Self-Training with Purpose Preserving Augmentation Improves Few-shot Generative Dialogue State Tracking

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Abstract

In dialogue state tracking (DST), labeling the dataset involves considerable human labor. We propose a new self-training framework for few-shot generative DST that utilizes unlabeled data. Our self-training method iteratively improves the model by pseudo labeling and employs Purpose Preserving augmentation (PPaug) to prevent overfitting. We increase the few-shot (10%) performance by approximately 4% on MultiWOZ 2.1 (Eric et al., 2019) and enhances the slot-recall 8.34% for unseen values compared to baseline.

1 Introduction

A task-oriented dialogue (TOD) system is a dialogue agent that aims to achieve users’ specific purposes which contain all of user’s requirements. A TOD system usually consists of several modules, among which dialogue state tracking (DST) is the primary module as it extracts a belief state that includes the user’s purpose (Young et al., 2013). A belief state is often represented as a set of slot-value pairs. For example, in Figure 1, the belief state has a slot Attraction-area and value Center that are required to achieve the user’s purpose (finding museum in the center of the city). Although DST is the core component of the dialogue system, labeling the DST is complex and expensive. Therefore, many few-shot methods have been proposed to address the data scarcity problem (Wu et al., 2019; Gao et al., 2020; Dingliwal et al., 2021; Lin et al., 2021).

In this study, we propose a new few-shot framework that effectively utilizes unlabeled data. In general, the amount of unlabeled dialogue data is abundant compared to labeled data. We focus on this and adopt self-training (ST) (Scudder, 1965) as a training strategy for few-shot generative DST. Recently, Mi et al. (2021) applied ST to few-shot DST to improve the accuracy. They use the classification-based DST as a backbone model and predict values by classifying a pre-defined value set called the ontology. However, their dependence on ontology has a flaw for few-shot DST: because the model can only predict values in the ontology, all plausible values should be collected to train the model. Collecting the ontology requires substantial labor and expert knowledge and is unsuitable for a few-shot DST that aims to reduce human effort. To perform DST without ontology data, we investigate the ST method based on the generative DST model, which is more challenging but ontology-free and can predict unseen values.

Many studies have demonstrated that including augmented data in ST helps prevent overfitting and achieves higher accuracy (Laine and Aila, 2016; Du et al., 2020; Xie et al., 2020). However, data augmentation in DST is challenging because an augmented sentence should include the belief state information needed to achieve the user’s purpose. There have been some attempts to augment DST data (Li et al., 2020a; Mi et al., 2021), but these approaches need to fine-tune a task-specific model for augmentation. To simplify the augmentation process, we developed a new mask infilling method that does not require fine-tuning. We integrate this method into our ST framework and name it Purpose-Preserving augmentation PPaug.
2 Method

2.1 Dialogue State Tracking (DST)

DST extracts the belief states from the user and the system’s conversation history. The conversation history for a turn $t$ is denoted as $C_t = (x_1, y_2, x_2, y_2, ..., x_t)$ where $x_i$ is a user utterance and $y_i$ is a system utterance. A belief state has the information required to achieve user’s purpose and is denoted as $B_t$ for turn $t$. A belief state consists of slot–value pairs $(s, v)$. Given dataset $C_t$ and prompt $m$, we use negative log-likelihood as a loss function as

$$L = - \sum_{i=1}^{t} \log p(B_i|m; C_i),$$

where $m$ is "translate dialogue to belief state :" (Su et al., 2021).

2.2 Self-Training (ST)

2.2.1 Initialization

The ST method utilizes both labeled data $L$ as well as unlabeled data $U$ in training. Before starting an ST iteration, we trained a teacher model with initial labeled data $L_0$, which contain only true labeled data, not pseudo-labeled data. The student and teacher models have the same model size.

2.2.2 Pseudo Labeling and Selection

At the beginning of the $i$-th ST iteration (Figure 2), the teacher model makes pseudo-labeled data $\tilde{U}_i$ by pseudo-labeling unlabeled data $U_i$ and calculates the confidence score for each pseudo label. The softmax value is generally used as the confidence score for the classification model (Bank et al., 2018; He et al., 2019; Zou et al., 2019). However, the generative model does not have an explicit softmax value for the predicted pseudo label. Therefore, we newly propose using the average softmax value as a confidence score for generative DST. Then, the selection module selects top-$k\%$ items using the confidence score. We move the selected items to the current labeled data $L_i$ from $\tilde{U}_i$ and denote the extended data as $\tilde{L}_i$. For hyperparameter $k\%$, we experimentally use 50%. The confidence score $S$ is as follows

$$\text{confidence score} = \frac{1}{N} \sum_{i=1}^{N} \frac{e^{w_i}}{\sum_{j \in \mathbb{V}} e^{w_j}},$$

where $N$, $w_i$ and $\mathbb{V}$ means the length of the word sequences, $i$-th word embedding and vocabulary set, respectively.

