Schema-Guided Multi-Domain Dialogue State Tracking with Graph Attention Neural Networks

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Abstract
Dialogue state tracking (DST) aims at estimating the current dialogue state given all the preceding conversation. For multi-domain DST, the data sparsity problem is also a major obstacle due to the increased number of state candidates. Existing approaches generally predict the value for each slot independently and do not consider slot relations, which may aggravate the data sparsity problem. In this paper, we propose a Schema-guided multi-domain dialogue State Tracker with graph attention networks (SST) that predicts dialogue states from dialogue utterances and schema graphs which contain slot relations in edges. We also introduce a graph attention matching network to fuse information from utterances and graphs, and a recurrent graph attention network to control state updating. Experiment results show that our approach obtains new state-of-the-art performance on both MultiWOZ 2.0 and MultiWOZ 2.1 benchmarks.

1 Introduction
Dialogue state tracking (DST) is a key component in task-oriented dialogue systems which cover certain narrow domains, such as booking restaurant and travel planning. The goal of DST is to extract user goals or intents hidden in human-machine conversation and represent them as a compact dialogue state, i.e. a set of slots and their corresponding values. For example, as illustrated in Fig. 1, (slot, value) pairs like (area, west) are extracted from the dialogue. High-qualified DST is essential for dialogue management (Young et al. 2013; Yu et al. 2014), where dialogue state determines the next machine action and system reply.

Recently, motivated by commercial applications like Apple Siri, Microsoft Cortana, Amazon Alexa, or Google Assistant, there is significant interest in adding numerous domains to these dialogue systems. Therefore, multi-domain based DST becomes crucial.

However, most traditional state tracking approaches focus on a single domain. They extract value for each slot predefined in the domain (Williams et al. 2013; Henderson, Thomson, and Williams 2014a; 2014b). These methods can be directly adapted to multi/mixed-domain conversations by replacing slots in a single domain with domain-slot pairs (i.e. domain-specific slots) predefined (Ramadan, Budzianowski, and Gasic 2018; Gao et al. 2019; Wu et al. 2019). Despite its simplicity, this approach for multi-domain DST suffers from two major drawbacks: 1) Relations among domain-specific slots are not considered, e.g., hotel-price_range and restaurant-price_range are actually the same and domain-independent. The slot relations may also consist of whether two slots are from the same domain and whether two slots have the same value type (e.g. location, day, date, time, number, bool etc.). 2) The approach extracts value for each slot independently, which may fail to capture features from slot co-occurrences. For example, hotels with higher stars are usually more expensive (price_range). These may aggravate the data sparsity problem.

To tackle these challenges, we emphasize that DST models should incorporate slot relations and support information interactions among different slots. To consider relations among domain-specific slots, we introduce schema graphs. In the graph, each node is a slot, and each edge between two slots means that they are from the same domain, or they have the same value type. To encode the graph and make information interactions among different slots, we adopt graph attention networks (GATs).

In this paper, we propose a schema-guided multi-domain dialogue state tracker with GATs. It is elegant to utilize GATs to extract schema information. Our approaches are evaluated on MultiWOZ 2.0 and MultiWOZ 2.1 benchmarks with extensive experiments. Contributions in this work are summarized as:

• We are the first to incorporate slot relations and model slot interactions in multi-domain DST to the best of our knowledge. This is also the first time that graph neural networks are exploited in DST.
• To fully encode the schema graph and dialogue context (user and system utterances), graph attention matching networks (GAMTs) are introduced in this paper, which include internal and external attention mechanisms.
• To exploit previous states in conversations, a novel recurrent GAT (RGAT) is proposed with gated recurrent units.

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In this section, we introduce graph attention networks (GATs), which are the basis of our proposed DST models in the next section.

