Abstract

The natural language generation (NLG) module in task-oriented dialogue systems translates structured meaning representations (MRs) into text responses, which has a great impact on users’ experience as the human-machine interaction interface. However, in practice, developers often only have a few well-annotated data and confront a high data collection cost to build the NLG module. In this work, we adopt the self-training framework to deal with the few-shot MR-to-Text generation problem. We leverage the pre-trained language model to self-augment many pseudo-labeled data. To prevent the gradual drift from target data distribution to noisy augmented data distribution, we propose a novel data selection strategy to select the data that our generation model is most uncertain about. Compared with existing data selection methods, our method is: (1) parameter-efficient, which does not require training any additional neural models, (2) computation-efficient, which only needs to apply several stochastic forward passes of the model to estimate the uncertainty. We conduct empirical experiments on two benchmark datasets: FEWSHOTWOZ and FEWSHOTSVD, and show that our proposed framework consistently outperforms other baselines in terms of BLEU and ERR.

1 Introduction

Virtual assistants help people better manage their tasks in daily life, such as finding a restaurant, booking a flight, setting up a reminder, etc. The Natural Language Generation (NLG) module is an essential component in virtual assistants: it translates structured dialogue meaning representations (MRs) into natural language responses that directly interact with users. As the terminal human-machine interaction interface, the NLG module has a great impact on users’ experience (Wen et al., 2015; Rastogi et al., 2020a; Kale and Rastogi, 2020; Peng et al., 2020). However, in real-world applications, developers often only have a few well-annotated data and confront a high data collection cost, which makes it a challenging and valuable research problem (Kale and Rastogi, 2020; Chen et al., 2020; Peng et al., 2020).

One straight-forward way to address the few-shot MR-to-Text generation problem is to collect more data under a feasible budget. The main challenges of this task then can be categorized into: (1) data augmentation challenge and (2) data selection challenge. The data augmentation challenge is that the noisy augmented data may lead the model to learn irrelevant patterns, and cause a distribution shift between augmented data distribution and target data distribution. This phenomena is also described as negative transfer in other works (Chen...)

Table 1: Some examples of our self-augmented data and data selection strategy. pθ is a generation model learned from the few-shot training set. text is the in-domain unlabeled MR (e.g. request is the dialogue intent, and (ref = ?) is the slot-value pair of the current intent). The model pθ generates the dialogue response conditioning on the unlabeled MR. For each self-augmented data, E[pθ] indicates the predictive mean of a set of {pθi}M=1, and Var[pθ] means the predictive variance of a set of {pθi}M=1. In this work, we propose to select the high E[pθ] and high Var[pθ] data to fine-tune our generation model pθ iteratively.

| Self-augmented Data | E[pθ] | Var[pθ] |
|---------------------|-------|---------|
| 1. request (ref = ?) & i am sorry i do not have any restaurants with those criteria | low | low |
| 2. inform (choice = many) @ request (food = ?) & there are many restaurants that serve vegetarian food | low | high |
| 3. inform (food = seafood) & it is seafood | high | low |
| 4. inform (pricerange = dontcare) @ request (pricerange = ?) & are there any special price ranges you are looking for? | high | high |
et al., 2011; Wang et al., 2019; Meftah et al., 2021; Feng et al., 2021). The data selection challenge is that the lack of annotated data and explicit reward objective makes it difficult to select the augmented data which can improve the model’s performance. On one hand, lack of well-annotated target data makes it challenging to estimate the actual target data distribution, which prevents us from effectively selecting the in-distribution augmented data; on the other hand, there could be multiple optimal generated responses given one structured MR, which implicitly requires coverage of different data property (e.g. informativeness, naturalness, diversity, etc.) when selecting the augmented data.

To deal with the data augmentation challenge, previous works propose to leverage prior knowledge about the target task. The prior knowledge is used to design handcraft rules (Wei and Zou, 2019; Feng et al., 2020), build task-specific data retriever (Xu et al., 2021), or leverage pre-trained language models (Peng et al., 2021; Fabbri et al., 2021; Heidari et al., 2021), etc. The augmented data distribution should be neither too close to nor too far away from the original training data distribution. However, the optimal divergence between the augmented and original data distribution usually varies across different domains and tasks, which requires expert knowledge to identify. To address the data selection challenge, some works leverage human judgements, which is difficult to scale up across different domains and tasks (Peris and Casacuberta, 2018; P.V.S and Meyer, 2019). Other works apply a fine-tuned Transformer-based model (Vaswani et al., 2017) to filter out the noisy augmented data, which is likely to overfit on the few-shot training data and thus being less effective in covering different data properties (Mi et al., 2021; Xu et al., 2021; Bakshi et al., 2021; Heidari et al., 2021; Mehta et al., 2022).

