TextAT: Adversarial Training with Token-Aware Perturbation for Natural Language Understanding

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Abstract

Adversarial training is effective in improving the robustness of neural networks. In NLP, languages are discrete in nature, separate tokens possess discrete semantics. Therefore, to incorporate adversarial training in sequence-level tasks, we introduce TextAT, a novel adversarial training strategy with token-aware perturbation. We first craft perturbations that are initialized using a fine-grained token-aware accumulated perturbations. Then we constrain these perturbations considering that inputs are separate tokens, instead of sequence-level regularization. We validate the effectiveness of such normalization method using large-scale Transformer-based language models. Experiments on GLUE benchmark and NER task show that our adversarial training strategy improves the performances on various tasks including text classification and sequence labeling.

1 Introduction

Neural networks are proved to be vulnerable under crafted adversarial samples. Recent works have shown that adversarial training is helpful in constructing robust neural networks (Goodfellow et al., 2014; Madry et al., 2018). Adversarial training use gradients from clean samples to construct perturbations and add these perturbations to input space as adversarial samples to train the neural networks. In this way, adversarial training minimizes the maximal risk of false-prediction, therefore, improve the robustness of neural networks.

In natural language processing fields, creating actual label-preserving adversarial samples is difficult. Miyato et al. (2017) created “virtual” adversarial samples using perturbations on the embedding space to run adversarial training.

Recent developments in pre-trained models have revolutionize most NLP tasks (Devlin et al., 2018; Liu et al., 2019; Yang et al., 2019; Radford et al., 2019). The capacity of pre-trained models is enormous and data used in pre-training is massive, while labeled data in downstream tasks is limited. Therefore, applying adversarial training or adversarial regularization during fine-tuning stage could help these pre-trained models achieve even better results (Zhu et al., 2020). However, the discrete nature of languages is less explored in adversarial training methods.

In this paper, we propose an adversarial training algorithm that takes the discrete nature of language into consideration. Previous adversarial training methods generate perturbations that are initialized randomly on the embedding space. Different from images or audios, word embeddings in NLP systems possess certain semantic knowledge. To take the property of word embeddings into consideration, perturbations over these word embeddings could be better designed. Therefore, we introduce two steps to create better adversarial samples: (1) global accumulated token perturbation; (2) discrete token normalization ball.

To generate perturbations that are aware of the semantic information of certain words, we accumulate the perturbations of the corresponding token in the vocabulary of the model during the entire training process of the training data. For certain words in a sequence, their corresponding perturbations are accumulated in previous training, therefore they contain certain token-aware information. These fine-grained perturbations can help create better adversarial samples.

Further, standard adversarial training methods usually constrain adversarial perturbations within a Frobenius normalization ball. We constrain perturbations at word-level discretely instead of considering the input sequence as a consistent vector. Instead of using traditional Frobenius normalization, we set the upper bounds of per-
turbations related to the discrete words to craft adversarial perturbations that are constrained more tightly.

![Figure 1: Illustration of adversarial sample space using different adversarial training algorithm.](image)

We draw an illustration in Figure 1 to show how token-aware perturbation works. Suppose that each sequence contains only two tokens, thus the input is a two-dimension vector. So we could illustrate the sequence as a data point in a two-dimension figure.

As seen, traditional adversarial training method shown in Figure 1(a) find perturbations around the input data-point considering that the input is inseparable. Regardless of the discrete tokens, the perturbation bound is a circle around the datapoint since perturbations are constrained by Frobenius normalization.

Our method generates perturbations that are token-aware therefore the perturbations can be constrained more tightly as shown in Figure 1(b). For a certain token, the perturbation is initialized based on the accumulation throughout the entire dataset and constrained by a token-aware normalization ball, so it can be more effective compared with random initialization and Frobenius normalization. In Figure 1(b), perturbations are token-aware, samples with same token would have a similar bound, therefore the perturbation ball is more flexible, which is an ellipse when there are only two tokens. The actually situation is that there could be hundreds of tokens in a sequence, the perturbation could be more flexible to fit into a more accurate classification margin.

Therefore with token-aware perturbation, we have better adversarial samples and can further improve the effectiveness of adversarial training.

