Self-Supervised Contrastive Learning with Adversarial Perturbations for Defending Word Substitution-based Attacks

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Abstract

In this paper, we present an approach to improve the robustness of BERT language models against word substitution-based adversarial attacks by leveraging adversarial perturbations for self-supervised contrastive learning. We create a word-level adversarial attack generating hard positives *on-the-fly* as adversarial examples during contrastive learning. In contrast to previous works, our method improves model robustness without using any labeled data. Experimental results show that our method improves robustness of BERT against four different word substitution-based adversarial attacks, and combining our method with adversarial training gives higher robustness than adversarial training alone. As our method improves the robustness of BERT purely with unlabeled data, it opens up the possibility of using large text datasets to train robust language models against word substitution-based adversarial attacks.

1 Introduction

Pretrained language models such as BERT (Devlin et al., 2019, inter alia) have had a tremendous impact on many NLP tasks. However, several researchers have demonstrated that these models are vulnerable to adversarial attacks, which fool the model by adding small perturbations to the model input (Jia and Liang, 2017).

A prevailing method to improve model robustness against adversarial attacks is adversarial training (Madry et al., 2018). In NLP, adversarial training in the input space has been challenging, as existing natural language adversarial attacks are too slow to generate adversarial examples *on the fly* during training (Alzantot et al., 2018; Ebrahimi et al., 2018; Ren et al., 2019). While some recent works (Wang et al., 2021c) have started exploring efficient input space adversarial training (e.g., for text classification), scaling adversarial training to pretrained language models like BERT has been challenging.

In this work, we in particular focus on improving the robustness of BERT against word substitution-based adversarial attacks. We propose an approach to adversarially finetune BERT-like models without using any labeled data. In order to achieve this, we rely on self-supervised contrastive learning (Chen et al., 2020). Self-supervised contrastive learning has recently gained attention in the community and contrastive learning has been used to learn better representations for text classification (Giorgi et al., 2021; Kim et al., 2021; Gao et al., 2021). However, how to use these methods to improve model robustness remains an open question.

We combine self-supervised contrastive learning with adversarial perturbations by using adversarial attacks to generate hard positive examples for contrastive learning. To efficiently create adversarial examples, we leverage an adversarial attack, that is capable of generating multiple adversarial examples in parallel. The attack adversarially creates hard positive examples for contrastive learning by iteratively replacing words to follow the direction of the contrastive loss (see fig. 2).

Experiments show that our method can improve the robustness of pretrained language models *without looking at the labels* (in other words, before finetuning). Additionally, by combining our method with adversarial training, we are able to obtain better robustness than conducting adversarial training alone (see section 4.4). Our study of the vector representations of clean examples and their corresponding adversarial examples indeed explains that our method improves model robustness by pulling clean examples and adversarial examples closer.

Our contributions[1] in this paper are two-fold. On the one hand, we improve the robustness of

*The first two authors contributed equally to this work.

[1] We will release our code at https://github.com/LotusDYH/ssl_robust

Findings of the Association for Computational Linguistics: NAACL 2022, pages 87 - 101
July 10-15, 2022 ©2022 Association for Computational Linguistics

the pretrained language model BERT against word substitution-based adversarial attacks by using self-supervised contrastive learning with adversarial perturbations (see section 3.2). On the other hand, to facilitate adversarial self-supervised contrastive learning, we create for BERT a word-level adversarial attack to create hard positive examples. The attack makes contrastive learning and adversarial training with *on-the-fly* generated adversarial examples possible. Additionally, we also show that our method is capable of using out-of-domain data to improve model robustness (see table 2 and section 4.4). This opens an opportunity for using large-scale unlabeled data to train robust language models against word substitution-based adversarial attacks.

2 Related Work

2.1 Adversarial Training for NLP

Adversarial training improves model robustness by augmenting clean examples with adversarial examples during training. Previous works on adversarial training for natural language mainly focus on perturbations in the vector space, while actual adversarial attacks create adversarial examples by changing natural language symbols. For example, Zhu et al. (2020) and Liu et al. (2020) improve model generalization ability by adversarial training on the word embedding space, without mentioning model robustness. However, they either ignore model robustness, or only test model robustness against the adversarial dataset ANLI, without paying attention to actual adversarial attacks. Other works conduct adversarial training in the word space (Alzantot et al., 2018; Ren et al., 2019). Still, they can only do adversarial training on a limited number of pre-generated adversarial examples due to the low efficiency of the attacks. A recent work (Wang et al., 2021c) conducts adversarial training efficiently in the word space, but their method is limited to non-contextualized models.

Apart from adversarial training, other supervised learning methods (Dong et al., 2021; Zhou et al., 2021; Wang et al., 2021a; Li and Qiu, 2020) have also been proposed to improve robustness. However, these methods are supervised and are not comparable to our work.

Our work also differs from previous works in natural language adversarial training. On the one hand, as opposed to previous works, which are supervised, we propose a self-supervised learning scheme to improve the robustness of pretrained language models. On the other hand, while previous works mostly focus on adversarial training in embedding space, we conduct efficient adversarial training with pretrained language models at the word level.

2.2 Contrastive Learning for NLP

Contrastive learning was first proposed in the image domain to improve model performance in a self-supervised fashion (He et al., 2020; Chen et al., 2020). These methods bring representations of similar examples closer and push representations of dissimilar examples further apart. Additionally, researchers also find that by adding adversarial perturbations during contrastive learning, image classification models become more robust against adversarial attacks (Kim et al., 2020).

In NLP, previous works on contrastive learning mainly focus on improving model generalization. Gunel et al. (2021) boost performance of RoBERTa by adding supervised signals during fine-tuning on downstream tasks. Lee et al. (2021) tackle the “exposure bias" problem in text generation by adding adversarial signals during contrastive learning. Other similar works include Pan et al. (2021), Giorgi et al. (2021), and Gao et al. (2021). Although these works have demonstrated the usefulness of contrastive learning in NLP applications, few have addressed the robustness of NLP models, particularly pretrained language models, against word substitution-based natural language adversarial attacks.

Recently, Wang et al. (2021b) claimed that their method improves model robustness against adversarial sets. However, such sets are pre-generated and are less challenging than adversarial examples generated on the fly by actual adversarial attacks (Jin et al., 2020; Ren et al., 2019). In this paper, we focus on improving the robustness of pretrained language models against word substitution-based adversarial attacks. We present the details of our method in section 3.

3 Methodology

In this section, we describe our method for self-supervised contrastive learning with adversarial perturbations. Specifically, section 3.1 gives the background and motivation of our problem, and section 3.2 describes the adversarial contrastive learning framework. Finally, in section 3.3, we

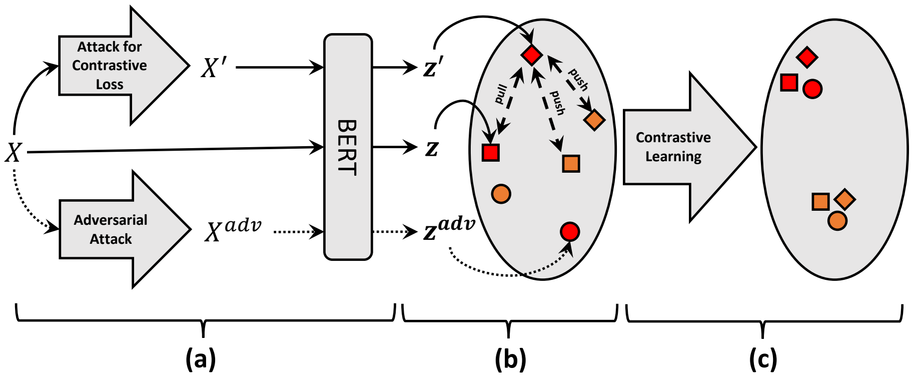


Figure 1: An illustration of our method. **(a)** For the original example X, we obtain the hard positive example X' by Geometry Attack for contrastive loss (see section 3.3). **(b)** Before contrastive learning, in the vector space, the clean example $\boldsymbol{z}$, the hard positive example $\boldsymbol{z}'$, and the adversarial example $\boldsymbol{z}^{adv}$ are far from each other. Contrastive learning pulls the clean example $\boldsymbol{z}$, and the hard positive example $\boldsymbol{z}'$ together. **(c)** After contrastive learning, the clean example $\boldsymbol{z}$, the hard positive example $\boldsymbol{z}'$, and the adversarial example $\boldsymbol{z}^{adv}$ are close. We omit MLP in this figure for simplicity. We use a different color to show another example from the dataset. See section 3 for details. Note that the adversarial example X^{adv} and its corresponding vector $\boldsymbol{z}^{adv}$ are not used in contrastive learning. We nevertheless show X^{adv} and $\boldsymbol{z}^{adv}$ for illustration purposes.

describe the adversarial attack used in contrastive learning.

