Repairing Adversarial Texts through Perturbation

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Abstract—it is known that neural networks are subject to attacks through adversarial perturbations, i.e., inputs which are maliciously crafted through perturbations to induce wrong predictions. Furthermore, such attacks are impossible to eliminate, i.e., the adversarial perturbation is still possible after applying mitigation methods such as adversarial training. Multiple approaches have been developed to detect and reject such adversarial inputs, mostly in the image domain. Rejecting suspicious inputs however may not be always feasible or ideal. First, normal inputs may be rejected due to false alarms generated by the detection algorithm. Second, denial-of-service attacks may be conducted by feeding such systems with adversarial inputs. To address the gap, in this work, we propose an approach to automatically repair adversarial texts at runtime. Given a text which is suspected to be adversarial, we novelly apply multiple adversarial perturbation methods in a positive way to identify a repair, i.e., a slightly mutated but semantically equivalent text that the neural network correctly classifies. Our approach has been experimented with multiple models trained for natural language processing tasks and the results show that our approach is effective, i.e., it successfully repairs about 80% of the adversarial texts. Furthermore, depending on the applied perturbation method, an adversarial text could be repaired in as short as one second on average.

Index Terms—Adversarial Text, Detection, Repair, Perturbation.

1 INTRODUCTION

Neural networks (NNs) have achieved state-of-the-art performance in many tasks, such as classification, regression and planning [1], [2], [3]. For instance, text classification is one of the fundamental tasks in natural language processing (NLP) and has broad applications including sentiment analysis [4], [5], spam detection [6], [7] and topic labeling [8]. NNs have been shown to be effective in many of these text classification tasks [9].

At the same time, NNs are found to be vulnerable to various attacks, which raise many security concerns especially when they are applied in safety-critical applications. In particular, it is now known that NNs are subject to adversarial perturbations [10], i.e., a slightly modified input may cause an NN to make a wrong prediction. Many attacking methods have been proposed to compromise NNs designed and trained for a variety of application domains, including images [11], [12], audio [13] and texts [14], [15], [16]. Multiple approaches like HotFlip [14] and TEXTBUGGER [17] have been proposed to attack NNs trained for text classification. TEXTBUGGER attacks by identifying and changing certain important characters (or words) in the text to cause a change in the classification result. For example, given the text “Unfortunately, I thought the movie was terrible” which is classified as ‘negative’ by an NN for sentiment analysis, TEXTBUGGER produces an adversarial text “Unf0rtunately, I thought the movie was terrible” which is classified as ‘neutral’, as shown in Fig 1. While the above perturbation is detectable with a spell checker, there are also attacking methods like SEAs [18] which generate adversarial texts that are hard to detect.

Efforts on defending against adversarial attacks fall into two categories. One is to train a robust classifier which either improves the accuracy on such examples, e.g., adversarial training [19], [20] and training models with pre-processing samples generated by dimensionality reduction or JPEG compression [21], [22], or decreases the success rate for attackers on generating adversarial samples, e.g., obfuscated gradients [23], [24]. None of these approaches, however, can eliminate adversarial samples completely [25] as the adversarial samples may not be a flaw of the model but features in data [26]. Alternative mitigation approaches alleviate the effects of such samples by detecting adversarial samples [27], [28], [29], [30].

Although most of the detecting approaches have focused on the image domain, simple approaches have been proposed to detect adversarial texts as well. One example is to apply a character/word checker, i.e., Gao et al. [31], to detect adversarial texts generated by HotFlip [14] and TEXTBUGGER [17]. Detecting adversarial samples is however not the end of the story. The natural follow-up question is then: what do we do when a sample is deemed adversarial? Some approaches simply reject those adversarial samples [30], [32], [33]. Rejection is however not always feasible or ideal. First, existing detection algorithms often generate a non-negligible amount of false alarms [29], [30], particularly so for the simple detection algorithms proposed for adversarial texts [34]. Second, rejection may not be an option for certain applications. For example, it is not a good idea to reject an edit in public platforms (e.g., Wikipedia, Twitter and GitHub) even if the edit is suspected to be maliciously crafted (e.g., toxic) [35]. Rather, it would be much better to suggest a minor “correction” on the edit so that it is no longer malicious. Lastly, rejecting all suspicious samples would easily lead to deny-of-service attacks.