Since we focus on incorporating adversarial training into text tasks, we name such training strategy **Text Adversarial Training**. Our method can boost current state-of-the-art large-scale pre-trained language models to achieve better results when fine-tuned to downstream tasks. We establish extensive experiments to evaluate the effectiveness of our proposed method. We boost the GLUE benchmark performance of BERT-base model from 79.3 to 80.9; In sequence labeling tasks, both ConLL2003 and Ontonotes NER tasks are improved by applying text adversarial training. Our text adversarial training algorithm is effective and can be easily applied to various kinds of NLP tasks.

## 2 Related Work

Adversarial attack (Goodfellow et al., 2014) is to find an imperceptible perturbation to mislead neural networks. In CV field, adversarial attacks are extensively explored (Carlini and Wagner, 2017) since it is easy to apply gradient over the continuous space in images. In NLP field, creating actually adversarial samples is more challenging, which usually requires extra knowledge such as pre-trained embeddings (Mrkšić et al., 2016; Jin et al., 2019) or language models (Alzantot et al., 2018; Li et al., 2020).

Derived from adversarial attack, adversarial training (Goodfellow et al., 2014) reverses the attacking process and uses generated perturbations as extra training samples to augment neural networks. In particular, projected gradient descent (PGD) (Madry et al., 2018) is applied in adversarial training. PGD algorithm projects gradients by a few steps to search for proper adversarial perturbations and use them in adversarial training to improve the robustness of neural networks. PGD approach calculates gradients multiple times to find proper perturbations, thus the calculation is massive. To apply adversarial training efficiently, FreeAT (Shafahi et al., 2019) and FreeLB (Zhu et al., 2020) are introduced to update both model parameters and adversarial perturbations simultaneously during backward passes. Through simultaneous updates, adversarial training is applied for "free" without additional calculation.
3 Text Adversarial Training with Token-Aware Perturbation

In this section, we will first introduce a standard adversarial training process and then illustrate two main components: (1) Global Accumulated Token Perturbations; (2) Normalization Ball based on discrete tokens. Finally, we will summarize the entire Text Adversarial Training algorithm.

3.1 Standard Adversarial Training

Normally, adversarial training aims to optimize parameter $\theta$ to minimize the maximum risk of mis-classification when adding perturbations to the original inputs. The perturbation $\delta$ is usually constrained by a norm ball $\epsilon$:

$$ \min_{\theta} \mathbb{E}(X,y) \left[ \max_{||\delta|| \leq \epsilon} L(f_{\theta}(X + \delta), y) \right] $$ (1)

where $y$ is the label of input sequence $X$ and $L$ is the loss function of parameter $\theta$. We normally use Frobenius norm to constrain $\delta$. As explored in PGD (Madry et al., 2018), the outer minimize function is non-convex, while the inner maximize function is non-concave. Still, the saddle-point problem can be solved by applying multiple steps of stochastic gradient descent to search for reliable perturbation $\delta$:

$$ \delta_t = \prod_{||\delta||_F \leq \epsilon} (\delta_{t-1} + \alpha g(\delta_{t-1})/||g(\delta_{t-1})||_F) $$ (2)

Here, $t$ is the step number of applying stochastic gradient descent, $g(\delta_t) = \nabla_{\delta} L(f_{\theta}(X + \delta), y)$ is the gradient respect to perturbation added to the input. $\prod_{||\delta||_F \leq \epsilon}$ projects the perturbation onto the Frobenius normalization ball. In this way PGD generates perturbation by multiple steps and these constrained adversarial perturbations used in training can improve the generalization ability in neural networks (Zhu et al., 2020). As explored in FreeLB (Zhu et al., 2020), NLP models can be further improved by applying adversarial training algorithms. In FreeLB algorithm, gradients are accumulated through multiple forward passes then backward once to optimize model parameter $\theta$, which is more efficient than PGD adversarial training. Therefore, we adopt FreeLB as our adversarial training framework. These adversarial training algorithms ignore the discrete property of languages and consider the input sequence as a concatenated vector. Our core idea is to allow adversarial training to be more effective while dealing with sequential texts. Therefore, we propose two important modifications considering the discrete nature of input sequence based on the structure of standard adversarial training process.

3.2 Global Accumulated Token Perturbation

Different from pixels in images or signals in audios, embeddings used in texts possess abundant semantic information (Pennington et al., 2014). Therefore, perturbations are less focused on certain tokens when randomly initialized within the batch processing.