3.1 Background and Motivation

In this work, we focus on text classification tasks[2]. Let us assume that we have an example text $X_i = \{w_1, w_2, \ldots, w_L\}$ with L words and let y_i be the corresponding class label for X_i. Our text classification model consists of a BERT encoder $f(\cdot)$ and an MLP classification head $c(\cdot)$.

We obtain the vector representation $\boldsymbol{h}_i \in \mathbb{R}^d$ of the example X_i by feeding X_i into the BERT encoder $f(\cdot)$. Then the MLP classification head $c(\cdot)$ takes $\boldsymbol{h}_i$ as input to give us the prediction. Formally, we have:

$$\begin{aligned} \boldsymbol{h}_i &= f(X_i) \\ \hat{y}_i &= c(\boldsymbol{h}_i) \end{aligned}$$

where $\hat{y}_i$ is the predicted label. We have $\hat{y}_i = y_i$ if the model prediction is correct.

A word substitution-based adversarial attack $a(\cdot)$ takes an original example X_i as input and generates an adversarial example X_i^{adv} by substituting the k-th original word w_k in X_i with another word w_k^{adv}. To make the orignal example X_i and the adversarial example X_i^{adv} close in semantics, existing works often use synonyms as substitutions (Ren et al., 2019; Morris et al., 2020).

By conducting the word substitution, the attack $a(\cdot)$ aims to fool the model with X_i^{adv}. Formally, we have:

$$\begin{aligned} X_i^{adv} &= a(X_i) \\ \boldsymbol{h}_i^{adv} &= f(X_i^{adv}) \\ \hat{y}_i^{adv} &= c(\boldsymbol{h}_i^{adv}) \end{aligned}$$

where $X_i^{adv} = \{w_1, w_2, \ldots, w_k^{adv}, \ldots, w_L\}, 1 \leq k \leq L$. Assuming the attack successfully fools the model, we would have $\hat{y}_i \neq \hat{y}_i^{adv}$. The key assumption in our approach is that although X_i and X_i^{adv} are very similar to each other at the word level, it is possible that the encoder f embeds them in such a way that the distance between their representations $\boldsymbol{h}_i$ and $\boldsymbol{h}_i^{adv}$ are large and the classification head $c(\cdot)$ predicts X_i and X_i^{adv} to be of different classes.

Thus, the goal of our method is to obtain a robust model, on which we have $y_i = \hat{y}_i$ and $\hat{y}_i = y_i^{adv}$. In other words, the robust model defends an adversarial example X_i^{adv} of the original example X_i successfully, if the robust model gives the same correct prediction on the original example X_i and the adversarial example X_i^{adv}. We use *attack success rate* as the evaluation metric for model robustness. The attack success rate is defined as the rate of an attack successfully fooling the model on all test examples.

To obtain a robust model, we optimize the encoder such that $\boldsymbol{h}_i$ and $\boldsymbol{h}_i^{adv}$ become similar to each other. We achieve this goal by conducting

[2] Although our formulation can also be extended to several other problems.

self-supervised contrastive learning on the encoder with adversarial perturbations, during which we use an attack to create *hard positive examples*, maximizing the contrastive loss. The rest this section gives the details of our method.

3.2 Self-Supervised Contrastive Learning with Adversarial Perturbations

Following previous works on self-supervised contrastive learning (He et al., 2020; Chen et al., 2020), we formulate our learning objectives as follows. Consider we have a batch of n examples and X_i is the i-th input, we first obtain $X_i' = t(X_i)$ as an augmentation of X_i by transformation $t(\cdot)$. We call X_i and X_i' a pair of positive examples. All other examples in the same batch are considered negative examples of X_i and X_i'.

To take advantage from using more negative examples, we use MoCo (He et al., 2020) as our framework, in which we employ an encoder f_q for the positive examples, and another momentum encoder f_k for the negative examples. We then have:

$$\boldsymbol{h}_i = f_q(X_i)$$
$$\boldsymbol{h}_i' = f_k(X_i')$$

where $\boldsymbol{h}_i, \boldsymbol{h}_i' \in \mathbb{R}^d$ are representations of X_i and X_i', respectively. During training, f_q and f_k are initialized the same. We update f_k momentarily:

$$\theta_k \leftarrow m \cdot \theta_k + (1-m) \cdot \theta_q$$

where θ_k and θ_q denote the parameters of f_k and f_q, respectively. We then have:

$$\boldsymbol{z}_i = g_q(\boldsymbol{h}_i)$$
$$\boldsymbol{z}_i' = g_q(\boldsymbol{h}_i')$$

where $\boldsymbol{z}_i, \boldsymbol{z}_i' \in \mathbb{R}^c$, $g_q(\cdot)$ and $g_k(\cdot)$ are MLPs with one hidden layer of sigmoid activation, respectively. Following Chen et al. (2020), we conduct contrastive learning on $\boldsymbol{z}$ instead of $\boldsymbol{h}$ to prevent the contrastive learning objective from removing information useful for downstream tasks. After contrastive learning, we use $\boldsymbol{h}$ as the sentence representation for downstream tasks.

Additionally, we also maintain a dynamic first-in-first-out queue for the negative examples. During training, before computing contrastive loss at the end of each batch, all encoded examples of the current batch are enqueued into the queue, and the oldest examples are dequeued simultaneously.

In our experiments, we use the attack described in section 3.3 or back-translation (Zhu et al., 2015) for augmentation $t(\cdot)$. Assume that we have an encoded example $\boldsymbol{z}_i$ and the encoded examples in the queue are $\{\boldsymbol{z}_0, \boldsymbol{z}_1, \cdots, \boldsymbol{z}_{Q-1}\}$, where Q is the size of the queue. Among the encoded examples in the queue, one of them is $\boldsymbol{z}_i'$, which forms a pair of positive examples with $\boldsymbol{z}_i$. We use contrastive loss to maximize the similarity between positive examples, while minimizing the similarity of negative examples. We then have:

$$\ell_i = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_i')/\tau)}{\sum_{k=0}^{Q} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)} \quad (1)$$

where τ is the temperature parameter, $\mathrm{sim}(\cdot,\cdot)$ is the similarity function, and Q is the size of the dynamic queue. In this paper, we compute similarity by dot product as in MoCo.

By optimizing eq. (1), the goal is to maximize the similarity of representations between similar (positive) pairs of examples while minimizing the similarity of representations between dissimilar (negative) examples. We use the geometry-inspired attack described in section 3.3 as the transformation $t(\cdot)$ to create pairs of examples that are similar on the word level but at the same time are distant from each other in the representation space.

