Back-Translated Task-Adaptive Pretraining: Improving Accuracy and Robustness on Text Classification

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Abstract

Language models (LMs) pretrained on a large text corpus and fine-tuned on a downstream task becomes a de facto training strategy for several natural language processing (NLP) tasks. Recently, an adaptive pretraining method retraining the pretrained language model with task-relevant data has shown significant performance improvements. However, current adaptive pretraining methods suffer from underfitting on the task distribution owing to a relatively small amount of data to re-pretrain the LM. To completely use the concept of adaptive pretraining, we propose a back-translated task-adaptive pretraining (BT-TAPT) method that increases the amount of task-specific data for LM repretraining by augmenting the task data using back-translation to generalize the LM to the target task domain. The experimental results show that the proposed BT-TAPT yields improved classification accuracy on both low- and high-resource data and better robustness to noise than the conventional adaptive pretraining method.

1 Introduction

In the history of natural language processing (NLP), the rise of large language models (LMs) trained on a huge amount of text corpora was a game-changer. Before the advent of these LMs, an NLP task-specific model was trained only on a small amount of labeled data. Due to the high cost of label annotation for text data, insufficient training data was always one of the main obstacles to NLP model progress (Liu et al., 2016). However, researchers found that large LMs trained on a huge amount of unlabeled, i.e., task-independent, text data, such as BERT (Devlin et al., 2019) or GPT-3 (Brown et al., 2020), significantly improved the performance of various NLP tasks just by beginning with a pre-trained LM and fine-tuning it using the task-specific labeled data. This strategy, i.e., combining a large pretrained LM with task-specific fine-tuning, outperformed the state-of-the-art models in various NLP tasks such as text classification (Howard and Ruder, 2018), natural language inference (Peters et al., 2018), summarization (Lewis et al., 2020), and question answering (Howard and Ruder, 2018; Lan et al., 2019).

Although pretrained LMs have generalized language representations based on the corpora collected from a wide range of domains, it is not sufficient to learn completely a specific domain of some downstream tasks. To overcome this limitation, adaptive pretraining that re-pretrains the pretrained LM with the task-relevant data before fine-tuning phase was proposed (Beltagy et al., 2019; Sun et al., 2019; Lee et al., 2020; Gururangan et al., 2020). In practice, however, it is challenging to obtain another in-domain data that share the same characteristics with the task data due to the scarcity of the tasks, such as developing an intent classifier using data collected from a newly-launched chatbot (Anaby-Tavor et al., 2020). Moreover, when only a few task data is available, adaptive pretraining on the task data is insufficient to generalize the LM to the task distribution. Hence, the task-adaptively pretrained LMs might still be underfitted on the task distribution even though one can achieve better performance by employing adaptive pretraining.

To solve this problem, we propose a back-translated task-adaptive pretraining (BT-TAPT) strategy that augments the task data based on back-translation to secure more amount of task-relevant data to better generalize the pretrained LMs to the target task domain. Although text augmentation has helped improve the generalization and robustness of NLP models in various tasks such as classification, translation, and question answering (Sen-
nrich et al., 2016b; Edunov et al., 2018; Yu et al., 2018; Wei and Zou, 2019; Xie et al., 2019), the augmented data are only used in the fine-tuning step thus far.

Figure 1 illustrates the expected advantage of the proposed BT-TAPT. In BT-TAPT, an adaptive pretraining of LM is first conducted with the original task data. The task corpus is then augmented based on the back-translation technique using an appropriate sampling method such as nucleus sampling (Holtzman et al., 2019). In this way, we can generate various paraphrases from the original task corpus. These augmented task corpora are used to re-pretrain the adaptively pretrained LM again to better generalize the LM for the target task domain. Based on these consecutive pretraining procedures, we can expect that the overlap between the language model domain and the target task domain would increase as described in Figure 1.

To verify the proposed BT-TAPT, we employed two well-known pretrained LMs: BERT and RoBERTA (Liu et al., 2019). The performance of BT-TAPT was evaluated on six text classification datasets and compared with two benchmark methods: pretrained LM and task-adaptive pretrained LM. In general, the experimental results show that the proposed BT-TAPT yields higher classification accuracy than the benchmark methods. In addition, we verified the robustness of BT-TAPT by generating five types of noise for the test dataset and comparing the performance with the benchmark methods. As expected, BT-TAPT showed more robust classification performance than the baseline methods, supporting that the back-translation-based augmented data improves the generalization ability of the pretrained LMs.

