Act-Aware Slot-Value Predicting in Multi-Domain Dialogue State Tracking

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Abstract

As an essential component in task-oriented dialogue systems, dialogue state tracking (DST) aims to track human-machine interactions and generate state representations for managing the dialogue. Representations of dialogue states are dependent on the domain ontology and the user’s goals. In several task-oriented dialogues with a limited scope of objectives, dialogue states can be represented as a set of slot-value pairs. As the capabilities of dialogue systems expand to support increasing naturalness in communication, incorporating dialogue act processing into dialogue model design becomes essential. The lack of such consideration limits the scalability of dialogue state tracking models for dialogues having specific objectives and ontology. To address this issue, we formulate and incorporate dialogue acts, and leverage recent advances in machine reading comprehension to predict both categorical and non-categorical types of slots for multi-domain dialogue state tracking. Experimental results show that our models can improve the overall accuracy of dialogue state tracking on the MultiWOZ 2.1 dataset, and demonstrate that incorporating dialogue acts can guide dialogue state design for future task-oriented dialogue systems.

Index Terms: dialogue state tracking, dialogue acts, task-oriented dialogue, reading comprehension

1. Introduction

With the rising demand of automatic human-machine interactions for accomplishing service tasks via a natural language dialogue, task-oriented dialogue systems have been developed and widely applied nowadays. Typically, a task-oriented dialogue system consists of four components: automatic speech recognition (ASR), natural language understanding (NLU), dialogue management (DM), and natural language generation (NLG). Dialogue state tracking (DST) is the core function of the DM module which tracks human-machine interactions and generates state representations for managing the conversational flow in a dialogue. Specifically, the DST system takes the results of a speech recognizer and a natural language understanding, combined with dialogue context at runtime to predict distributions over a set of pre-defined variables. In a task-oriented dialogue, dialogue states are the probability distributions of user’s goals in belief space until the current user utterance.

Representations of dialogue states are dependent on the domain ontology and the involved user’s goals. Table 1 shows an example of state representations within a task-oriented service dialogue between a user and a system for cross-domain travel and accommodation. Among services via a natural language dialogue, some have well-defined objectives to achieve, e.g. reserving hotels or booking train tickets, in which typical dialogue state representations are a set of \((slot, value)\) pairs, e.g., \((destination, cambridge)\) and \((day, wednesday)\) in a train ticket booking service. The objective of DST is therefore to accurately estimate the user’s goals in previous dialogue and to represent them as such slot-value pairs. Such slot-value representations are widely used in quite a few task-oriented dialogues, such as ATIS \(\cite{2}\), DSTC2 \(\cite{3}\), MultiWOZ 2.0/2.1 \(\cite{4, 5}\), etc.

In a human dialogue, speech acts are illocutionary actions contained in utterances that change dialogue states \(\cite{6}\). Similarly, those representing the illocutions of utterances in a human-machine dialogue are known as dialogue acts. Generally speaking, dialogue acts are defined in domain ontology and serve the functions of conducting particular tasks, having potentials to guide user utterances and enhance the performance of DST as auxiliary inputs. As an example in Table 1, the “Request” act by the system can result in a dialogue state transformation in the “train” domain.

Early works on DST regard speech acts as noisy observations of dialogue acts to update dialogue states. Assuming fixed domain ontology, a line of generative methods \(\cite{7, 8}\) are proposed to represent dialogue states at each turn by modeling the joint probabilities in a belief space, which costs enormous manual efforts and limits the scalability to multi-domain dialogues. More recent works represent dialogue states as a set of slot-value pairs \(\cite{9, 10}\), where discriminative models have

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Table 1: An example of cross-domain dialogue with dialogue state representations and system dialogue acts in MultiWOZ 2.1

| USER: Hi, I am looking for a train that is going to cambridge and arriving there by 20:45, is there anything like that? |
| Dialogue States: |
| TRAIN: destination=cambridge, arriveby=20:45 |
| SYSTEM: Where will you be departing from? |
| USER: I am departing from Birmingham New Street. |
| Dialogue States: |
| TRAIN: destination=cambridge, arriveby=20:45, departure=birmingham new street |
| Dialogue Acts: Inform, Request |
| SYSTEM: Can you confirm your desired travel day? |
| USER: I would like to leave on Wednesday. |
| Dialogue States: |
| TRAIN: destination=cambridge, arriveby=20:45, departure=birmingham new street, day=wednesday |
| Dialogue Acts: Request |
| SYSTEM: I have booked your train tickets, and your reference number is #1114454. |
| USER: Thanks so much. I would also need a place to stay. I am looking for something with 4 stars and has free WiFi. |
| HOTEL: stars=4, internet=yes, type=hotel |
| Dialogue Acts: OfferBooked |

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proved their capabilities in tracking dialogue states, by modeling DST as multi-task classification or question answering problems. Recent discriminative DST models estimate user’s goals directly from the dialogue context, ignoring the NLU module and dialogue acts. However, using dialogue acts not only helps reason how dialogue states are predicted, but also improves compatibility of the DST model to existing pipeline dialogue systems and scalability to new domains.

