Abstract

Most adversarial attack methods that are designed to deceive a text classifier change the text classifier’s prediction by modifying a few words or characters. Few try to attack classifiers by rewriting a whole sentence, due to the difficulties inherent in sentence-level rephrasing as well as the problem of setting the criteria for legitimate rewriting.

In this paper, we explore the problem of creating adversarial examples with sentence-level rewriting. We design a new sampling method, named RewritingSampler, to efficiently rewrite the original sentence in multiple ways. Then we propose a new criteria for modification, called a sentence-level threat model. This criteria allows for both word- and sentence-level changes, and can be adjusted independently in two dimensions: semantic similarity and grammatical quality. Experimental results show that many of these rewritten sentences are misclassified by the classifier. On all 6 datasets, our RewritingSampler achieves a better attack success rate than our baseline.

1 Introduction

Recently, a number of researchers have studied adversarial attacks in depth, aiming to improve the robustness of deep learning models, especially in image classification (Goodfellow et al., 2015; Carlini and Wagner, 2017; Papernot et al., 2016a). Generally, these attacks slightly perturb an image in such a way that an image classifier ends up misclassifying it. By adding adversarial images into a training set, the classifier can learn from them, and resist similar attacks after deployment (Madry et al., 2018). These adversarial images are not the first type of auxiliary data to be added to training sets. Data augmentation was introduced much earlier than adversarial training, and has since become standard for training image classifiers (He et al., 2016). Data augmentation expands the training set by making global changes to images, such as scaling, rotating, and clipping, so that the classifier can defend against such changes. As such, data augmentation and adversarial training are complementary to each other, and can be used concurrently to improve the robustness of an image classifier.

The global changes made by data augmentation and the tiny changes made by adversarial training motivated us to consider whether both of these attack types also exist for natural language models. Recent works (Liang et al., 2017; Samanta and Mehta, 2018; Papernot et al., 2016b; Jin et al., 2020) have shown that word- or character-level attacks can generate adversarial examples. These attacks use edit distance as a threat model. This threat model considers an attacker that can make up to a certain number of word or character substitutions, such that each new word has a similar semantic meaning to the original one. These methods can only make tiny changes to a sentence, and after an attack, the original sentence and adversarial sentence look very similar. After surveying the literature, we found that little work has been done regarding the sentence-level changes.

In this paper, we explore the problem of an adversarial attack with sentence-level modifications. For example, the attacker could change a sentence

Table 1: Adversarial example with sentence-level rewriting. RewritingSampler changes the sentence from passive voice to active voice by replacing 4 words. None of the word substitutions (Turkey -> EU, is -> puts, put-> Turkey, EU->full) have similar meanings, but the meaning of the sentence doesn’t change.
from passive to active voice while keeping the sentence’s meaning unchanged, as shown in Table 1. One challenge inherent to this problem is defining a proper threat model. An edit distance threat model prefers word-level modifications. While it can preserve meaning, sentence-level modification can lead to a large edit distance. To overcome this issue, we propose a sentence-level threat model, where we use the sum of word embeddings to constrain the semantic similarity, and we use a GPT2 language model (Radford et al., 2019) to constrain the grammatical quality. The other challenge involves effectively rewriting sentences. Although humans can rephrase a sentence in multiple ways, it is hard to generate these modifications using an algorithm. We solve the problem under a conditional BERT sampling framework (CBS). (Devlin et al., 2019).

Our contributions are summarized as follows:

• We propose CBS, a flexible framework to conditionally sample sentences from a BERT language model.

• We design RewritingSampler, an instance of CBS, which can rewrite a sentence while retaining its meaning. It can be used to attack text classifiers.

• We propose a sentence-level threat model for natural language classifiers. It allows sentence-level modifications, and is adjustable in semantic similarity and grammatical quality.

• We evaluate RewritingSampler on 6 datasets. We show that existing text classifiers are non-robust against sentence rewriting. With the same semantic similarity and grammatical quality constraints, our method achieves a better success rate than existing word-level attacking methods.