2.2.3 Student Training

After the pseudo labeling and selection, we create an augmented dataset $A_i$ using $\tilde{L}_i$ and train the student model with $A_i$ and $\tilde{L}_i$. In the machine translation domain, He et al. (2019) used noised data in the pre-training stage and achieved favorable regularization for the subsequent fine-tuning. Following their success, we first pre-trained the model with $A_i$ as noise and then fine-tuned it with the $\tilde{L}_i$. The best student model for validation data in the fine-tuning stage becomes a teacher model in next iteration, and the extended data $\tilde{L}_i$ is used as labeled data $L_{i+1}$. We also set $U_{i+1}$ as $U_i$ after deleting selected top-$k\%$ items.

2.3 Purpose-Preserving Data Augmentation

To prevent overfitting and get more accurate pseudo label (Laine and Aila, 2016; Du et al., 2020; Xie et al., 2020), we conduct data augmentation in student training. For data augmentation, we leverage
the masked language model (MLM). The MLM augments a sentence by replacing the tokens with \(<\text{mask}\>\) and infilling it with appropriate tokens. For augmented sentences in DST, containing the belief state information is critical to accurately perform the user’s conversation purpose. To do so, when choosing the tokens to be masked, we exclude the tokens overlapped with the belief state, which has important information about the user’s purpose. As we change less-important tokens (not overlapped with belief state), our method does not need task-specific fine-tuning. Our method, called purpose-preserving augmentation PPaug, is described in Figure 3.

PPaug has certain advantages when combined with ST. During each ST iteration, the teacher model assigns a pseudo-label to unlabeled data. When augmenting the data, we utilize not only the initial gold label, but also the pseudo label. This enables a more diverse augmented dataset as the pseudo label increases through each ST iteration.

3 Experiments

3.1 Setup

To examine our ST and augmentation method in a few-shot environment, we conduct an experiment in which only 10% of data are labeled and the others are unlabeled. We used the MultiWOZ 2.1 dataset (Eric et al., 2019), which is the most frequently used benchmark in TOD research. It has seven domains (Hotel, Restaurant, Attraction, Train, Taxi, Hospital, and Police) and includes 8,000 elements of dialogue related to tour information. For evaluation, we mainly use joint goal accuracy (JGA), which is the number of correct turns divided by the total number of turns; a turn is counted as correct if all of its predicted slots and values match the true slot-value pairs.

We employ the pre-trained T5-small (Raffel et al., 2020) for our backbone DST structure. We obtain the generated belief state (\(B_t\)) as an output in a natural language form as in Figure 1. For data augmentation, we use RoBERTa-base (Liu et al., 2019) as an MLM model. Appendix A has more details of the implementation.

| Model | Few-shot JGA [%] |
|-------|------------------|
| T5    | 40.98 ± 0.71     |
| + PPaug (\(L_0\)) | 41.32 ± 0.34 |
| + ST  | 42.17 ± 1.04     |
| + ST + PPaug w/o pseudo label (\(L_0\)) | 42.75 ± 0.34 |
| + ST + PPaug (\(\tilde{L}\)) | **44.09 ± 0.10** |

Table 1: Ablation study of our model reporting the joint goal accuracy (JGA) on MultiWOZ 2.1 in a few-shot (10%) and a full-data setting.

| Model | In-train slot-recall [%] | Unseen slot-recall [%] |
|-------|-------------------------|------------------------|
| T5    | 89.17                   | 89.00                  |
| + PPaug (\(L_0\)) | 88.87                  | 88.80                  |
| + ST  | 89.00                   | 89.00                  |
| + ST + PPaug w/o pseudo label (\(L_0\)) | 88.80                  | 42.43                  |
| + ST + PPaug (\(\tilde{L}\)) | **89.27**              | **46.58**              |

Table 2: Analysis for In-train and Unseen Values reporting few-shot (10%) slot-recall on the MultiWOZ 2.1 test set.