We illustrate our method in fig. 1. In fig. 1 (b) and (c), by conducting contrastive learning and using the Geometry Attack generated adversarial examples as hard positives, the vector representations obtained from the model become *invariant* to the adversarial attacks.

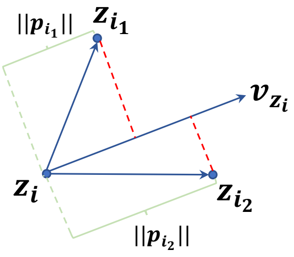

$||\boldsymbol{p}_{i_1}||$
$\boldsymbol{z}_{i_1}$
$\boldsymbol{v}_{\boldsymbol{z}_i}$
$\boldsymbol{z}_i$
$\boldsymbol{z}_{i_2}$
$||\boldsymbol{p}_{i_2}||$

Figure 2: An illustration of one iteration in Geometry Attack for contrastive loss. See section 3.3 for details.

3.3 Creating Hard Positive Examples by Geometry Attack

As mentioned in section 3.2, we use an attack as the transformation $t(\cdot)$ during contrastive learning.

We describe how this attack creates adversarial examples for contrastive loss during self-supervised contrastive learning (see fig. 1 (b)) in this subsection.

Inspired by Meng and Wattenhofer (2020), who leverage geometry of representations to generate natural language adversarial examples for text classification tasks, we also use the geometry of pre-trained representations to create adversarial examples for contrastive loss. The created adversarial examples are used as positive examples of the original examples in our contrastive learning framework, and at the same time are created to maximize the contrastive loss. Hence, we refer to adversarial examples created by the attack as *hard positive examples*.

The intuition of our attack is that we repeatedly replace words in the original texts such that in each iteration, the replaced word increases the contrastive loss as much as possible. To be specific, consider an example X_i, we then have:

1. **Determine Direction for Sentence Vector** Compute the gradients of ℓ_i with respect to $\boldsymbol{z}_i$. In this step, we find the direction we should move from $\boldsymbol{z}_i$ to increase the contrastive loss ℓ_i. We have the gradient vector $\boldsymbol{v}_{z_i} = \nabla_{\boldsymbol{z}_i} \ell_i$.
2. **Choose Original Word to be Replaced** Compute the gradients of ℓ_i with respect to input word embeddings of X_i. For words tokenized into multiple tokens, we take the average of the gradients of the tokens. In this step, we find the word w_t which has the most influence in computing ℓ_i. Specifically, assuming we have L words, then we choose $t = \arg\max_t\{||\boldsymbol{g}_1||, ||\boldsymbol{g}_2||, \ldots, ||\boldsymbol{g}_L||\}$, where $\boldsymbol{g}_k$ is the gradients of l_i with respect to the embeddings of word w_k, $1 \le k \le L$.
3. **Generate Candidate Set** Suppose we choose the word w_t in step 2. In this step, we use a pre-trained BERT to choose the most probable candidates w_t to replace it in the original text. We have the candidates set = $\{w_{t_1}, w_{t_2}, \cdots, w_{t_T}\}$. Following Jin et al. (2020), we filter out semantically different words from the candidate set by discarding candidate words of which the cosine similarity of their embeddings between the embeddings of w_t is below a threshold ϵ. We set the threshold $\epsilon = 0.5$ and use counter-fitted word embeddings (Mrkšić et al., 2016) to compute the cosine similarity.
4. **Choose Replacement Word** Replace w_t with words in the candidates set, resulting in text vectors $\{\boldsymbol{z}_{i_1}, \boldsymbol{z}_{i_2}, \cdots, \boldsymbol{z}_{i_T}\}$. We compute delta vector $\boldsymbol{r}_{i_j} \leftarrow \boldsymbol{z}_{i_j} - \boldsymbol{z}_i$. The projection of $\boldsymbol{r}_{i_j}$ onto $\boldsymbol{v}_{z_i}$ is: $\boldsymbol{p}_{i_j} \leftarrow \frac{\boldsymbol{r}_{i_j} \cdot \boldsymbol{v}_{z_i}}{||\boldsymbol{v}_{z_i}||}$. We select word w_{t_m}, where $m \leftarrow \operatorname{argmax}_j ||\boldsymbol{p}_{i_j}||$. In other words, w_{t_m} results in the largest projection $\boldsymbol{p}_{i_m}$ onto $\boldsymbol{v}_{z_i}$.
5. **Repetition** Replace w_t with w_{t_m} in X_i, then we have $\boldsymbol{z}_i \leftarrow \boldsymbol{z}_{i_m}$. Repeat step 1-4 for N iterations, where N is a hyperparameter of our method. We expect ℓ_i to increase in each iteration.

Figure 2 illustrates an iteration of our attack, in which we have two options to choose from the candidate set. This attack can be easily implemented in a batched fashion, making it possible for us to generate adversarial examples *on the fly* during training. Furthermore, our efficient implementation makes it possible to conduct contrastive learning with adversarial perturbations as well as adversarial training with adversarial examples generated on the fly. We give a speed comparison of our attack and other attacks in appendix D. We also give pseudocode of the attack in algorithm 1 of appendix A.

4 Experiments

4.1 Datasets and Evaluation Metrics

We test how our method improves model robustness on four text classification datasets: AG's News, Yelp, IMDB, and DBpedia (See appendix B for details).

We report the *attack success rate* and the *replacement rate* of the attacks as the evaluation metrics. Following Alzantot et al. (2018); Ebrahimi et al. (2018), to prevent the model accuracy on clean examples from confounding the results, we define the success rate of an attack on all *correctly classified* examples in the test set. Lower success rates indicate higher robustness. The replacement rate refers to the percent of original words replaced in the clean example. Higher replacement rates indicate that the attack needs to replace more words to fool the model, and thus mean that the model is more robust.

4.2 Attacks for Evaluating Robustness

We use four word substitution-based adversarial attacks to evaluate the model robustness.

Geometry Attack We use the same attack described in section 3.3 to generate adversarial examples for sentence classification tasks by replacing contrastive loss with *cross-entropy classification loss*. We set the maximum number of replaced words to 20.

TextFooler, **PWWS**, and **BAE-R** We use the default implementations from TextAttack (Morris et al., 2020).

All these attacks will give up and terminate once the *maximum number of replaced words* (sometimes also called *perturbation budget*) is reached.

4.3 Experimental Design

We have the following hypotheses for our method:

H1: Self-supervised contrastive learning improves model robustness against adversarial attacks. Moreover, using adversarial perturbations during contrastive learning further improves robustness.

To validate this hypothesis, we set three different pretraining schemes:

`BTCL`: Pretraining with back-translation as the transformation $t(\cdot)$ for self-supervised contrastive learning.

`ADCL`: Pretraining with Geometry Attack for contrastive loss (see section 3.3) as transformation $t(\cdot)$ for self-supervised contrastive learning.

`NP`: Apart from the above two settings, we also add a *No Pretraining* baseline to understand the general effectiveness of contrastive learning.

H2: Combining self-supervised contrastive learning with adversarial training gives higher robustness than conducting adversarial training alone.

We use different finetune strategies to understand how adding adversarial training to our method affects model robustness. We have two settings:

`FTC`: We finetune the pretrained model on the clean examples of the corresponding downstream dataset.

`ADV`: We conduct adversarial training by leveraging supervisedly generated adversarial examples. Note that our adversarial training is different from previous works (Ren et al., 2019; Alzantot et al., 2018), which merely finetune the model on a fixed number of pre-generated adversarial examples. Instead, our adversarial training scheme is similar to Madry et al. (2018), where the model is finetuned on clean examples and adversarial examples generated *on the fly* during each batch of training.

We use Geometry Attack for adversarial training as the remaining three attacks are not efficient enough to generate adversarial examples *on the fly* (see appendix D for details).

H3: Our contrastive learning method is capable of using out-of-domain data to improve the model robustness.