Beyond rejection, in the image domain, a variety of techniques are proposed to mitigate the effect of the adversarial samples after these samples are identified. For example, Pixeldefend [36]...
We implemented our approach as a self-contained toolkit targeting NNs trained for text classification tasks. Our experiments on multiple real-world tasks (e.g., for sentiment analysis and topic labeling) show that our approach can effectively and efficiently repair adversarial texts generated using two state-of-art attacking methods. In particular, we successfully repair about 80% of the adversarial texts, and depending on the applied perturbation method, an adversarial text could be repaired in as few as 1 second on average.

In summary, we make the following main contributions.

- We propose the first approach to repair adversarial texts.
- We propose, as a part of our overall approach, an approach for detecting adversarial texts based on an enhanced variant of differential testing.
- We implement a software toolkit and evaluate it on multiple state-of-the-art NLP tasks and models.

The rest of the paper is organized as follows. In Section 2, we present relevant background. In Section 3 the details of our approach are presented. Section 4 shows our experimental setup and results. We discuss related works in Section 5 and conclude in Section 6.

2 Background

In this section, we present a background that is relevant to this work.

2.1 Text Classification

Text classification is one of the most common tasks in Natural Language Processing (NLP). The objective is to assign one or several pre-defined labels to a text. Text classification is widely applied in many applications such as sentiment analysis [4], [5], topic detection [8] and spam detection [6], [7]. Neural networks (NNs) have been widely adopted in solving text classification tasks. In particular, Recurrent Neural Networks (RNNs), e.g., LSTM [42] and GRU [43], designed to deal with sequential data, are commonly applied in many NLP tasks. In addition, Convolutional Neural Networks (CNNs) are shown to achieve similar results on text classification tasks [44]. In this work, we focus on RNNs and CNNs and leave the evaluation of other models to future work.

2.2 Generating Adversarial Texts

In the following paragraphs, we introduce state-of-the-art approaches to generate adversarial texts for NNs.

The outputs of the models (in the form of probability vectors) based on KL divergence [41] to identify the correct label. Furthermore, we apply the sequential probability ratio test (SPRT) algorithm to systematically evaluate the confidence of each possible label and output the most-likely-correct label based on majority voting only if it reaches certain level of statistical confidence.

Our answer is differential testing combined with majority voting. Given two or more NNs trained for the same task, our intuition is that if there is a disagreement between the NNs, the labels generated by the NNs are not reliable. Due to the transferability of adversarial samples [11], a label agreed upon by the NNs may still not be reliable. We thus propose to compare rectified the suspicious input images by changing them slightly towards the training distribution. Akhtar et al. [37] attached a network to the first layer of the target NN to reconstruct clean images from the suspicious ones. Agarwal et al. [38] proposed to use wavelet transformation and inverse wavelet to remove the adversarial noise. Besides, Goswami et al. [39], [40] proposed a selective dropout method which mitigates the problem of adversarial samples by removing the most problematic filters of the target NN.

However, to the best of our knowledge, the question of whether we can effectively repair adversarial texts has been largely overlooked so far. Even worse, the aforementioned mitigation approaches can not be easily extended to the text domain due to several fundamental new challenges. To address the gap, in this work, we aim to develop an approach that automatically repairs adversarial texts. That is, given an input text, we first check whether it is adversarial or not. If it is deemed to be adversarial, we identify a slightly mutated but semantically equivalent text which the neural network correctly classifies as the suggested repair.

Two non-trivial technical questions must be answered in order to achieve our goal. First, how do we generate slightly mutated but semantically equivalent texts? Our answer is to novely apply adversarial perturbation methods in a positive way. One of such methods is the SEAs attacking method which generates semantically ‘equivalent’ texts by applying neural machine translation (NMT) twice (i.e., translate the given text into a different language and back). Another example is a perturbation method which is developed based on TEXTBUGGER, i.e., identifying and replacing important words in a sentence with their synonyms. Second, how do we know what is the correct label, in the presence of adversarial texts?

Our answer is differential testing combined with majority voting. Given two or more NNs trained for the same task, our intuition is that if there is a disagreement between the NNs, the labels generated by the NNs are not reliable. Due to the transferability of adversarial samples [11], a label agreed upon by the NNs may still not be reliable. We thus propose to compare
that these operations usually lead to a meaningless word and as a consequence, such attacks are easily detected by a spell-checker.