3.2 Experiment of ST with PPaug

Ablation Study To evaluate and analyze the contribution of each method we applied, we perform the ablation study in a few-shot environment (10% of the labeled data). We add our methods one by one from the baseline model (T5). As summarized in Table 1, augmentation (41.32%) and ST (42.17%) both increase the baseline accuracy and show more significant improvement (44.09%) when used together. In addition, we examine the effect of the pseudo label in data augmentation. Data augmentation without a pseudo label (using only the initial gold label \(L_0\)) has a lower accuracy (42.75%) than with the pseudo label \(\tilde{L}\) (44.09%). This shows that the teacher model’s pseudo label improves the data augmentation quality. For reference, we added JGA in a full data setting.

In-train and Unseen Value Compared to ST for classification DST, our ST method has the advantage of generating values that are not present in the train data. To explore the effect of ST and PPaug on unseen values, we divide test dataset values into
### Table 3: JGA [%] and increasing rate [%] with respect to the amount of labeled data in a few-shot setting.

| Labeled-data | 5%  | 10% | 20% | 30% | 40% |
|--------------|-----|-----|-----|-----|-----|
| TS           | 34.77 | 40.98 | 44.72 | 46.63 | 47.88 |
| + ST + PPaug | 39.35 | 44.09 | 47.33 | 48.39 | 48.93 |
| Increasing Rate | 13.17 | 7.59 | 5.84 | 3.77 | 2.19 |

### Table 4: Comparison with other selection criteria (confidence score) in ST. Reporting few-shot (10%) JGA.

| Selection Criteria | JGA [%] |
|--------------------|---------|
| Max                | 42.67   |
| Random             | 43.39   |
| Average            | 44.09   |

### Table 5: Comparison with other selection methods reporting few-shot (10%) JGA.

| Selection Method | JGA [%] |
|------------------|---------|
| Random-50%       | 43.08   |
| Select-All       | 43.56   |
| Top-50% (Proposed approach) | 44.09   |
| Top-20%          | 43.41   |
| Top-50% (Proposed approach) | 44.09   |
| Top-80%          | 43.10   |

### Table 6: Comparison of training method in student model training reporting few-shot (10%) JGA.

| Training method | JGA [%] |
|-----------------|---------|
| Fine-tuning ($A + \tilde{L}$) | 43.58 |
| Pre-training ($A$) + fine-tuning ($\tilde{L}$) | 44.09 |

### Analysis of ST

**Amount of Labeled Data** To examine the effectiveness of ST and PPaug in diverse few-shot environments, we experiment by changing the amount of labeled data to 5%, 10%, 20%, 30%, and 40%. Our ST and PPaug method has a more pronounced effect when there are less labeled data than when there are enough labeled data (Table 3). ST strives to utilize unlabeled data, and PPaug aims to supplement the insufficient data. Therefore, when the labeled data is not enough, our method is more helpful in increasing the accuracy.

### 3.3 Analysis of ST

**Selection Criteria (confidence score).** In Table 4, we compare our proposed selection criteria (average softmax value of tokens) with (i) Max: max softmax value of tokens; and (ii) Random: random softmax value of tokens. Our method shows better accuracy than other selection criteria, and 'Max' performs worse than the 'Random' method. There are some tokens that the decoder produces frequently irrespective of the text input (e.g., slot name or punctuation ":", and the softmax value of these tokens is relatively high than other tokens. Therefore, the max softmax value does not represent the model’s confidence of the generated belief state well and even worse than the randomly chosen value.

**Selection Methods** In Table 5, we compare our selection method (top-k%) with other methods including random-<i>k</i>% and select-all (Du et al., 2020; Vu et al., 2021). These methods show lower accuracy than using top-<i>k</i>%<sup>1</sup>. In addition, we change the hyperparameter <i>k</i> and compare the results. In this experiment, 50% shows the best accuracy. When using the top-80% selector, the model is trained with inaccurate pseudo-labeled data in the early training phase, degrading the performance. Top-20% is slightly better than top-80% but converges slowly compared to others.

**Training Method in Student Model** We pre-train the student model using augmented data ($A$), then fine-tune it with extended labeled data ($\tilde{L}$) in order to utilize the regularization effect of $A$. To see the effect of this separation, we train $A$ and $\tilde{L}$ in the same fine-tuning step as in Mi et al. (2021) and compare the result. In table 6, the accuracy of the 'pre-train ($A$) and fine-tuning ($\tilde{L}$)' model is better than 'fine-tuning ($A + \tilde{L}$)'. This indicates that separating the training step is better for preventing overfitting and making a more accurate result.

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<sup>1</sup>We referred to https://github.com/jasonwu0731/trade-dst
Table 7: Comparison with other augmentation methods using the MultiWOZ 2.1 dataset in ST.

| Language model | Label   | JGA [%] |
|----------------|---------|---------|
| Mask           | Maintaining | 44.09   |
|                | Changing   | 42.73   |
| Generative     | Maintaining | 44.02   |
|                | Changing   | 43.37   |

Table 8: The results of promising variants of PPaug on the MultiWOZ2.1 dataset in ST based on few-shot (10%) environment.

