Efficient Dialogue State Tracking by Masked Hierarchical Transformer

Min Mao, Jiasheng Liu, Jingyao Zhou, Haipang Wu
Hithink RoyalFlush Information Network Co., Ltd., Zhejiang, China
{maomin, liujiangsheng, zhoujingyao, wuhaipang}@myhexin.com

Abstract
This paper describes our approach to DSTC 9 Track 2: Cross-lingual Multi-domain Dialog State Tracking, the task goal is to build a cross-lingual dialog state tracker with a training set in rich resource language and a testing set in low resource language. We formulate a method for joint learning of slot operation classification task and state tracking task respectively. Furthermore, we design a novel mask mechanism for fusing contextual information about dialogue, the results show the proposed model achieves excellent performance on DSTC Challenge II with a joint accuracy of 62.37% and 23.96% in MultiWOZ (en → zh) dataset and CrossWOZ (zh → en) dataset, respectively.

Introduction
Task-oriented dialogue has a wide range of applications to handle everyday tasks such as booking hotels, movie tickets and restaurants, etc. The system for supporting these tasks mostly adopts a pipelined modular architecture, which usually contains a natural language understanding (NLU) module for recognizing users’ intent, a dialogue state tracking (DST) module for extracting and tracking the dialogue states, a policy (POL) module for deciding the system action and a natural language generation (NLG) module for generating the response according to the system action. DST module is the core component of a task-oriented dialogue system since the system response is dependent on its result. An excellent DST can improve the user experience by reducing the number of interactions. The challenge in DSTC 9 Track 2 (Gunasekara et al. 2020) is to build a cross-lingual Multi-domain DST which can track the dialogue state with resource-poor language whose original dataset is resource-rich language. The dataset of this challenge is based on MultiWOZ 2.1 (Eric et al. 2019) and CrossWOZ (Zhu et al. 2020). Competitors should track the dialogue state in Chinese with MultiWOZ 2.1 dataset and in English with CrossWOZ dataset, respectively.

To solve the above tasks, we propose a multi-task model to predict the dialogue state and the state operation at each turn. The main contributions are as follows:

• To simplify the problem we use machine translation systems such as Google Translate, Baidu Translate to translate the training dataset from resource-rich language to resource-poor language, thereby the task can be considered as a traditional DST problem whose train and test dataset in the same language.
• The dialogue state extracts from the dialogue history whose text usually has more than 512 tokens, but the encoder stack of Transformer usually has the length limit (512 tokens). We propose a general method to fusion the features from any length of historical turns by defining different masked self-attention structures in the transformer network. Furthermore, we use this feature fusion method to extract the global context information and local context information, respectively, merge those two representations to predict the dialogue state.
• We adjust the model construction which is proposed in Shan et al. (2020) by adding a masked hierarchical transformer module, due to its local information module only contains the feature from a single turn. The added module can merge multi-turn features as the local representations so that the local representations can be used to predict multi-class classification such as state operation prediction. We use a three-class state operation prediction as to the auxiliary task. However, that is a bi-class classification task in Shan et al. (2020) due to the local representation module in their method only contain the information from the current turn.
• Exploring data augmentation to improve the model performance.

Related Work
Traditional DST methods can be divided into two major types: open-vocabulary (Le, Socher, and Hoi 2020; Goel, Paul, and Hakkani-Tür 2019; Wu et al. 2019) and predefined-ontology (Lee, Lee, and Kim 2019; Shan et al. 2020). The former one generates slot value at each turn by a generative model such as the decoder stack in RNN and Transformer, and the latter predefines the dialogue ontology and simplifies the DST models into a classification problem. The open-vocabulary methods can partly track un-
Table 1: An example dialogue. At the last turn (the 4-th turn), the underlined value of slot “food” is corrected by the information at the 2-nd turn.

seen slot values but usually has a lower performance than the predefined-ontology methods. Since the ontology in the ninth DSTC Track 2 Cross-lingual Dialog State Tracking Task is predefined, we here use the Predefined-ontology methods aims to achieve better performance.