While in H1 and H2, we use the same dataset for pretraining and finetuning, we want to test how our method can leverage out-of-domain data. Hence, we have two additional experimental settings:

`In-Domain`: We use the same dataset during contrastive learning and finetuning.

`Out-of-Domain`: We use different datasets for contrastive learning and finetuning.

H4: By optimizing eq. (1), our method pulls the representations of the clean samples and their corresponding hard positive examples closer in the vector space while pushing other different examples further. In this way, the representations of clean examples and their adversarial examples are also closer in the vector space.

We validate this hypothesis by conducting a vector space study. See section 4.4 for details.

Note that to avoid confusing adversarial examples generated during contrastive learning and adversarial examples generated during finetuning, we refer to the former as *hard positive examples* (see section 3.3).

4.4 Results

Table 1 shows the experimental results for validating H1 and H2. For each dataset, when evaluating the model robustness, we use the same perturbation budget across different settings. Note that although the replacement rates vary across different settings of the same dataset, *the perturbation budget for the same attack is the same* in these settings. By using the same perturbation budget, we ensure that the success rates of the attacks provide us with a fair evaluation of the robustness of the model (Wang et al., 2021c; Ren et al., 2019).

H1: To validate H1, we focus on rows with the `FTC` setting during finetuning. We can observe that models without any contrastive pretraining (`NP`) are the most vulnerable to adversarial attacks. For example, the success rate of the Geometry Attack for AG's News dataset is 86.2% for the `NP` model. In contrast, for `BTCL` and `ADCL`, the success rate of the Geometry Attack is at least 5.6% lower than this setting. This shows that *self-supervised contrastive learning does improve model robustness*.

Additionally, we can also see from table 1 that `ADCL` improves the model robustness more than `BTCL`. For example, in the IMDB dataset, the model pretrained with `ADCL` is 9.1% more robust than the model pretrained with `BTCL` (93.3% → 84.2%), showing that *using adversarial perturbations during contrastive learning further improves model robustness against adversarial at-*

Dataset	Pretrain	Finetune	Acc. (%)	Success Rate (%) ↓				Replaced (%) ↑			
				Geometry	TextFooler	PWWS	BAE-R	Geometry	TextFooler	PWWS	BAE-R
AG	NP	FTC	94.2	86.2	87.6	63.6	17.9	18.6	25.7	20.9	7.4
		ADV	94.4	*20.7*	*25.1*	*26.1*	*10.7*	*20.5*	*29.3*	**22.3**	**7.7**
	BTCL	FTC	94.4	80.6	84.6	63.1	17.7	18.1	24.6	20.9	7.5
	ADCL	FTC	94.3	76.5	80.7	55.9	14.1	19.1	26.7	*22.6*	*7.5*
		ADV	94.4	**18.7**	**23.5**	**24.7**	**9.7**	**20.6**	**29.3**	22.2	7.2
Yelp	NP	FTC	97.1	94.6	94.3	97.0	42.1	10.6	10.4	7.1	6.7
		ADV	96.2	*38.8*	*52.4*	*62.7*	*22.2*	*12.8*	**17.3**	**11.3**	**8.8**
	BTCL	FTC	97.1	92.3	91.6	94.8	39.2	11.0	10.1	7.7	6.9
	ADCL	FTC	97.0	88.6	88.2	91.1	37.8	10.4	10.5	7.4	6.9
		ADV	96.1	**35.6**	**50.1**	**61.0**	**21.0**	**13.4**	*17.1*	*11.2*	*8.3*
IMDB	NP	FTC	92.3	98.7	99.0	99.2	54.0	3.5	6.5	4.3	3.0
		ADV	92.0	*51.4*	*75.3*	*79.1*	*35.1*	*7.4*	**12.7**	**9.3**	**3.6**
	BTCL	FTC	92.5	93.3	96.6	95.1	52.0	4.5	7.4	4.4	3.3
	ADCL	FTC	92.4	84.2	87.8	87.8	48.0	3.7	8.7	5.1	2.3
		ADV	91.9	**48.7**	**74.4**	**77.6**	**31.8**	**8.1**	*12.4*	*9.1*	*3.5*
DBpedia	NP	FTC	99.2	79.6	79.3	46.7	14.3	17.8	23.2	16.2	13.3
		ADV	99.0	*13.9*	*16.5*	*17.7*	*10.9*	**21.6**	*28.2*	**18.9**	**14.1**
	BTCL	FTC	99.2	77.4	76.8	45.1	13.0	18.9	22.8	18.1	13.1
	ADCL	FTC	99.1	73.6	74.5	42.6	11.6	18.2	22.9	17.6	12.8
		ADV	99.0	**12.4**	**14.8**	**16.2**	**10.1**	*20.1*	**28.6**	*18.2*	*13.8*

Table 1: Experimental results for H1 and H2. In-Domain setting is used. We **bold** the best results, while the second best is in *italic*.

tacks. Hence, we do not combine BTCL with ADV in later experiments for simplicity.

To further understand how contrastive learning improves the model robustness, we study the transferability of the adversarial examples between models without any contrastive pretraining (NP) and the models pretrained with ADCL. To be specific, the models are first pretrained using either NP or ADCL, and then finetuned on clean examples (FTC). Then, we use a NP model to generate adversarial examples on the test set of each dataset, and then test the corresponding model pretrained with ADCL on these adversarial examples. And vice versa.

Table 3 shows the results. We can see that adversarial examples generated by models pretrained with ADCL have much higher success rates on models without any contrastive pretraining (NP). For example, for the AG's News dataset, the success rates increase by 32.1%, 35.3%, 33.8%, and 22.1% for Geometry Attack, TextFooler, BAE-R, and PWWS, respectively. This demonstrates that by self-supervised contrastive learning with adversarial perturbations, the models become more robust against attacks.

H2: To validate H2, we compare two settings of NP + ADV and ADCL + ADV. We note that when compared with conducting adversarial training alone (NP + ADV), *combining our self-supervised contrastive learning method with adversarial training (ADCL + ADV) constantly results in higher robustness*. In other words, the adversarial attacks have lower success rates and higher replacement rate in ADCL + ADV models than in NP + ADV models. For instance, for the IMDB dataset, the ADCL + ADV model is 2.7% more robust than the NP + ADV model, when both models are tested against the Geometry Attack (Success rates of Geometry attack: ADCL + ADV: 48.7%, NP + ADV: 51.4%; Replacement rates: ADCL + ADV: 8.1%, NP + ADV: 7.4%).

Note that when test NP + ADV models and ADCL + ADV models against the other three adversarial attacks, ADCL + ADV models do not show an advantage over NP + ADV models in terms of replacement rates, despite that ADCL + ADV models still constantly make lower success rates against the adversarial attacks. We argue that this is because we use the Geometry Attack for adversarial training during finetuning, and the adversarial examples from the Geometry Attack might not fully match the distribution from the other attacks. Nevertheless, we can still conclude that ADCL + ADV models are more robust than NP + ADV models.