3.4 Analysis of PPaug

Other Augmentation Method Table 7 compares our text augmentation method with other commonly used methods, including EDA (Wei and Zou, 2019), AEDA (Karimi et al., 2021), back-translation (Sennrich et al., 2015), and CoCoAug (Li et al., 2020b). We apply each augmentation method to the ST framework. The result shows that our PPaug achieves higher accuracy than the other methods. Note that among the experimental results, EDA has the lowest result. This is because EDA randomly drops or changes the words for augmentation, making it difficult to maintain the user’s original purpose. This shows the importance of protecting the original user’s purpose for augmentation in DST.

Variants of PPaug In this experiment, we investigate other variants of PPaug. Each variant is applied to the ST in a few-shot environment (10% of labeled data is available). We examine an MLM or a generative model (Gen) as the pre-trained model and also distinguish the cases with respect to the label states: maintaining (Maintain) and changing (Change). For the generative model, we trained the model as in Li et al. (2020a) with 10% of the labeled data. Figure 4 and Appendix A.2 provide illustration and details of the implementation.

The first method (MLM-Maintain) is the same as PPaug; it shows the best result among the set of compared methods (Table 8). The second method, MLM-Change, has lower performance than PPaug. Unlike MLM-Maintain, MLM-Change can directly change the user’s main purpose (utterance and belief state tokens). The MLM-Change model freely changes the user’s purpose to the domain that is not included in MultiWOZ2.1 (Appendix A.4). This confuses the model. The Gen-Maintain and Gen-Change methods produce sentences with a generative language model. Gen-Maintain and Gen-Change each obtain quite reasonable results, but their performances are lower than PPaug. Note that only 10% of the labeled dataset is available in this few-shot experiment, and it may not be sufficient for fine-tuning the generative augmentation model. This leads to relatively poor augmented sentences. When the labeled data is scarce, MLM-Maintain performs better than the generative models, which need to be fine-tuned. Appendix A.4 provides an examples of the augmentations.

4 Conclusion

This study proposes ST framework suitable for generative DST and devises a new effective data augmentation method (PPaug). In the ablation study, not only does the proposed ST and PPaug individually improve the accuracy, but they show a synergistic effect when operated together. Additionally, compared to the baseline model, the performance in generating unseen value is greatly improved. As this is the first attempt to adopt ST in generative DST, we thoroughly examine the proposed selection process (average of softmax) and
we experiment with variants of PPaug and discuss their results.

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Appendix

A.1 Detailed implementation

In ST, we iterate the training loop until we reach 10 epochs with early stopping. To select the pseudo label, we select the top-50% in terms of the confidence score. In augmentation, we randomly choose 20% of tokens to change as \(<mask>\), slightly more than the default setting of BERT (Devlin et al., 2018) (15%), and double the size of the original sentence set. To pre-train the student model, we train the model for 20 epochs with early stopping, and in fine-tuning, we train for 10 epochs with early stopping. We implement a backbone generative DST model using T5-small (Raffel et al., 2020), which has six encoder/decoder layers and a hidden model of size 512. We use an NVIDIA A5000 graphics processing unit for all training, and an AdamW (Loshchilov and Hutter, 2017) optimizer with a learning rate of 5e-5. We set the batch size to 128 and implement T5-small based on the Huggingface Library (Wolf et al., 2020).

A.2 Detailed implementation for Table 8 results

Here, we explain the implementation of the experiment in Section 3.4 variants of ppaug. For MLM augmentation, we use the pre-trained RoBERTa-base (Liu et al., 2019), and for the generative language model (Gen), we use T5-small (Raffel et al., 2020). The generative model is fine-tuned to generate conditioned utterances given $C_t$ and $B_t$ using 10% of the labeled data following Li et al. (2020a). The MLM-Maintain method is the same as our PPaug method described in Section 2.3. For the MLM-Change method, when choosing the tokens to replace \(<mask>\), we choose the tokens overlapped with the belief state and also change the belief state’s tokens as per the MLM’s result. The Gen-Maintain method generates various sentences via beam search (Graves, 2012) using the same label as the original text. Finally, the Gen-Change method generates various sentences via beam search (Graves, 2012) with a changed label. In Gen-Change, to change the label appropriately, we build a slot–value dictionary from the 10% of initial labeled.