To incorporate dialogue acts in discriminative DST models, we propose an act-aware dialogue state tracker (ADST) to predict slot-value pairs for tracking dialogue states with reasoning and high accuracy. We utilize system dialogue acts because they are easier to acquire and are closely relevant to dialogue system design. Furthermore, we exploit advances in reading comprehension (RC) to extend our DST models for task-oriented dialogues with more free-form domain ontology. Inspired by the RC-based work on DST, we formulate the DST problem as predicting values by querying with two types of slots: categorical slots and non-categorical slots. For categorical slots, we implement multiple-choice RC to choose from a predefined set of limited values, e.g., the “hotel parking” slot with a provided value set [Yes, No, Don’t Care, None]. For non-categorical slots, slots are firstly determined to be either Don’t Care, None or a span extracted from dialogue context, and then the system takes a span-based RC approach to predict values as probabilities of start and end positions in the dialogue context, e.g., “20:45” for the “train arrival time” slot. With the formulation of DST as reading comprehension tasks, our model can predict slot-values without pre-defined value sets by extracting values directly from the dialogue context. We also take advantage of pre-trained ELMo embeddings to learn word syntax and semantics in dialogue context. In short, our contributions are as follows. (1) We leverage dialogue acts to attend on slots which bring about accuracy improvement on DST; (2) we propose models for categorical and non-categorical slots formulating DST as RC tasks with scalability; (3) we show dialogue acts are a list of all possible values with two special values: span, none. For categorical slots, slots are firstly determined to be either Don’t Care, None or a span extracted from dialogue context, and then the system takes a span-based RC approach to predict values as probabilities of start and end positions in the dialogue context, e.g., “20:45” for the “train arrival time” slot. With the formulation of DST as reading comprehension tasks, our model can predict slot-values without pre-defined value sets by extracting values directly from the dialogue context. We also take advantage of pre-trained ELMo embeddings to learn word syntax and semantics in dialogue context. In short, our contributions are as follows. (1) We leverage dialogue acts to attend on slots which bring about accuracy improvement on DST; (2) we propose models for categorical and non-categorical slots formulating DST as RC tasks with scalability; (3) we show dialogue acts are a list of all possible values with two special values: span, none.

2. Methods

2.1. Problem Formulation

We denote the tokenized user utterance as \( u^{\text{user}} \) and the tokenized agent utterance as \( u^{\text{agent}} \) at dialogue turn \( t \). The context \( C_t \) of the given dialogue at turn \( t \) is defined as the concatenation of the previous agent and user utterances, i.e., \( C_t = \{ u^{\text{agent}}, u^{\text{user}}, \ldots, u^{\text{agent}}, u^{\text{user}} \} \). \( C_t \) is analogous to a passage in reading comprehension where the model predicts answers. The sequence of system dialogue acts until turn \( t \) is defined as the concatenation of the previous agent and user utterances, i.e., \( A_t = \{ a_1, a_2, \ldots, a_t \} \), where \( a_t = \{ a_1', a_2', \ldots, a_t' \} \) represents the number of dialogue acts in turn \( t \). For task-oriented dialogues in each domain \( d \in D \), the domain ontology defines a set of slots \( S_d = S_d^C \cup S_d^R \), where \( S_d^C \) and \( S_d^R \) are the sets of categorical and non-categorical slots without overlapping. For categorical slots \( S_d^C \), we construct a passage \( C_s \), a question \( q_{d,s} = \{ d, s \} \) and options \( O_{d,s} = \{ V_c, \text{none, dont care} \} \) as those in multiple-choice reading comprehension. \( V_c \) is the set of possible values in each slot \( s \in S^C \). Specifically, a question consists of a domain name and a slot name, and options are a list of all possible values with two special values: none and dont care. For non-categorical slots \( S_d^R \), the passage and the question would be the same but options are \( O_{d,s} = \{ \text{span, none, dont care} \} \), which substitutes with a span instead of a predefined set of values. If the option of “span” applies, predicting values from the dialogue context is equivalent to querying passage \( C_s \) with \( q_{d,s} \) to find the best matched span in the passage.

Figure 1 shows the overall architecture of our proposed models, mainly consisting of a context encoder, one attention layer attending dialogue context, another attention layer attending system dialogue acts, and two similarity measure modules.