3 Conditional BERT Sampling Framework

In this section, we introduce our conditional BERT sampling (CBS) framework, a flexible framework that can sample sentences conditioned on some criteria from a BERT language model. Figure 1 shows the framework.

The framework starts with a seed sentence $u^{(0)} = \{ u_1^{(0)}, \ldots, u_l^{(0)} \}$. It iteratively sample and replace words in the seed sentence for $N$ times. Within the $i$-th iteration, the algorithm contains following steps to generate $u^{(i)}$:

• Randomly pick a position $k^{(i)}$. For any $k' \neq k^{(i)}$, $u_{k'}^{(i)} = u_{k'}^{(i-1)}$.

• Replace the $k^{(i)}$-th position in $u^{(i-1)}$ with the special mask token in a BERT language model.
Figure 1: CBS is a flexible framework to sample sentences conditioned on certain criteria from a BERT language model.

model, and compute the language model word distribution over the BERT vocabulary as $p_{lm}$.

- Depending on the criteria we want to satisfy, we design an enforcing word distribution over the BERT vocabulary as $p_{enforce}$.

- The proposal word distribution is $p_{proposal} = p_{lm} \times p_{enforce}$. We use the sum of log probability distribution in our implementation for convenience. Then we sample a candidate word $z$ from $p_{proposal}$.

- We use a decision function $h(\cdot)$ to decide whether to use the proposed word $z$ or retain the word in the previous iteration $u_{k(i)}$.

After $N$ iterations, we use $u^{(N)}$ as the sampling output. We can use minibatch to sample sentence in parallel for efficiency.

The advantage of this framework is its flexibility. By properly set the enforcing word distribution and the decision function, CBS can sample sentences satisfying many different criteria.

4 Rewriting Sampling Method

In this section, we introduce RewritingSampler, an instance of CBS framework. The objective of RewritingSampler is to rewrite a sentence while retaining its meaning.

Specifically, given a sentence $x = \{x_1, \ldots, x_l\}$, we set the seed sentence $u^{(0)} = x$. After $N$ iterations of update, $u^{(N)}$ still have the same meaning as $x$, but it is a different sentence. In RewritingSampler, we use word embedding similarity to compute a semantic enforcing distribution. The decision function always accepts the proposed word.

4.1 Semantic Enforcing distribution

The semantic enforcing distribution enforces the sampled sentence to have a similar GloVe (Pennington et al., 2014) embedding. GloVe word embeddings can effectively capture the semantic meaning of a sentence. Reimers and Gurevych (2019) show that using the average of GloVe word embeddings to represent the meaning of a sentence can achieve competitive performance on various tasks. We use GloVe embeddings to derive the enforcing distribution because of its efficacy and simplicity. Let

$$R(u) = \sum_{i=1}^{l} E(u_i) [u_i \notin \text{stopwords}]$$

be the semantic representation of a sentence given by the sum of word embeddings, where $E(u_i)$ is the GloVe word embedding of $u_i$, and $1[\cdot]$ is the indicator function. When replacing the $k$-th word in $u$, the unnormalized enforcing distribution is
defined as
\[ p_{\text{penforce}}(z) = \exp(-\kappa \max(0, \sigma - \text{similarity})). \]
where
\[ \text{similarity} = \cos \text{sim}(R(u_{i-k}, z), R(x)). \]  

(2)

\( \sigma \) is the similarity threshold. If replacing \( u_k \) with \( z \) can create a sentence with similarity higher than the threshold, the enforcing probability for \( z \) is high. Otherwise, the probability also depends on the smoothing parameter \( \kappa \). Larger \( \kappa \) means more rigorous enforcement on the similarity.

### 4.2 Word piece embeddings

The \( p_{\text{lm}}(\cdot) \) works on a 30k-word-piece BERT vocabulary, while \( p_{\text{penforce}}(\cdot) \) works on a 400k-word GloVe vocabulary. We decide to build our method on word-piece level, meaning that we tokenize the sentence into BERT word-pieces at the beginning. In each step, we sample and replace one word-piece. This design leads to an efficiency issue when computing \( R(u) \) in \( p_{\text{penforce}}(\cdot) \).