GAT is a special type of graph neural networks (GNNs). GNN is a deep neural network associated with a graph (Scarselli et al. 2009). We first give some notations before describing the details of GNN and GAT. We denote the graph as $G = (V, E)$, where $V$ and $E$ are the set of nodes $x_i$ and the set of edges $e_{ij}$ respectively. $N(x_i)$ denotes the neighbors of node $x_i$, $N_+(x_i)$ is the set including $x_i$ and all neighbors of $x_i$, i.e., $N_+(x_i) = N(x_i) \cup \{x_i\}$.

For each node $x_i$ in the graph, there is an input feature $x_i$, GNN takes $x_i$ as the initial embedding $h_i^0$ for node $x_i$, then updates its embedding from one step (or layer) to the next with following operations.

**Sending Messages** At $l$-th step, each node $x_i$ will send a message $m_i^l$ to all nodes $x_j \in N_+(x_i)$:

$$m_i^l = f_{msg}^l(h_i^{l-1}),$$

where $f_{msg}^l(\cdot)$ is a message function for each node at $l$-th step. For simplicity, in GNN a linear transformation $f_{msg}^l(\cdot)$ is often used:

$$f_{msg}^l(h_i^{l-1}) = W_m h_i^{l-1},$$

where $W_m$ is a weight matrix for optimization.

**Aggregating Messages** After sending messages, each node $x_i$ will aggregate messages from its neighbors and itself,

$$e_i^l = f_{agg}^l(\{m_j^l | x_j \in N_+(x_i)\}),$$

where the function $f_{agg}^l(\cdot)$ is the aggregation function for every node at $l$-th step. The biggest difference between GAT and traditional GNNs is that they have different aggregation functions. In traditional GNNs, all received messages are treated equally, i.e.,

$$e_i^l = f_{agg}^l(\{m_j^l | x_j \in N_+(x_i)\}) = \frac{1}{N_i} \sum_{j \in N_+(x_i)} m_j^l,$$

where $N_i$ is the number of nodes in $N_+(x_i)$. However, in practice, some messages are more important than others. Similar to self-attention model for machine translation (Vaswani et al. 2017), different weights $a_{ij}^l$ are specified to different messages $m_j^l$ in GAT. Here $a_{ij}^l$ is the normalized similarity of the embedding between the two nodes $x_i$ and $x_j$ in an unified space, i.e.,

$$a_{ij}^l = \frac{e_{sim}^l(h_i^{l-1}, h_j^{l-1})}{\sum_{k \in N_+(x_i)} e_{sim}^l(h_i^{l-1}, h_k^{l-1})},$$

where $f_{sim}^l(\cdot)$ is the similarity function,

$$f_{sim}^l(h_i^{l-1}, h_j^{l-1}) = (W_{a1} h_i^{l-1})^T (W_{a2} h_j^{l-1}),$$

where $W_{a1}$ and $W_{a2}$ are learnable weights for projections. Once obtained, these normalized attention coefficients $a_{ij}^l$ are used to compute a linear combination of messages,

$$e_i^l = f_{agg}^l(\{m_j^l | x_j \in N_+(x_i)\}) = \sum_{x_j \in N_+(x_i)} a_{ij}^l m_j^l.$$
Once obtained, \( \hat{a}_{ij} \) will be normalized with a feature-

wised multi-dimensional softmax (MD-softmax) function,

where \( \odot \) represents element-wise product of two vectors.

**Updating Embedding** After aggregating messages, each

t node will update its embedding from \( \mathbf{h}^{l-1}_i \) to \( \mathbf{h}^l_i \).

\[
\mathbf{h}^l_i = f_{ue}(\mathbf{e}^l_i, \mathbf{h}^{l-1}_i).
\]

(10)

The updating function \( f_{ue}(\cdot) \) can be a MLP function,

\[
f_{ue}(\mathbf{e}^l_i, \mathbf{h}^{l-1}_i) = \mathbf{W}_{ue1}^{l} \sigma(\mathbf{W}_{ue2}^{l} \mathbf{e}^l_i + \mathbf{b}_{ue1}^{l}) + \mathbf{b}_{ue2}^{l},
\]

(11)

where \( \mathbf{W}_{ue1}^{l} \) and \( \mathbf{W}_{ue2}^{l} \) are learnable parameters.