2.2. Encoding

2.2.1. Context Encoding

Denoting the \( i \)-th word in \( C_s \) as \( c_i \), we combine word embedding, role embedding and binary exact match features for \( c_i \) as the input to the encoder. Specifically, word embeddings \( W^e = [W^\text{ELMo}; W^\text{Char}] \) are formed by concatenating \( W^\text{ELMo} \) which are ELMo pre-trained word embeddings and \( W^\text{Char} \) which are character-level tokens encoded by CNNs. \( W^e \in \mathbb{R}^{(C_s+1) \times w} \), where \( w \) is the sum of word embedding dimension and character embedding dimension while \( |C_s| \) is the number of word tokens in the dialogue context. Role embeddings \( W^r \) are symbols “SYS” or “USER” to distinguish the system and the user in a dialogue. Exact match features \( W_{\text{exact}} \) are binary vectors that reflect where each pre-defined value in the domain ontology is shown in the previous dialogue context. The final input to the encoder is denoted as \( W^e = [W^e; W^r; W_{\text{exact}}] \). Then we use a bidirectional GRU to encode \( W^e \) into \( W^c \in \mathbb{R}^{|G(C_s)| \times w} \), i.e., \( X^e = \text{BiGRU}(W^e) \), and let the number of bidirectional hidden states be \( w \), such that the dimension of encoder’s output is the same as that of \( W^c \).

2.2.2. Dialogue Act and Slot-Value Encoding

The input dialogue act embeddings \( W^a \) are concatenated word embeddings of system dialogue acts in previous turns. We construct similar word embeddings \( q^d, q^c \in \mathbb{R}^w \) for each domain and slot, respectively. For each dialogue, there are \( M \) domain-slot combinations corresponding to \( M \) questions. As for categorical slots, we sum \( q^d \) and \( q^c \) with each value embedding \( W^v \) in the value set \( V^c \) in addition to “none”, “dont care”, and stack them together to construct option embeddings \( P^i_{d,s} = q^d + q^c + w^c_i \), where \( N \) is the number of values in the value set \( V^c \), and \( w^c_i \in \mathbb{R}^w \) is the \( i \)-th value in \( V^c \).

2.3. Dialogue Context Attention

We implement an attention model similar to [21] that computes attention weights between dialogue context and slots. Assuming \( R, S \) are two matrices with the same columns \( h \), the attention function is defined as:

\[
\text{Attention}(R, S)_h = \text{softmax}(\langle [R_h; S_h]; R, S \rangle; k) \tag{1}
\]

where \( k \in \mathbb{R}^{wh} \) is a trainable vector, \( \circ \) is element-wise multiplication, \( \langle \cdot \rangle \) is vector concatenation across column. According to the above definition, the attention weights are computed as:

\[
\alpha^d_{i,j} = \text{Attention}_d(X^d, q^d + q^c), \quad \text{and } \quad \alpha^c_{i,j} \in \mathbb{R}^{C(C_i)}
\]

Then the attended slot vector over dialogue context is \( Q^d_{d,s} = (X^d)^T \cdot \alpha^d_{i,j} \). As a result, \( Q^d_{d,s} \in \mathbb{R}^w \) is the output of slot embeddings which are dependent on the dialogue context.

2.4. Dialogue Act Attention

In order to fuse information from system dialogue acts, we compute an attended slot vector over dialogue acts following Equation(1). The attention weight of a querying slot attending to acts
is given as $\alpha^{k_2}_{d,s} = Attention_k_2(W^{act}, Q^{d,s}_{(d,s)}) \in \mathbb{R}^{|A_t|}$, where $W^{act} \in \mathbb{R}^{|A_t| \times w}$ is the word embedding of the dialogue acts and $|A_t|$ is the total number of system dialogue acts in previous turns. After that, we obtain a slot vector attended by system acts as $Q^a_{d,s} = (W^{act})^T \cdot \alpha^{k_2}_{d,s} \in \mathbb{R}^w$.

Then $Q^a_{d,s}$ is combined with $Q^d_{d,s}$ and the original slot embedding, i.e. $Q^d_{d,s} = Q^a_{d,s} + Q^d_{d,s} + q^0 + q^*$, which can be regarded as the final slot embeddings dependent on both the previous dialogue acts and the context. Such that dialogue acts are incorporated in slots.