To explain this issue and our solution, we clarify the notations in this subsection. \( x = \{x_1, \ldots, x_l\} \) and \( u = \{u_1, \ldots, u_l\} \) are the original sentence and the sampled sentence respectively. Each sentence has \( l \) word-pieces. \( x_i \) and \( u_i \) are word-pieces in the BERT vocabulary.

The computation of \( p_{\text{lm}}(z|u_{-i}) \) is simple. We can replace \( u_i \) with a special mask token and call the BERT model. We can get the probabilities for all 30k word-pieces with only one BERT call. The difficulties come from the semantic enforcing distribution, in particular \( R(u) \). We need to compute embeddings for 30k different sentences. These sentences are very similar, except that the \( i \)-th word-piece is different. However, the \( i \)-th word-piece can concatenate with neighboring word-pieces to form words. Thus, we have to address the 30k sentences one by one. For each sentence, we need to convert word-pieces to words, then look up embeddings from the embedding table. Looping, conversion, and lookup are inefficient operations.

If we have word-piece embeddings \( E' \in \mathbb{R}^{30k \times d} \), such that \( R(u) \approx \sum_{k=1}^{l} E'(u_k) \), where \( d \) is the dimension of GloVe embeddings, we can avoid these operations. We can first compute a vector \( c = \sum_{1 \leq k \leq l, k \neq i} E'(u_k) \). Then we compute the 30k representations by adding \( c \) to each row of \( E' \). This improvement can significantly speed up the method. For this reason, we train word-piece embeddings. The word-piece embeddings are trained such that the addition of word-piece embeddings is close to the word embedding. For example, the word ‘hyperparameter’ is tokenized to two word pieces, ‘hyper’ and ‘##parameter’, then \( E'(\text{hyper}) + E'(\text{##parameter}) \approx E(\text{hyperparameter}) \).

We train the word-piece embeddings as follows. Let \( w = \{w_1, \ldots, w_N\} \) be the concatenation of all sentences in the corpus tokenized by words. Let \( E(w) \in \mathbb{R}^{N \times d} \) be the word embeddings for all words. Let \( E' \in \mathbb{R}^{30k \times d} \) be the word-piece embeddings. Let \( T(w) \in \mathbb{R}^{N \times 30k} \) be an indicator for word-piece tokenization.

\[ T(w)_{i,j} = \begin{cases} 1 & \text{if } w_i \text{ is tokenized to } \text{the } j\text{-th word-piece,} \\ 0 & \text{otherwise.} \end{cases} \]

We train the word-piece embeddings \( E' \) by minimizing the absolute error

\[ \min_{E'} ||E(w) - T(w)E'||_1, \]

(3)

where \(||\cdot||_1\) sums up the absolute value of all entries in a matrix (Aka. entrywise matrix norm). We optimize Eq. (3) using stochastic gradient descent. In each step, we sample 5000 words from \( w \), then update \( E' \) accordingly.

### 4.3 Other details

**Fine-tuning BERT for attacking purpose:** For a dataset with \( C \) classes, we fine-tune \( C \) different BERT language models. For the \( i \)-th language model, we exclude training data from \( i \)-th class, so that the sampled sentences are more likely to be misclassified.

**Blocked sampling:** Blocked sampling replaces more than one word in one step. It can overcome highly correlated words. For example, ‘i am’ are highly correlated words. If we want to sample an alternative word for ‘i’, we probably get the same word ‘i’. Using a 2-blocked sampling, we can replace these two words together in one step, and overcome the issue.

**Fix entity names:** Changing entity names can drastically change the meaning of a sentence, and we observe that it is easier for the sampler to remove an entity name than to add a new one. For this reason, we prevent our RewritingSampler from deleting entity names from a sentence. We
use the stanza (Qi et al., 2020) package to recognize entity names in the data. In any particular step, if the current word is also the last occurrence of the entity name in the sentence, we skip this step to ensure that entity name still appears in the sentence. Although RewritingSampler cannot delete entity names, it is allowed to move them to other positions in a sentence. For example, if an entity name appears once at the beginning of the sentence, RewritingSampler can generate the same entity name at another sentence position in one iteration, then remove the entity name from the beginning in later iterations.

