Context-Sensitive Generation Network for Handling Unknown Slot Values in Dialogue State Tracking

Puhai Yang, Heyan Huang, and Xian-Ling Mao

Abstract—As a key component in a dialogue system, dialogue state tracking plays an important role. It is very important for dialogue state tracking to deal with the problem of unknown slot values. As far as we known, almost all existing approaches depend on pointer network to solve the unknown slot value problem. These pointer network-based methods usually have a hidden assumption that there is at most one out-of-vocabulary word in an unknown slot value because of the character of a pointer network. However, often, there are multiple out-of-vocabulary words in an unknown slot value, and it makes the existing methods perform bad. To tackle the problem, in this paper, we propose a novel Context-Sensitive Generation network (CSG) which can facilitate the representation of out-of-vocabulary words when generating the unknown slot value. Extensive experiments show that our proposed method performs better than the state-of-the-art baselines.

Index Terms—task-oriented dialogue system, dialog state tracking, unknown slot value, pointer network

1 INTRODUCTION

Currently, the research and application of dialogue systems are widely concerned, especially for task-oriented dialogue systems, such as booking tickets and ordering restaurants. Dialogue state tracking is a key component of a task-oriented dialogue system. By parsing dialogue history, dialogue state tracking extracts users intentional state, such as intention, slot, and value, as the input of dialogue manager for system decision making. For example, (price, cheap) and (area, centre) are extracted from “I am looking for a cheap restaurant in the centre of the city” as users state.

Traditionally, dialogue state tracking is typically solved using discriminative approach [1] [2] [3], which is based on the assumption that all slot values are known in advance. In reality, however, it is impossible to know all the slot values, dialogue state tracking models often encounter slot values that have never been seen in training, which are also known as unknown slot values [4]. Thus, recently, researches on dialogue state tracking mainly concentrates on the generative method [5] [6] [7] [8], which attempt to solve the problem of unknown slot values by generating novel words through vocabulary-based distribution.

However, the generative method almost always depends on pointer network [9] to extract unknown slot values on account of the fact that unknown slot values often contain the out-of-vocabulary word. And the validity of pointer network to extract unknown slot values is usually based on the assumption that the unknown slot value contains not more than one out-of-vocabulary word. Invariably, in the decoder, pointer network use word embedding to represent each word, and all out-of-vocabulary words are represented by a uniform embedding, such as UNK. So that multiple out-of-vocabulary words in an unknown slot value are indistinguishable, as shown in Fig. 1(a), which confuses the decoder that uses the word embedding as input.

In fact, there is often more than one out-of-vocabulary words in an unknown slot value, the pointer network cannot distinguish these different out-of-vocabulary words only by word embedding, and the information of these out-of-vocabulary words cannot be adequately represented by a uniform embedding. Due to the input uncertainty that

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Fig. 1. Two different representations of words: word embedding and contextual representation. The yellow unit is the word in the vocabulary, the red unit is out-of-vocabulary word, the blue unit refers to the vocabulary space representation of the word, namely word embedding, and the green unit refers to the representation of the word in a specific context.
comes with this situation during decoding, the output of the decoder will gradually deviate, resulting in the error of the unknown slot value.

To tackle the drawback, we emphasize that the input of the decoder should be infused with more information than just the word embedding. In this paper, we propose a novel Context-Sensitive Generation network (CSG) for the unknown slot value problem in dialog state tracking. Our proposed model joins word contextual information, as shown in Fig 1(b), to the input of the decoder. So that different out-of-vocabulary words can be distinguished by word contextual information, and word contextual information can also enrich the representation of the word, which used to be represented only by word embedding.

The main contributions of this paper are as follows:

- We propose a novel context-sensitive generation network that utilizes word contextual information to overcome the problem of uncertain information caused by out-of-vocabulary words.
- On the most influential MultiWOZ 2.1 benchmark, our model has obvious advantages over the state-of-the-art baselines in the extraction of unknown slot values.

The rest of the paper is organized as follows: Related work is briefly introduced in section 2 and the shortcomings are pointed out. In section 3, The main structure of our proposed model is described in detail. Experiments and analysis are presented in section 4, followed by conclusions in section 5.