After updating node embedding \( L \) steps, we will obtain the context-aware embedding \( \mathbf{h}^L_i \) for each node \( x_i \).

**3 Method**

In a multi-domain dialogue system, there are a set of do-

mains \( D \) that users and the system can converse about. For each domain \( d \in D \), there are \( nd \) slots. Each slot \( s \) cor-

responds to a specific aspect of the user intent (e.g. price) and can take a value (e.g. cheap) from a candidate value set defined by a domain ontology. The dialogue state \( S \) can be defined as a set of slot-value pairs, e.g. \( \{ \text{price=cheap, area=west} \} \).

At \( t \)-th dialogue turn, the dialogue state is \( S_t \), which is

used as a constraint to frame a database query. Based on the

results of database query and \( S_t \), the systems give a response

\( U_{t+1}^{sys} \) to the user. Then the user inputs a new sentence \( U_{t+1}^{usr} \).

A state tracker then updates the dialogue state from \( S_t \) to

\( S_{t+1} \) according to \( U_{t+1}^{sys} \) and \( U_{t+1}^{usr} \). The whole dialogue process can be represented as \( \{ S_0, U_1^{sys}, U_1^{usr}, S_1, U_2^{sys}, U_2^{usr}, S_2, \ldots, S_{T-1}, U_T^{sys}, U_T^{usr}, S_T \} \).

Traditionally, lots of DST models predict dialogue state

according to the whole dialogue context up to date. They
do not explicitly model the dialogue state update process.

In contrast, our proposed SST model explicitly updates di-

alogue state from \( S_t \) to \( S_{t+1} \) depending on \( U_{t+1}^{sys} \) and \( U_{t+1}^{usr} \),

i.e.

\[
S_{t+1} = f_{sst}(S_t, U_{t+1}^{sys}, U_{t+1}^{usr}).
\]

(12)

Our SST model consists of two modules: ontology schema and utterance matching module and state updating module. As shown in Fig. 2, the first module learns the context representation for each token in domain schema and utterance and harvests useful information from each other. The second module updates dialogue state from \( S_t \) to \( S_{t+1} \) according to slot-specified information obtained by the first module.
3.1 Ontology Schema and Utterance Matching with GAMT

In previous work, ontology schema information is not fully utilized in learning dialogue utterance representation. Here we propose graph attention matching networks (GAMTs) to learn the representations of ontology schema and dialogue utterance simultaneously.

We first define a token-level schema graph $G^1 = (V^1, E^1)$ according to the original ontology scheme. An example is shown in Fig. 3(a). The graph nodes consist of all domain tokens, e.g. taxi, hotel, restaurant, and all slot tokens, e.g. name, food, destination. There are edges between slots and the domain which the slots belong to. If some slots/domain is described with more than one word, e.g. book, people, it will be divided into single tokens, e.g. book, people, and there is an edge between them.

We define another graph $G^2 = (V^2, E^2)$ according to the dialogue utterance. The graph nodes consist of all words in the latest system response and user utterance pair $(U_{i-1}^{sys}, U_{i-1}^{usr})$. All nodes in the graph are connected.

In GAMT, for each node $x^k_i \in V^k (k = 1, 2)$, the embedding $h^k_i$ is updated at each step to take into account not only the aggregated messages from its neighbors but also the cross-graph messages from another graph. The input feature of each node in $G^1$ is the corresponding token embedding, and the input feature of each node in $G^2$ is the sum of the token embedding, the segmentation embedding, and the position embedding as shown in Fig. 2. Here we use pretrained word-embedding as the token embedding and random initialized embedding as the segmentation embedding. They are updated during the training process. We use sine and cosine functions of different frequencies as the position embedding (Vaswani et al. 2017). Compared with GAT, here and cosine functions of different frequencies as the position embedding.