2.5. Value Classification for Categorical Slots

For each categorical slot, a value is to be selected from a predefined value set $V^v_{d,s}$. Inspired by [19], we compute probability of a value by calculating the bi-linear similarity between possible options $F^v_{d,s}$ and a final slot representations $Q^d_{d,s}$:

$$y^v_{d,s} = softmax(F^v_{d,s} \cdot \Theta^v Q^d_{d,s})$$

where $\Theta^v$ is a trainable weight matrix. Denoting $y^v_{d,s}$ as the encoded true label type, the loss function for span type prediction is:

$$L_{type} = \sum_{t} \sum_{d,s} CrossEntropy(p^{span}_{t,d,s}, y^v_{d,s})$$

Then we denote binary vectors of the true start and end positions as $y_{t,d,s}^{\text{start}}$ and $y_{t,d,s}^{\text{end}}$, respectively. The cross entropy loss for predicting span positions is as following:

$$L_s = \sum_{t} \sum_{d,s} CrossEntropy(p_{t,d,s}^{\text{start}}, y_{t,d,s}^{\text{start}}) + \sum_{t} \sum_{d,s} CrossEntropy(p_{t,d,s}^{\text{end}}, y_{t,d,s}^{\text{end}})$$

Finally, the total loss is defined as $L = L_v + L_{type} + L_s$.

3. Experiments

3.1. Dataset

We train and evaluate our models on the MultiWOZ 2.1 dataset [5], which is a cross-domain task-oriented dialogue dataset collected from 7 domains containing over 10,000 multi-turn dialogues. MultiWOZ 2.1 contains 13 dialogue acts and 30 (domain, slot) combinations with hundreds of possible values. We split the dataset into training, development and test set the same as the original setting, and only use 5 most frequent domains in the dataset: \{restaurant, hotel, train, attraction, taxi\}.

3.2. Training Details

For the input context embeddings, we combine ELMo word embeddings with a length of 512, character embeddings with a length of 100, role embeddings with a length of 128 and one-hot exact matching features indicating occurrences of predefined values. For the context encoder, we use a one-layer bi-directional GRU with hidden units of the same length as ELMo embeddings combining character embeddings. ReLu [23] activation is used for all feed-forward layers. The learning rate is 0.001 with the ADAM optimizer [24] and the batch size is 24 in our joint training on 30 categorical and non-categorical slots.
### 3.3. Results

Table 2 lists the experimental results on MultiWOZ 2.1 test set, where the joint goal accuracy is the average accuracy of predicting all slot-values for a turn correctly, while the slot goal accuracy is the average accuracy of predicting the value of a slot correctly. We compare our models with: (1) DS-DST [17] which uses BERT-based RC approaches to handle different slot types jointly, (2) DSTQA [18] which constructs slots with domain ontology for a RC-based model enhanced by a dynamic knowledge graph, (3) CHAN [25] which fine-tunes BERT in a hierarchical attention network to leverage relevant dialogue context, and 4) STARC [15] which pre-trains on RC dataset then fine-tunes on task dialogues to alleviate data scarcity problems.

We first train a model taking all slots as categorical, comparing it with the categorical-only models: DS-DST picklist, DSTQA w/o span, and CHAN. We achieve 56.70% joint goal accuracy and 97.71% slot goal accuracy on categorical-only slot-value predictions, which is close to the state-of-the-art joint and slot goal accuracy on the MultiWOZ 2.1 test set. In contrast to the current state-of-the-art model, our model is lightweight and can be scaled to non-categorical slots. In our hybrid model, we take all number- or time-related slots as non-categorical, whereas other slots as categorical, and train all slots jointly. We compare our results with those of STARC, DS-DST and DSTQA w/ span. We obtain outperformed results of 56.12% and 97.62% on joint and slot goal accuracy, due to the advantages of exploiting RC approaches and using system dialogue acts as auxiliary inputs.

| Model | Joint Goal Accuracy | Slot Goal Accuracy |
|-------|---------------------|--------------------|
| DS-DST picklist [17] | 53.30 | - |
| DSTQA w/o span [18] | 51.44 | 97.24 |
| CHAN [25] | 58.55 | 98.14 |
| ADST (Ours) all categorical | 56.70 | 97.71 |
| w/o Non-Categorical Slots: | | |
| STARC [15] | 49.48 | - |
| DS-DST [17] | 51.21 | - |
| DSTQA w/ span [18] | 51.36 | 97.22 |
| ADST (Ours) hybrid | 56.12 | 97.62 |

### 4. Conclusion

We propose an act-aware method for multi-domain DST by incorporating system dialogue acts and dialogue context in previous turns to predict slot-value pairs up to the current turn. Our models combine dialogue acts, dialogue context and domain ontology, and leverages reading comprehension approaches to predict slots for both categorical and non-categorical slots. Experimental results show that attentions on both dialogue acts and dialogue context not only improve the joint goal accuracy on MultiWOZ 2.1, but also expand capacities of dialogue systems on reasoning how dialogue states are guided and transformed. The analysis and visualizations indicate that our model is able to use information of system dialogue acts to improve DST on specific slots. We believe that this idea of leveraging dialogue acts in discriminative DST models will improve their scalability for new domains and will contribute to the design of task-oriented dialogue systems for new services.
5. References

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