2 RELATED WORK

As we mentioned above, the generative method usually depends on pointer network [9] to solve the unknown slot value problem when in dialog state tracking (DST). The validity of pointer network implies the assumption that slot value contains not more than one out-of-vocabulary word, which is the motivation of this paper. At present, researches on generative DST mainly focus on two categories: extractive DST and hybrid DST.

The Encoder-Decoder structure based on pointer network has been used in many researches [10] [11] [12]. These models are designed to directly copy the words in the input text, which is different from the traditional generative method of modeling vocabulary distribution, but more like a variant of sequence labeling [13]. Since almost all slot values are contained in the dialogue history, pointer network-based extractive DST was proposed for DST modeling [1], and the extractive DST can also solve the unknown slot value problem. This method can copy slot values directly from the dialogue history, but it faced with the problem of subsequent processing, because some slot values need to be inferred instead of being directly contained in the dialogue history.

Pointer-Generator Networks (PGN) [14], a hybrid between sequence-to-sequence attentional model [15] and a pointer network, has received a lot of attention since it was proposed, and there are also many relevant studies in DST [3] [7] [6]. Different from the extractive method, PGN-based DST, hybrid DST we called, can copy words from the input text via pointer network while maintaining the ability to generate novel words using vocabulary-based distribution. Therefore, the hybrid DST does not require subsequent processing modules.

In general, current generative DST methods are basically depend on pointer network to solve unknown slot value problem. However, as we mentioned in the previous section, pointer network is faced with the problem of uncertain input information in decoding. When there are multiple out-of-vocabulary words in an unknown slot value, the unknown slot value generated by the pointer in pointer network will be deviated.

3 CONTEXT-SENSITIVE GENERATION NETWORK

In this section, we describe (1) the framework of our proposed model and (2) different schemes to leverage context information in our model. The code for this paper is available online.

3.1 Framework

In our model (shown in Fig 2), the encoder is used to generate the vector representation of dialogue history and the contextual representation of each word. It is important to note that the encoder can be any encoding model, such as bi-LSTM [16] and bi-GRU [17]. The input of the encoder is the dialogue history \( H = [w_1, ..., w_l] \in \mathbb{R}^{l \times d_{emb}} \), which is the concatenation of all words in the dialogue history. \( l \) is the length of dialogue history and \( d_{emb} \) is the size of word embedding. The output of the encoder consists of two parts, one is the hidden state \( S \in \mathbb{R}^{d_{hid}} \) at the last encoding step, which is the initial input state of the decoder, and the other is the output \( OT = [o_1^{enc}, ..., o_l^{enc}] \in \mathbb{R}^{l \times d_{hid}} \), consisting of the output of the encoder at each encoding step, \( d_{hid} \) is the hidden size. In our model, we assume that \( OT \) is not only a representation of the dialogue history, but also a contextual representation of each word in the dialogue history. Therefore, \( OT \) can be used to enhance the representation of out-of-vocabulary word in decoding.

At the initial step of decoding, we use the slot embedding as input to the decoder. It is important to point out that the slot embedding does not have to be the input to the decoder, but can also be placed in the output, which is not the focus of this paper. At decoding step \( t \), the output \( o_{dec} \in \mathbb{R}^{d_{hid}} \) of the decoder is used to generate the attention \( p_t^{history} \in \mathbb{R}^l \) over each word in dialogue history.

\[
p_t^{history} = \text{softmax}(OT \cdot (o_t^{dec})^T)
\]

Then, the position \( pos_t \) of the \( t \)th word of slot value in the input dialogue history is determined by the maximum attention in \( p_t^{history} \).

\[
pos_t = \arg \max_{i \in [1, ..., l]} p_t^{history}
\]

At decoding step \( t + 1 \), The pointer network traditionally take the embedding \( w_{pos_t} \) of the word selected in step \( t \) as the input \( I_{t+1} \) of the decoder. However, the information in the embedding of the out-of-vocabulary word is incomplete and cannot effectively represent the word. As we mentioned

1. https://github.com/yangpuhai/CSG
above, the output \( OT \) of the encoder can be seen as the contextual representation of each word in dialogue history. Therefore, our proposed model combines the embedding of word and its contextual representation as input to the decoder.

\[
I_{t+1} = \text{com}(w_{pos}, o_{pos}^{enc})
\]

Where \( \text{com} \) is the way \( w_{pos} \) and \( o_{pos}^{enc} \) are combined, and we will discuss the different combination schemes in the following.