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Updating Embedding After aggregating messages, each node will update its embedding from $h^{i-1}_t$ to $h^i_t$,

$$h^i_t = f^i_{ue}([e^{1-1,l}_i, e^{2-1,l}_i], h^{i-1}_t),$$  (16)

where $[\cdot, \cdot]$ is the concatenation of two vectors. The function $f^i_{ue}(\cdot)$ is a MLP as shown in Eq. (11).

After updating node embedding $L_1$ steps with GAMT, we can obtain contextual representations $h^{1,L_1}_i$ for each node $x^1_i$ in $G^1$ and $h^{2,L_1}_j$ for each node $x^2_j$ in $G^2$. $h^{1,L_1}_i$ includes not only information from the related tokens (i.e. neighbors) in ontology schema, but also useful information from dialogue utterance. Similarly, $h^{2,L_1}_j$ includes not only contextual information in dialogue utterance, but also useful information from ontology schema.

We then obtain slot representation vector $g_s$ based on $h^{1,L_1}_i$ for each slot $s$. Assuming a slot consists of one or more tokens in $G^1$, a feature-wised score vector is calculated with an MLP for each token, and then normalized with MD-softmax. Finally, the node embeddings $h^{1,L_1}_i$ for these tokens are weighted with the normalized scores to obtain $g_s$.

3.2 Dialogue State Updating with RGAT

The state updating module takes $g_s$, as input, and updates the dialogue state for each slot $s_i$. As introduced in Section 1, there may be underlying relations between slots in multi-domain dialogue state tracking. In order to capture the interaction between slots, we propose to use recurrent attention graph neural networks (RGAT) for state updating.

We first define a domain-specific slot-level schema graph $G$. Fig. 3(b) is an example. The nodes of $G$ consist of all slots, e.g. hotel-name, taxi-destination. There is an edge between two slots if they belong to the same domain. If two slots belong to different domains but some of their candidate values are the same, there is also an edge between them. For example, in Fig. 3(b), there is an edge between hotel-name and taxi-destination, because the taxi destination may be a hotel.

The input feature of each node $x_i$ is the embedding vector $v_i$ of value for the corresponding slot $s_i$ at $t$-th turn. RGAT takes $v_i$ as the initial embedding $h^{i-1}_i$ for node $x_i$ (i.e. slot $s_i$), then updates its embedding from one step to the next similar to GAT. However, the most significant difference between GAT and RGAT is that the parameters of RGAT in all steps are shared, and their node embedding updating functions are different.

Updating Embedding After aggregating messages, each node will update its embedding from $h^{i-1}_t$ to $h^i_t$,

$$h^i_t = f^i_{ue}([e^{1-1,l}_i, e^{2-1,l}_i], h^{i-1}_t),$$  (16)

where $[\cdot, \cdot]$ is the concatenation of two vectors. The function $f^i_{ue}(\cdot)$ is a MLP as shown in Eq. (11).
Updating Embedding After aggregating messages, each node will update its embedding from \( h_i^{l-1} \) to \( h_i^l \),
\[
h_i^l = f_{ue}(e_i, h_i^{l-1}, g_{si}),
\]
where the function \( f_{ue}(\cdot) \) is an improved GRU cell:
\[
\begin{align*}
\hat{z}_{i,1}^l &= W_{z,1}[e_i, h_i^{l-1}, g_{si}] + b_{z,1}, \\
\hat{z}_{i,2}^l &= W_{z,2}[e_i, h_i^{l-1}, g_{si}] + b_{z,2}, \\
\hat{z}_{i,3}^l &= W_{z,3}[e_i, h_i^{l-1}, g_{si}] + b_{z,3}, \\
z_{i,1}^l, z_{i,2}^l, z_{i,3}^l &= \text{MD-softmax}(\hat{z}_{i,1}^l, \hat{z}_{i,2}^l, \hat{z}_{i,3}^l), \\
\hat{r}_{i,1}^l &= \text{sigmoid}(W_{r,1}[e_i, h_i^{l-1}, g_{si}] + b_{r,1}), \\
r_{i,2}^l &= \text{sigmoid}(W_{r,2}[e_i, h_i^{l-1}, g_{si}] + b_{r,2}), \\
\hat{h}_i^l &= \text{tanh}(Wh[E_{si}, r_{i,1}^l \odot \hat{e}_i^l, r_{i,2}^l \odot h_i^{l-1}]), \\
h_i^l &= z_{i,1}^l \odot \hat{h}_i^l + z_{i,2}^l \odot h_i^{l-1} + z_{i,3}^l \odot e_i^l,
\end{align*}
\]
where MD-softmax is the feature-wise multi-dimension softmax function. \( z_{i,1}, z_{i,2}, \) and \( z_{i,3} \) are three gates that control information flow. In particular, \( z_{i,1} \) controls information from the latest dialogue context. If \( z_{i,1} = 1 \), then the value of corresponding slot \( s_i \) will change to new value. \( z_{i,2} \) controls information from its last dialogue state. If \( z_{i,2} = 1 \), then the value of corresponding slot \( s_i \) will remain unchanged. \( z_{i,3} \) controls information from its neighbours. If \( z_{i,3} = 1 \), then the value of corresponding slot \( s_i \) will be copied from some value of its neighbours. All parameters \( W \) and \( b \) are shared across steps.