**TEXTBUGGER.** TEXTBUGGER is a general framework for crafting adversarial texts [17]. Given an input text, it first identifies the most important sentence and then the most important word. A word is the most important if changing it leads to the most decrease in the classification confidence. After a word is selected, five operations are applied to generate adversarial texts. Four of the five operations, i.e., inserting a space in the word, deleting a character, swapping two characters and substituting a character with a similar one (like “o” to “0”), are character-level operations which aim to generate “human-imperceptible” texts. Similarly, adversarial texts generated by these operations are easily detected by a spell-checker. The last operation is to substitute the selected word with a synonym (hereafter \( \text{Sub-W} \)), which is hard to detect and likely semantic-preserving.

**TEXTFOOLER.** TEXTFOOLER is another recent method to generate adversarial texts [43]. Instead of sorting sentences by importance at first, TEXTFOOLER directly performs word importance ranking, and then replaces the words in the ranking list one by one with a synonym until the prediction of the target model is changed. In general, HotFlip, TEXTBUGGER, and TEXTFOOLER share the same idea of crafting adversarial texts, and they mainly differ in the substitution of selected words. Among the three methods, TEXTFOOLER is more likely to generate more natural adversarial texts since it takes the part of speech into account when selecting synonyms.

**SEAs.** SEAs aims to generate semantic-equivalent adversarial texts by paraphrasing [18] based on Neural Machine Translation (NMT). NMT is a category of NNs which are trained for machine translation and has achieved state-of-the-art performance in machine translation [46], [47], [48]. SEAs applies NMTs to generating semantic-preserving texts as adversarial texts. That is, SEAs translates an input sentence into multiple foreign languages and then translates them back to the source language using NMTs. After that, SEAs selects an adversarial text among those according to a semantic score, which measures how semantic-preserving is the text with respect to the original input.

## 3 Our Repair Approach

Our aim is to automatically repair adversarial texts. We define our problem as follows. Given a text input \( x \) and a pair of different NNs \( (f_1, f_2) \) which are trained for the same task, how to automatically check whether \( x \) is likely adversarial and generate a repair of \( x \) if \( x \) is deemed adversarial? Note that we assume the availability of two models \( f_1 \) and \( f_2 \). In practice, multiple models can be easily obtained by training with slightly different architectures, or different training sets, or through model mutation [30].

Figure 2 shows the overall workflow of our approach. Given an input text \( x \) and two models \( (f_1, f_2) \), we first check whether \( x \) is likely adversarial. If the answer is positive, we apply adversarial perturbation to generate a set of texts \( X^* \) such that each \( x \in X^* \) is slightly different from \( x \) and likely semantically equivalent to \( x \). Afterwards, we apply a statistical testing method to identify the most-likely correct label of \( x \) (with a guaranteed level of confidence) based on \( X^* \) and output a text in \( X^* \) which is slightly different from \( x \) as the repair. In the following paragraphs, we present the details of each step.

### 3.1 Adversarial Text Detection

Given an input text \( x \), we first check whether it is adversarial (i.e., crafted by an attacker through adversarial perturbation). There are multiple methods for detecting adversarial perturbations in the image domain [27], [50]. The topic is relatively less studied in the text domain [29]. Other than detection using a spell-checker, to the best of our knowledge, the only approach is the one mentioned in [34], which focuses on re-training for improving robustness rather than detecting adversarial texts. In our work, we propose a detection method which is inspired by differential testing [49].

Applying differential testing naively in our context (i.e., claim that \( x \) is adversarial if the labels generated by \( f_1 \) and \( f_2 \) are different) is problematic. Adversarial samples in the image domain are known to have transferability between different models [50], i.e., \( f_1 \) and \( f_2 \) may generate the same wrong label given the same adversarial text. To examine how effective naive differential testing is, we conduct an empirical study to evaluate the transferability of adversarial texts. We train two different models, one TextCNN and one LSTM, for sentiment analysis on three widely used standard datasets (i.e., NA [51], RTMR [52] and IMDB [53]). The performance of the models used for the clean text is shown in Table 2. Afterwards, we generate 1000 adversarial texts on each dataset using TEXTBUGGER for the TextCNN model (respectively the LSTM model) and check the accuracy of the LSTM model (respectively the TextCNN model) with regards to these adversarial texts. Table 1 shows the results where the second column shows the transferability of the adversarial texts generated by attacking the TextCNN model and the third column shows that of the adversarial texts generated by attacking the LSTM model. We confirm that adversarial texts indeed transfer between different models (which is similar to adversarial images [54]). For instance, more than 40% of adversarial texts fool both models in the case of the NA and RTMR datasets.