3.2 Context Utilization Schemes

In this paper, we believe that words should have not only vocabulary space representation, that is, word embedding \( w_{pos} \), but also contextual representation \( o_{pos}^{enc} \). In the traditional Encoder-Decoder model, only word embedding is usually considered and contextual representation is ignored. When a word is an out-of-vocabulary word, it is common to use a uniform word embedding UNK to represent the word. In this way, the information of the word cannot be adequately represented, which will lead to the deviation of the results. Therefore, we propose to combine the embedding and contextual representation of words, so that not only the information in words is enhanced, but also the unknown slot value problem can be effectively addressed.

In order to make effective use of contextual information, we propose different schemes combining contextual information with word embedding, as follows:

**Enc:** \( I_{t+1} = o_{pos}^{enc} \). The contextual representation is used directly as the representation of the word.

**Sum:** \( I_{t+1} = w_{pos} + o_{pos}^{enc} \). The sum of the word embedding and contextual representations is used as the representation of the word.

**Cat:** \( I_{t+1} = [w_{pos}, o_{pos}^{enc}] \). The concatenation of the word embedding and contextual representations is used as the representation of the word.

**Pws:** \( I_{t+1} = p_{weight}^{t} \times w_{pos} + (1 - p_{weight}^{t}) \times o_{pos}^{enc} \). As mentioned in section 2, pointer network [9] is used in Pointer-Generator Networks (PGN) [14] to solve the unknown slot value problem, so our model can be generalized to improve PGN. In traditional PGN, while generating the attention \( p_{vocab}^{t} \) for the dialogue history, the distribution \( p_{vocab}^{t} \) for the vocabulary space is also calculated, and then weighted sum is made according to the proportion \( p_{weight}^{t} \), which is usually calculated in different ways in different models [6] [14]. Here, we weighted the sum of word embedding and contextual representation according to the proportion \( p_{weight}^{t} \). It should be pointed out that this scheme is only suitable for PGN generalization model.

4 Experiments

4.1 Dataset

Our experiments are conducted on MultiWOZ 2.1 dataset [18], which is the latest corrected version of the MultiWOZ dataset [19]. Compared with the DSTC2 dataset [20], which is the traditional standard dialog state tracking benchmark, MultiWOZ 2.1 containing around 10K dialogues, with each dialogue averaging 13.68 turns. And there are more than 30 slots and over 4500 possible slot values in MultiWOZ 2.1. More importantly, since there are slot values containing
multiple words in MultiWOZ 2.1 dataset, that is consistent with the problem of extracting unknown slot value containing multiple out-of-vocabulary words studied in this paper, so MultiWOZ 2.1 dataset is selected as benchmark. Further, we eliminate the slots in MultiWOZ 2.1 whose slot value contains only one word, and the final dataset contain 7 slots: traindestination, train-departure, attraction-name, restaurant-name, hotel-name, taxi-destination, taxi-departure in 5 domains: train, attraction, restaurant, hotel, taxi. And the modified dataset consists of training, validation, and testing, which contain 32,233, 5,431, and 5,568 dialogue utterances respectively.

It should be noted that the slot values of the validation and test sets of the original MultiWOZ 2.1 dataset do not contain the unknown slot value. For experimental investigation, we select some words from the slot values of the validation and test sets as out-of-vocabulary words to simulate the unknown slot value problem. Specifically, we randomly select the word in the slot values from the validation set and test set in different proportions, and then discard the word from the training set vocabulary. Meanwhile, any sample containing the word in the training set changes the word to the character UNK, but keeps the sample for training purposes. In order to highlight the experimental comparison, we discard the negative samples that do not contain any slot values in the data set without changing the experimental conclusion. The statistics of the modified dataset are shown in Table 1. Importantly, the out-of-vocabulary ratio mentioned in this paper refers to the ratio of out-of-vocabulary words in all slot values in the validation and test sets.

