Simple Data Augmentation with the MASK Token Improves Domain Adaptation for Dialog Act Tagging

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Abstract

The concept of Dialogue Act (DA) is universal across different task-oriented dialogue domains - the act of “request” carries the same speaker intention whether it is for restaurant reservation or flight booking. However, DA taggers trained on one domain do not generalize well to other domains, which leaves us with the expensive need for a large amount of annotated data in the target domain. In this work, we investigate how to better adapt DA taggers to desired target domains with only unlabeled data. We propose MASKAUGMENT, a controllable mechanism that augments text input by leveraging the pre-trained MASK token from BERT model. Inspired by consistency regularization, we use MASKAUGMENT to introduce an unsupervised teacher-student learning scheme to examine the domain adaptation of DA taggers. Our extensive experiments on the Simulated Dialogue (GSim) and Schema-Guided Dialogue (SGD) datasets show that MASKAUGMENT is useful in improving the cross-domain generalization for DA tagging.

1 Introduction

Dialog act (DA) tagging, one of the important NLU components of modern task-oriented dialog systems, aims to capture the speaker’s intention behind the utterances at each dialog turn. Several different schema and taxonomies have been introduced by several different researchers (Core and Allen, 1997; Stolcke et al., 2000; Bunt et al., 2010; Mezza et al., 2018) over the years. However, the main focus of the recent work (Kumar et al., 2018; Chen et al., 2018; Raheja and Tetreault, 2019) on DA tagging was on human-human social conversations (Godfrey et al., 1992; Jurafsky et al., 1997), which is less applicable for task-oriented setting.

Recently, several task-oriented dialogue datasets (Shah et al., 2018; Henderson et al., 2014; Budzianowski et al., 2018) have been released. However, the discrepancy in their annotation schema hinders the progress on building DA taggers that can generalize across domains and possibly datasets. To address this issue, Paul et al. (2019) propose a universal schema for DAs by aligning annotations for multiple existing corpora. In this regard, another useful corpora employed as a testbed in this work is Schema-guided dialogues (SGD) (Rastogi et al., 2020), which covers 20 domains under the same DA annotation schema.

It is often challenging and costly to obtain a large amount of in-domain dialogues with annotations. However, unlabeled dialogue corpora in target domain can easily be curated from past conversation logs or collected via crowd-sourcing (Byrne et al., 2019; Budzianowski et al., 2018) at a more reasonable cost. The goal of this work is to investigate how to leverage pre-trained masked language models (e.g., BERT) to better adapt DA taggers to unseen domains with available unlabeled dialogues. Pre-trained language models (Devlin et al., 2019; Liu et al., 2019) have been successful for several NLP tasks including dialogue systems (Wolf et al., 2019).
We formulate this objective simply as a classification problem with binary labels. Let $D_k \subseteq D$ be the predefined set of $m$ different DAs in the schema. The objective of dialogue act tagging is to determine a subset of DAs $A_k$ of DAs that apply to the current turn $T_k$ given the conversation history $D_{k:} = [T_1, T_2, \ldots , T_k]$ so far. We formulate this objective simply as a classification problem with binary labels $y_j \in \{0, 1\}$ for each act $a_j$ where $y_j = 1$ if $a_j \in A_k$ and $y_j = 0$ otherwise. As defined above, dialogue act tagging is a turn-level classification problem, hence every turn $T_k$ constitutes: (i) a labeled example $(D_k, A_k)$ if we have a set $A_k$ of DA annotations, or (ii) an unlabeled example $(D_k, \cdot)$ otherwise.

2.2 Model

Given a conversation history $D_k$ as input, we first convert it into a sequence of words by concatenating user and system utterances. Before concatenating each utterance, we prepend it with corresponding speaker tag using [SYS] and [USR] special tokens indicating system and user sides, respectively. Finally, the whole flattened sequence is finalized by prepending it with [CLS] special token to obtain the final dialogue history representation:

$$x = [CLS][USR] T_1 [SYS] T_{i+1} \ldots$$ (1)

The segment ids are set to 0 and 1 for the tokens of past turns and the current turn, respectively.

For DA tagging task, dialogue history $x$ is used as input to pre-trained language model $M$, and the model computes a probability vector $p_\theta (\cdot|x) = \sigma(WM(x) + b)$ where $M(x) \in \mathbb{R}^d$ is the output contextualized embedding corresponding to CLS token, $W \in \mathbb{R}^{m \times d}$ and $b \in \mathbb{R}^m$ are trainable weights of a linear projection layer, $\sigma$ is the sigmoid function, $\theta$ denotes the entire set of trainable parameters of model $M$ along with $(W, b)$, and finally $p_\theta (a_j|x)$ indicates the probability of tag $a_j$ being triggered. The following objective is used to train the model parameters.