To tackle this problem, we accumulate the perturbations of discrete tokens throughout the training process. We create global accumulated perturbation $Z \in \mathbb{R}^{N \times D}$, where $N$ is the vocabulary size of model embedding space. For each batch, adversarial perturbations are initialized by the corresponding perturbation from the global accumulated perturbation $Z$. After $K$ steps of adversarial training forward pass, we accumulate the gradients calculated by the given data $X = [w_0, \cdots, w_t, \cdots]$ and update the global accumulated perturbation $Z$. These perturbations are learned throughout the entire dataset, therefore are fine-grained perturbations compared with random initialized perturbations.

In this way, the global token perturbation $Z$ is learned as training proceeds. The adversarial perturbations initialized by these global token perturbations contain fine-grained information that can be helpful in the adversarial training process. As shown in Figure 1, the perturbations are more imperceptible while still serve as effective virtual adversarial samples.

3.3 Normalization Ball of Discrete Tokens

In PGD adversarial training, the perturbation process considered input sequence $X$ as an inseparable matrix and directly calculate Frobenius normalization of the perturbation. Yet language possesses diversified tokens within one input sequence, therefore the normalization ball should not consider the entire sequence as a simple matrix. When we use perturbations that are token-level accumulated, it is intuitive to consider using a token-level normalization ball. Therefore we propose a novel normalization ball to constrain perturbations considering the property of discrete tokens.
Algorithm 1 Text Adversarial Training with Token-Aware Perturbation

Require: Training Samples $S = \{ (X = [w_0, \ldots, w_i, \ldots], y) \}$, perturbation bound $\epsilon$, adversarial steps $K$, adversarial step size $\alpha$, model parameter $\theta$

1: Initialize global accumulated perturbation $Z$:
2: $Z \in \mathbb{R}^{N \times D} \leftarrow \frac{1}{\sqrt{D}} U(-\epsilon, \epsilon)$
3: for epoch $= 1, \ldots, K$
5: Initialize perturbation :
6: $\delta_0 \leftarrow \frac{1}{\sqrt{D}} U(-\epsilon, \epsilon)$
7: $\eta_0 \leftarrow Z_{[w_i]}$
8: Initialize gradient of $\theta$ :
9: $g_0 \leftarrow 0$
10: for $t = 1, \ldots, K$
11: \hspace{1em} Accumulate gradients of $\theta$
12: $g_t \leftarrow g_{t-1} + \frac{1}{N} \nabla_{(X, y)} L(f_\theta(X + \delta_{t-1} + \eta_{t-1}), y)]$
13: Update perturbation $\delta$ and $\eta$:
14: $g^*_t \leftarrow \nabla_{\delta} L(f_\theta((X + \delta_{t-1} + \eta_{t-1}), y))$
15: $\delta^*_t \leftarrow \delta_{t-1} + \alpha \cdot \eta_t / \|g^*_t\|_F$
16: $g^*_t \leftarrow \nabla_{\eta} L(f_\theta((X + \delta_{t-1} + \eta_{t-1}), y))$
17: $\eta^*_t \leftarrow \eta_{t-1} + \alpha \cdot \eta_t / \|g^*_t\|_F$
18: Clip the perturbation into norm ball:
19: $\delta_t \leftarrow \frac{\|\delta^*_t\|_F}{\max(\|\delta^*_t\|_F)} \cdot \delta^*_t$, $\eta_t \leftarrow \frac{\|\eta^*_t\|_F}{\max(\|\eta^*_t\|_F)} \cdot \eta^*_t$
20: $\delta_t \leftarrow \prod_{i \in C} \|\delta_i + \eta_i\|_F < \epsilon(\delta_t)$, $\eta_t \leftarrow \prod_{i \in C} \|\delta_i + \eta_i\|_F < \epsilon(\eta_t)$
21: \hspace{1em} end for
22: Accumulate Global Token Perturbation:
23: $Z_{[w_i]} \leftarrow \eta_t$
24: Update model parameter:
25: $\theta \leftarrow \theta - g_K$
26: \hspace{1em} end for
27: \hspace{1em} end for

Since our core idea is to take the discrete nature of texts into consideration, we constrain perturbations with a tighter token-level normalization ball instead of naive Frobenius normalization ball. We add a token-level scaling index $n^t = \frac{\|\delta^*_t\|_F}{\max(\|\delta^*_t\|_F)}$ for perturbation $\delta^*_t$ of word $w^t$ to the normalization ball. Further, since global accumulated perturbations are accumulated over discrete tokens, we could apply a trick here that we use token level Frobenius normalization over these perturbations.