We thus need a more reliable way to check whether \( x \) is adversarial. Our remedy is to further measure the difference between the prediction distributions of the two models. Concretely, the output of a neural network for multi-class classification is a probability vector \( f(x) = [p_0, p_1,\ldots, p_K] \), where \( f \) is a model and \( p_i \) is the probability of the input being class \( i \) and \( K \) is the total number of classes. We enhance differential testing by comparing the difference of two models’ probability vectors. That is, the input \( x \) is regarded adversarial if the difference of the probability vectors is larger than a threshold.

We adopt KL divergence \( (D_{KL}) \) to measure the difference between the two probability vectors. Formally, let \( f_1(x) = \)
Fig. 2: Framework of our approach. Given an input text, we first check if it is adversarial with two models $f_1$ and $f_2$, and then we continually generate mutated text to restore its true label with SPRT if it is identified as adversarial.

**Algorithm 1: isAdversarial($x, f_1, f_2, \epsilon$)**

1. let $c_1$ be the output label according to $f_1(x)$;
2. let $c_2$ be the output label according to $f_2(x)$;
3. if $c_1 \equiv c_2$ and $D_{KL}(x) < \epsilon$ then
   4. return false;
5. return true;

$$D_{KL}(f_1(x), f_2(x)) = -\sum_{i=1}^{K} p_i \ln \frac{q_i}{p_i} \quad (1)$$

Hereafter, we write $D_{KL}(x)$ to denote $D_{KL}(f_1(x), f_2(x))$. Intuitively, $D_{KL}(x)$ is smaller if two distributions are more similar. Our hypothesis is that if the input is not adversarial, the probability vectors $f_1(x)$ and $f_2(x)$ should be similar and thus the difference $D_{KL}(x)$ should be small; otherwise it should be large. This is confirmed empirically as we show in Section 4.

Algorithm 1 shows the details of our adversarial sample detection algorithm, where $\epsilon$ is a threshold. An input $x$ is considered to be normal (refer to line 3) only if the labels generated by the two models are the same, and the $D_{KL}(x)$ is below the threshold. Otherwise, the input is regarded as adversarial. The remaining question is how to set the value of $\epsilon$, which we solve using the standard method of golden-section search as we discuss in Section 4.

**Example 1.** Table 3 shows an example on how our adversarial sample detection algorithm works. The first row is a normal text from the RTMR dataset, and the second row is an adversarial text generated using SEAs. The third and fourth rows are the probability vectors generated by the two models respectively. The task is sentiment analysis and thus there are two possible labels. Note that while the original text is correctly labeled ‘positive’, both models label the adversarial text ‘negative’. The fifth row is the KL divergence of the two probability vectors. Although the adversarial text fools both models, its $D_{KL}(x)$ is larger than the threshold and thus is identified as adversarial. Note that the threshold as shown in sixth row is selected empirically as we explain in Section 4.

| Original text | an appealingly juvenile trifle that delivers its share of laughs and smiles |
|---------------|-----------------------------------------------------------------------------|
| Adversarial text $x$ | a delightful childish trifle that can bring laughter and a smile |
| $f_1(x)$ TextCNN | [0.9696, 0.0304] |
| $f_2(x)$ LSTM | [0.6809, 0.3191] |
| $D_{KL}(x)$ | 0.2688 |
| $\epsilon$ | 0.1110 |

### 3.2 Semantic-Preserving Perturbation

Once we identify an adversarial text $x$, the next challenge is how to automatically repair the input. In general, a repaired text $x'$ should satisfy the following conditions: 1) $x'$ should be syntactically similar to $x$ and semantically equivalent to $x$; 2) $x'$ should be classified as normal by our adversarial sample detection algorithm; and 3) $x'$ should be labeled correctly. In the following paragraphs, we describe how to systematically generate a set of candidate repairs $X^*$ satisfying 1) and discuss how to identify a repair among the candidates that satisfies all the conditions in Section 3.3.

We generate candidate repairs through perturbation, i.e., the same technique for generating adversarial texts except that they are used in a positive way this time. In particular, three different adversarial perturbation methods are applied to generate syntactically similar and semantically equivalent texts. Applying multiple perturbation methods allows us to compare their performance as well as identify the right method for different usage scenarios.

The first one is random perturbation. Let $x = [w_1, w_2, \cdots, w_n]$ where $w_i$ is a word in the text $x$. To apply random perturbation on $x$, we randomly select $g$ words in $x$ and replace them with their synonyms. Note that to preserve the semantics, $g$ is typically small. In particular, for each selected word $w_i$, we identify a ranked list $[w_{i1}, w_{i2}, \cdots, w_{iL}]$ of its synonyms of size $L$ according to their distances to $w_i$ measured in the embedding space. As a result, we obtain $g \times L$ perturbations. We refer this method as RP in the following paragraphs.