On the other hand, traditional DST models (Henderson, Thomson, and Young [2014] Chao and Lane [2019]) usually neglect the dialogue history and consider only utterances at current turn. To avoid the problem of lacking historical context, recent researchers employ autoregressive models to extract historical information. Some of them use a low-level network such as RNN, GRU to interactions between context and slots [Lee, Lee, and Kim 2019] Goel, Paul, and Hakkani-Tür [2019], others use partial context only [Kim et al. 2019], Sharma, Choubey, and Huang [2019]. These methods cannot extract the relevant context in an effective way.

Since the transformer network has been proposed in 2017 (Vaswani et al. 2017), the large-scale pre-trained model such as BERT (Devlin et al. 2018), RoBERTa (Liu et al. 2019) demonstrate a strong effect on NLP tasks. However, due to the maximum sequence length limit (eg. 512 for BERT-Base), these models unable to tackle sequences that are composed of thousands of tokens. We here use the feature fusion method on dialogue history, the method can fuse any partial history information through a predefined mask in the transformer network. Furthermore, we consider the historical dialogue information as global information and utterance at the current turn and its adjacency dialogue history as the local information which is in contrast to most existing DST methods depending on either local or global information only. Whilst the local feature aims to predict state operations (UPDATE, CARRYOVER, DONTCARE) and the global feature exploits relevant context from dialogue history. To the end, we formulate a two-branch architecture, with one branch for learning localized state operation and the other for learning slot value extraction. The two branches are not independent but synergistically jointly learned concurrently. We wish to discover and optimize jointly correlated complementary feature selections in the local and global representations.

Approach

Problem definition

We assume a dialogue with turns \( D = \{ (A_1, U_1), ..., (A_T, U_T) \} \) where \( A_t \) denotes Agent response, \( U_t \) denotes user utterance at turn \( t \), the predefined ontology as \( O = \{ (s, v_s), s \in S, v_s \in V \} \) where \( S \) is the set of slot names, here the slot name is denoted as domain-slot, for example, “restaurant-name”. \( V \) is the total set of slot values and \( v_s \) is the set of slot values belong to slot \( s \), i.e. \( v_s \subseteq V \), we define \( B_t = \{ (s^*_1, v^*_1), 1 \leq j \leq J \} \) as the belief state at each turn \( t \), where \( J \) is the total number of slots. We add “none” to the no value slot at current turn.

Joint Learning Multi Loss

Figure [I] shows the design of the proposed model architecture. The joint learning model consists of two branches Transformer network: (1) The local branch learning the state transition of each slot; (2) Another global branch responsible for learning the slot value label of each slot at each turn. For discovering correlated complementary information between local and global feature selections, the joint learning scheme is considered with two principles as follows:

- Shared low-level features. We construct the two types of branches on a shared lower BERT model. The intuition is that, the low-level features such as word and phrase representations which are common to all patterns in the same sentences. The local and global feature learning branches are two related learning tasks, sharing the low-level BERT model reduces the model overfitting risks.

- Multi-task independent learning. For learning the maximizing of complementary discriminative features from local and global representations, the remaining layers of two branches are learned independently which aims to preserve both local saliences in state operation prediction and global robustness in dialogue history representation.

Feature Fusion

We encoded the turn-level sentence by the BERT-base model due to its length is usually less than 128. On the other hand, since the sentence length in context-level is usually more than 512, we use the masked hierarchical transformer to fuse the feature from each turn. In addition, we fuse total historical context as a global representation that contains all dialogue information up to now and \( n \)-history context as a local representation at the current turn. The local representation is also used to predict state operation at the current turn (eg.
Due to the state operation cannot be decided by a single turn, we here use $n$-history context as the local representation ($n \geq 1$). We also adjust the model construction in [Shan et al. (2020)] by adding a masked hierarchical transformer module after the BERT encoder.

**Network Construction**

As shown in Figure 1, the slot names and slot values are encoded by the same BERT with fixed weights. The dialogue is first encoded by a trainable BERT in turn-level and then fuse the turn-level features for global and local representations, respectively. Moreover, the global and the local representations are merged by a gate mechanism. The vectors from this gate mechanism are then used to compute the distance with slot value labels (similar to Shan et al. (2020)). Furthermore, the local representations are used for predicting state operations as an auxiliary task. To make the text more aligned with Figure 1, we will describe each module in more detail.