We can rewrite the normalization ball constraint in Equation 2 as:
\[
\delta^*_t = n^t \cdot (\delta^*_{t-1} + \alpha g(\delta^*_{t-1}) / \|g(\delta^*_{t-1})\|_F) \quad (3)
\]
\[
\delta_t = \prod_{|\delta^*_t|_F \leq \epsilon} (\delta^*_t) \quad (4)
\]

Through such a constrain ball, less important words are less likely to be altered by adversarial perturbations. The overall perturbation is therefore less destructive to the original clean data while maintaining an adversarial effect.

3.4 Overall Process

The overall process of our method is illustrated in Algorithm 1: we first randomly initialize the global accumulated perturbation $Z$; during training, we add both in-batch initialized perturbation and global accumulated perturbation on the embedding space as adversarial perturbations to run the adversarial training algorithm.

We use $\delta$ as the in-batch initialized perturbation and $\eta$ as the perturbation accumulated in perturbation $Z$. Here $\delta$ is different from one used in previous sections, where $\delta$ stands for the only perturbation to the original sample.
We add up two perturbations $\delta$ and $\eta$ in our **Text Adversarial Training**. Global accumulated perturbation allows perturbations to be aware of the entire data distribution rather than in-batch data distribution only.

Perturbations are constrained within a token-level normalization ball rather than a naive Frobenious normalization ball by applying scaling index to the perturbation as well as normalization on the token-level of the input sequence. We update in-batch perturbation $\delta$ with normalization over the entire sequence while update global accumulated perturbation $\eta$ with token-level normalization. As mentioned above, global accumulated perturbations are more independent therefore updating them with token-level normalization helps generate better adversarial perturbations during $K$ steps of forward passes. We constrain both in-batch perturbation $\delta$ and global accumulated perturbation $\eta$ with normalization ball with token-level scaling index. We further explore different normalization strategies in the following section. Then the model is optimized with accumulated gradients of multiple steps of forward passes which could be any previous adversarial training framework.

4 **Experiments**

To explore the effectiveness of discrete token normalization method, we run extensive experiments over most common tasks in NLP: text classification, sentence pair relation prediction, named entity recognition, common sense reasoning. We use popular benchmarks: GLUE (Wang et al., 2019), CoNLL 2003 (Tjong Kim Sang and De Meulder, 2003) and test based on most popular pre-trained model BERT (Devlin et al., 2018).

4.1 **Datasets**

**GLUE Dataset** GLUE dataset is a collection of natural language understanding tasks:

- MNLI (Williams et al., 2018) is Multi-genre Natural Language Inference task containing 393K sentence pairs as training set evaluated by accuracy.
- QQP \footnote{https://www.quora.com/q/quoradata/First-Quora-Dataset-Release-Question-Pairs} is Quora Question Pairs task formulated as classification task of sentence pairs evaluated by accuracy and recall, containing 364K sentence pairs in the training set.
- RTE (Dagan et al., 2005) is Recognizing Textual Entailment with training set containing 2.5K sentence pairs evaluated by accuracy.
- QNLI (Rajpurkar et al., 2016) is Question NLI task derived from SQuAD Machine Reading Comprehension Task. QNLI is formulated as a simple sentence pair classification task evaluated by accuracy, with training set containing 108K sentence pairs.
- MRPC (Dolan and Brockett, 2005) is Microsoft Research Paraphrase Corpus evaluated by accuracy, and contains 3.7K sentence pairs as training set.
- CoLA (Warstadt et al., 2018) is Corpus of Linguistic Acceptability, which is a text classification task evaluated by MCC.
- SST-2 (Socher et al., 2013) is Standard Sentiment Treebank which is a standard text sentiment classification task containing 67K sentences of training set.
- STS-B (Agirre et al., 2007) is Semantic Textual Similarity Benchmark formulated as a regression task evaluated by Pearson and Spearman correlation, containing 7K training dataset.

**NER Dataset**

Since our approach focus on adversarial training concerning discrete tokens, we believe that such method would improve the performance of sequence labeling tasks. Therefore, we run NER (Named Entity Recognition) task using CoNLL2003 dataset (Tjong Kim Sang and De Meulder, 2003) and Ontonotes dataset (Weischedel et al., 2011).

CoNLL 2003 dataset contains 12K training samples with 4 types of entities. Ontonotes dataset contains 60K training samples with 18 types of entities.

**Text Classification Dataset**

In GLUE dataset, only SST-2 is a standard text classification task. We further run several popular classification dataset consists news-genre classification and movie review classification which are longer sequences.