In this work, we propose to self-train a pre-trained language model in order to augment more data without additional human annotations. The overall framework is illustrated in Figure 1. We feed unlabeled MRs into the language model to obtain pseudo-labeled responses, and fine-tune the language model using both manual-labeled original training data and pseudo-labeled data generated by the model itself. Previous work (Zhang et al., 2017) shows that self-training with all pseudo-labeled data can result in gradual drift from target data distribution to noisy augmented data distribution. To alleviate this problem, Mukherjee and Awadallah (2020) proposes to select the augmented data that the model is uncertain about. The intuition is that the model is likely to gain little by learning from the data: (1) it always has high confidence on, which is too easy and non-informative; (2) it always has low confidence on, which may be too difficult or noisy.

Inspired by Mukherjee and Awadallah (2020), we develop a self-training framework for the few-shot MR-to-Text generation problem with a novel uncertainty-based data selection strategy. Specifically, we apply the Monte Carlo Dropout method (Gal and Ghahramani, 2016) to estimate the uncertainty of the model on each augmented data.
sample, and select the data which the model is most uncertain about. Table 1 illustrates some examples of the self-augmented data generated under our self-training framework. We describe the model uncertainty using the predictive mean \( \mathbb{E}[p_\theta] \) and predictive variance \( \text{Var}[p_\theta] \): a low \( \mathbb{E}[p_\theta] \) indicates the model finds the augmented data noisy, while a low \( \text{Var}[p_\theta] \) means that the model thinks the augmented data is either too easy or too difficult to learn from. We propose to select the high \( \mathbb{E}[p_\theta] \) and high \( \text{Var}[p_\theta] \) data for further model fine-tuning, which can help the model gain more information about the target data. The advantages of our method are: (1) parameter-efficient, which does not require training additional neural models; (2) computation-efficient, which only needs to apply several stochastic forward pass to get different sets of model parameters.

We conclude the contributions of this work as follows:

1. Propose a novel uncertainty-aware self-training framework for the few-shot MR-to-Text generation problem in task-oriented dialogue systems, which applies efficient data augmentation and effective data selection techniques to alleviate the distribution drift in traditional self-training framework.

2. Show that our method can consistently outperform other few-shot NLG baselines on two benchmark datasets: FewShotWOZ (Peng et al., 2020) and FewShotSGD (Xu et al., 2021).

3. Conduct in-depth empirical analysis on three components that have great impacts on the self-training framework: the initialization of pre-trained language model, the selection of self-augmented data and the model training hyper-parameters.

2 Related Works

Task-oriented Dialogue Generation. Previous NLG methods generate system responses by: (1) designing handcraft response templates and filling in slot-value pairs from system actions, or (2) building data-driven neural models, which encode systems actions into latent feature representations and decode natural language responses with more diversity in realization. However, both approaches cause high data collection cost. The template-based methods (Langkilde and Knight, 1998; Cheyer and Guzzoni, 2006) require collecting a comprehensive set of templates to cover all possible combinations of dialog acts and slot-value pairs, while data-driven methods (Wen et al., 2015, 2017; Zhu et al., 2019) require collecting thousands of system action and response pairs to make the neural model generate fluent responses.

Few-shot NLG. Recent works on few-shot NLG mainly focus on developing or adapting pre-trained language models. Peng et al. (2020) presents the first few-shot NLG benchmark for task-oriented dialog systems, and develops a pre-trained language model which can be fine-tuned with only a few domain-specific labels to adapt to new domains. Chen et al. (2020) applies the switch mechanism to combine the information from both input data and pre-trained language models, which achieves good performance in table-to-text generation tasks. Schick and Schütze (2021) provides pre-trained language models with simple task descriptions to adapt them to new text generation tasks. Chang et al. (2021) studies the training data selection strategies in few-shot NLG, and finds that clustering-based selection strategy consistently helps generative models get better performance than randomly sampling.

Self-training for NLG. While there has been some works applying the self-training method to improve the model’s generalization ability in NLG tasks, they often use a single Transformer-based model to augment and select the data, which may heavily overfit on the few-shot training data in the early iteration. Some works (Mi et al., 2021; Xu et al., 2021) leverage the self-training framework to pseudo-label the unlabeled data and select the training data based on the confidence score from a single student model. Other works (Kedzie and McKeown, 2019; He et al., 2020) show that the noisy self-training is able to utilize unlabeled data and improve the performance of the supervised baseline. However, their observations come from a large-scale training data, which may not necessarily hold in the few-shot data setting. We also find some works (Bakshi et al., 2021; Heidari et al., 2021; Mehta et al., 2022) share very similar self-training framework with this work, where they leverage generation models to produce pseudo-labeled data. However, they use very different data selection strategy, which relies on training addi-
Active Learning for NLG. Another line of works applies the active learning method to build data-efficient models. Peris and Casacuberta (2018); P.V.S and Meyer (2019) design data selection functions to select a subset of representative unlabeled data for human to annotate, and get better model performance by leveraging human annotation. However, the additional requirement of human judgements will increase the difficulty of adapting the method across different domains. Compared with the active learning methods, our self-training framework does not require additional human judgements, which can be easier adapted to different tasks across different domains.