**Multi-round sampling and dynamic constraints:** To get high-quality adversarial sentences, we run the sampler multiple times. We start with a natural sentence of $\{x_1, \ldots, x_l\}$, and the true label $y$. Their objective is to find a sentence $u$ that can trigger an incorrect prediction $f(u) \neq y$. The set of sentences from which $u$ is chosen is specified by a threat model. In this section, we discuss existing threat models and propose our sentence-level threat model.

We have been able to find two existing threat models. In $k$-word-substitution (Jia et al., 2019), the attacker can substitute at most $k$ words of the original sentence, and the new words must be similar to original words under cosine similarity. So

$$\Delta_k(x) = \{u | \sum_{i=1}^{l} 1[x_i \neq u_i] \leq k \land \cos_sim(E(x_i), E(u_i)) \geq \epsilon\},$$

where $1[\cdot]$ is the indicator function, $E(\cdot)$ outputs the embedding of a word, and $\cos_sim(\cdot)$ computes the cosine similarity. $k$ and $\epsilon$ are parameters for the threat model. This threat model bounds the number of word changes in a sentence, and so does not support sentence-level modifications.

In similarity-based distance (Jin et al., 2020), the attacker can choose sentences under some neural-network-based similarity measurement. So

$$\Delta_{sim}(x) = \{u | \cos_sim(H(x), H(u)) \geq \epsilon\}$$

where $H(\cdot)$ is a universal sentence encoder (USE) (Cer et al., 2018). Using a neural network to define a threat model makes the threat model hard to analyze.

We propose our sentence-level threat model to overcome these issues. We use a neural network to check the grammatical quality of a sentence, and we use word embeddings to measure the semantic distance between two sentences. This is defined as

$$\Delta(x) = \{u | \text{ppl}(u) \leq \lambda \text{ppl}(x) \land \cos_sim(R(u), R(x)) \geq \epsilon\},$$

where $\text{ppl}(\cdot)$ is the perplexity of a sentence, $R(\cdot)$ is the representation of a sentence defined in Eq. (1), $\lambda$ and $\epsilon$ are adjustable criterion for the threat model. Perplexity is the inverse probability of a sentence normalized by the number of words.

$$\text{ppl}(x) = p(x)^{-\frac{1}{T}} = \left[ \prod_{i=1}^{T} p(x_{i+1} | x_1, \ldots, x_{i-1}) \right]^{-\frac{1}{T}}.$$  \hspace{1cm} (5)

Thus a sentence with correct grammar has low perplexity. We use the GPT2 language model (Rafford et al., 2019) to compute Eq. (5) because of its high quality and computational ease. The language model is used to measure the grammatical quality of the adversarial sentence, and so is independent of the classifier we are trying to attack. $\lambda$ is the criteria for grammatical quality. A smaller $\lambda$ enforces better quality.

Our threat model not only captures two important properties – grammatical quality and semantic similarity – it also allows for the independent control of these two properties through two adjustable criterion, and for flexible rewriting of the sentence.

6 **Experiment**

In this section, we show the results of experiments on 4 text classification datasets, and 2 natural language inference (NLI) datasets. For classification datasets, the attacker’s objective is to modify the sentence and get it misclassified. For NLI datasets, a classifier is trained to infer the relation of a premise and a hypothesis among three options: neutral, entailment and contradiction. The attacker should rewrite the hypothesis to change the classifier’s output.

6.1 **Experimental settings**

**Baseline:** We compare our method with TextFooler (Jin et al., 2020), a recent black-box attack method. TextFooler is different from our
Ori (Tech): Nokia plans to boost memory for phones. New handsets from the mobile phones global leader will have hard disk to store more songs and pictures in a move to tap the rapidly growing smartphone market.