Our experiments also show that during con-

Dataset	Domain	Pretrain	Acc. (%)	Success Rate (%) ↓				Replaced (%)↑			
				Geometry	TextFooler	PWWS	BAE-R	Geometry	TextFooler	PWWS	BAE-R
AG	-	NP	94.2	86.2	87.6	63.6	17.9	18.6	25.7	20.9	7.4
	In-Domain	BTCL	94.4	80.6	84.6	63.1	17.7	18.1	24.6	20.9	**7.5**
		ADCL	94.3	**76.9**	**80.7**	**55.9**	**14.1**	**19.1**	**26.7**	**22.6**	**7.5**
	Out-of-Domain	ADCL	94.1	*79.2*	*84.0*	*60.4*	*16.3*	*18.7*	*25.9*	*21.9*	**7.5**
IMDB	-	NP	92.3	98.7	99.0	99.2	54.0	3.5	6.5	4.3	3.0
	In-Domain	BTCL	92.5	93.3	96.6	95.1	52.0	**4.5**	7.4	4.4	**3.3**
		ADCL	92.4	**84.2**	**87.8**	**87.8**	**48.0**	3.7	**8.7**	*5.1*	2.3
	Out-of-Domain	ADCL	92.5	*92.3*	*95.7*	*94.5*	*50.1*	*4.4*	*8.6*	**5.3**	*3.1*

Table 2: Comparison of Out-of-Domain with In-Domain. We use the DBpedia dataset as the out-of-domain dataset for AG's News and IMDB. Models are finetuned on clean examples after pretraining (FTC). Best results are **bolded**, while the second best are in *italic*.

Dataset	Attack	Success Rate (%)	
		NP → ADCL	ADCL → NP
AG	Geometry	30.2	62.3
	TextFooler	19.7	55.0
	BAE-R	26.4	60.2
	PWWS	28.3	50.4
Yelp	Geometry	30.1	36.4
	TextFooler	22.4	28.0
	BAE-R	37.4	41.5
	PWWS	34.8	36.3
IMDB	Geometry	38.2	41.4
	TextFooler	22.1	25.2
	BAE-R	28.9	30.8
	PWWS	24.7	26.0
DBpedia	Geometry	34.6	52.2
	TextFooler	27.5	42.8
	BAE-R	32.5	55.8
	PWWS	55.3	58.8

Table 3: Transferability of adversarial examples. The models are pretrained under either NP or ADCL, and then finetuned on clean examples. NP → ADCL: Generate adversarial examples with the model pretrained with NP, then test the model pretrained with ADCL on these adversarial examples. Same applies to ADCL → NP.

trastive learning, the queue size (see section 3.2) has an impact on the final performance. We give the detailed analysis in appendix C.

H3: For the Out-of-Domain setting, we use the DBpedia dataset as the out-of-domain dataset for the AG's News and IMDB datasets, mainly because (1) Computational limits: While using larger datasets such as BookCorpus or Wikipedia might be more useful, conducting self-supervised contrastive learning on these datasets exceeds the limits of our computational infrastructure; (2) The DBpedia dataset is several times larger than AG's News and IMDB. This should give us a glimpse of what it looks like when we scale self-supervised contrastive learning with adversarial perturbations to even larger out-of-domain datasets; (3) The DBpedia dataset (topic classification on Wikipedia) has a different task and domain compared to the AG's News dataset (news classification from a newspaper) and IMDB dataset (sentiment classification on movie reviews). This discrepancy allows us to understand how *out-of-domain* datasets could help.

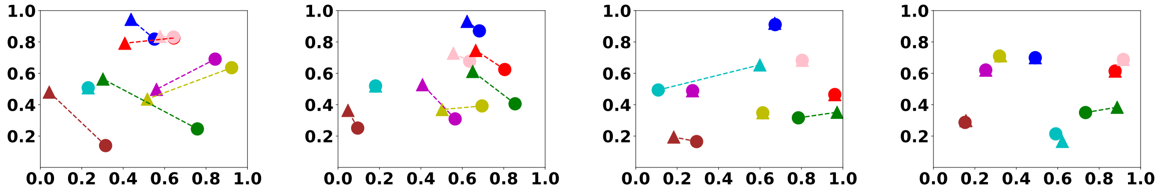
Table 2 shows our results. We can see that models pretrained with ADCL under the Out-of-Domain setting are more robust than models without any pretraining at all (NP). This shows that *our method can improve model robustness using out-of-domain data.* For instance, for the IMDB dataset, the success rate of TextFooler decreases from 98.7% for FT models to 92.3% for Out-of-Domain ADCL models. This shows that our method can improve the model robustness even if the dataset used for contrastive learning is from a completely different domain. Note that in table 2, after pretraining, we finetune the model on clean examples (FTC).

We also notice that models pretrained with ADCL under the Out-of-Domain setting are not as robust as models pretrained with ADCL under the In-Domain setting. This indicates we might need to use much larger unlabeled raw datasets to obtain more improvements.

H4: To validate this hypothesis, we study the vector representations of $M = 1000$ clean examples of the AG's News dataset and their corresponding adversarial examples. We obtain the adversarial examples by attacking a NP + FTC model.

Let $\boldsymbol{v}_1, \boldsymbol{v}_2 ... \boldsymbol{v}_M$ and $\boldsymbol{v}'_1, \boldsymbol{v}'_2 ... \boldsymbol{v}'_M$ be the vector representations of the clean examples and corresponding adversarial samples, respectively. For each setting, we evaluate three metrics:

- Average distance d_{pos} between each of the posi-



(a) NP + FTC (b) ADCL + FTC (c) NP + ADV (d) ADCL + ADV

Figure 3: t-SNE plot of the vector representations of clean examples and adversarial examples from the AG's News dataset. Markers of the same color indicate a pair of clean example (○) and adversarial example (△). Check section 4.4 for the evaluation settings. The ranges of x-axis and y-axis are normalized to [0, 1]. We connect each clean example by a dotted line to its corresponding adversarial example.

Dataset	Distance ($d_{pos}/d_{neg}/\delta$)			
	NP + FTC	ADCL + FTC	NP + ADV	ADCL + ADV
AG	2.4/3.9/1.5	1.8/4.0/2.2	0.7/4.1/3.4	0.7/4.4/3.7
Yelp	3.5/3.7/0.2	2.9/4.0/1.1	0.7/3.2/2.5	0.5/3.4/2.9
IMDB	3.0/3.7/0.7	2.3/3.8/1.5	0.6/3.4/2.8	0.6/3.8/3.2
DBpedia	2.8/4.8/2.0	2.3/5.1/2.8	0.4/4.9/4.5	0.4/5.2/4.8

Table 4: Vector space study. For each setting, we evaluate three metrics: (a) Average distance between positive pairs; (b) Average distance between negative pairs; (c) Difference between (a) and (b).

tive pairs v_i and v'_i, where $1 \leq i \leq M$. Then we have:

$$d_{pos} = \frac{1}{M} \sum_{i=1}^{M} d(\boldsymbol{v}_i, \boldsymbol{v}'_i)$$

where $d(\cdot, \cdot)$ denotes the distance between two vectors.

- Average distance d_{neg} between negative pairs:

$$d_{neg} = \sum_{i=1}^{M} \sum_{j=1}^{M} \frac{\mathbb{1}_{i \neq j}(d(\boldsymbol{v}_i, \boldsymbol{v}_j) + d(\boldsymbol{v}_i, \boldsymbol{v}'_j))}{2(M-1)}$$

- Difference $\delta = d_{neg} - d_{pos}$ between (a) and (b).

Furthermore, we evaluate the above metrics under the following settings:

- NP + FTC: Finetune on clean examples.
- ADCL + FTC: First do ADCL pretraining, and then finetune on clean examples.
- NP + ADV: Finetune with adversarial training.
- ADCL + ADV: First do ADCL pretraining. Then finetune with adversarial training.

Table 4 shows the results. We can see that our method (1) increases the distance between negative pairs in all settings; (2) decreases the distance between positive pairs in NP + FTC and ADCL + FTC models, while the distances between positive pairs barely change in NP + ADV and ADCL + ADV models; (3) increases δ in all settings. The above observations validate H4 in section 4.3, and further explain that our method achieves higher robustness by pushing vector representations of clean examples and adversarial examples closer.

In fig. 3, we further give qualitative analysis on the distances between clean examples and adversarial examples of the AG's News dataset by showing the t-SNE plot. We can see from the plot that the distances between the clean examples and the corresponding adversarial examples are closer when we apply ADCL pretraining, and that combining ADCL with ADV gives the smallest distance between supervised adversarial examples. Additional plots of other datasets are available in appendix H.