4.2 Baselines

It is mentioned in section 2 that existing generative dialog state tracking (DST) models are mainly divided into two types, pointer network-based extractive DST and pointer-generator networks (PGN)- based hybrid DST. Therefore, our baselines include two types, the extractive model: SpanPtr [4] and SeqPtr, and the hybrid model: HD [6] and TRADE [7]. Next, we give a brief introduction to these models:

SpanPtr: This model uses pointer network to generate the start and end positions of slot values in a dialogue, and then extracts the slot values by copying.

SeqPtr: This is our modified version of the SpanPtr, this model generates the position of each word in the slot value in the dialogue instead of just the start and end positions.

HD: Hierarchical structure is considered in this model, where multiple classifiers are used to predict the existence of each slot, and then the slot information is used to generate the slot value with PGN.

TRADE: This is the current state-of-the-art model on the MultiWOZ dataset. It uses a slot gate to predict whether slot values need to be generated, and there is a PGN-based state generator in the model to generate slot values.

All baselines and our models are set with the same parameters. Bi-GRU and GRU are used as encoder and decoder respectively. The dimension of word embedding and hidden state are both 400, and the dropout ratio is set to 0.2. All models are trained using the Adam optimizer with a batch size of 32, and all training consists of 50 epochs with early stopping on the validation set. In addition, word dropout is used on all models to improve generalization. More importantly, teacher forcing [21] with ratio of 0.5 is adopted by all models in decoding, except for the word contextual representation on PGN-based DST, in order to be consistent with baseline.

4.3 Results

The joint accuracy of dialog state tracking (DST) on the modified MultiWOZ 2.1 dataset in different out-of-vocabulary ratios is shown in Table 2 and Fig 3. As an illustration of the name of our model, for example, SpanPtr CSG(Enc) refers to the improved DST model after adding the context-sensitive generation network we proposed into SpanPtr, where the utilization scheme of context is Enc.

It should be emphasized here that the proposed model is mainly for the handling of unknown slot value containing multiple out-of-vocabulary words. In addition, since the MultiWOZ 2.1 dataset is target at complex DST in multiple domains, the final joint accuracy is not only relate to the extraction of unknown slot values, but also depend to other factors, such as cross-domain learning. Under this premise, according to Table 2 in general, our model performs as well as all baselines when there are less than 38% unknown slot values containing multiple out-of-vocabulary words (out-of-vocabulary ratio is less than 70%). And when there are more than 38% unknown slot value with multiple out-of-vocabulary words (the out-of-vocabulary ratio is greater than 70%), our model is almost al ways outperforming all baselines. What can also be observed is that compared with pointer network-based DST, the context utilization scheme Enc does not perform very well on pointer-generator networks-based DST, this should be related to the fact that no force teaching is taken in training for the word contextual representation.

The experiments in the individual restaurant domain can better highlight the superiority of our model over all baselines, as shown in Fig 3 where the performance of all DST models is unaffected by knowledge sharing across domains. Here, we can observe more clearly that when out-of-vocabulary ratio exceeds 70% (the proportion of unknown slot values containing multiple out-of-vocabulary
### Table 2
Joint accuracy of dialog state tracking in multiple domains with different out-of-vocabulary ratios on MultiWOZ 2.1 dataset.