Consequently, our contribution can be summarized as follows:

- We propose a new adaptive pretraining method (BT-TAPT) that can generalize LMs to task distribution using back-translation-based augmented downstream task corpus.
- BT-TAPT enhances the performance of downstream tasks.
- BT-TAPT shows better robustness to noisy text data.

2 Background

This section briefly reviews three key components of the study: masked language model, language model adaptation, and text data augmentation.

2.1 Masked Language Model

Masked language model (MLM) proposed in Devlin et al. (2019) is a pretraining method that predicts original tokens in a sentence where some tokens are masked with a special token \( [\text{MASK}] \). Let \( X = (x^{(1)}, x^{(2)}, ..., x^{(N)}) \) denote a set of unannotated sentences, where \( x = (t_1, t_2, ... t_M) \) is a sequence of tokens in a sentence, and \( t_i \in x \) is a token in a sequence. In the pretraining process of the masked language model, noise is added to the sequences \( x \) by randomly replacing some tokens with \( [\text{MASK}] \) token. Let \( \hat{x} \in \hat{X} \) be a noised sentence and \( \bar{x} \in \bar{X} \) be a subset of tokens that is randomly replaced. The training objective can be formulated as follows:

\[
\min_{\theta} L_{\text{MLM}}(\theta; \hat{X}, \bar{X}) = - \sum_{\hat{x}, \bar{x}\in \hat{X}, \bar{X}} \log p_{\theta}(\hat{x}|\bar{x}).
\]

Because MLMs do not require any task-specific labels, they can be trained on a large unannotated corpus, which makes researchers believe they can learn a general representation of single or even multiple languages. This belief has been partially supported because pretrained MLMs based on a gigantic text corpus followed by fine-tuning on a small task-specific data often outperform the state-of-the-art models for a wide range of NLP tasks (Liu et al., 2019; Lan et al., 2019; Song et al., 2019; Raffel et al., 2020).
2.2 Language Model Adaptation

LMs are pretrained with a vast amount of corpora from different domains such as BOOKCORPUS (Zhu et al., 2015), WIKIPEDIA, CC-NEWS (Liu et al., 2019), OPENWEBTEXT (Gokaslan and Cohen, 2019), and STORIES (Trinh and Le, 2018). Contrary to the expectation that LMs can properly generalize the language representation despite the text corpora based on which the LMs are trained, LMs have been reported that they are highly dependent on the training data domain. Moreover, their performances on other domains are not as good as on the training data domain.

To resolve this issue, language model adaptation, which re-pretrain the LMs before fine-tuning for specific tasks (Sun et al., 2019; Gururangan et al., 2020), was proposed. There are two main streams in language model adaptation: domain-adaptive pretraining (DAPT) and task-adaptive pretraining (TAPT). DAPT re-pretrains the LM based on a new dataset on the same domain of a target task, whereas TAPT directly re-pretrain the LM using the given target task. If a task domain is uncommon or the data acquisition cost is expensive, TAPT can be more suitable than DAPT.

2.3 Text Data Augmentation

Data augmentation for NLP is less actively used than image augmentation thus far. While many simple label-unchanged operations exist for images such as flipping, rotation, cropping, and translation, languages barely have such operations. Hence, synonym replacement using WordNet has been the most popular augmentation method in NLP (Wang and Yang, 2015; Zhang et al., 2015).

Recently, easy data augmentation (EDA) techniques consisting of synonym replacement, random insertion, random swap, and random deletion proved useful for text classification (Wei and Zou, 2019). Despite the performance enhancement, the EDA has a significant limitation that the semantics of the original sentences are usually damaged except the synonym replacement (Kumar et al., 2020). As an alternative to preserving the semantics of original sentences, back-translation, translating a sentence $x_{source}$ in the source language into the other language and then translates it back into $x_{source}$ in the source language, was proposed. The technique showed to improve the performances in various NLP tasks, such as machine translation (Sennrich et al., 2016a), question answering (Yu et al., 2018), and semi-supervised text classification (Xie et al., 2019).

3 Proposed method

We introduce a back-translated task-adaptive pretraining (BT-TAPT), a new adaptive pretraining strategy that helps adaptive pretraining when task data is insufficient, and in-domain data is unavailable. The overall process of BT-TAPT is shown in Figure 2.