Supervised tagging loss (STL). This objective is used to update the DA tagger via the supervision coming from labeled source data $S$. We use binary cross-entropy loss $J_{STL}(\theta; x, y)$ defined as:

$$- [y \cdot \log p_\theta (\cdot|x) + (1 - y) \cdot \log(1 - p_\theta (\cdot|x))]$$ (2)

2.3 Learning with MASKAUGMENT

Semi-supervised learning (SSL) (Berthelot et al., 2019, 2020; Sohn et al., 2020; Li et al., 2020) is
an effective approach for improving deep learning models by leveraging in-domain unlabeled data. Unlike traditional SSL setting, our objective is to primarily address the underlying source-to-target domain shift. In prior work (Xie et al., 2019; Wei and Zou, 2019), unsupervised data augmentation methods including word replacement and back-translation have been shown useful for short written text classification. However, such augmentation methods are shown to be less effective (Shleifer, 2019) when used with pre-trained models. Besides, back-translation is less applicable in our scenario as translation of multi-turn dialogue itself is a rather challenging task compared to short text.

Instead, we propose a simple and controllable data augmentation—MASKAUGMENT—to explore a new unsupervised teacher-student learning scheme for domain adaptation of DA taggers. MASKAUGMENT augments the original text input by randomly replacing its tokens with Mask token at a specified probability. We follow the masking policy in (Devlin et al., 2019). Formally, let $z(x|x, \epsilon)$ denote the MASKAUGMENT as a stochastic transformation with $\epsilon$-probability for input $x$. Below we define three fine-tuning objectives leveraging MASKAUGMENT that are used in addition to $J_{STL}$.

**Masked tagging loss (MTL).** We incorporate MASKAUGMENT into the STL objective by perturbing its input sequence $x$ as follows:

$$J_{MTL}(\theta; x, y, \epsilon) = \mathbb{E}_{\bar{x} \sim z(x|x, \epsilon)} [J_{STL}(\theta; \bar{x}, y)].$$

**Masked LM loss (MLM).** This is the original objective that BERT is pre-trained with. The objective of MLM training is to correctly reconstruct a probability. We follow the masking policy in (De-

**Teacher-Student Learning with Disagreement Loss (DAL).** We adopt consistency regularization (Sajjad et al., 2016; Laine and Aila, 2017) widely used in traditional SSL (Berthelot et al., 2019; Sohn et al., 2020; Li et al., 2020) and define disagreement loss, which employs MASKAUGMENT in a novel way to give rise to an unsupervised teacher-student training. The core idea is to contrast the amount of controllable perturbations to learn more generalizable representations. We propose a stochastic imputation-based teacher and student selection by leveraging MASKAUGMENT. As in Figure 2, we sample two augmentations $\bar{x}^{(t)} \sim z(\bar{x}|x, \epsilon_t)$ and $\bar{x}^{(s)} \sim z(\bar{x}|x, \epsilon_s)$ for teacher and student, respectively. We take $\epsilon_t < \epsilon_s$ to ensure that the teacher augmentation $\bar{x}^{(t)}$ retains more of the original content $x$ than the student augmentation $\bar{x}^{(s)}$, hence is more reliable. The disagreement loss $J_{DAL}(\theta; x, \epsilon_t, \epsilon_s)$ is then computed as the binary cross-entropy loss between the teacher $p_{\theta}(\cdot | \bar{x}^{(t)})$ and the student $p_{\theta}(\cdot | \bar{x}^{(s)})$ distributions as in Eq. 2, treating teacher as the soft target ($y$).

### 3 Experiments

#### 3.1 Datasets

**GSIM** (Shah et al., 2018) consists of machine-machine task-oriented dialogues in two tasks of two different domains: buying a movie ticket (GMov) and reserving a restaurant table (GRes). It contains 1500/469/1117 dialogues for the train/dev/test sets. Following (Paul et al., 2019), its dialogue acts are mapped to 13 tags in universal schema.

**SGD** (Rastogi et al., 2020) consists of 22,825 schema-guided single/multi-domain dialogues where domains can have multiple schemas, each defined by a set of tracking slots. We use single-domain dialogues of smaller sizes including music (SMusic), media (SMedia), ride-sharing (SRide) as source domains to study generalization on flights (SFlights), the largest one, as the target domain.

#### 3.2 Training and Implementation Details

The final loss function is the sum of the active ones among $J_{STL}$, $J_{MTL}$, $J_{DAL}$, $J_{MLM}$ except $J_{MLM}$ is multiplied with 0.1 when active. DAL is activated after 1 epoch of training with the remaining objectives. We perform a tuning of $\epsilon_t \in [0, 0.1]$ and $\epsilon_s \in [0.1, 0.5]$ for DAL objective. We optimize the loss using AdamW (Loshchilov and Hutter, 2017). The learning rate is tuned on $[10^{-5}, 5 \times 10^{-5}]$ with no warm-up steps. We use a batch of 16 examples with maximum sequence length of 128, which covers around 9.9, 10.3, 9.9 turns on average for train, dev, test splits, respectively. We use transformers library\(^1\) for our implementation.