The second one is based on the idea of TEXTBUGGER with the Sub-W operation [17]. That is, we first identify the important sentences, and replace the important words in the sentence with
Algorithm 2: TBPerturb(x, g, f₁, f₂)

1. Let Cₙ be the importance scores for each sentence in x;
2. for sᵢ ∈ x do
3.     Cₛ(i) = DₓKL(sᵢ);
4. end for
5. S ← sort the sentences in x according to Cₛ;
6. for sᵢ ∈ Sordered do
7.     Let Cₕᵣ be the importance scores for each word in sᵢ;
8.     for wⱼ ∈ sᵢ do
9.         Compute Cₜᵣ(j) according to Eq. [2];
10.     end for
11.     W ← sort the words in sᵢ according to Cₜᵣ;
12.     combs ← select g words according to S and W;
13.     x' ← replace each word w ∈ combs in x with synonyms;
14. return x'.

their synonyms. Note that different from TEXTBUGGER [17], our goal is to decrease DₓKL(x) so that the perturbed text passes the enhanced differential testing. Thus, we evaluate the importance of a sentence and a word based on its effect on DₓKL(x) (instead of the effect on the model prediction as in [17]). Concretely, to obtain the importance of a sentence sᵢ, we calculate DₓKL(f₁(sᵢ), f₂(sᵢ)). A sentence with a larger DₓKL is considered more important. Within a sentence, we obtain the importance of a word wⱼ by measuring the DₓKL of the sentence with and without wⱼ, i.e.,

\[ DₓKL(f₁(sᵢ), f₂(sᵢ)) - DₓKL(f₁(sᵢ \setminus wⱼ), f₂(sᵢ \setminus wⱼ)) \tag{2} \]

A word causing a larger decrease of DₓKL is more important. Afterwards, the important words are replaced with their synonyms to generate perturbations. The details are shown in Algorithm 2.

We refer this method to SubW in the following paragraphs.

The third one is to generate semantic-preserving texts using NMT in a way similar to SEAs. Formally, an NMT is a function T(s, d, x) : Xₛ → Xₓ, where s is the source language, d is the destination language and x is the input text. The basic idea is to translate the input text into another language and then translate it back, i.e., the new text is \( x' = T(d, s, T(s, d, x)) \). By varying the target language d (e.g., French and Germany), we can generate multiple perturbations this way. Furthermore, it is possible to translate across multiple languages to generate even more perturbations. For instance, with two target languages d₁ and d₂, we can generate \( x' = T(d₂, s, T(d₁, d₂, T(s, d₁, x))) \) as perturbations. Note that compared to perturbations generated using random perturbation or Algorithm 2, the texts generated through NMT might have a different length or syntactical structures, which results in a larger distance in the embedding space. It would be interesting to evaluate whether such a difference affects the effectiveness of our approach. For the sake of convenience, we refer this paraphrase-based perturbation approach to ParaPer in the following paragraphs.

Example 2: Table 5 shows an example of our semantic-preserving perturbation with different methods. The original text is shown in the first row (i.e., the adversarial text shown in Table 4). The perturbed texts using random perturbation and Algorithm 2 are shown in the second and third row. For SEAs perturbation, we translate the original text into Hungarian, which is then translated back into English (shown in the last row). Note that the perturbed text generated by SEAs may have a different number of words.

3.3 Voting for the correct label

After generating a set of texts \( X^* \) which are slightly mutated from \( x \) and yet are semantically equivalent to \( x \), our next step is to identify a member \( x' \) of \( X^* \) that satisfies 2) \( x' \) should be classified as normal by our adversarial sample detection algorithm and 3) \( x' \) is correctly labeled. Satisfying 2) is straightforward. That is, we filter those in \( X^* \) which are determined to be adversarial using Algorithm 1. The result is a set \( X^* \) such that every y in \( X^* \) satisfies \( f₁(y) = f₂(y) \) and \( DₓKL(y) < \epsilon \). Satisfying 3) requires us to know what the correct label is. Our idea is that we can ‘vote’ and decide on the correct label. Our hypothesis is that the majority of texts in \( X^* \) are likely classified correctly and thus a democratic decision would be correct. This idea is inspired by the observation made in [50], which shows that adversarial samples (with wrong labels) in the image domain have a high label-change rate when perturbations are applied [50]. In other words, perturbing adversarial samples would often restore the correct label. One interpretation is that adversarial samples are generated by perturbing normal samples just enough to cross the classification boundary, and thus a slight mutation often restores the original label. We evaluate this hypothesis empirically in Section 4.