3.1 Task Data is Insufficient

While using TAPT contributes to task-specific performance improvement, Gururangan et al. (2020) showed that continued pretraining using human-curated unlabeled data – corpus from the same source with task data – ensured additional performance gain, which is named human-curated TAPT. Simultaneously, the automatic selection approach retrieving unlabeled data aligning with the task data distribution from the in-domain corpus is also proven beneficial. Despite the favorable results, using those methods is impossible when human-curated data or in-domain data are unavailable. Motivated by this limitation, we propose an advanced adaptive pretraining approach requiring only task data.

3.2 Back-Translated TAPT

If the amount of task data is insufficient during TAPT, the LM may still be underfitted on the task domain. In this case, the LM would be more generalized to the task if more task-related sentences...
were available. The proposed BT-TAPT is an additional adaptation method using human-like task-related sentences. To make plausible sentences, we use a back-translation using a nucleus(top-\(p\)) sampling. We used the nucleus sampling instead of traditional beam search because the former can better implement the purpose of augmentation than the latter, creating label-unchanged and semantic-preserved data that are not exactly the same as the original data. Although back-translated sentence using beam search tends to be an almost identical sentence to the original sentence, sentences generated by back-translation using the proper sampling method are usually paraphrases of the original sentence, which have various expressions without significantly deviating from the domain of the original data.

When the LM is further pretrained only with task data, noises applied to the input at every epoch are changing the location of the [MASK] tokens and infinitesimal random word transition. Otherwise, noise used in BT-TAPT includes not only the change of [MASK] positions or word transition but also synonym replacement or rephrasing facilitated by the sampling-based back-translation.

### 3.3 BT-TAPT Process

We first apply TAPT on the pretrained LM to expose it to the task domain sentence with correct grammar. Then, we generate multiple sentences with back-translation. We adopt nucleus sampling with \(p = 0.95\) to ensure proper diversity and fluency for the generated sentences. We generate 20 sentences for each original sentence to expose the LM to semantically and syntactically sufficiently diverse expressions. We further re-pretrain the LM with those sentences where domain-related but less accurate expressions appear. Learning from those paraphrases, the LM can cover a broader range of task distribution, as depicted in figure 1. After the entire adaptive pretraining phase is completed, the LM is fine-tuned on the task data.

### 4 Experiments

We verify the proposed BT-TAPT based on six widely-studied classification datasets with two well-known pretrained LMs: BERT and RoBERTA. We compare the performances of BT-TAPT with two benchmark methods: base pretrained model and TAPT.

#### 4.1 Datasets & Performance Metrics

Four sentiment classification datasets, i.e., IMDB (Maas et al., 2011), MR (Pang and Lee, 2005), SST2 (Socher et al., 2013), and AMAZON (He and McAuley, 2016; Gururangan et al., 2020) and two other classification datasets, i.e., TREC (Li and Roth, 2002) question classification and AGNEWS (Zhang et al., 2015) topic classification, were used in the experiments. As a classification performance metric, a simple accuracy was used except for AMAZON, for which the macro-\(F_1\) is used owing to the class imbalance.

We divided the datasets into two groups: datasets with more than 20,000 training examples were considered high-resource datasets, while the others were considered low-resource datasets. To formulate additional low-resource datasets, IMDB and AGNEWS were down-sampled 2,500 per class, and AMAZON was down-sampled 10% of the training dataset. The description of each dataset is summarized in Table 1.

#### 4.2 Training Details

As the pretrained LMs, BERT-base and RoBERTA-base trained from huggingface (Wolf et al., 2020) were employed. For back-translation, we employed the transformer-big model of Facebook (Ng et al., 2020)
Table 2: Average classification performance with the standard deviation (subscripted) for each test dataset with three benchmark methods with two base LMs under a low-resource setting. Note that the performance metric for AMAZON dataset is macro-$F_1$ measure while that of the other datasets are the simple accuracy.