3 Proposed Methods

3.1 Setup

In task-oriented dialogue systems, the NLG module aims at translating a structured dialogue meaning representation \( A \) into a natural language response \( x = \{x_1, ..., x_T\} \). A structured dialogue meaning representation \( A \) consists of a list of dialogue intent \( I_k \) and its corresponding slot-value pairs \( \{(s_{i,k}, v_{i,k})\}_{i=1}^{P_k} \):

\[
A = \{I_k, (s_{1,k}, v_{1,k}), ..., (s_{P_k}, v_{P_k})\}_{k=1}^{K}\tag{1}
\]

where the intent \( I_k \) distinguishes different types of system actions, and the slot-value pairs \( \{(s_{i,k}, v_{i,k})\}_{i=1}^{P_k} \) shows the category names and their content information to be expressed in the response. For example, inform (area = west; choice = many), where inform is the intent, area and choice are the slot names, west and many are the slot values.

We define \( p_\theta(x \mid A) \) as the generation model which generates the response \( x \) in an autoregressive way conditioning on \( A \):

\[
p_\theta(x \mid A) = \prod_{t=1}^{T} p_\theta(x_t \mid x_{1:t-1}, A) \tag{2}
\]

where \( \theta \) is the model parameter. The learning of \( \theta \) is done by maximizing the log-likelihood of the conditional probabilities in Equation 2 over the training set \( D_L \):

\[
\mathcal{L}_\theta(D_L) = \sum_{n=1}^{|D_L|} \sum_{t=1}^{T_n} \log p_\theta(x_{t,n} \mid x_{1:t-1,n}, A_n) \tag{3}
\]

In the few-shot MR-to-Text generation setting, the size of training data \( |D_L| \) is a very small number (e.g. \( \leq 50 \)).

3.2 Self-training Framework

To augment the training data with no additional human annotation cost, we leverage the pre-trained language model to automatically generate pseudo responses conditioning on the unlabeled MRs. Our overall self-training framework is demonstrated in Figure 1 and the detailed procedure is shown in Algorithm 1.

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**Algorithm 1: Self-training for MR-to-Text Generation**

**Input:** Labeled MR-to-Text pairs \( D_L \), unlabeled in-domain MRs \( D_U \), generation model \( p_\theta \), number of self-training iterations \( S \)

**Output:** A fine-tuned generation model \( p_\theta \)

1: Initialize \( p_\theta \) and train \( p_\theta \) on \( D_L \)
2: for \( s = 1, \ldots, S \) do
3: Initialize \( D_A = \emptyset \) and \( D_L' = \emptyset \)
4: // Data Augmentation
5: for \( A'_n \in D_U \) do
6: Generate response \( x'_n \sim p_\theta(x'_n \mid A'_n) \)
7: \( D_A \cup \{(x'_n, A'_n)\} \)
8: end for
9: // Data Selection
10: for \( (x_n, A_n) \in D_L \cup D_A \) do
11: Compute \( \mathbb{E}[p_\theta] \) using Eq. (7)
12: Compute \( \mathbb{V}[p_\theta] \) using Eq. (8)
13: end for
14: Compute \( \bar{\mu} \) and \( \bar{s} \) using Eq. (9)
15: for \( (x'_n, A'_n) \in D_A \) do
16: if \( \mathbb{E}[p_\theta] > \bar{\mu} \) and \( \mathbb{V}[p_\theta] > \bar{s} \) then
17: Compute \( \bar{x}'_n \) using Eq.(4),(5),(2)
18: \( D_L' \cup \{(\bar{x}'_n, A'_n)\} \)
19: end if
20: end for
21: Fine-tune \( p_\theta \) on \( D_L \cup D_L' \)
22: end for
We first initialize a pre-trained language model SC-GPT (Peng et al., 2020) as the generation model \( p_0 \), which achieves good performance on the MR-to-Text generation task in task-oriented dialog systems. We directly train the generation model \( p_0 \) on the original labeled training set \( D_L \) for a few epochs in order to adapt it to the target domain. Then, we sample massive unlabeled MRs \( D_U \) from the target domain, and feed them into the generation model \( p_0 \) to obtain the pseudo responses and construct the self-augmented MR-to-Text pairs \( D_A \).

To avoid the gradual drift from target data distribution to noisy self-augmented data distribution, we apply the Monte Carlo Dropout method (Gal and Ghahramani, 2016) to obtain a set of \( \{ p_\theta \}_{i=1}^M \) by randomly dropping out some model parameters of \( p_0 \), then we select the self-augmented MR-to-Text pairs based on their predictive mean and predictive variance of the set of \( \{ p_\theta \}_{i=1}^M \). Specifically, we select the data with high predictive mean and predictive variance, which the generation models \( \{ p_\theta \}_{i=1}^M \) does not always have high confidence on. We define the selected data as high-uncertainty data \( D_{L'} \), and further fine-tune the generation model \( p_0 \) on the original labeled data \( D_L \) and the high-uncertainty data \( D_{L'} \). We repeat the model fine-tuning, data augmentation and data selection process iteratively until reaching the maximum self-training iterations. Intuitively, fine-tuning the generation model \( p_0 \) on the self-augmented data can be viewed as training the model with a stochastic regularization on the model parameters, which can alleviate overfitting and improve model’s generalizability on the unseen test set.