**Dialogue History Encode**

As the belief state is dependent on the historical dialogue, [Shan et al. (2020)] use a masked hierarchical transformer to encode the dialogue context. We extend this method to encode the context as global and local representations with two different mask metrics. An example of Masked Self-Attention is shown in Figure 2.

The information of utterance at each turn is aggregated by a trainable BERT and the utterance at turn $t$ is consisted of user utterance $U_t$ and agent response $A_t$ (Lee, Lee, and Kim 2019). We denote the turn input as $D_t = [CLS] \oplus A_t \oplus SEP \oplus U_t \oplus SEP$ and the turn-level informations $h_t$ is encoded by BERT as follows:

$$h_t = \text{BERT}_{\text{attr}} (D_t)$$  \hspace{1cm} (1)

The slot name $s$ and the slot value $v$ in [Lee, Lee, and Kim (2019)] are encoded by a fixed weights BERT. The sequence of slot name and slot value are denote as $q_s = [CLS] \oplus s \oplus SEP$ and $q_v = [CLS] \oplus v \oplus SEP$, the outputs of token $[CLS]$ in both $q_s$ and $q_v$ are used to represent the information of slot name and slot value, respectively.

$$h_s = \text{BERT}_{\text{slot}} (q_s)$$ \hspace{1cm} (2)

$$h_v = \text{BERT}_{\text{slot}} (q_v)$$ \hspace{1cm} (3)

For more general situations, the slot value at a single turn cannot be discriminate only by current utterance, but is dependent on previous turns, as shown in Table 1. Furthermore, the local feature with $n$-historical context $c_{s,t}^{\text{loc}}$ at turn $t$ can be defined as a multi-head attention between slot name and context of $n$-history, where $n$-history denotes $n$ turns of dialogue history before current turn $t$, i.e. $\{ uttr_{t-n}, uttr_{t-n+1}, ..., uttr_t \}$. Formally, $c_{s,t}^{\text{loc}}$ can be denoted as follows:

$$c_{s,t}^{\text{loc}} = \text{MultiHead}(h_s, c_{s,t-n \leq i \leq t}, c_{s,t-n \leq i \leq t})$$ \hspace{1cm} (4)

Where $c_{s,t-n \leq i \leq t}$ is the masked hierarchical encoder result. Figure 3 shows what $n$-history mask matrix looks like and $c_{s,t-n \leq i \leq t}$ is denoted as follows:

$$m^0 = [c_{s,1}^{\text{word}}, c_{s,2}^{\text{word}}, ..., c_{s,t}^{\text{word}}] + [PE(1), PE(2), ..., PE(t)]$$

$$m^N = \text{MaskedTransformer}(m^{N-1}, m^{N-1}, m^{N-1})$$

$$c_{s,t-n \leq i \leq t} = m^N$$ \hspace{1cm} (5)
Figure 2: Masked Transformer. The position with -inf value in mask matrix will be masked, since the softmax of -inf is zero.

Where $m^N$ is the output of $N$-layers MaskedTransformer. $PE(\cdot)$ denotes positional encoding define in Devlin et al. (2018), $c_{s,t}^{\text{word}}$ is the MultiHead Attention between slot name and utterance tokens at turn $t$, which can be defined as follows:

$$c_{s,t}^{\text{word}} = \text{MultiHead}(h_s, h_t, h_t)$$  \hspace{1cm} (6)

We use $c_{s,0 \leq i \leq t}$ and $c_{s,t-n \leq i \leq t}$ are the global and local contextual information, respectively. The feature fusion method is shown in Figure 1, we expect this feature can better represent the dialogue information through balancing the information from global and local context.

Finally, we take the method of Shan et al. (2020) to compute the loss for slot-value prediction, the probability distribution of slot value $p(v_t \mid U_t, A_t, s)$ at turn $t$ and its loss are defined as follows:

$$p(v_t \mid U_{\leq t}, A_{\leq t}, s) = \frac{\exp(-||d_{s,t} - h_v||)}{\sum_{v' \in V_s} \exp(||d_{s,t} - h_{v'}||)}$$

$$L_{sv} = \sum_{s \in S} \sum_{t=1}^{T} -\log(p(v_t \mid U_{\leq t}, A_{\leq t}, s))$$  \hspace{1cm} (7)

Where $d_{s,t}$ denotes the encoder result with slot name $s$, it will be used to match each slot value representation $h_v$ belongs to $s$.

