliary task is another approach of a few-shot DST. The named-entity recognition task was combined with the DST task to reduce the number of network parameters and increase generalization ability across the domain [4, 5]. The language modeling task was also used with the main DST task, and the combination increased the accuracy in a long context dialogue [6].

In this study, we introduce a few-shot reading comprehension DST with a Self-Feeding approach (SF-DST). We used a text-to-text structure for generative, ontology-free DST and designed a self-feeding belief state input to summarize the previous turn. Applying self-feeding belief state is the first attempt in the RC format DST. Furthermore, we developed a slot-gate auxiliary task which helps to classify whether a slot is mentioned in the dialogue.

Our model achieved the best accuracy in a few-shot experiment for four domains on MultiWOZ 2.0 [7], and achieved close to the current state-of-the-art in a supervised setting on MultiWOZ 2.1 [8]. In analysis, we investigated the effect of self-feeding belief state input and auxiliary task in various few-shot settings. To summarize our approach and contributions:

- We propose Self-Feeding reading comprehension DST (SF-DST), an ontology-free few-shot model to track belief state. SF-DST has a text-to-text structure and includes self-feeding belief state input. We showed that the belief state helps understand multi-turn dialogue by
Figure 2: The proposed SF-DST model's architecture. Our model has a text-to-text structure and uses the reading comprehension method. The model receives questions, dialogue history, and predicted previous belief state as inputs (self-feeding).

In addition to the DST task, the model is trained on a slot-gate auxiliary task (marked with a dashed line).

2. Methods

2.1. Problem statement

Conversation $C$ for time step $t$ is denoted as $C_t = \{x_1, y_1, \ldots, y_{t-1}, x_t\}$, where $x_t$ means user utterance and $y_t$ means system utterance. The belief state $B_t$ at turn $t$ is composed of slot $s \in S$ and value $v \in V$. $V$ includes don’t care and not mentioned values and notation $v_s$ means value for slot $s$. Question set $Q$ consists of $q_s$ which is predefined before training (e.g., $s$: attraction.name, $q_s$: What is the attraction name?). Auxiliary set $A$ consists of $a_s$, and ‘Are they talking about [slot]?’ is the inquiry form. $a_s$ is also predefined before training (e.g., $s$: attraction.name, $a_s$: Are they talking about attraction name?).

2.2. SF-DST

SF-DST has text-to-text structure for generative, ontology-free DST (Figure 2). The input value consists of dialogue history $C_t$, corresponding question for slot $q_s$, and previous belief state $B_{t-1}$. The model answers the question for all slots at each dialogue turn $t$, and the predicted answers $v_s$ become $B_t$. We did not use a gold belief state as input in both training and inference time; instead, we designed a self-feeding belief state method in which the predicted belief state from the previous turn becomes the current turn’s input belief state. We separate user and system utterances by using [user] and [sys], and add index words Context, Question and Belief to distinguish each input part:

$$v_s = \text{seq2seq}(C_t, q_s, B_{t-1}).$$  \hspace{1cm} (1)

We use negative log-likelihood as a loss function given $C_t$, $q_s$, and $B_{t-1}$ as

$$L_{\text{belief}} = -\sum^n_{i=1} \log p(v_i|C_t, q_s, B_{t-1}),$$  \hspace{1cm} (2)

where $n$ denotes the total number of slots.

2.3. Auxiliary task

Some extractive DSTs use a two-step system. These systems first classify whether the slot is mentioned in dialogue, and if classified as mentioned, then finds the answer span from dialogues [9, 10, 11, 12]. This classification module is called slot-gate. By splitting the DST task into two models, this strategy can lower the strain on each model. However, this cascading approach risks error propagation and requires a relatively long inference time. Instead of a cascading strategy, we directly answered a question and trained a slot-gate task as an auxiliary task. The auxiliary task is trained as a question-answering form (Figure 2) and ‘Are they talking about [slot]?’ is the inquiry format. The answer is Yes if the slot value is in belief state $B_t$, and not mentioned otherwise; i.e., the main DST question aims to generate a specific value, whereas the auxiliary question aims to classify the slot’s mention in the dialogue. The auxiliary task uses the context $C_t$, previous belief state $B_{t-1}$ and auxiliary question $a_s$ as input which has the same form as (1) except the slot question, and uses loss function (2). To train the auxiliary task with the main DST task, our model uses a joint loss function with hyperparameter $a$

$$L = L_{\text{belief}} + aL_{\text{aux}}.$$  \hspace{1cm} (3)

We set $a$ empirically to 0.7.