|           | IMDB   | AMAZON | AGNEWS | TREC | MR    | SST2  |
|-----------|--------|--------|--------|------|-------|-------|
| BERT      | 92.2±3 | 60.8±3 | 92.1±1 | 96.7±1| 86.5±7| 91.0±7|
| + TAPT    | 93.0±2 | 67.0±8 | 92.7±1 | 96.0±3| 85.7±3| 90.6±3|
| + BT-TAPT | 93.3±2 | 67.3±9 | 92.7±1 | 96.9±3| 86.0±4| 92.4±3|
| RoBERTA   | 94.2±3 | 63.7±9 | 92.4±1 | 96.7±3| 89.7±3| 93.8±5|
| + TAPT    | 94.4±2 | 64.5±8 | 92.6±1 | 96.5±3| 89.4±4| 93.8±5|
| + BT-TAPT | 94.4±1 | 67.7±8 | 92.6±1 | 96.5±3| 89.7±3| 93.8±5|

Table 3: Average classification performance with the standard deviation (subscripted) for each test dataset with three benchmark methods with two base LMs under a high-resource setting. The performance metrics are same with Table 2. † denotes a high-resource setting where the entire dataset is used.

|          | †IMDB  | †AMAZON | †AGNEWS |
|----------|--------|---------|---------|
| BERT     | 93.7±1 | 65.3±4 | 94.1±1  |
| + TAPT   | 94.8±2 | 68.1±8 | 94.7±2  |
| + BT-TAPT| 95.1±1 | 69.7±9 | 94.6±1  |
| RoBERTA  | 95.1±1 | 65.7±2 | 94.6±3  |
| + TAPT   | 95.6±1 | 68.5±2 | 94.9±1  |
| + BT-TAPT| 95.7±0 | 69.2±9 | 95.0±1  |

4.3 Text Classification Performance

Tables 2 and 3 show the classification performance of each dataset in the high- and low-resource settings, respectively. In both tables, we can observe that further re-pretraining with the augmented dataset based on the back-translation improves the model either in terms of classification accuracy or the model stability regardless of the base pretrained LM. The proposed BT-TAPT yields either higher classification accuracy without the increase in standard deviation than TAPT (e.g., IMDB with BERT, SST2 with BERT, and MR with RoBERTA) or reduce the performance variation while maintain-

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2https://github.com/pytorch/fairseq/tree/master/examples/translation
Table 4: The average performance of the fine-tuned BERT-base model on IMDB low-resource test dataset with further re-pretraining using additional data generated from various augmentation technique after TAPT is applied.

| Augmentation   | Accuracy    |
|---------------|-------------|
| TAPT          | 93.0 ± 0.2  |
| None          | 92.8 ± 0.2  |
| + EDA         | 92.7 ± 0.2  |
| + Embedding   | 92.9 ± 0.2  |
| + TF-IDF      | 92.9 ± 0.4  |
| + Back-Translation | 93.3 ± 0.3  |

4.4 Comparing Augmentation Methods

We compared back-translation with other widely used augmentation methods – EDA, Embedding, and TF-IDF on adaptive pretraining. Embedding (Mrkšić et al., 2016) replaces an arbitrary token with a close token in the embedding space. In contrast, TF-IDF (Xie et al., 2019) replaces uninformative words with low TF-IDF scores in sentences while preserving those with high TF-IDF scores. As a baseline, we also include the model without any augmentation method, which means the TAPT is applied again with the same training steps for the other augmentation methods.

We first applied TAPT on BERT-base for 50K steps using the IMDB low-resource dataset and then re-pretrained using the augmented dataset generated from each method using a transformation probability of 0.1. Table 4 shows the classification accuracy for different augmentation methods.

Figure 4: Accuracy of BERT fine-tuned on IMDB low-resource test dataset after applying BT-TAPT using different numbers of back-translated paraphrase per original sentence.
Figure 5: Accuracy of fine-tuned BERT with different order of TAPT and back-translation (BT) in BT-TAPT for IMDB low-resource test dataset.

Figure 6: Test accuracy of BERT fine-tuned on the varying amount of task data. The indicated quantity of IMDB dataset were used in TAPT, BT-TAPT, and fine-tuning.

4 shows the classification accuracy regarding the number of augmentations. In general, classification accuracy increases with TAPT as the number of back-translated sentences increases and becomes mature beyond a certain number of augmentations. Because the performance differences beyond 20 augmentations are marginal, we chose 20 as the final number of back-translated augmentations per sentence.