After updating node embedding \( L_2 \) steps, we will obtain the embedding \( h_i^{L_2} \) for each node \( x_i \). It is the new hidden state of slot \( s_i \). We calculate the dot product between the hidden vector and each of the embedding vectors of the candidate values. The softmax function is performed with the results to give a distribution of probabilities \( p_{t+1,i} \) for all candidate values, i.e.
\[
p_{t+1,i} = \text{softmax}(E_{si}^l h_i^{L_2}),
\]
where \( E_{si} \) is the value embedding matrix. Each row corresponds to an embedding vector for a candidate value. \( E_{si} \) is initialized with pre-trained word embedding. If a slot value consists of more than one word, the initialized embedding is the concatenation of the mean-pooling and max-pooling of all words. The embedding matrix is updated during training. When training the whole DST model, we update the cross-Entropy (CE) loss between the predicted probabilities and the given label for all slots.

3.3 General SST models

In previous sections, our SST model only takes dialogue context in the latest turn (i.e. latest user utterance and system response) into consideration for each time. It can be naturally extended to encode dialogue context with more turns, i.e. the DST formula in Eq. (12) can be reformulated as follows,
\[
S_t = f_{sst-k}(S_{t-k}, U_{t-k+1}^{sys}, U_{t-k+1}^{uss}, \ldots, U_t^{sys}, U_t^{uss}),
\]
where \( k \) is the number of selected dialogue turns, and the corresponding SST model is referred to SST-\( k \).

4 Experiments

4.1 Setup

Data We choose MultiWOZ 2.0 (Budzianowski et al. 2018) and MultiWOZ 2.1 (Eric et al. 2019) as our training and evaluation datasets, both of which are task-oriented corpora comprised of dialogues between human and human.

Unlike some common datasets such as DSTC2 which merely focuses on the restaurant search domain, there are 35 slots in MultiWOZ 2.0 with nearly 2000 candidate values over seven domains. Following previous work TRADE (Wu et al. 2019), we only use five of them since the other two domains barely appear, and they are neither in the development set nor in the test set. Besides, it is worth mentioning that there are a certain number of error annotations in this dataset. Firstly, the values in the ontology and the dialog context are not always the same. For example, the value in the context is \( eastern \) but ontology uses \( east \) instead. Secondly, delayed markups can sometimes be found in the process of dialog state updates, which exert an influence on model training.

To alleviate the problems mentioned above, MultiWOZ 2.1 is released recently. More than 32% of state annotations have been modified, especially in name slots. It contains 55718 turn-level training samples from 8133 dialogues (only five domains) with 7368 turns of the test set.