**State Operation Decoder** We define $O = \{\text{CARRYOVER}, \text{DONTCARE}, \text{UPDATE}\}$ as the state operation category set. An operation $r_i^t$ of slot $j$ is classified by state operation predictor, the mean of each category as follows:

- **CARRYOVER**: slot value is unchanged.
- **UPDATE**: slot value is changed to a new value from previous one.
- **DONTCARE**: slot neither needs to be considered important nor be tracked in the dialogue.

**Input Representation for State Operation** As the conversation progresses, the state operation at each turn is determined by the previous dialogue state and the current dialogue turn. The flow of state can be modeled by autoregressive decoders. Therefore, we use RNN as our decoder.

Table 2 shows the joint accuracy of baseline models and our model on MultiWOZ (en → zh) and CrossWOZ (zh → en) human val datasets. Our model achieves 50.16% and 11.87% with 0.96% and 0.57% improvement respectively.

| Model            | Ontology | MultiWOZ(en → zh) | CrossWOZ(zh → en) |
|------------------|----------|-------------------|-------------------|
| TRADE            | ×        | 29.65             | 7.9               |
| NADST            | ✓        | 31.21             | 8.3               |
| SUMBT            | ✓        | 49.4              | 10.6              |
| CHAN             | ✓        | 50.16             | 11.3              |

Table 2: Joint accuracy on human val sets of MultiWOZ(en → zh) and CrossWOZ(zh → en), respectively. The ontology column indicates if the model is based on predefined ontology or not.

model, $v^\text{loc}_{s,t}$ and $h^\text{loc}_{s,t-1}$ as the model inputs:

$$h^\text{loc}_{s,t} = \text{RNN}(v^\text{loc}_{s,t}, h^\text{loc}_{s,t-1})$$  \hspace{1cm} (8)

Where $h^\text{loc}_{s,t}$ is the representation of state operation at turn $t$.

The probability distribution over state operations $p^{\text{sop}}_{s,t}$ and its loss are defined as follows:

$$p^{\text{sop}}_{s,t} = \text{softmax}(W_{\text{sop}} h^\text{loc}_{s,t})$$

$$L_{\text{sop}} = \sum_{s \in S} \sum_{t=1}^{T} - (Y^{\text{sop}}_{s,t})^T \log(p^{\text{sop}}_{s,t})$$  \hspace{1cm} (9)

Where $W_{\text{sop}}$ is a linear project to obtain operation probability distribution $p^{\text{sop}}_{s,t}$ and $Y^{\text{sop}}_{s,t}$ is the operation label of slot $s$ at turn $t$.

Therefore, we take the sum of losses metioned above as the final joint loss $L_{\text{joint}}$ as following:

$$L_{\text{joint}} = L_{sv} + L_{\text{sop}}$$  \hspace{1cm} (10)

**Experiment**

**Baseline Models**

We compare the performance of the proposed method with the following models:

- **SUMBT**: Using a trainable BERT to encode system and user utterances and a fixed weighted BERT to encode slot-type and slot-value information and predict the slot-value label based on a certain metric Lee, Lee, and Kim (2019).
- **CHAN**: Employing a contextual hierarchical network to fuse contextual information and exploiting the same method in SUMBT to predict the slot-value label Shan et al. (2020).
- **NADST**: Generate dialogue state at each turn by a non-autoregressive decoder model Le, Socher, and Hqi (2020).
- **TRADE**: Using an Encoding Decoding model to generate slot-value label Wu et al. (2019).

Table 2 shows the joint accuracy of baseline models and our model on MultiWOZ (en → zh) and CrossWOZ (zh → en) human val datasets. Our model achieves 50.16% and 11.87% with 0.96% and 0.57% improvement respectively.
Figure 3: n-history mask. The blocks with 0 score in the mask matrix means the corresponding utterance is attendable.

### Table 3: The Top-10 number of slot values modified

| Slot name                      | # of total slot values | # modified slot values | % of slot values modified |
|--------------------------------|------------------------|------------------------|---------------------------|
| attraction-type                | 10925                  | 0                      | 0                         |
| attraction-name                | 290                    | 0                      | 0                         |
| restaurant-name                | 276                    | 363                    | 99.9%                     |
| hotel-name                     | 186                    | 288                    | 99.5%                     |
| taxi-destination               | 1108                   | 204                    | 96.8%                     |
| restaurant-block-time          | 198                    | 158                    | 74.2%                     |

### Table 4: The ablation study of the state transition prediction and the data Augmentation on MultiWOZ(en → zh) and CrossWOZ(zh → en), respectively.