We use AG’s NEWS dataset that predicts the news-type containing 112K training samples. And we use IMDB dataset \footnote{https://datasets.imdbws.com/} of polarity sentiment
Table 1: Evaluation results on the development set of GLUE benchmark.

Table 2: Evaluation results on the test set of GLUE benchmark. Results use the evaluation server on GLUE website. QNLI* in FreeLB is formed as pairwise ranking task.

4.2 Implementations
We test our Text Adversarial Training algorithm based on BERT models. All models are implemented with Huggingface-Transformers. Specifically, we run NER task with cased BERT-BASE model, and other tasks with uncased model. We run all experiments with hyper parameters same as used in fine-tuning BERT for downstream tasks. Typically, we use learning rate 2e-5, 4 NVIDIA Titan XP GPU with total batch-size 32.

In GLUE dataset, we train all tasks based on masked language model released. We do not further fine-tune on the trained MNLI model for tasks like RTE as done by other baselines. Further, we treat QNLI task as a simple classification task, not as a pairwise ranking task which is the trick introduced by Liu et al. (2019).

4.3 Experiment Results
As seen in Table 1, 2, 3, our Text Adversarial Training algorithm improves fine-tuned models by a large margin.

Generally, textAT lifts the evaluation dataset performance of the BERT-base model from an average 79.3 to 80.9, tested on GLUE server.

Table 3: Evaluation results on the development set of CoNLL2003 dataset and Ontonotes dataset.

use token-aware adversarial training, our algorithm still has a 0.4 point performance boost. STS-B task tested on evaluation server has some rather strange result, we assume that regression task may not be work well in generalization of our method. The SMART (Jiang et al., 2019) algorithm uses a regularization method which uses the model output instead of the golden label $y$ in the training process. According to Jiang et al. (2019), such method is more robust when dealing with noisy labels. Such algorithm is parallel to our algorithm. Since our core idea is about introducing token adversarial training into consideration, we only list the regularization method for comparison.

In tasks like RTE or MRPC, the model perfor-


| Model               | IMDB | AG’s NEWS |
|---------------------|------|-----------|
| BERT-ReImp          | 95.0 | 90.0      |
| FreeLB-ReImp        | 95.4 | 90.5      |
| TextAT(ours)        | 95.7 | 90.9      |

Table 4: Evaluation results on the development set of Text Classification Datasets.

Performance is improved by a larger margin using our text adversarial training. We assume this is because the training sets in these tasks are limited to only a few thousands of samples, which indicates that our method can be helpful in tasks that lack of training data. We will discuss the effectiveness of our method when dealing with insufficient data in the following section.

In sequence labeling tasks, text adversarial training method can still boost the performance in both CoNLL 2003 NER dataset and Ontonotes NER dataset. While in CoNLL 2003 dataset, traditional adversarial training is even worse. Therefore, we can assume that text adversarial training is effective in dealing with sequence-level tasks. We can assume that when the task is about sequence labeling, the perturbation over discrete tokens help the model better recognize the difference between tokens, therefore improves the model performance.

In standard text classification tasks, text adversarial training is also effective. When dealing with rather long sequences in IMDB dataset, performance is still lifted by 0.3 point compared with FreeLB method.

Instead of using global accumulated perturbations, we initialize perturbation \( \eta \) the same as the way we initialize in-batch perturbation \( \delta \). Two perturbations are normalized differently, one by regular Frobenius normalization and one by discrete token normalization.

As seen in Table 5, without using global accumulated perturbation, performances are considerably lower. Meanwhile, performances are higher than using regular Frobenius normalization only, which indicates that discrete token normalization method is also working while dealing with in-batch initialized perturbations.

We also setup experiments to test whether discrete token normalization ball is helpful in text adversarial training. When not using discrete normalization ball, we normalize both in-batch perturbations and global accumulated perturbations using Equation 2, which considers input sequence as a matrix.

As seen in Table 5, without discrete normalization, performances are considerably lower, indicating that global accumulated perturbation works best when incorporating discrete token-level normalization.

Both global accumulated perturbations used during the entire training process and the discrete token normalization over these perturbations are effective. Therefore, we can summarize that in text adversarial training, it is important to take the discrete nature of texts into consideration to craft perturbations that concerns the variance between tokens.

### 4.4 Ablations

We run ablation studies to explore the effectiveness of the key components in our adversarial training algorithm:

We setup ablation experiments to test the effectiveness of global accumulated perturbations. Instead of using global accumulated perturbations, we initialize perturbation \( \eta \) the same as the way we initialize in-batch perturbation \( \delta \). Two perturbations are normalized differently, one by regular Frobenius normalization and one by discrete token normalization.