Hyperparameters We use pretrained GloVe embeddings (Pennington, Socher, and Manning 2014) and character embeddings (Hashimoto et al. 2017) to represent words both in the dialogue turns and the slot tokens. Then a dense layer with the output size of 180 has been adopted, and the size of all hidden layers is 180. The number of GAMT steps/layers \( L_1 \) is three on both datasets. Each model is trained by RMSPROP with a learning rate of 0.0001 and a batch size of 32.

4.2 Main Results

Table 1 shows our results on both MultiWOZ 2.0 and MultiWOZ 2.1 test sets. Here joint goal accuracy is used as the evaluation metric. We compare our model with several previous baselines.

The existing models can be divided into two categories, the classification-based models and the generative models. The classification-based ones include: MDBT (Raman, Budzianowski, and Gasic 2018), which uses multiple bi-LSTMs to encode utterances of system and user; GLAD (Zhong, Xiong, and Socher 2018), a global-local self-attention model; GCE (Nouri and Hosseini-Asl 2018), a global-conditioned encoder; HJST (Eric et al. 2019) and FJST (Eric et al. 2019), which refer to the Flat Joint State Tracker and the Hierarchical Joint State Tracker respectively. and SUMBT (Lee, Lee, and Kim 2019), a slot-utterance matching belief tracker. To break through the restraint of ontology values, some generative models are proposed. For example, Neural Reading DST model (Gao et al. 2019), which utilizes an attention-based neural network to point to the slot values in the utterances; HyST (Goel, Paul, and Hakkani-Tür 2019), a hybrid joint state tracking model learning the optimal method for each slot type, and TRADE
Table 1: Joint goal accuracy on MultiWOZ 2.1 and MultiWOZ 2.0 test set vs. various approaches as reported in the literature.

| DST Models    | Joint Acc. MultiWOZ 2.1 | Joint Acc. MultiWOZ 2.0 |
|---------------|-------------------------|-------------------------|
| MDBT          | -                       | 15.57                   |
| GLAD          | -                       | 35.57                   |
| GCE           | -                       | 36.27                   |
| HJST          | 35.55                   | 38.4                    |
| FJST          | 38.0                    | 40.2                    |
| SUMBT         | -                       | 46.65                   |
| Neural Reading DST | 36.40                | 39.41                   |
| HyST          | 38.1                    | 42.33                   |
| TRADE         | 45.6                    | 48.6                    |
| SST-1         | 52.55                   | 47.59                   |
| SST-2         | 55.23                   | 51.17                   |
| SST-3         | 54.22                   | 49.29                   |

(Wu et al. 2019), a transferable dialogue state generator using a copy mechanism.

Our SSTs belong to classification-based models. Here SST-1, SST-2, and SST-3 are compared with these baselines. From the results, we can find that our best model SST-2 outperforms all baseline models and achieves the new state-of-the-art on both datasets.

Among our models, SST-2 performs best on both datasets. Especially, SST-2 and SST-3 perform much better than SST-1 on MultiWOZ 2.0. The reason is that there are some errors in labels, and one of the most common error types is delayed markup, i.e., slot values were annotated one or more turns after the value appeared in the user utterances. For SST-1, when delayed markup appears, SST-1 can’t find the value in the last utterance. Therefore, using more dialogue context (e.g., SST-2, SST-3) will benefit training and prediction.

4.3 Analysis

Ablation Analysis Table 2 illustrates the ablation experiment for our SST-2 model. We find a ~2% drop of performance when the graph relation is removed in RGAT. It shows that information exchange between slots is necessary. In Table 3, we present an example to show the effect of the graph in RGAT. We can see that the model with the graph correctly gets the dialogue state, even though the user does not offer hotel-book_day directly. The model makes the accurate reference of the phrase “for the same day” through the context, and the value of train-day is copied as the value of hotel-book_day. However, the model without graph can not predict the correct value of hotel-book_day.

We also investigate the effect of interaction between the ontology graph and the utterance. We remove the cross attention between them in all steps except the last step in GAMT and find a ~1% drop of performance. It indicates that multiple times of interaction can make better alignment between ontology and utterance.