| Models               | out-of-vocabulary ratios (%) |
|----------------------|------------------------------|
|                      | 0    | 10   | 20   | 30   | 40   | 50   | 60   | 70   | 80   | 90   | 100  |
| SpanPtr             | 63.2 | 62.8 | 61.8 | 60.8 | 59.5 | 60.0 | 59.7 | 56.2 | 54.8 | 54.1 | 47.5 |
| SpanPtr_CSG(Sum)    | 62.6 | 61.9 | 62.9 | 60.3 | 61.0 | 59.1 | 58.2 | 57.9 | 55.8 | 54.5 | 49.9 |
| SpanPtr_CSG(Cat)    | 63.2 | 62.4 | 63.2 | 62.1 | 60.5 | 60.0 | 59.2 | 57.2 | 56.1 | 55.5 | 52.4 |
| SeqPtr              | 64.8 | 64.1 | 64.2 | 61.5 | 61.2 | 60.4 | 59.9 | 57.0 | 56.7 | 55.9 | 50.4 |
| SeqPtr_CSG(Enc)     | 63.5 | 62.9 | 62.9 | 61.5 | 62.1 | 61.1 | 58.6 | 58.0 | 57.0 | 55.4 | 51.2 |
| SeqPtr_CSG(Sum)     | 64.8 | 63.4 | 63.0 | 60.9 | 61.8 | 60.0 | 58.9 | 58.3 | 56.9 | 56.4 | 52.3 |
| SeqPtr_CSG(Cat)     | 64.0 | 63.6 | 63.8 | 60.8 | 62.2 | 60.7 | 58.8 | 59.6 | 56.5 | 54.9 | 48.3 |
| HD_CSG(Enc)         | 66.3 | 66.7 | 64.8 | 65.0 | 61.6 | 61.2 | 57.3 | 59.3 | 57.4 | 55.1 | 48.4 |
| HD_CSG(Sum)         | 65.9 | 64.8 | 65.1 | 62.9 | 61.3 | 59.1 | 58.2 | 57.3 | 56.0 | 54.2 | 47.5 |
| HD_CSG(Cat)         | 65.6 | 66.7 | 65.8 | 64.2 | 63.2 | 61.9 | 57.1 | 59.6 | 57.8 | 54.6 | 48.9 |
| HD_CSG(Pws)         | 65.8 | 65.6 | 64.4 | 63.0 | 62.8 | 59.6 | 59.4 | 58.5 | 58.0 | 56.5 | 49.7 |
| TRADE               | 65.8 | 66.0 | 66.6 | 65.8 | 62.6 | 60.4 | 62.8 | 59.7 | 59.1 | 58.1 | 51.0 |
| TRADE_CSG(Enc)      | 65.7 | 64.9 | 65.4 | 64.1 | 62.4 | 58.3 | 60.2 | 59.1 | 56.9 | 56.9 | 50.0 |
| TRADE_CSG(Sum)      | 67.4 | 67.4 | 66.6 | 65.1 | 63.7 | 62.2 | 61.3 | 61.9 | 59.6 | 57.3 | 52.7 |
| TRADE_CSG(Cat)      | 65.3 | 66.1 | 65.8 | 65.1 | 63.7 | 60.0 | 61.5 | 59.8 | 59.6 | 57.1 | 52.1 |
| TRADE_CSG(Pws)      | 66.8 | 65.9 | 65.9 | 64.7 | 64.0 | 60.9 | 58.7 | 59.9 | 58.7 | 54.2 | 51.1 |

Fig. 3. Joint accuracy of dialog state tracking in domain restaurant with different out-of-vocabulary ratios on MultiWOZ 2.1 dataset.

Fig. 4. Comparison of the models correct predictions when slot values contain different numbers of words in domain restaurant on MultiWOZ 2.1 dataset. OOV0.0 refers to the out-of-vocabulary ratio of 0%, where the unknown slot value is not included. OOV1.0 refers to an out-of-vocabulary ratio of 100%, in which case all slot values are unknown slot values.

5 Conclusion
In this paper, we point out the defects of the current pointer network-based dialogue state tracking model in extracting unknown slot values, and propose a novel model to extract unknown slot values more effectively by enhancing the representation of word with the word contextual information, namely, context-sensitive generation network (CSG). And the method can also be generalized to improve pointer-generator networks based dialogue state tracking model. We also propose different context utilization schemes for the CSG, among which the Sum and Cat schemes proved to have very good performance and exceed the state-of-the-art models on MultiWOZ 2.1 dataset. In addition, our model performs better in extracting unknown slot values containing multiple out-of-vocabulary words than all baselines.

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