5 Conclusion and Future Work

In this paper, we improve the robustness of pretrained language models against word substitution-based adversarial attacks by using self-supervised contrastive learning with adversarial perturbations. Our method is different from previous works as we can improve model robustness without accessing annotated labels. Furthermore, we also conduct word-level adversarial training on BERT with *on-the-fly* generated adversarial examples. Our adversarial training is different from previous works in that (1) it is on the word level; (2) we generate adversarial examples on the fly, instead of generating a fixed adversarial set beforehand. Experiments show that our method improves model robustness. We find that combining our method with adversarial training results in better robustness than conducting adversarial training alone. In the future, we plan to scale our method to even larger out-of-domain datasets.

Ethical Considerations

To the best of our knowledge, the data used in our work does not contain sensitive information. Although our models are evaluated on academic datasets in this paper, they could also be used in sensitive contexts, e.g. healthcare or legal scenarios. It is essential that necessary anonymization and robustness evaluation is undertaken before using our models in these settings.

Acknowledgements

Mrinmaya Sachan acknowledges support from an ETH Zürich Research grant (ETH-19 21-1) and a grant from the Swiss National Science Foundation (project #201009) for this work.

References

Moustafa Alzantot, Yash Sharma, Ahmed Elgohary, Bo-Jhang Ho, Mani Srivastava, and Kai-Wei Chang. 2018. Generating natural language adversarial examples. In *EMNLP*.

Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey E. Hinton. 2020. A simple framework for contrastive learning of visual representations. In *ICML*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *NAACL*.

Xinshuai Dong, Anh Tuan Luu, Rongrong Ji, and Hong Liu. 2021. Towards robustness against natural language word substitutions. In *ICLR*.

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. 2018. HotFlip: White-box adversarial examples for text classification. In *ACL*.

Tianyu Gao, Xingcheng Yao, and Danqi Chen. 2021. Simcse: Simple contrastive learning of sentence embeddings. In *EMNLP*.

John Giorgi, Osvald Nitski, Bo Wang, and Gary Bader. 2021. DeCLUTR: Deep contrastive learning for unsupervised textual representations. In *ACL*.

Beliz Gunel, Jingfei Du, Alexis Conneau, and Ves Stoyanov. 2021. Supervised contrastive learning for pretrained language model fine-tuning. In *ICLR*.

Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross B. Girshick. 2020. Momentum contrast for unsupervised visual representation learning. In *CVPR*.

Robin Jia and Percy Liang. 2017. Adversarial examples for evaluating reading comprehension systems. In *EMNLP*.

Di Jin, Zhijing Jin, Joey Tianyi Zhou, and Peter Szolovits. 2020. Is bert really robust? a strong baseline for natural language attack on text classification and entailment. In *AAAI*.

Minseon Kim, Jihoon Tack, and Sung Ju Hwang. 2020. Adversarial self-supervised contrastive learning. In *NeurIPS*.

Taeuk Kim, Kang Min Yoo, and Sang-goo Lee. 2021. Self-guided contrastive learning for BERT sentence representations. In *ACL*.

Seanie Lee, Dong Bok Lee, and Sung Ju Hwang. 2021. Contrastive learning with adversarial perturbations for conditional text generation. In *ICLR*.

Linyang Li and Xipeng Qiu. 2020. Tavat: Token-aware virtual adversarial training for language understanding. *arXiv preprint arXiv:2004.14543*.

Xiaodong Liu, Hao Cheng, Pengcheng He, Weizhu Chen, Yu Wang, Hoifung Poon, and Jianfeng Gao. 2020. Adversarial training for large neural language models. *arXiv preprint arXiv:2004.08994*.

Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In *ACL*.

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. 2018. Towards deep learning models resistant to adversarial attacks. In *ICLR*.

Zhao Meng and Roger Wattenhofer. 2020. A geometry-inspired attack for generating natural language adversarial examples. In *COLING*.

John Morris, Eli Lifland, Jin Yong Yoo, Jake Grigsby, Di Jin, and Yanjun Qi. 2020. TextAttack: A framework for adversarial attacks, data augmentation, and adversarial training in NLP. In *EMNLP: System Demonstrations*.

Nikola Mrkšić, Diarmuid Ó Séaghdha, Blaise Thomson, Milica Gašić, Lina M. Rojas-Barahona, Pei-Hao Su, David Vandyke, Tsung-Hsien Wen, and Steve Young. 2016. Counter-fitting word vectors to linguistic constraints. In *NAACL*.

Xiao Pan, Mingxuan Wang, Liwei Wu, and Lei Li. 2021. Contrastive learning for many-to-many multilingual neural machine translation. In *ACL*.

Shuhuai Ren, Yihe Deng, Kun He, and Wanxiang Che. 2019. Generating natural language adversarial examples through probability weighted word saliency. In *ACL*.

Boxin Wang, Shuohang Wang, Yu Cheng, Zhe Gan, Ruoxi Jia, Bo Li, and Jingjing Liu. 2021a. Infobert: Improving robustness of language models from an information theoretic perspective. In *ICLR*.

Dong Wang, Ning Ding, Piji Li, and Haitao Zheng. 2021b. CLINE: Contrastive learning with semantic negative examples for natural language understanding. In *ACL*.

Xiaosen Wang, Yichen Yang, Yihe Deng, and Kun He. 2021c. Adversarial training with fast gradient projection method against synonym substitution based text attacks. In *AAAI*.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. *arXiv preprint arXiv:1509.01626*.

Yi Zhou, Xiaoqing Zheng, Cho-Jui Hsieh, Kai-Wei Chang, and Xuanjing Huang. 2021. Defense against synonym substitution-based adversarial attacks via Dirichlet neighborhood ensemble. In *ACL*.

Chen Zhu, Yu Cheng, Zhe Gan, Siqi Sun, Tom Goldstein, and Jingjing Liu. 2020. Freelb: Enhanced adversarial training for natural language understanding. In *ICLR*.

Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In *ICCV*.

A Geometry Attack for Contrastive Loss

Algorithm 1 is the pseudocode of our Geometry Attack for contrastive loss. Refer to Section 3.3 for more details.

B Datasets

Dataset	Labels	Avg Len	Train	Test
AG's News	4	44	120K	7.6K
IMDB	2	292	25K	25K
DBPedia	14	67	560K	70K
Yelp	2	177	560K	38K

Table 5: Statistics of the datasets.

The statistics of each dataset are shown in Table 5. In our work, the maximum sequence length is set to 128 for AG's News and DBpedia, 256 for Yelp, and 512 for IMDB. To save time during evaluating the model robustness against attacks, we randomly select a part of the test examples in each dataset for evaluation. Specifically, we select 1,000 samples from IMDB, 2,000 samples from Yelp, and 5,000 samples from DBpedia. We use all 7,600 samples from the AG's News test set for evaluation.

AG's News[3] Topic classification dataset with four types of news articles: World, Sports, Business and Science/Technology.

IMDB (Maas et al., 2011) Binary sentiment classification dataset on positive and negative movie reviews.

Yelp Yelp review dataset for binary sentiment classification. Following Zhang et al. (2015), reviews with star 1 and 2 are considered negative, and reviews with star 3 and 4 are considered positive.

DBpedia (Zhang et al., 2015) Topic classification dataset with 14 non-overlapping classes. Both content and title fields are used in our work.

C Effect of Queue Size

We conduct additional experiments to study the effect of queue size. We use a queue size of 8192, 16384, 32768, and 65536 under the setting of ADCL+FT for the AG's News dataset. As is shown in Table 6, a larger queue size generally helps improve the model robustness. However, we also notice that when the queue size is too large (65536), the model robustness starts to decrease. We argue that this is because a too large queue size results in less frequent queue updates, which makes the vectors in the queue stale.