4.6 Comparison of BT-TAPT Strategies

We investigated all possible strategies of back-translation deployment in BT-TAPT. TAPT & BT implies using both task and back-translated data for re-pretraining simultaneously. BT → TAPT and TAPT → BT refer to the re-pretraining with back-translated data and further re-pretraining with task data sequentially and vice versa. As seen in Figure 5, applying TAPT followed by re-pretraining with back-translated sentences yields the highest accuracy with the smallest variation. However, simultaneously using the back-translated sentences on re-pretraining enlarges the deviation even though it improves the accuracy, which implies that the language model should adjust to the target domain with a well-formed corpus first and then be exposed to various domain-related augmented sentences.

4.7 Performance on Small Datasets

In a real-world situation, the task data is commonly insufficient. To validate that the BT-TAPT can effectively handle the data shortage, we conducted additional experiments with only 100, 500, and 1,000 sentences of the IMDB dataset. As shown in Figure 6, BT-TAPT is found to be much beneficial under an extremely low-resource circumstance because the performance is noticeably improved with only 100 sentences. Thus, this result supports that expression-diversified but semantic-preserved augmented texts based on back-translation can help LMs adapt to the domain distribution.

5 Robustness to Noise

When applying the fine-tuned classifier to a real task, not only the clean data, which were sufficiently observed during the model training, but also the noisy data often come during the inference. We expect the proposed TP-TAPT to be more robust to various noises because the model trained with BT-TAPT encounters more diverse contexts than TAPT. To verify this assumption, we constructed another noisy-test dataset by applying corruption or perturbation and compared the classification performances of the three models.

5.1 Type of Noises

Five different realistic noise types were generated for the test datasets AGNEWS, SST2, MR, and TREC6. Note that these noise are added only to the test dataset, not the training dataset.

**Synonym** Replace the random word in the sentence with its synonyms using WordNet thesaurus (replacement probability = 0.1).

**BT beam** Generate a paraphrase using back-translation with beam search. This method does not shift the original sentence substantially because the beam search does not employ sampling. Nevertheless, it produces more changes than the synonym replacement.

**BT top-p** Generate multiple paraphrases using
back-translation with nucleus sampling. It creates diverse but partially incorrect sentences.

**Char swap** Generate random character-level noises with transformation probabilities of 0.1. The noise consists of deleting, adding, or changing the order of characters in a sentence.

**InvTest** Apply the invariance test proposed in Ribeiro et al. (2020). The invariance test applies label preserving-perturbations such as changing numbers or location names. The fine-tuned classifier should generate the same output whether the input changes by the invariance test.

Among the five noises scenarios, **BT beam** and **BT top-p** used English → German and German → English machine translation model adopted from Ng et al. (2019), which is the same model used in section 4. CharSwap, Synonym, and InvTest used the TextAttack (Morris et al., 2020) python package. As randomness exists in all methods except for the BT beam, where the maximum probability is used for decoding, we created five different noised datasets for each dataset.

### 5.2 Result

To evaluate the robustness of **TAPT** and **BT-TAPT**, we measured the *accuracy gain*, the amount of classification accuracy change on the noised test set after **TAPT** or **BT-TAPT** was applied. Figure 7 shows the *accuracy gain* regarding each dataset under different noise-added settings. Note that because the first two noise types, i.e., **BT beam** and **BT top-p** can generate similar sentences to **BT-TAPT**, **BT-TAPT** always improves the base re-pretrained model with a significant margin for most datasets, whereas **TAPT** sometimes fails to improve the base model performances. Beside these back-translation-based noises, **BT-TAPT** still reports favorable accuracy gains. However, **TAPT** not only achieves less significant accuracy gain than **BT-TAPT**, but also it degenerates the pre-trained model (negative accuracy gain) even though it re-pretrained the base LMs. Consequently, we can conclude that the proposed **BT-TAPT** is more robust to unexpected data variations. Thus, the proposed method will be practically helpful in real-world tasks where languages are dynamically changing, evolving, and sometimes intentionally or unintentionally breaking.

### 6 Conclusion

In this paper, we proposed **BT-TAPT**, a new adaptive pretraining method for generalizing LMs to task domains when task data is insufficient. In contrast to **TAPT** that only uses task-related unlabeled data, the proposed **BT-TAPT** generates augmented data based on back-translation and use it for further re-pretrain the LMs.

Experiments on six text classification datasets show that the **BT-TAPT** not only improved the classification accuracy but also reduced the deviation. Moreover, **BT-TAPT** was found to be more practical for small datasets and robust to various noises. Future work will consider applying **BT-TAPT** to the other NLP tasks such as question answering or summarization.
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