3.3 Data Augmentation

**Before Selection.** We collect as many as possible unlabeled MRs from the target domain, and feed them into the generation model \( p_0 \) to get the pseudo responses. We use nucleus sampling (Holtzman et al., 2020) to sample the output token \( x'_t \) from the probability distribution \( p_0(x'_t \mid x'_{1:t-1}, A') \). Upon completing the response \( x' \), we add the pseudo-labeled MR-to-Text pair \( (x', A') \) into the augmented dataset \( D_A \).

**After Selection.** To further alleviate the “noise” in the selected uncertain data, we leverage the model ensemble method to smooth out the final model output logits. Specifically, we take an average pooling on the output logits of a set of models. The set of models \( \{ g_i \}_{i=1}^O \) are obtained via randomly dropping out some model parameters during inference. For each generation model \( g_i \), given an unlabeled \( A' \) sampled from \( D_A \), we compute its output logit at the decoding timestamp \( t \):

\[
    h^i_t = g_i(h_{1:t-1}, A')
\]

where \( h^i_t \in \mathbb{R}^{d \times V} \), \( d \) is the latent model dimension and \( V \) is the vocabulary size. Then, we apply an average pooling over the set of output logits on each latent model dimension:

\[
    \bar{h}_t = \frac{1}{O} \sum_{i=1}^O h^i_t
\]

where \( \bar{h}_t \in \mathbb{R}^{d \times V} \), and \( O \) is a hyper-parameter that specifies the number of sampled models during inference. We pass the final output logits \( \bar{h}_t \) into a softmax function to obtain the final probability distribution of the generation model same as Equation 2.

3.4 Data Selection

As discussed in section 1, the model is likely to learn little from the too easy or too difficult data. Therefore, we select the self-augmented data that the model is most uncertain about. Inspired by the previous work (Mukherjee and Awadallah, 2020), we use the Monte Carlo Dropout method (Gal and Ghahramani, 2016) to estimate the predictive uncertainty of each observed data pair. We enable dropouts before every hidden layer in the generation model, and perform several stochastic forward passes through the model for each MR-to-Text pair.

**Uncertainty Estimation.** For each self-augmented data pair \( (x', A') \), we apply \( M \) stochastic forward passes through the model, and get i.i.d. outputs \( \{ p_\theta(x' \mid A') \}_{i=1}^M \) using Equation 2, which are empirical samples from an approximated posterior distribution (Gal, 2016):

\[
    p(x \mid A) \approx \int p_\theta(x \mid A) q(\theta) d\theta \approx \frac{1}{M} \sum_{i=1}^M p_\theta(x' \mid A')
\]

where \( q(\theta) \) is the Dropout distribution (Srivastava et al., 2014), and \( M \) is a hyper-parameter that specifies the number of sampled models during data selection. Then, we estimate the predictive mean
We sort the data according to its predictive mean \( \theta \).

A high predictive mean \( \mu \) is the total number of remaining datapoints (i.e. non-outliers) used to estimate the Gaussian distribution.

For each self-augmented data pair \( (x', A') \), we identify it as the \textit{uncertain} data if it has high \( \mathbb{E}[\theta] \) (i.e. above the average predictive mean \( \mu \)) and high \( \text{Var}[\theta] \) (i.e. above the average predictive variance \( \bar{s} \)). The high \( \mathbb{E}[\theta] \) means this data pair is less likely containing “noisy” tokens that are rarely observed in the training set. The high \( \text{Var}[\theta] \) means this data pair sometimes makes the model confused, and further learning from this data pair may help the model gain additional information about the target data distribution. We also explored other data selection strategy, e.g. selecting high \( \mathbb{E}[\theta] \) and low \( \text{Var}[\theta] \) data pairs, selecting low \( \mathbb{E}[\theta] \) and high \( \text{Var}[\theta] \) data pairs, etc. Empirically, we find selecting high \( \mathbb{E}[\theta] \) and high \( \text{Var}[\theta] \) data pairs generally brings more performance improvements than other strategies.