Queue Size	Original Acc. (%)	Success (%)	Replaced (%)
Vanilla	94.2	86.2	18.6
8192	94.4	77.8	18.9
16384	94.3	76.9	18.7
32768	94.3	**76.5**	19.1
65536	94.4	76.7	19.3

Table 6: Effect of queue size. We use the Geometry Attack to evaluate the robustness of each model. The FT model is finetuned without contrastive learning.

D Speed of Different Attacks

We show in Table 7 the average number of seconds each attack needs for one example. We obtain the average time by attacking 1000 examples and then taking the average. We can observe that the Geometry attack is at least four times faster than TextFooler, and 4 to 10 times faster than PWWS and BAE-R.

Attack	AG's News	IMDB	DBpedia	Yelp
Geometry	0.44	2.02	0.69	1.16
TextFooler	2.48	8.69	2.89	4.86
PWWS	6.29	21.86	2.52	10.27
BAE-R	5.37	24.10	7.74	16.03

Table 7: Average number of seconds each attack needs for an example.

E Adversarial Training with Pre-generated Examples

We compare two different methods for adversarial training:

- **Pre-generated** We pre-generate for each example in the training set an adversarial example. We then augment the original training set with the adversarial examples. Finally, the model is finetuned on the augmented dataset.

- **On-the-fly** This setting is the same as ADV in Table 1, where we generate adverarial examples on the fly for each mini-batch during training.

Table 8 shows the results on the AG's News dataset. We can see that on all four attacks, adversarial training with on-the-fly generated adversarial

[3] http://groups.di.unipi.it/~gulli/AG_corpus_of_news_articles.html

Algorithm 1 Geometry Attack for Contrastive Loss

```
**Input:** Example $X_i = \{w_1, w_2, \dots, w_L\}$, encoder $f$ and MLP $g$
**Output:** Adversarial example $X_i'$
Initialize $\boldsymbol{z}_i \leftarrow g(f(X_i))$
**for** iter = 1 to $N$ **do**
    calculate $\ell_i$ using Equation 1
    $\boldsymbol{v}_{z_i} \leftarrow \nabla_{\boldsymbol{z}_i} \ell_i$
    $\boldsymbol{E} \leftarrow \texttt{BertEmbeddings}(X_i') = \{\boldsymbol{e}_1, \boldsymbol{e}_2, \dots, \boldsymbol{e}_L\}$
    $\boldsymbol{G} \leftarrow \nabla_{\boldsymbol{E}} \ell_i = \{\boldsymbol{g}_1, \boldsymbol{g}_2, \dots, \boldsymbol{g}_L\}$
    $t \leftarrow \arg\max_t ||\boldsymbol{g}_t||$
    $C \leftarrow \texttt{BertForMaskedLM}(\{w_1, \cdots, w_{t-1}, \texttt{[MASK]}, w_{t+1}, \cdots, w_L\})$
    $C \leftarrow \texttt{Filter}(C)$ // construct candidates set $C = \{w_{t_1}, w_{t_2}, \cdots, w_{t_T}\}$; filter using counter-fitted embeddings
    **for** each $w_{t_j} \in C, 1 \leq j \leq T$ **do**
        $X_{i_j} \leftarrow \{w_1, \cdots, w_{t-1}, w_{t_j}, w_{t+1}, \cdots, w_L\}$
        $\boldsymbol{z}_{i_j} \leftarrow g(f(X_{i_j}))$
        $\boldsymbol{r}_{i_j} \leftarrow \boldsymbol{z}_{i_j} - \boldsymbol{z}_i$
        $\boldsymbol{p}_{i_j} \leftarrow \frac{\boldsymbol{r}_{i_j} \cdot \boldsymbol{v}_{z_i}}{||\boldsymbol{v}_{z_i}||}$
    **end for**
    $m \leftarrow \arg\max_j ||\boldsymbol{p}_{i_j}||$
    $X_i \leftarrow X_{i_m}$
    $\boldsymbol{z}_i \leftarrow \boldsymbol{z}_{i_m}$
**end for**
$X_i' \leftarrow X_i$
**return** $X_i$
```

Dataset	**Success Rate / Replaced (%)**			
	Geometry	TextFooler	PWWS	BAE-R
Pre-generated	55.3/17.1	59.4/22.6	42.0/17.4	16.5/7.3
On-the-fly	20.7/20.5	25.1/29.3	26.1/22.3	10.7/7.7

Table 8: Comparison between adversarial training with pre-generated adversarial examples and on-the-fly generated adversarial examples.

examples gives higher robustness than adversarial training with pre-generated adversarial examples.

F Implementation Details

In our paper, we use PyTorch Lightning[4] and HuggingFace Transformers[5] in our implementation. We use BERT as the encoder $f(\cdot)$, and the representation of the [CLS] symbol in the last layer is used for $\boldsymbol{h}$. $g(\cdot)$ is a two-layer MLP, of which the output size c is 128. $g(\cdot)$ uses Tanh as activation function in the output layer. We use FP16 in training step to reduce GPU memory usage, and use FusedAdam from DeepSpeed[6] as the optimizer. We enable DeepSpeed ZeRO Stage 2 to further speed up training. We conduct all our experiments on 8 RTX TITAN GPUs.

Contrastive learning For Geometry Attack for contrastive loss, to reach a balance between attack success rate and efficiency, the maximum number of iterations K is set to 10 for AG's News, DBpedia, and Yelp, and 15 for IMDB dataset. We do not perturb words that were already perturbed in previous iterations. For an example $X_i = \{w_1, w_2, \dots, w_L\}$, at most $min\{K, 0.2 \cdot L\}$ words can be perturbed. For each word $w_t, 1 \leq t \leq L$, the upper limit of the candidate set size T is set to 25. Due to the various maximum lengths in downstream datasets and GPU memory limits, we use different batch sizes for different datasets. During contrastive learning, the batch size is set to 1024 for AG's News and DBpedia, 448 for Yelp, and 192 for IMDB.

Fine-tuning During finetuning, we train the model for two epochs for AG's News and DBpedia, 3 for

[4] https://www.pytorchlightning.ai/

[5] https://huggingface.co/transformers/

[6] https://www.deepspeed.ai/

Yelp, and 4 for IMDB. The learning rate is set to $2e-5$ and is adjusted using linear scheduling.

Adversarial training For adversarial training, the number of training epochs is set to 3 with an additional first epoch of finetuning on clean examples. The adversarial examples are generated *on the fly* in each batch during training. For the Geometry Attack in adversarial training, at most $\mathtt{min}\{K, 0.4 \cdot \mathtt{len}(X_i)\}$ words can be perturbed in an example. The upper limit of the candidate set size is set to 50.

Back Translation We use pretrained translation models `opus-mt-en-roa` and `opus-mt-roa-en` from Helsinki-NLP to generate one translation for each example.