3. Experiment

We performed experiments on MultiWOZ 2.0 and MultiWOZ 2.1 dataset, which are multi-domain TOD datasets collected using a ‘wizard of oz’ setting. MultiWOZ 2.1 is a clean and accurate version of MultiWOZ 2.0. Both have seven domains (Hotel, Restaurant, Attraction, Train, Taxi, Hospital, and Police) and contain about 8,000 dialogues. We excluded the Hospital and Police domains during training, because they are only included in training data. We use joint goal accuracy (JGA) to evaluate

Table 1: Joint goal accuracy on MultiWOZ 2.1 in a supervised setting. Models focused on a few/zero shot are marked with †.

| Model        | JGA [%] | Ontology | Type |
|--------------|---------|----------|------|
| TRADE †      | 46.00   | need     | G    |
| STARC †      | 49.48   | need     | C+S  |
| DSTQA †      | 51.17   | need     | C+S  |
| DS-DST       | 51.21   |          | C+S  |
| GPT2QA †     | 52.58   |          | G    |
| SST-2        | 55.23   | need     | C    |
| TrippPy      | 55.29   |          | S    |
| FPDS\text{turn} | 57.88   | need     | C    |
| SF-DST (ours)| 56.96   |          | G    |

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Table 2: Joint goal accuracy [%] on MultiWOZ 2.0. We use 2.0 version to compare with other models. Models that require ontology are marked with †.

| Model     | Hotel 1% | Hotel 5% | Hotel 10% | Restaurant 1% | Restaurant 5% | Restaurant 10% | Attraction 1% | Attraction 5% | Attraction 10% | Train 1% | Train 5% | Train 10% | Taxi 1% | Taxi 5% | Taxi 10% |
|-----------|----------|----------|-----------|---------------|---------------|---------------|--------------|--------------|---------------|----------|----------|-----------|--------|--------|---------|
| TRADE     | 19.73    | 37.45    | 41.42     | 42.42         | 55.70         | 60.94         | 35.88        | 57.55        | 63.12         | 59.83    | 69.27    | 71.11     | 63.81  | 66.58  | 70.19   |
| DSTQA †   | N/A      | 50.18    | 53.68     | N/A           | 58.95         | 64.51         | N/A          | 70.47        | 71.60         | N/A      | 70.35    | 74.50     | N/A    | 70.90  | 74.19   |
| STARC †   | 45.91    | 52.59    | 57.37     | 51.65         | 60.49         | 64.66         | 40.39        | 65.34        | 66.27         | 65.67    | 74.11    | 75.08     | 72.58  | 75.35  | 79.61   |
| SF-DST    | 54.15    | 58.61    | 59.71     | 57.28         | 68.92         | 70.14         | 61.24        | 76.69        | 79.35         | 71.60    | 76.05    | 78.25     | 65.74  | 67.48  | 72.06   |

Table 3: Joint goal accuracy [%] on MultiWOZ 2.1 and use of external data. The result of SimpleTOD, MinTL, SOLOIST and PPTOD are referenced from [19].

| Model     | External Data | Training Size (%) |
|-----------|---------------|-------------------|
|           |               | 1                 | 5                 | 10                |
| SimpleTOD | No            | 7.91              | 16.14             | 22.37             |
| MinTL     | No            | 9.25              | 21.28             | 30.32             |
| SOLOIST   | Yes           | 13.21             | 26.53             | 32.42             |
| PPTOD_matt| Yes           | 27.85             | 39.07             | 42.36             |
| SF-DST    | No            | 28.35             | 39.39             | 44.60             |

End-to-end TOD systems generally has DST, Policy, and NLG modules, and in the real world, our model could be used as a DST module of these systems. Therefore, we compared SF-DST with other DSTs in the TOD systems. We varied the training data rate as 1%, 5%, or 10% and compared with SimpleTOD [20], MinTL [21], SOLOIST [22] and PPTOD [19]. SF-DST yielded the best accuracy in all few-shot settings (Table 3). Our model does not rely on external data, so it can be simply implemented in existing TOD systems. From this result, we anticipate that our model can improve the TOD system as a plug-and-play DST module.

4. Analysis

4.1. Ablation study

| Ablation                                | JGA [%] |
|-----------------------------------------|---------|
| SF-DST (this work)                      | 44.60   |
| - Self-feeding belief state             | 42.31   |
| - Auxiliary task                        | 42.69   |
| - Self-feeding belief state + Gold belief state | 38.55   |

We perform an ablation study to investigate which component contributes to accuracy in a few-shot environment (10%). We observe that both self-feeding belief state and auxiliary task are essential to increase the accuracy (Table 4). Additionally, we trained the model with the gold belief state (+ Gold belief state in table) instead of self-feeding belief state. The JGA showed a significant decrease (38.55%) compared to training with a self-feeding belief state (44.60%). When the gold belief state is given during the training, the model depends on the belief state rather than the conversation. This causes the performance degrades in the inference stage, where the gold belief...
4.2. Analysis of self-feeding belief state input

Table 5: Analysis of self-feeding belief state input. We separate the dialogue by the previous turn length and evaluate turn JGA.

| Model               | Previous dialogue turns |
|---------------------|-------------------------|
|                     | 1 to 3                  |
|                     | 4 to 6                  |
|                     | 7+                      |
| SF-DST              | 54.68                   |
| – belief state (ablation) | 52.16           |