### 4 Experiments

#### 4.1 Setups

**Benchmark Datasets.** We evaluate our method on two few-shot MR-to-Text generation benchmark datasets: \textsc{FewShotWOZ} (Peng et al., 2020) and \textsc{FewShotSGD} (Xu et al., 2021). \textsc{FewShotWOZ} has 7 domains and an average number of 50 training examples and 473 test examples per domain. \textsc{FewShotSGD} has 16 domains and an average number of 35 training examples and 5,618 test examples per domain. The detailed data statistics of each domain are demonstrated in Table 2 and Table 3.

| Restaurant | Laptop | Hotel | TV | Attraction | Train | Taxi |
|------------|--------|-------|----|------------|-------|------|
| # Training Pairs | 51 | 51 | 51 | 51 | 50 | 50 | 40 |
| # Test Pairs | 129 | 1,379 | 78 | 680 | 340 | 657 | 47 |
| # Augmented Pairs | 10,000 | 10,000 | 10,000 | 10,000 | 7,035 | 10,000 | 6,527 |

| Homes | Media | Movies | Music | Rentalcars | Ridesharing | Services | Travel |
|-------|-------|--------|-------|------------|-------------|----------|--------|
| # Training Pairs | 21 | 14 | 30 | 21 | 50 | 48 | 50 | 14 |
| # Test Pairs | 5,636 | 5,689 | 7,371 | 7,326 | 2,879 | 8,197 | 7,939 | 5,281 |
| # Augmented Pairs | 5,657 | 5,703 | 7,604 | 7,347 | 50 | 48 | 14 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 |

Table 2: Data statistics for the manual-labeled data \( D_L \) and the pseudo-labeled data \( D_A \) on \textsc{FewShotWOZ}.

| Restaurant | Laptop | Hotel | TV | Attraction | Train | Taxi |
|------------|--------|-------|----|------------|-------|------|
| # Training Pairs | 50 | 50 | 50 | 25 | 23 | 11 | 50 | 50 |
| # Test Pairs | 9,618 | 4,016 | 2,725 | 5,326 | 3,320 | 1,935 | 4,272 | 8,312 |
| # Augmented Pairs | 10,000 | 10,000 | 10,000 | 7,035 | 50 | 48 | 14 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 |

| Homes | Media | Movies | Music | Rentalcars | Ridesharing | Services | Travel |
|-------|-------|--------|-------|------------|-------------|----------|--------|
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| # Augmented Pairs | 5,657 | 5,703 | 7,604 | 7,347 | 50 | 48 | 14 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 |

Table 3: Data statistics for the manual-labeled data \( D_L \) and the pseudo-labeled data \( D_A \) on \textsc{FewShotSGD}.

We evaluate our method on two few-shot MR-to-Text generation benchmark datasets: \textsc{FewShotWOZ} (Peng et al., 2020) and \textsc{FewShotSGD} (Xu et al., 2021). \textsc{FewShotWOZ} has 7 domains and an average number of 50 training examples and 473 test examples per domain. \textsc{FewShotSGD} has 16 domains and an average number of 35 training examples and 5,618 test examples per domain. The detailed data statistics of each domain are demonstrated in Table 2 and Table 3.

Table 2: Data statistics for the manual-labeled data \( D_L \) and the pseudo-labeled data \( D_A \) on \textsc{FewShotWOZ}.

Table 3: Data statistics for the manual-labeled data \( D_L \) and the pseudo-labeled data \( D_A \) on \textsc{FewShotSGD}.

\[ \mathbb{E}[\theta] \approx \frac{1}{M} \sum_{i=1}^{M} p_i(x' \mid A') \]  

\[ \text{Var}[\theta] \approx \frac{1}{M} \sum_{i=1}^{M} (p_i(x' \mid A') - \mathbb{E}[\theta])^2 \]

A high predictive mean \( \mathbb{E}[\theta] \) indicates on average the sampled models are confident on predicting the current \( (x', A') \), while a high predictive variance \( \text{Var}[\theta] \) means not all sampled models are confident on predicting the current \( (x', A') \). We compute \( \mathbb{E}[\theta] \) and \( \text{Var}[\theta] \) of each MR-to-Text pair in both manual-labeled \( D_L \) and pseudo-labeled \( D_A \).

**Selection Strategy.** We calculate the corpus-level predictive mean \( \bar{\mu} \) and predictive variance \( \bar{s} \) in both manual-labeled \( D_L \) and pseudo-labeled \( D_A \) as the threshold for selecting the \textit{uncertain} data. We sort the data according to its predictive mean \( \mathbb{E}[\theta] \) and predictive variance \( \text{Var}[\theta] \) in an ascending order respectively, and remove the outliers (i.e. first and last 1% of datapoints). We assume the predictive mean scores and predictive variance scores follow different Gaussian distributions, and estimate the mean of the Gaussian as:

\[ \bar{\mu} = \frac{1}{N} \sum_{n=1}^{N} p_n, \quad \bar{s} = \frac{1}{N} \sum_{n=1}^{N} v_n \]

where \( p_n \) is the predictive mean \( \mathbb{E}[\theta] \) and \( v_n \) is the predictive variance \( \text{Var}[\theta] \) of the \( n \)-th datapoint, \( N \) is the total number of remaining datapoints (i.e. non-outliers) used to estimate the Gaussian distribution.