A.3 Masking Rate of PPaug

In PPaug, we randomly choose the some tokens to change as \(<mask>\). We experiment different masking rate (10%, 20%, 40%, 60% and 80%) to find best masking rate. Table 9 summarizes the results of each masking rates in the PPaug.

| Masking rate [%] | JGA [%] |
|-----------------|--------|
| 10              | 43.56% |
| 20 (Proposed approach) | 44.09% |
| 40              | 43.53% |
| 60              | 43.15% |
| 80              | 43.22% |

Table 9: Comparison with each other masking rate in the PPaug reporting few-shot (10%) JGA on the MultiWOZ 2.1 test set.
**A.4 Example of Augmented Sentence with Variants of PPaug**

This section shows the examples of Variants of PPaug and its error type.

### Example of MLM-Change

| Example 1 | Original                                                                 | Augmented                                                                 |
|-----------|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | 1 would just like to arrive by 16:00 please.                              | 1 would just like to arrive by 16:45 please.                              |
|            | [train][time] 16:00                                                      | [train][time] 16:45                                                      |

### Example 2 - Replace with out of domain (MultiWOZ2.1) value

| Original                                                                 | Augmented                                                                 |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | Is the gonville a good quality hotel?                                    | Is the gonville a good quality watch?                                     |
| [hotel][value type] hotel                                                  | [hotel][value type] watch                                                 |

### Example 3 - Replace with inadequate value for slot

| Original                                                                 | Augmented                                                                 |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | I would, thanks. I need a table for 6 on Sunday.                         | I would, thanks. I need a table for 6 on the table.                       |
| [restaurant][value people] 6, [value day] sunday                           | [restaurant][value people] 6, [value day] table                            |

### Example 4 - Replace with inadequate value for slot

| Original                                                                 | Augmented                                                                 |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | The restaurant should serve asian oriental food.                          | The restaurant should serve asian orientalis.                             |
| [restaurant][type] oriental food                                           | [restaurant][type] orientalis                                              |

### Example of Gen-Maintain

| Example 1 | Original                                                                 | Augmented                                                                 |
|-----------|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | I would like to find a museum to visit.                                  | I am looking for a museum to visit.                                       |
|            | [attraction][area] museum                                                  | [attraction][area] museum                                                  |

### Example 2 - Omit the information

| Original                                                                 | Augmented                                                                 |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | I would like to book a room for 3 days starting Tuesday. There is a total of 3 people. | I would like to book a room for 3 nights starting on tues                   |
| [hotel][value stay] 3 days [value day] tuesday [value people] 3 people    | [hotel][value stay] 3 days [value day] tuesday [value people] 3 people     |

### Example 3 - Omit the information

| Original                                                                 | Augmented                                                                 |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | Yes, can you find me a cheap place to eat serving chinese food?            | I would like a chinese restaurant.                                         |
| [restaurant][price] cheap, [type] chinese                                 | [restaurant][price] cheap, [type] chinese                                 |

### Example 4 - Generate informative words not in belief state

| Original                                                                 | Augmented                                                                 |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------|
| **Belief state** | I need a train departing from kings lynn.                                | Yes, I am looking for a train leaving kings lynn on the same day as my hotel check in date. |
| [train][area] kings lynn                                                  | [train][area] kings lynn                                                  |
### Example of Gen-Change

| Example 1 |
|-----------|
| **Original** | I need a **guest house** in the **east** please. |
| **Belief state** | [hotel][type] **guest house** [area]**east** |
| **Augmented** | I would like a **hotel** in the **west**. |
| **Belief state** | [hotel][type] **hotel** [area]**west** |

| Example 2 - Not matched with slot |
|-----------------------------------|
| **Original** | I also need information on cambridge book and print gallery. |
| **Belief state** | [attraction][area] cambridge book and print gallery |
| **Augmented** | Yes, I would like to book a **taxi** to go to the cinema. |
| **Belief state** | [attraction] **cinema** |

| Example 3 - Omit the information |
|----------------------------------|
| **Original** | The center of town would be best. |
| **Belief state** | [hotel][area] center of town |
| **Augmented** | Yes please book it for 6 people at 15:00 on tuesday. |
| **Belief state** | [hotel][value people] 6 people [time] 15:00 [value day] tuesday [area] **centre** |

| Example 4 - Omit the information, Generate informative words not in belief state |
|-------------------------------------|
| **Original** | I am looking for places to go in the east side of town. Do you have any suggestions? |
| **Belief state** | [attraction][area] east side of town |
| **Augmented** | I would like to leave the hotel on **Wednesday**. |
| **Belief state** | [taxi][departure] hotel [attraction][area] **west** |