**Data Augmentation**

We found that the human evaluation dataset is generated through real-life conversations, while the training data is generated by Google translator, so it is not as natural as human language. In this work, we consider data augmentation to improve model performance. We use translation services provided by Tencent, Baidu, and our translation model to translate the source language to the target language. We also find that MultiWOZ(en → zh) and CrossWOZ(zh → en) are provided by different organizers, both of them have some annotation errors, so we here use different methods to correct slot value labels.

For the MultiWOZ(en → zh) dataset we using the label in MultiWOZ_2.2 as right labels to correct the older ones, and the changes of each slot on MultiWOZ(en → zh) are shown in Table 5.

For the CrossWOZ(zh → en) dataset we found that the belief states at some turns are not inherited its previous turns. We consider these as the labeling errors that need to be corrected, so we here use the concept of state transition (carryover, update, dontcare, delete) to correct the belief state at each turn.

We estimate the effectiveness of the back-translation data augmentation and state transition prediction task. The joint accuracy reduces by 0.58% with removing the state operation prediction task and reduces by 8.4% with no data augmentation. Moreover, the performance decreases by 9.4% with removing both of them. Table 4 demonstrates that the data augmentation and state transition prediction task are crucial for DST.

### Table 5: MultiWOZ Leaderboard (Best Submissions).

| Team                | Joint(%) | Slot(%) | Slot P/R/F1 | Joint/pub/pri | Rank |
|---------------------|----------|---------|-------------|---------------|------|
| i(ours)             | 23.96    | 92.94   | 14.25/16.37 | N/A           | 3    |
| 2                   | 13.99    | 91.92   | 14.41/13.58 | N/A           | 3    |
| Baseline            | 7.21     | 85.13   | 7.41/7.00   | N/A           | 3    |

### Table 6: CrossWOZ Leaderboard (Best Submissions).

**Overall Results**

We train the model with different n-history as the local information and we finally choose 1-history as the best length for the joint learning.

By using above improvements, we achieve the result with joint accuracy of **62.37%** and **23.96%** on MultiWOZ(en → zh) and CrossWOZ(zh → en) datasets, respectively.

With this end-to-end model, we achieve Top 1 in MultiWOZ(en → zh) dataset, and Top 2 in CrossWOZ(zh → en) dataset. The results of MultiWOZ(en → zh) and CrossWOZ(zh → en) tasks are shown in Table 5 and 6 respectively. The Organizers found that the CrossWOZ(zh → en) test data miss “name” labels when the user accepts the attraction/hotel/restaurant recommended by the system (Gunasekara et al. 2020). Table 7 shows the updated leaderboard for CrossWOZ. Moreover, although the evaluation was updated in CrossWOZ(zh → en), our algorithm is still ranked second in the updated CrossWOZ Leaderboard, which shows that our method has better generalization ability.

### Conclusion

In this paper, we introduce a general feature fusion method as the solution in DSTC 9 Track 2 competition, which can...
merge any parts of context feature from dialogue history. We also construct a multi-task network to improve the feature representation ability. Our proposed model is ranked first in MultiWOZ (en → zh) and second in CrossWOZ (zh → en) respectively. The proposed model is based on predefined ontology, and we will investigate an open-vocabulary model in the future.

References

Aujogue, J.-B.; and Aussem, A. 2019. Hierarchical Recurrent Attention Networks for Context-Aware Education Chatbots. In 2019 International Joint Conference on Neural Networks (IJCNN), 1–8. IEEE.

Budzianowski, P.; Wen, T.-H.; Tseng, B.-H.; Casanueva, I.; Ultes, S.; Ramadan, O.; and Gašić, M. 2018. Multiwoz—a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling. arXiv preprint arXiv:1810.00278.