Adv (Business): Nokia adds to growing US mobile market. Nokia handsets and camera phones, a move that promises hard drive memory for digital pictures and music, will help to boost the rapidly growing mobile phone market.

Ori (Sport): Eagles remain unbeaten. David Akers kicked a 50-yard field goal in overtime to help the Eagles to a 34-to-31 victory over the Cleveland Browns. Donovan McNabb matched a career high with four touchdown passes.

Adv (World): Eagles Top Browns. Davidrizer kicks a 50-yard field goal and team routs the Eagles with a 21-to-22 victory over the Cleveland Browns. Donovan McNabb’s field goal was short...

Ori (Business): Still no beef resolution after latest talks. NEW YORK, (Aug. 30, 2004) - Cattle farmers and haulers finally looking for a quick end to a 15-month ban on live cattle exports to the US are out of luck after Canadian Agriculture Minister Andy Mitchell

Adv (World): Agreement not immediately heading for an end. NEW YORK - (Oct. 20, 2004) - Cattle farmers and ranchers are worried that a compromise resolution on a 20-year ban on British beef imports around the world is not in progress. Ex - Minister Andy Mitchell

Table 2: Original (Ori) and adversarial (Adv) sentences on AG dataset. None of these adversarial sentences can be aligned with original sentences word-by-word, but they are coherent and have similar meanings.

RewritingSampler because it only makes word-level changes.

Datasets: We use four text classification datasets AG’s News (Zhang et al., 2015), Movie Reviews (MR) (Pang and Lee, 2005), Yelp Reviews (Zhang et al., 2015), and IMDB Movie Reviews (Maas et al., 2011). We use two NLI datasets, Stanford Natural Language Inference (SNLI) (Bowman et al., 2015), and Multi-Genre Natural Language Inference (MNLI) (Williams et al., 2017). Dataset details are shown in Table 3.

| Name  | Type    | #C | Cased | Train/Test | Len |
|-------|---------|----|-------|------------|-----|
| AG    | Topic   | 4  | Y     | 120k/7.6k  | 54  |
| MR    | Senti   | 2  | N     | 9k/1k      | 24  |
| Yelp  | Senti   | 2  | Y     | 160k/38k   | 182 |
| IMDB  | Senti   | 2  | Y     | 25k/25k    | 305 |
| SNLI  | NLI     | 3  | Y     | 570k/10k   | 15/8|
| MNLI  | NLI     | 3  | Y     | 433k/10k   | 28/11|

Table 3: Dataset details. Topic, Senti, and NLI mean topic classification, sentiment classification and natural language inference respectively. #C means number of classes. Cased means whether the dataset is cased or uncased. Len is the number of BERT word-pieces in a sentence. For the NLI dataset, the two numbers in Len represent the length for the premise and the hypothesis respectively.

Classifier: For all datasets, we use the BERT-base classifier (Devlin et al., 2019) (#layers=12, hidden_size=768). We use an uncased model on MR, and use cased models for other datasets. We train the classifier on 20k batches (5k batches on MR), with batch size 32. We use Adamw optimizer (Loshchilov and Hutter, 2019) and learning rate 0.00002.

Evaluation Metric: We evaluate the efficacy of the attack method using the after attack accuracy. Lower accuracy means the attacker is more effective in finding adversarial examples. We use two threat model setups, \( \lambda = 2, \epsilon = 0.95 \) and \( \lambda = 5, \epsilon = 0.90 \). None of the attack methods ensure that the output satisfies a threat model, so after we execute the TextFooler and RewritingSampler, we filter adversarial sentences using the threat model. Only those adversarial sentences that satisfy the threat model criteria are considered to be successful attacks. The first threat model is more rigorous than the second one, so fewer sentences can be considered as successful attacks in the first threat model, and the after-attack accuracy will be higher on the first threat model. Note that when we filter adversarial examples using a threat model, we use the GloVe word embeddings to compute the similarity. Word-piece embeddings are only used in the RewritingSampler attacking method.