For each self-augmented data pair \( (x', A') \), we identify it as the \textit{uncertain} data if it has high \( \mathbb{E}[\theta] \) (i.e. above the average predictive mean \( \bar{\mu} \)) and high \( \text{Var}[\theta] \) (i.e. above the average predictive variance \( \bar{s} \)). The high \( \mathbb{E}[\theta] \) means this data pair is less likely containing “noisy” tokens that are rarely observed in the training set. The high \( \text{Var}[\theta] \) means this data pair sometimes makes the model confused, and further learning from this data pair may help the model gain additional information about the target data distribution. We also explored other data selection strategy, e.g. selecting high \( \mathbb{E}[\theta] \) and low \( \text{Var}[\theta] \) data pairs, selecting low \( \mathbb{E}[\theta] \) and high \( \text{Var}[\theta] \) data pairs, etc. Empirically, we find selecting high \( \mathbb{E}[\theta] \) and high \( \text{Var}[\theta] \) data pairs generally brings more performance improvements than other strategies.

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Table 3: Data statistics for the manual-labeled data \( D_L \) and the pseudo-labeled data \( D_A \) on \textsc{FewShotSGD}.

\[ \mathbb{E}[\theta] \approx \frac{1}{M} \sum_{i=1}^{M} p_i(x' \mid A') \]  

\[ \text{Var}[\theta] \approx \frac{1}{M} \sum_{i=1}^{M} (p_i(x' \mid A') - \mathbb{E}[\theta])^2 \]
Table 4: Evaluation results on FEWSHOTWOZ (BLEU↑, ERR↓). The results of SC-GPT and AUG-NLG come from Xu et al. (2021), the results of Direct-FT, ST-ALL and ST-Uncertain come from our implementation.

Table 5: Evaluation results of BLEU scores on FEWSHOTSGD. The results of GPT2 and AUG-NLG come from Xu et al. (2021), the results of Direct-FT, ST-ALL and ST-Uncertain come from our implementation.

Unlabeled MRs. The above two benchmark datasets are sampled and constructed based on the three datasets: RNNLG (Wen et al., 2016), MultiWOZ (Budzianowski et al., 2018) and SGD (Rastogi et al., 2020b). In order to ensure the augmented MRs are within the target domain, we collect all unlabeled MRs from the training set of RNNLG, MultiWOZ and SGD. For FEWSHOTWOZ, we collect an average number of 9,080 unlabeled MRs per domain. For FEWSHOTSGD, we collect an average number of 7,532 unlabeled MRs per domain. The detailed data statistics of each domain are demonstrated in Table 2 and Table 3.

Evaluation Methods. Following the prior works (Wen et al., 2015; Peng et al., 2020; Xu et al., 2021), we use BLEU score and Slot Error Rate (ERR) for automatic evaluation. BLEU score measures the n-gram overlap between generated responses and ground-truth references. ERR is computed by exact matching the slot tokens in the generated responses as \( ERR = (p+q)/N \), where \( N \) is the total number of slots in the MR, and \( p, q \) is the number of missing and redundant slots in the generated response. For each MR, we generate five responses and select the top one with the lowest ERR as the final output.

Baselines. We compare our method with four baselines. (1) SC-GPT (Peng et al., 2020) is the state-of-the-art pre-trained language model for NLG in task-oriented dialogue systems, which is further fine-tuned on the target domain data; (2) AUG-NLG (Xu et al., 2021) leverages the pre-trained SC-GPT model, first trains it on its automatically augmented data, then fine-tunes it on the target domain data; (3) Direct-FT is our replication of SC-GPT, where we leverage the pre-trained SC-GPT model and directly fine-tune it on the target domain data; (4) ST-ALL is the traditional self-training framework which learns from all self-augmented data without any data selection; (5) ST-Uncertain is our method, in addition to our proposed data selection strategy, we apply a rule-based parser (Kedzie and McKeown, 2019) to filter out invalid responses that do not match the slot-value pairs in the input MRs on the FEWSHOTWOZ dataset in order to achieve lower ERR.

Implementation Details. For all self-training methods, we start with the model checkpoint from the Direct-FT baseline. For the learning rate, we use the linear rate scheduler with start rate ranging from 1e-6 to 2e-5 across different domains. In each

| Restaurant | Laptop | Hotel | TV | Attraction | Train | Taxi |
|------------|--------|-------|----|------------|-------|------|
| BLEU | ERR | BLEU | ERR | BLEU | ERR | BLEU | ERR | BLEU | ERR |
| SC-GPT | 30.48 | 6.89 | 33.51 | 5.38 | 38.30 | 8.24 | 33.82 | 7.32 | 17.06 | 8.82 |
| AUG-NLG | 34.20 | 2.99 | 34.32 | 2.83 | 34.96 | 6.59 | 34.99 | 5.53 | 22.50 | 10.40 |
| Direct-FT | 35.11 | 1.80 | 34.55 | 6.40 | 37.65 | 0.55 | 36.63 | 4.27 | 23.18 | 1.82 |
| ST-ALL | 34.24 | 3.29 | 34.64 | 10.60 | 37.47 | 11.54 | 36.22 | 8.26 | 24.24 | 4.66 |
| ST-Uncertain | 36.12 | 1.19 | 35.33 | 5.90 | 37.47 | 11.54 | 38.07 | 3.78 | 25.35 | 1.51 |