For the steps in RGAT, we tried the number from one to six to observe the change of model performance. We find that SST-2 with 2 and 4 steps achieves the best performance on MultiWOZ 2.0 and MultiWOZ 2.1, respectively. The result on MultiWOZ 2.0 is presented in Figure 4. It indicates that more than 1 step is needed for fusing the history state and the useful information in the current utterance.

Error Analysis Domain-specific slot accuracy of SST-2 and TRADE 1 on MultiWOZ 2.0 test set is shown in Table 4. We find that our model can achieve higher accuracy than TRADE for most of the slots. However, in the taxi domain, the accuracy for most slots in this domain is lower than TRADE. The reason may be that the values of slots in the taxi domain are much longer (e.g., address, name), which are more suitable for generative models like TRADE.

Figure 4: Results of different number of steps in RGAT on MultiWOZ 2.0 test set.

5 Related Work

Dialogue State Tracking Traditional dialogue state tracking models rely on semantics extracted by natural language understanding to predict the current dialogue states (Young et al. 2013; Williams et al. 2013; Henderson, Thomson, and Williams 2014b; Yu et al. 2015; Sun et al. 2014b; 2014a; Xie et al. 2015; Yu et al. 2016), or jointly learn language understanding in an end-to-end way (Henderson, Thomson, and Young 2014a; 2014b). These methods heavily rely on hand-crafted features and complex domain-specific lexicons for delexicalisation, which are difficult to extend and scale to new domains.

Recently, most works about DST focus on encoding dialogue context with deep neural networks (such as CNN, RNN, LSTM-RNN, etc.) and predicting a value for each possible slot (Mrkšić et al. 2017; Xu and Hu 2018; Zhong, Xiong, and Socher 2018; Ren et al. 2018; Xie et al. 2018). For multi-domain DST, slot-value pairs are extended to

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1The official code https://github.com/jasonwu0731/trade-dst is used.
domain-slot-value pairs for target (Ramadan, Budzianowski, and Gasic 2018; Gao et al. 2019; Wu et al. 2019). However, they do not explicitly consider slot relations, which may mitigate the data sparsity problem. They also predict the value for each slot independently, which can not capture label dependency. Beyond DST, relations and similarities between slots are also utilized in language understanding (Zhu and Yu 2018; Zhao, Zhu, and Yu 2019b), while it lacks an interaction mechanism between slots and utterances.

**Graph Neural Network** Recently, there has been a surge of interest in Graph Neural Network (GNN) approaches for representation learning of graphs (Scarselli et al. 2009; Veličković et al. 2018). They can aggregate information from graph structure and encode node features, which can be exploited to learn to reason and introduce unordered structure information. Many GNN variants are proposed and also applied in various NLP tasks, such as text classification (Yao, Mao, and Luo 2019), machine translation (Marcheggiani, Bastings, and Titov 2018), dialogue policy optimization (Chen et al. 2018b; 2019; 2018a) etc. We are the first to introduce GNN in DST to the best of our knowledge.

### 6 Conclusion

We introduce a schema-guided multi-domain dialogue state tracker with graph attention networks, which involves slot relations and learns deep feature representations for each slot dependently. All slots from different domains and their relations organized as schema graphs. Graph attention matching network and recurrent graph attention network are proposed to fully encode dialogue utterances, schema graphs, and previous dialogue states. Our approach achieves state-of-the-art joint goal accuracy on both MultiWOZ 2.0 and 2.1 benchmarks. In this paper, the schema is automatically constructed according to ontology. In the future, we will investigate to use more complex schema (Rastogi et al. 2019). We will also exploit generative models for value prediction, which could enable the tracker to generate values out of domain ontology. To overcome the data sparsity problem, we would like to try data augmentation methods (Zhao, Zhu, and Yu 2019a; Cao et al. 2019).

### Acknowledgments

This work has been supported by the National Key Research and Development Program of China (Grant No. 2017YFB1002102) and the China NSFC projects (No. 61573241). We thank the anonymous reviewers for their thoughtful comments and efforts towards improving this manuscript.

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