Language model for RewritingSampler: We use a BERT-based language model (#layers=12, hidden_size=768). For each dataset, we fine-tune the language model 20k batches on the training set (5k batches on MR dataset), with batch size 32 and learning rate 0.0001. We follow the masking strategy in Devlin et al. (2019) and 20% masked words.

6.2 Results on AG dataset

For each sentence, we run RewritingSampler 2 rounds, and each round contains 50 iterations. Overall, we generate 100 neighboring sentences for each original sentence. In the first round, we set the soft semantic constraint \( \sigma = 0.98 \) to find
sentences with very high similarity. If there is a sentence that can change the classification within the 50 iterations of the first round, we skip the second round. Otherwise, we reduce the constraint to $\sigma = 0.95$ in the second round to increase the chance of finding an adversarial sentence. We set $\kappa = 1000$. We try blocked-sampling with three different block sizes (block = 1, 3, 5).

Table 4 shows our experimental results on the AG dataset. We observe that our method outperforms TextFooler on both threat models. Using block = 1 can get the best performance on the more rigorous threat model, while a larger block size gives a better performance on the less rigorous threat model. RewritingSampler can rewrite a sentence differently with a larger block size, but it is hard to rewrite a sentence very differently while keeping the similarity as high as 0.95. Figure 3 shows the change rate of adversarial sentences. A larger block size leads to a larger change rate.

| Model                | $\lambda = 2$ | $\lambda = 5$ |
|----------------------|---------------|---------------|
| TextFooler            | 84.0          | 66.7          |
| TextFooler (block=1)  | **76.8**      | 55.6          |
| TextFooler (block=3)  | 78.7          | 49.6          |
| TextFooler (block=5)  | 81.5          | **49.3**      |

Table 4: Results on AG Dataset. We report the accuracy (%) of the cased BERT classifier after attack.

On Figure 2 (left) we compare adversarial examples found by RewritingSampler and TextFooler on AG dataset. Each ‘x’ or ‘.’ in the figure represents one pair of original and adversarial sentences. The x-axis is the perplexity ratio $\text{ppl}(u)/\text{ppl}(x)$. The y-axis is the cosine similarity between sentence pairs using GloVe representations (left) and universal sentence encoder representation (right).

In Jin et al. (2020), the similarity between sentences is measured by USE (Cer et al., 2018). So we also measure the similarity using USE for comparison, shown on Figure 2 (right).

Figure 4 compares the word-piece change rate between TextFooler and our method. Our method changes many more words because it is allowed to make sentence-level changes.

Figure 3: Compare word-piece change rate between different block size on AG dataset. The dashed vertical line shows the average change rate.
6.3 Results on sentiment datasets

On all three datasets, we also run RewritingSampler 2 rounds with \( \sigma = 0.98 \) and \( \sigma = 0.95 \). We set \( \kappa = 1000 \). On MR, we run 50 iterations each round. Because Yelp and IMDB have much longer sentences, we run 3 iterations in each round for efficiency. To compensate for the reduction in iterations, we save intermediate sentences every 10 steps, and use the intermediate sentences to attack the model. Table 5 shows the results. Our method gets better performance on most cases.

6.4 Results on NLI datasets

On both NLI datasets, we also run RewritingSampler 2 rounds with \( \sigma = 0.95 \) and \( \sigma = 0.90 \). We set \( \kappa = 1000 \). We run 10 iterations each round. We use two threat models, \( (\epsilon = 0.9, \lambda = 2) \) and \( (\epsilon = 0.8, \lambda = 5) \). We use smaller \( \epsilon \) because adversarial sentences by TextFooler have lower similarity. Table 6 shows the results. Our method consistently and significantly outperforms our baseline. Figure 5 shows a scatter plot of the adversarial sentences found by RewritingSampler on SNLI. RewritingSampler is superior in both semantic similarity and grammatical quality.