| Restaurant | Hotels | Flights | Calendar | Banks | Weather | Buses | Events |
|------------|--------|---------|----------|-------|---------|-------|--------|
| BLEU | ERR | BLEU | ERR | BLEU | ERR | BLEU | ERR | BLEU | ERR |
| GPT2 | 8.98 | 8.84 | 12.18 | 5.27 | 6.09 | 10.52 | 7.77 | 9.17 |
| AUG-NLG | 17.83 | 17.23 | 17.58 | 10.45 | 8.94 | 13.57 | 14.26 | 18.68 |
| Direct-FT | 25.35 | 22.02 | 26.75 | 24.45 | 25.47 | 26.03 | 20.86 | 26.30 |
| ST-ALL | 24.49 | 22.20 | 27.43 | 25.89 | 25.56 | 31.62 | 16.53 | 24.70 |
| ST-Uncertain | 24.43 | 22.17 | 26.43 | 23.37 | 26.47 | 25.11 | 21.11 | 25.14 |

| Homes | Media | Movies | Music | Rentalcars | Ridesharing | Services | Travel |
|-------|-------|--------|-------|------------|-------------|----------|--------|
| BLEU | ERR | BLEU | ERR | BLEU | ERR | BLEU | ERR | BLEU | ERR |
| GPT2 | 3.75 | 3.17 | 10.05 | 5.79 | 6.79 | 13.87 | 9.79 | 2.08 |
| AUG-NLG | 12.27 | 8.62 | 11.96 | 12.76 | 13.32 | 15.54 | 16.82 | 14.35 |
| Direct-FT | 24.53 | 26.55 | 26.39 | 23.45 | 20.08 | 21.28 | 27.78 | 25.18 |
| ST-ALL | 24.45 | 27.47 | 26.98 | 23.44 | 19.96 | 21.30 | 27.76 | 25.47 |
| ST-Uncertain | 25.05 | 26.15 | 27.63 | 27.96 | 20.75 | 22.65 | 28.19 | 25.62 |
self-training iteration, the training epochs range from 5 to 20 across different domains, and the batch size is set to 4 across all domains. We use the AdamW optimizer (Loshchilov and Hutter, 2019) with default weight decay to update the parameters. The model is trained on an NVIDIA GeForce GTX 1080 Ti GPU server with 12GB memory until reaching the maximum self-training iteration, which is set to 5 across all domains. For generation, we use nucleus sampling with \( p = 0.9 \) across all experiments. For evaluation, we save all model checkpoints at each self-training iteration, and report the best-performed model among all iterations (not necessarily the last iteration).

4.2 Result Analysis

**FEWSHOTWOZ** Table 4 shows the automatic evaluation results on FEWSHOTWOZ. Our ST-Uncertain outperforms other baselines across all domains in both BLEU and ERR. In addition, we find that ST-ALL generally performs worse than Direct-FT, which reveals the distribution drift problem in traditional self-training framework. If the model learns from all pseudo-labeled data, it will gradually drift from target data distribution to noisy augmented data distribution.

**FEWSHOTSGD** Table 5 illustrates the automatic evaluation results on FEWSHOTSGD. Note that GPT2 and AUG-NLG are using GPT-2 (Radford et al., 2019) as the base model, while our Direct-FT, ST-ALL and ST-Uncertain are using SC-GPT as the base model. The big performance gap between the prior work and our implementation shows that the pre-trained language model has a great impact on the model performances in the few-shot data setting. Besides, our ST-Uncertain outperforms other baselines in 10 out of 16 domains, which demonstrates the effectiveness of our data selection strategy. However, we find that ST-ALL has better performance than ST-Uncertain in some domains (e.g., weather, media, etc.) where the number of training pairs is smaller than 15. In this case, the model may have not learned well on the target domain data yet, therefore, learning from all pseudo-labeled data can help it better generalize to the unseen test set.

4.3 Ablation Study

To validate the effectiveness of our proposed method, we further conduct ablation study on our ST-Uncertain by removing the predictive variance \( \text{Var}[p_0] \) and the rule-based filter. Table 6 represents the automatic evaluation results on FEWSHOTWOZ. We observe that removing the predictive variance \( \text{Var}[p_0] \) during data selection will lead to degraded performances in both BLEU and ERR across all domains, which emphasizes the importance of sampling different model parameters in order to better estimate the model uncertainty. Additionally, we find that removing the rule-based filter will lead to worse performances in ERR across all domains, which reveals that the model is likely to generate incorrect pseudo responses, and those incorrect self-augmented data will cause the model to learn irrelevant patterns and perform worse on the unseen test set.