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Both global accumulated perturbations used during the entire training process and the discrete token normalization over these perturbations are effective. Therefore, we can summarize that in text adversarial training, it is important to take the discrete nature of texts into consideration to craft perturbations that concerns the variance between tokens.

| Method | RTE | MRPC | CoLA |
|--------|-----|------|------|
| GAP    |     | 75.0 | 88.0 | 62.0 |
|        | ✓   |      |      |      |
| DNB    | ✓   | 73.0 | 87.5 | 60.3 |
|        |     |      |      |      |
|       | ✓   | 72.5 | 87.0 | 59.5 |
|       |     |      |      |      |
|       | ✓   | 70.0 | 86.0 | 57.5 |
|       |     |      |      |      |

Table 5: Ablation Studies; GAP is using Global Accumulated Perturbation; DNB is using Discrete Normalization Ball.

### 5 Analysis

In this section, we construct comprehensive experiments to explore the effectiveness of our adversarial training algorithm.

**Global Accumulated Perturbation of Different Tokens**

Considering that global accumulated perturbation \( Z \) is conditioned over different tokens in the embedding space of the given model, certain tokens may play more vital roles in adversarial training. Specifically, BERT attaches special tokens into the input sequence: [CLS] token is concatenated in the front of the sequence while [SEP] token is attached to tails of input sentences. In fine-tuning on GLUE benchmark, BERT uses [CLS] token to predict the label while this token actually does not possess any semantic information.
To explore how adversarial perturbations on these special tokens effect the adversarial training process, we establish experiments filtering out the perturbations on these tokens.

As seen in Table 6, neglecting special tokens would harness the adversarial training process, which indicates that adversarial perturbations added to these special tokens is effective. Though these special tokens do not possess semantic meanings, only serve as aggregation function or separation of sentences. On the other hand, adding perturbations on these special tokens only is not enough, which indicates that the adversarial training algorithm based on these pre-trained models is not merely a process focusing on the special tokens. Global accumulated perturbations over the entire embedding space can further lift the performances.

| Method | RTE  | MRPC | CoLA |
|--------|------|------|------|
| ST     | ✓    | ✓    | 75.0 | 88.0 | 62.0 |
| NT     | ✓    | ✓    | 73.0 | 86.5 | 60.6 |
| ST     | ✓    | ✓    | 73.5 | 87.0 | 61.0 |

Table 6: Global Accumulated Perturbations of Different Tokens, ST perturbates special tokens; NT perturbates normal tokens. Tested on dev set using BERT-BASE model.

Visualization of global Accumulated Perturbations

To explore the effectiveness of global accumulated perturbations, we visualize the accumulated perturbations using TSNE (van der Maaten and Hinton, 2008).

We visualize the initial global accumulated perturbation $Z$ and after training the perturbation $Z$ using the development set of CoLA task based on BERT-BASE model. We only randomly choose 1 thousand words without the special tokens.

As seen in Figure 2, the initialized perturbations are well-distributed. After global accumulation, some of the perturbations becomes relatively little while some are diversified. This indicates that global accumulated perturbations learn the diversified information in different tokens and improve the model performance through adversarial training process.

![TSNE visualization of global accumulated perturbation](image)

Figure 2: TSNE visualization of global accumulated perturbation.

Corpus Size

As already shown in Table 2, our adversarial training algorithm is more effective in dealing with RTE, CoLA tasks than MNLI and QQP tasks. We intuitively believe that the corpus size of the task may be cause. Therefore, we use different proportions of training set in MNLI task to fine-tune pre-trained models.

As seen in Figure 3, text adversarial training is more powerful when dealing with relatively smaller training set. When we train MNLI task with only 2000 training pairs, text adversarial training can lift the performance by a larger margin than training with full 400K dataset.

![Performance of MNLI Dataset trained with different training data size](image)

Figure 3: Performance of MNLI Dataset trained with different training data size.

Since in NLP field, obtaining high quality dataset is costly, using our text adversarial training method is an effective way to boost the model trained with limited data.

6 Conclusion

In this paper, we focus on apply adversarial training in NLP tasks and propose TextAT algorithm to improve the performances of large-scale pre-trained models exemplified by BERT. Experiments show that our algorithm is effective in creating perturbations that can further improve the model performances.
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