| Dataset      | Acc    | \( \epsilon \) | \( \lambda \) | Acc    | \( \epsilon \) | \( \lambda \) |
|--------------|--------|----------------|--------------|--------|----------------|--------------|
| MR           | 86.0   | 0.95, 2        | 60.1         | SNLI   | 89.4           | 0.90, 2      |
|              |        | 0.90, 5        | 26.9         |        | 0.80, 5        | 48.4         |
| Yelp         | 97.0   | 0.95, 2        | 60.7         | Yelp   | 85.1           | 0.90, 2      |
|              |        | 0.90, 5        | 23.5         |        | 0.80, 5        | 37.0         |
| IMDB         | 90.9   | 0.95, 2        | 60.7         | IMDB   | 83.7           | 0.90, 2      |
|              |        | 0.90, 5        | 22.2         |        | 0.80, 5        | 33.3         |
| SNLI-Matched | 85.1   | 0.90, 2        | 64.6         | MNLI-Mismatched | 83.7        | 0.90, 2      |
|              |        | 0.80, 5        | 36.9         |        | 0.80, 5        | 24.2         |

Table 5: Results on sentiment analysis datasets.

Table 6: Results on NLI datasets.

Figure 4: Change ratio on AG’s News dataset.

Figure 5: Scatter plot of adversarial examples found by RewritingSampler and TextFooler on SNLI dataset. Each ‘x’ or ‘.’ in the figure represents one pair of original and adversarial sentences. The x-axis is the perplexity ratio \( \frac{\text{ppl}(u)}{\text{ppl}(x)} \). The y-axis is the cosine similarity between GloVe representations.

7 Discussion

Our RewritingSampler is reasonably efficient. The most time-consuming portion involves computing \( p_{\text{BERT}}(u_i | u_{-i}) \) because the complexity of BERT is \( O(l^3) \), where \( l \) is the number of wordpieces in a sentence. As it runs the BERT model once for each step, the complexity of one iteration of sampling is \( O(l^3) \). On an RTX 2080 GPU, we can finish 3 iterations of sampling for a 50-wordpiece sentence per second.

Our method can outperform TextFooler for two reasons. First, the sampling procedure is capable of generating more different sentences. TextFooler only makes word substitutions, so their diversity of sentences is low. Second, in TextFooler, the criteria for choosing a word substitution is the words’ semantic similarity. It uses ad-hoc filtering to ensure grammatical correctness. On the contrary, RewritingSampler jointly considers the se-
mantic similarity and grammatical quality, so it can make a better choice when sampling words.

8 Conclusion
In this paper, we explore the problem of generating adversarial examples with sentence-level modifications. We propose a Gibbs sampling method that can effectively rewrite a sentence with good grammatical quality and high semantic similarity. Experimental results show that our method achieves a higher attack success rate than other methods. In the future, we will explore the use of this RewritingSampler for data augmentation.
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Notation Description

\((x, y)\) One sentence and label pair, where \(x = \{x_1, x_2, \ldots, x_l\}\) is a sequence of \(l\) words.

\(\Delta(x)\) A set of sentences that are considered similar to \(x\).

\(\hat{y} = f(x)\) \(f(\cdot)\) is a text classifier and \(\hat{y}\) is the predicted label.

\(u\) A sampled sentence.

\(\text{ppl}(\cdot)\) Perplexity of a sentence.

\(E(\cdot)\) GloVe embedding table \(E(x) \in \mathbb{R}^{l \times 300}\).

\(\text{cos}_\text{sim}(a, b)\) the cosine similarity between \(a\) and \(b\).

\(R(x)\) the semantic meaning embedding of a sentence.

\(\epsilon\) the semantic meaning threshold for our threaten model.

\(\lambda\) the perplexity threshold for our threaten model.

\(\kappa\) smoothing parameter for the semantic enforcing distribution in RewritingSampler.

\(\sigma\) threshold for the semantic enforcing distribution in RewritingSampler.

Table 7: Notations.
Figure 8: Scatter plot and change ratio for IMDB dataset.

Figure 9: Scatter plot and change ratio for MNLI dataset.
Gates and Ballmer get pay raises. Bill Gates and Steve Ballmer each received total compensation of $901,667 in Microsoft Corp.'s 2004 fiscal year, up 4.4 percent from $863,447 one year ago.