Although accurate DST requires an understanding of the entire dialogue, it is challenging when the dialogue has many turns. In this experiment, we analyzed the effect of the belief state according to the conversation length in a multi-turn circumstance. We separated the dialogue into three classes by the number of previous turns: short-length dialogue (one to three turns), medium-length dialogue (four to six turns), and long-length dialogue (seven or more turns). We trained the model with and without belief state in a few-shot setting (10%) and used the average of turn JGA. Our self-feeding belief state improved both short-length dialogue and medium-length dialogue (Table 5). This means that the belief state, which summarizes previous conversation information, helped the model to understand the multi-turn conversation. However, the JGA decreased when the dialogue was extended (more than seven turns). As the dialogue progressed, the probability of error propagating from the previous belief state increased, so the accuracy dropped. Therefore, finding a self-feeding method that reduces error propagation is a worthy future goal.

4.3. Error analysis and effect of auxiliary task

Table 6: Changed error and JGA rate by adopting auxiliary task on MultiWOZ 2.1. Upper triangle 3.48 means an error rate increases 3.48% point.

| Error Type | Training Size(%) |
|------------|------------------|
|            | 1                |
|            | 5                |
|            | 10               |
| Wrong      | △3.48            |
| Ignore     | ▽16.47           |
| Spurious   | △8.97            |
| JGA        | △13.96           |

To examine the effect of the slot-gate auxiliary task, we classified the errors as Wrong, Ignore, and Spurious [2, 3]. Wrong means that the model correctly predicts the existence of the answer but predicts the wrong value. Ignore means that the answer exists, but the model ignores it. Spurious means that the answer is not mentioned, but the model predicts some value. We trained our model with and without auxiliary tasks at various training sizes and calculated the changed error and JGA rate by adapting the auxiliary task (Table 6). Overall, JGA was improved in all data settings. This result indicates that the auxiliary task helped to find accurate answers. In the case of error type, ignore, and spurious errors decreased; this result means that the auxiliary task was helpful to classify whether a slot is mentioned in the dialogue. However, the wrong type error grows in all settings. Adopting the auxiliary task increases the number of attempts to find the answer in dialogue when the answer exists, and this causes the growth of the wrong type error. Future work should find an auxiliary task that decreases all types of errors.

4.4. Implicit answers and auxiliary task

Table 7: Changed JGA by adopting auxiliary task on MultiWOZ 2.1. Upper triangle 5.74 means a JGA increases 5.74% point.

| Slot Type | Training Size(%) |
|-----------|------------------|
|           | 1                |
|           | 5                |
|           | 10               |
| Explicit  | △5.74            |
| Implicit  | △5.74            |

Finding the proper answer becomes increasingly challenging when the dialogue does not include an exact match. For example, assume the user said, "I want to find a place to see a movie." In that situation, even if the attraction type is not explicitly given, the model should infer the attraction type as theater. This implicit answer circumstance is common in the real world, and we experimented to determine whether our auxiliary question assists in such conditions. We chose ten slots with a high probability of exact matching answers (explicit slot) and ten slots with a low probability of exact matching answers (implicit slot) [2]. In the case of explicit slots, 99.12% of the answers were exactly found in dialogue, compared to 70.34% in implicit slots. We experimented in a few-shot setting and used the JGA of targeted slots. Our auxiliary task improved JGA in all training data set and slot types (Table 7). Asking whether the slot is mentioned helps find an answer even if there is no exact match exists.

5. Conclusion

This paper proposed a generative few-shot DST that has a reading comprehension approach. Our text-to-text model is ontology-free and does not use external data. As an input, we devised a self-feeding belief state and showed that summarized information of belief state is helpful for multiple turn dialogue. Also, we developed a slot-gate auxiliary task. This task reduces the ignore and spurious type errors. As a result, in a few-shot experiment, SF-DST was more accurate than the previous methods for four domains on MultiWOZ 2.0 and was close to the state-of-the-art in a supervised experiment on MultiWOZ 2.1.

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2train.day, restaurant.area, hotel.star, attraction.area, hotel.day, hotel.area, restaurant.day, hotel.people, hotel.day, restaurant.pricerange
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A. Appendix

A.1. Parameter size

| Models | #Parameter |
|--------|------------|
| MinTL [21] | 400M |
| GPT2QA [3] | 355M |
| SST-2 [16] | 110M |
| TripPy [11] | 110M |
| SimpleTOD [20] | 110M |
| STARC [2] | 110M |
| SOLOIST[22] | 110M |
| PPTOD_small [19] | 60M |
| SF-DST(ours) | 60M |

A.2. Detailed implementation

We implement SF-DST using T5-small [23], which has six encoder/decoder layers, and the hidden model has size 512. All models are trained using an NVIDIA A5000 GPU for five epochs with early stopping. For optimization, we use AdaFactor [24]. The batch size is 16 in the few-shot setting and 32 in the supervised setting. We implement T5-small based on HuggingFace library [25].