4.4 Other Important Components in Self-training NLG Framework

In our preliminary experiments, we explore different data selection strategies and model training hyper-parameters, and we find they also have big impacts on the model performances. Therefore, we provide our empirical results and analysis on these key components in the self-training framework to gain more insights.

**Data Selection Strategies.** Table 7 reports the automatic evaluation results of different data selection strategies under our ST-Uncertain framework in the restaurant domain of FEWSHOTWOZ dataset. First, we find that selecting low \( E[p_0] \) data does not help the model achieve higher BLEU or lower ERR. This is probably because low \( E[p_0] \) data includes some “rare” tokens that seldom appear in the training set, which are very likely to be out-of-domain data. Second, we observe that selecting high \( E[p_0] \) and low \( \text{Var}[p_0] \) data also does not bring much performance improvement for the model. The reason for this phenomena is that the model already learns well from high \( E[p_0] \) and low \( \text{Var}[p_0] \) data since different model parameters consistently assign a high likelihood for this data. Therefore, additional learning from these data will not bring more improvement for the model performances.

**Model Training Hyper-parameters.** Table 8 reports the automatic evaluation results of different model training hyper-parameters under our ST-Uncertain framework in the attraction domain of FEWSHOTWOZ dataset. Generally, we observe that the learning rate has a big impact on the model performances. Smaller learning rate can give lower
### Ablation Study Results on FEWSHOTWOZ (BLEU↑, ERR↓).

| ST-Uncertain | Laptop | Hotel | TV | Attraction | Train | Taxi |
|--------------|--------|-------|----|-----------|-------|------|
| RESTAURANT   | BLEU   | ERR   | BLEU | ERR       | BLEU  | ERR  |
| 36.12        | 1.19   | 35.33 | 5.90 | 38.07     | 0.00  | 38.70| 3.78 |
| 36.65        | 0.00   | 37.07 | 6.59 | 38.37     | 4.39  | 25.35| 0.79 |

| w/o Var(\[p\]) | Laptop | Hotel | TV | Attraction | Train | Taxi |
|----------------|--------|-------|----|-----------|-------|------|
| 32.76          | 2.69   | 34.81 | 10.34 | 37.07     | 6.59  | 25.17| 4.78 |
| 36.65          | 0.00   | 37.07 | 6.59 | 38.37     | 4.39  | 25.17| 4.78 |

| w/o filter     | Laptop | Hotel | TV | Attraction | Train | Taxi |
|----------------|--------|-------|----|-----------|-------|------|
| 35.70          | 1.80   | 35.53 | 11.48 | 38.04     | 4.39  | 24.11| 2.38 |
| 35.53          | 1.80   | 35.53 | 11.48 | 38.04     | 4.39  | 24.11| 2.38 |

Table 6: Ablation study results on FEWSHOTWOZ (BLEU↑, ERR↓).

| E[\[p\]] | Var(\[p\]) | BLEU↑ | ERR↓ |
|-----------|-------------|-------|------|
| 1         | low         | 31.51 | 2.99 |
| 2         | low         | 32.79 | 3.89 |
| 3         | high        | 33.11 | 2.69 |
| 4         | high        | 36.12 | 1.19 |

Table 7: Different data selection strategy comparison in the restaurant domain of FEWSHOTWOZ.

| Epoch | LR   | BLEU↑ | ERR↓ |
|-------|------|-------|------|
| 1     | 10   | 24.21 | 1.82 |
| 2     | 1e-6 | 23.90 | 2.16 |
| 3     | 10   | 24.28 | 1.25 |
| 4     | 10   | 23.46 | 1.25 |
| 5     | 20   | 25.35 | 0.79 |

Table 8: Different model training hyper-parameters comparison in the attraction domain of FEWSHOTWOZ, where Epoch is the number of training epochs within a self-training iteration, and LR is the initial learning rate at the beginning of each training epoch.

ERR score, but may not bring higher BLEU score if the training epoch is not enough. Larger learning rate can make the model get better BLEU score in a few training epochs, but may cause high ERR score. Finally, we think a good combination of learning rate and training epoch can help the model achieves the best performance under the self-training framework, but the specific values vary across different domains.

### 5 Conclusion

In this work, we propose a new data augmentation and selection approach under the self-training framework to deal with the few-shot MR-to-Text generation problem in task-oriented dialogue systems. To alleviate the gradual drift from target data distribution to noisy augmented data distribution in self-training, we propose to select the augmented data based on the model’s predictive uncertainty. To smooth out the noise in the self-augmented data, we take an average on the output logits of an ensemble of models during inference. Empirical experimental results show that our method outperforms other baselines on two benchmark datasets, which highlights the importance of model uncertainty as a single generation model easily overfits on the few-shot training data. In conclusion, this work proposes a simple yet effective approach to select self-augmented data for training the NLG module in the few-shot data setting. However, our method only focuses on single-turn dialogue generation, and the problems may become more complicated in multi-turn dialogue generation, which we are going to investigate in the future research.

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