Adv (Business): Gates and Ballmer pay one million. Bill Gates and Steve Ballmer both received dividends of $495,801 each in Microsoft Corp.'s 2004 fiscal year, up 2.5 percent from $351,681 a year earlier.

Viruses keep on growing. Most IT Managers won’t question the importance of security, but this priority has been sliding between the third and fourth most important focus for companies.

Adv (Business): Guaranteed investing? Most IT Managers don’t question the importance of security, but this priority has been sliding between the third and fourth most important focus for companies.

Czech Republic’s Cell Operators Fined (AP). AP - All three cell phone operators in the Czech Republic were fined a total of $1.7 million for breaching competition rules, officials said Thursday.

Adv (World): Czech Republic’s Mobile Operators Fined (AP). AP - Three large mobile phone operators in the Czech Republic are fined an average of $3.2 billion for breached banking rules, officials said Saturday.

Guaranteed investing? Most IT Managers don’t question the importance of security, but this priority has been sliding between the third and fourth most important focus for companies.

Japanese baseball players set to strike. Japanese baseball players will strike for the first time if owners proceed with a proposed merger of two teams, the players’ union said Monday.

Adv (World): Japan baseball players go on strike. Baseball players go on strike for the first time in two years, with one member of the strike, the players’ union said Monday.

Football Association charges Bolton striker over spitting incident. Bolton striker El-Hadji Diouf was cited for improper conduct by the Football Association on Monday after spitting in the face of an opponent.

Adv (World): Football. Bolton cited on spitting charge. Bolton striker El-Hadji Diouf was accused of improper conduct by the Football Association on Tuesday for spitting in the face of the striker.

Japanese baseball players set to strike. Japanese baseball players will strike for the first time if owners proceed with a proposed merger of two teams, the players’ union said Monday.

Adv (World): Japan baseball players go on strike. Baseball players go on strike for the first time in two years, with one member of the strike, the players’ union said Monday.

Sox lose Kapler to Japan. Outfielder Gabe Kapler became the first player to leave the World Series champion Boston Red Sox, agreeing to a one-year contract with the Yomiuri Giants in Tokyo.

Adv (World): Sox take Katum to Japan. Outfielder Gabe Kapler became the first player to major the World Series champion Boston Red Sox by agreeing to a one-year contract with the Yomiuri Giants . . .

Colgate-Palmolive Announces Job Cuts. Toothpaste maker Colgate-Palmolive said today it is cutting 4,400 jobs and closing a third of its 78 factories around the world. The group, which makes products such as Colgate

Adv (World): Colgate-Palmolive Announces Job Cuts. Mihiran software maker Colgate-Palmolive said that it is cutting 1,500 jobs and shutting a number of about 39 factories around the world. The group, which makes products such as Colgate

Table 8: More examples on AG dataset.

Ori (negative): the things this movie tries to get the audience to buy just won’t fly with most intelligent viewers.
Adv (positive): this rather intelligent movie tries to buy the audience out. it doesn’t ‘t try to get viewers out.

Ori (negative): not at all clear what it’s trying to say and even if it were i doubt it would be all that interesting.
Adv (positive): not at all clear what it’s trying to say , but if it had to say it would , just as interesting.

Ori (negative): what starts off as a potentially incredibly twisting mystery becomes simply a monster chase film.
Adv (positive): what starts out as a twisting and potentially mystery becomes quite a monster chase film.

Ori (negative): it’s probably not easy to make such a worthless film . . .
Adv (positive): it’s not too easy to make up for worthless film, though.

Ori (positive): even better than the first one!
Adv (negative): even better , the first two!

Ori (positive): not only a coming - of - age story and cautionary parable, but also a perfectly rendered period piece.
Adv (negative): not only a coming - of - age story and cautionary parable, but also a period - rendered piece.

Ori (positive): a well - done film of a self - reflexive, philosophical nature.
Adv (negative): a well - made film of a self - reflexive but philosophical nature.

Table 9: Examples on MR dataset