Chao, G.-L.; and Lane, I. 2019. Bert-dst: Scalable end-to-end dialogue state tracking with bidirectional encoder representations from transformer. arXiv preprint arXiv:1907.03040.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Eric, M.; Goel, R.; Paul, S.; Sethi, A.; Agarwal, S.; Gao, S.; and Hakkani-Tür, D. 2019. Multiwoz 2.1: Multi-domain dialogue state corrections and state tracking baselines.

Gao, S.; Sethi, A.; Agarwal, S.; Chung, T.; and Hakkani-Tür, D. 2019. Dialog state tracking: A neural reading comprehension approach. arXiv preprint arXiv:1908.01946.

Goel, R.; Paul, S.; and Hakkani-Tür, D. 2019. Hyst: A hybrid approach for flexible and accurate dialogue state tracking. arXiv preprint arXiv:1907.00883.

Gunasekara, C.; Kim, S.; D’Haro, L. F.; Rastogi, A.; Chen, Y.-N.; Eric, M.; Hedayatnia, B.; Gopalakrishnan, K.; Liu, Y.; Huang, C.-W.; Hakkani-Tür, D.; Li, J.; Zhu, Q.; Luo, L.; Liden, L.; Huang, K.; Shayandeh, S.; Liang, R.; Peng, B.; Zhang, Z.; Shukla, S.; Huang, M.; Gao, J.; Mehri, S.; Feng, Y.; Gordon, C.; Alavi, S. H.; Traum, D.; Eskenazi, M.; Beirami, A.; Eunjoon; Cho; Crook, P. A.; De, A.; Geramifard, A.; Kottur, S.; Moon, S.; Poddar, S.; and Subba, R. 2020. Overview of the Ninth Dialog System Technology Challenge: DSTC9.

Henderson, M.; Thomson, B.; and Young, S. 2014. Word-based dialog state tracking with recurrent neural networks. In Proceedings of the 15th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL), 292–299.

Hochreiter, S.; and Schmidhuber, J. 1997. Long short-term memory. Neural computation 9(8): 1735–1780.

Kim, S.; Yang, S.; Kim, G.; and Lee, S.-W. 2019. Efficient dialogue state tracking by selectively overwriting memory. arXiv preprint arXiv:1911.03906.

Le, H.; Socher, R.; and Hoi, S. C. 2020. Non-autoregressive dialog state tracking. arXiv preprint arXiv:2002.08024.

Lee, H.; Lee, J.; and Kim, T.-Y. 2019. Sumbt: Slot-utterance matching for universal and scalable belief tracking. arXiv preprint arXiv:1907.07421.

Liu, Y.; Ott, M.; Goyal, N.; Du, J.; Joshi, M.; Chen, D.; Levy, O.; Lewis, M.; Zettlemoyer, L.; and Stoyanov, V. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Ren, L.; Xie, K.; Chen, L.; and Yu, K. 2018. Towards universal dialogue state tracking. arXiv preprint arXiv:1810.09587.

Shan, Y.; Li, Z.; Zhang, J.; Meng, F.; Feng, Y.; Niu, C.; and Zhou, J. 2020. A Contextual Hierarchical Attention Network with Adaptive Objective for Dialogue State Tracking. arXiv preprint arXiv:2006.01554.

Sharma, S.; Choubey, P. K.; and Huang, R. 2019. Improving dialogue state tracking by discerning the relevant context. arXiv preprint arXiv:1904.02800.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is all you need. In Advances in neural information processing systems, 5998–6008.

Wu, C.-S.; Madotto, A.; Hosseini-Asl, E.; Xiong, C.; Socher, R.; and Fung, P. 2019. Transferable multi-domain state generator for task-oriented dialogue systems. arXiv preprint arXiv:1905.08743.

Yang, Z.; Dai, Z.; Yang, Y.; Carbonell, J.; Salakhutdinov, R. R.; and Le, Q. V. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems, 5753–5763.

Zhang, J.-G.; Hashimoto, K.; Wu, C.-S.; Wan, Y.; Yu, P. S.; Socher, R.; and Xiong, C. 2019. Find or classify? dual strategy for slot-value predictions on multi-domain dialog state tracking. arXiv preprint arXiv:1910.03544.

Zhu, Q.; Huang, K.; Zhang, Z.; Zhu, X.; and Huang, M. 2020. Crosswoz: A large-scale chinese cross-domain task-oriented dialogue dataset. arXiv preprint arXiv:2002.11893.