G Hard Positive Examples from Geometry Attack for Contrastive Loss

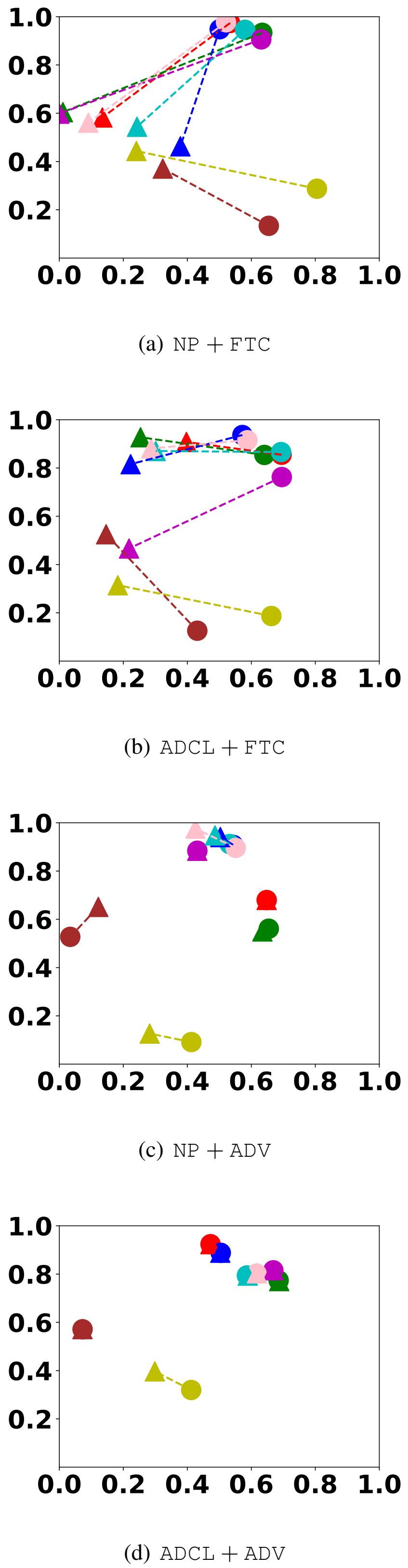
In Table 9, we show hard positive examples generated by our Geometry Attack for contrastive loss from the AG's News dataset.

`Original`	Zurich employees plead guilty in probe new york (reuters) - two senior insurance underwriters at zurich american insurance co pleaded guilty on tuesday to misdemeanors related to bid-rigging in the insurance market.
`Adversarial`	Zurich employees plead guilty in probe new york (reuters) - two senior insurance agents at zurich american insurance co testified guilty on tuesday to violations related to bid-rigging in the insurance market.
`Original`	Black watch troops move into position the first units of a black watch battlegroup are due to arrive today in their new positions south of baghdad as tony blair indicated that more british troops may replace them in the american - controlled zone before the end of the year.
`Adversarial`	Black watch troops move into place the first units of a black watch operation are due to arrive today in their new positions south of baghdad as tony blair indicated that more british troops may replace them in the american - controlled zone before the end of the year.

Table 9: Hard positive examples generated by Geometry Attack for contrastive loss. Blue words in the original examples are replaced by red words in the adversarial examples.

H Additional t-SNE plots

We give t-SNE plots of the vector representations of clean examples and adversarial examples from Yelp, IMDB and DBpedia in fig. 4, fig. 5 and fig. 6, respectively.



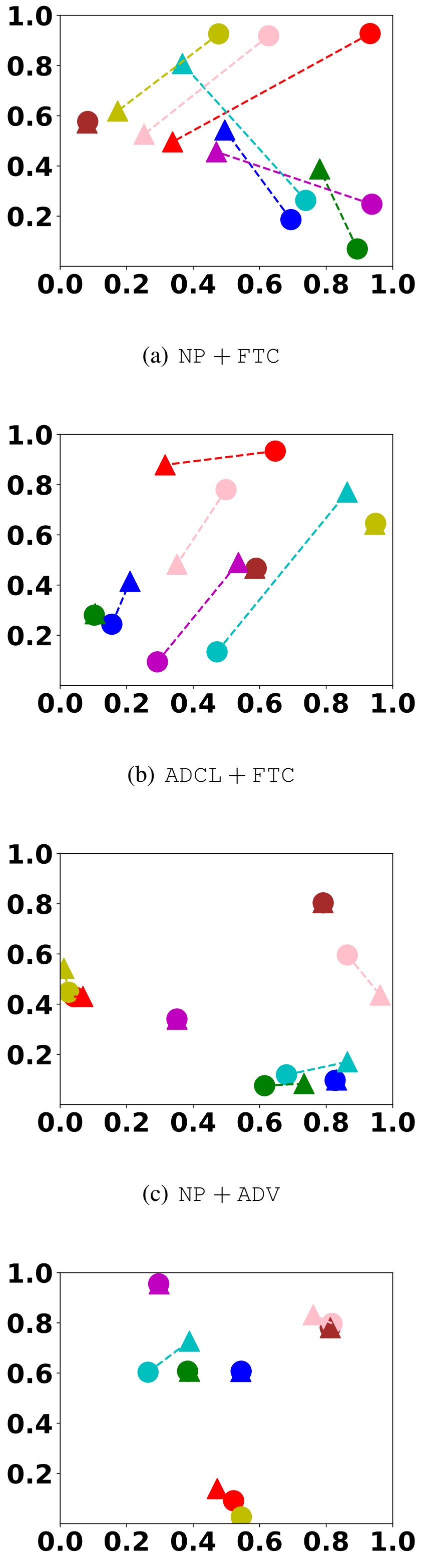
(a) `NP + FTC`

(b) `ADCL + FTC`

(c) `NP + ADV`

(d) `ADCL + ADV`

Figure 4: t-SNE plot of the vector representations of clean examples and adversarial examples from the Yelp dataset.



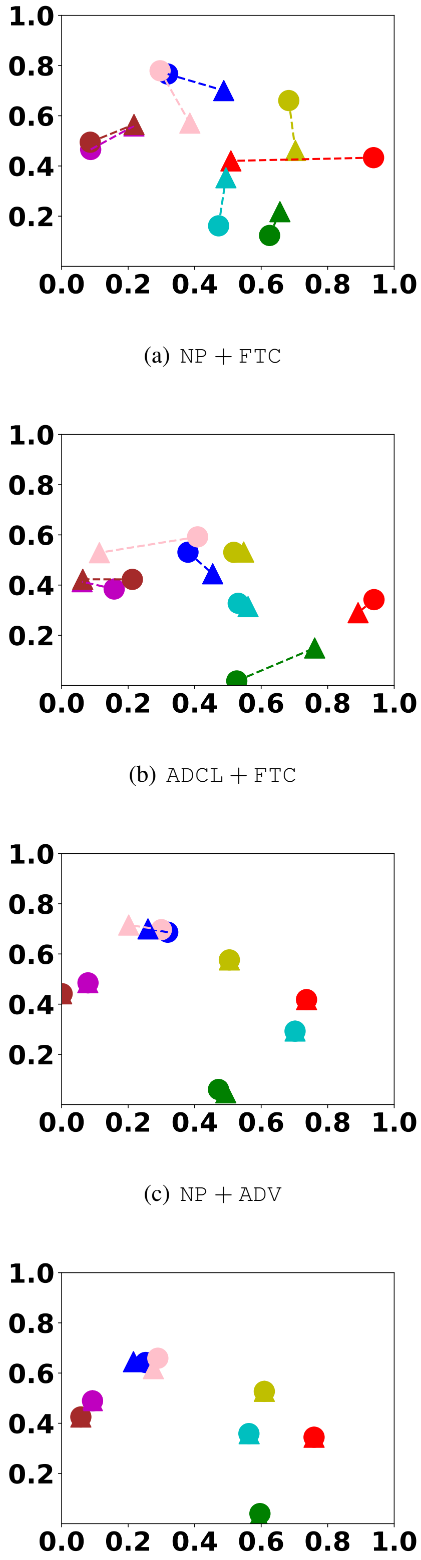
(a) NP + FTC

(b) ADCL + FTC

(c) NP + ADV

(d) ADCL + ADV

Figure 5: t-SNE plot of the vector representations of clean examples and adversarial examples from the IMDB dataset.



(a) NP + FTC

(b) ADCL + FTC

(c) NP + ADV

(d) ADCL + ADV

Figure 6: t-SNE plot of the vector representations of clean examples and adversarial examples from the DBpedia dataset.