#### 3.3 Results and Discussion

We begin our discussion with our main findings on domain adaptation as presented in Table 1. We explore the effect of incorporating our proposed MTL and DAL objectives on top of STL (baseline) for both Transformer (Vaswani et al., 2017) and BERT (Devlin et al., 2019) models. Transformer baseline model on DA tagging with STL

\(^1\)https://github.com/huggingface/transformers

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Table 1: Micro-F1 scores on the test set of source and target domains with combinations of STL, MTL, and DAL objectives. scratch-BERT is initialized from original bert-base-uncased. Transformer is a randomly initialized version of scratch-BERT.

| Model | Dev | Test |
|-------|-----|------|
| STL   | 87.9| 91.9 |
| STL + MLM | 91.0| 93.2 |
| STL + MTL + DAL | 92.8| 94.0 |
| STL + MTL + DAL + MLM | 94.1| 94.4 |

Table 2: Micro-F1 scores on target (GRes) domain for pre-BERT (obtained by domain-adaptive pre-training) in comparison with scratch-BERT (initialized from BERT) across different fine-tuning objectives. We also highlight the effect of MLM when used as a fine-tuning objective on unlabeled target domain examples in the second and fourth rows.

| Model | Precision | Recall |
|-------|-----------|--------|
| STL   | 87.8      | 89.6   |
| STL + MTL + DAL | 91.0| 95.3   |
| pre-BERT | 91.8      | 92.1   |
| pre-BERT | 93.1      | 95.6   |

Table 3: Precision and recall scores on target (GRes) domain for pre-BERT and scratch-BERT including dev set results.

| Model | #Dials: 10 | #Dials: 20 | #Dials: 50 |
|-------|------------|------------|------------|
| scratch-BERT | 53.3 | 65.5 | 73.6 |
| pre-BERT | 59.8 | 73.9 | 82.9 |

Table 4: F1 scores on target domain (GRes) under the low-resource setting. #Dials denote the number of labeled dialogues (randomly sampled) used in the source domain (GMov). We report the average of 3 runs with different samples.

Domain-adaptive pre-training (pre-BERT). As shown useful by Gururangan et al. (2020), we explore domain-adaptive pre-training of BERT model on the combination of source and target domain dialogues with MLM loss before fine-tuning it on the task. As presented in Table 2, pre-BERT helps improve the F1 score on the target domain (GRes) by up to 2.2% over the strong scratch-BERT model across different training objectives. Incorporating 

The effect of MLM in fine-tuning. We also conduct experiments on using MLM as unsupervised fine-tuning objective on the target domain dialogues. As shown in Table 2, it helps improve the cross-domain generalization performance. Specifically, our ultimate model (last row) achieves 94.1% and 94.4% F1 scores on the target domain for scratch-BERT and pre-BERT models, respectively.

Consistent gains on precision and recall. In Table 3, we demonstrate that our proposed approach leads to consistent gains on both precision and recall. While the improvement is consistent, we observe that MaskAugment significantly helps close the recall gap between scratch-BERT and pre-BERT (i.e., from 2.5% to 0.3% on the dev set and from 1.3% to 0.6% on the test set).

Low-resource setting for source domain. As shown in Table 4, we observe that the benefit of
 MASKAUGMENT through DAL and MTL objectives becomes larger as the number of labeled dialogues in the source domain gets smaller. The effect of domain-adaptive pre-training also becomes stronger, providing 12% improvement over scratch-BERT when only 10 labeled dialogues are available in the source domain while achieving 85.1% F1 score on the target domain with 50 labeled dialogues when combined with MASKAUGMENT. 

Adaptation performance across DAs. In Table 5, we present additional analysis on the adaptation performance across the set of all dialog acts in the schema. MASKAUGMENT provides significant improvement across most of the DAs including frequent ones such as request and sys-offer while not hurting the performance much (if not improving) on other frequent acts such as affirm and inform. For scratch-BERT setting, baseline (STL) objective obtains superior performance on less frequent DAs including sys-negate, sys-notify-failure, and thank-you, for which the performance drop is mostly bridged in pre-BERT setting. On the other hand, Pre-BERT provides consistent adaptation improvement over scratch-BERT across all dialog acts except for sys-negate and sys-notify-failure.

Qualitative analysis of the approach. In Figures 3a and 3b, we provide examples for improved predictions on sys-offer and request acts, respectively. These are some of the most frequent DAs that MASKAUGMENT can provide a significant (5-20%) improvement over the baseline approach for both scratch-BERT and pre-BERT settings. In Figure 3c, we include an example where scratch-BERT with MASKAUGMENT fails on predicting sys-notify-failure act correctly as opposed the baseline. However, most of such failure cases vanish for pre-BERT setting, where the gap in F1 score drops from 11.4% in scratch-BERT to only 0.5% in pre-BERT as shown in Table 5.

4 Conclusion
We study cross-domain generalization of pre-trained language models for DA tagging. While the fine-tuned BERT model performs well on in-domain DA tagging, its cross-domain generalization is still not satisfactory. To combat this shortcoming, we investigate domain adaptation through the proposed unsupervised teacher-student training that leverages the MASKAUGMENT method for data augmentation. Our empirical results show that the proposed training scheme leads to significant improvements on domain adaptation for dialog act taggers. In the future, we plan to explore MASKAUGMENT for other tasks in NLP domain.

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