Based on the hypothesis, we formulate the problem as a statistical testing problem. That is, we present it with a set of hypotheses (e.g., the correct label of a text is \( c_i \), where \( c_i \) is one of the labels) and the problem is to identify the hypothesis which is most likely true with statistical confidence. To solve the problem, we adopt hypothesis testing [55] to guarantee that the probability of choosing the correct label is beyond a threshold, say \( \rho \). That is, given a label \( c_i \), we systematically test the null hypothesis \( (H₀) \) and the alternative hypothesis \( (H₁) \) which are defined as follows.

\[ H₀(c_i) : P(f(x) = c_i) \geq \rho \]
\[ H₁(c_i) : P(f(x) = c_i) < \rho \]

Given \( X^* \) which contains only texts that are semantically equivalent to \( x \), we estimate \( P(f(x) = c_i) \) as follows.

\[ P(f(x) = c_i) = \frac{|y \in X^* \land f₁(y) = c_i|}{|X^*|} \tag{5} \]

Note that all texts in \( X^* \) have the same label according to model \( f₁ \) and \( f₂ \) after filtering as mentioned above. We remark as long as we set \( \rho \) to be more than 0.5, we guarantee that only one \( H₀(c_i) \) for some \( c_i \) is accepted. In general, given a limited number of perturbations, it might be possible that none of the \( H₀(c_i) \) is accepted.

Since there are multiple labels, we maintain a pair of hypotheses for each \( c_i \in C \) and perform a hypothesis testing procedure for every pair. There are two ways for performing hypothesis testing. One is the fixed-size sampling test (FSST), which performs the test on a fixed number of samples. That is, we first generate a set \( X^* \) with a sufficiently large number of samples, calculate \( P(f₁(x) = c_i) \) for each label \( c_i \) according to (4), and then compare the result with \( \rho \). The drawback of FSST is that we must determine what is the minimum number of samples required such that the error bounds are satisfied. Typically, FSST requires a large number of samples [56].

In general, the more samples that we use, the more accurate the result would be. On the other hand, the more samples required, the more computational overhead there is, which may be problematic.
TABLE 4: Example of semantic-preserving perturbation

| Original text | Perturbed with RP | Perturbed with SubW |
|---------------|-------------------|---------------------|
| a delightful childish trifle that can bring laughter and a smile | a charming silly trifles that can bring laughter and another smile | a delightful childlike trifling that can bring laughter and a smile |

| Source language | Target language | Translated text |
|-----------------|-----------------|-----------------|
| Hungarian       | English         | Egy elragadó gyerekes apróság, ami nevetést és mosolyt hoz |
|                 |                 | A delightful childish little thing that can bring laughter and smiles |

Algorithm 3: hypTest$(c_i, X^*, f_1, \alpha, \beta, \sigma, \rho)$

1. Let $k$ be the size of $X^*$;
2. Let $z$ be the size of $\{y | y \in X^* \land f_1(y) = c\}$;
3. Let $\alpha, \beta, \sigma, \rho$ be the parameter of hypothesis testing;
4. $p_0 = \rho + \sigma$;
5. $p_1 = \rho - \sigma$;
6. $\text{sprt}_\text{ratio} \leftarrow \text{Pr}(z, k, p_0, p_1)$;
7. if $\text{sprt}_\text{ratio} \leq \frac{\beta}{\alpha}$ then
8. Accept the hypothesis that $H(c) \geq p_0$;
9. return;
10. if $\text{sprt}_\text{ratio} \geq \frac{1-\beta}{\alpha}$ then
11. Accept the hypothesis that $H(c) \leq p_1$;
12. return;
13. return Inconclusive;

if such repairing is to be carried out in an online manner (e.g., for suggesting repaired forum posts timely). We thus propose to use the sequential probability ratio test (SPRT [57]), which dynamically determines the number of samples required and is known to be faster than FSST [58]. Central to SPRT is to repeatedly sample until enough evidence is accumulated to make a decision (accepting either hypothesis).

Algorithm 4 shows the details on how SPRT is applied in our work to decide whether to accept hypothesis $H_0(c_i)$ or not for label $c_i$. Note that $\alpha$ is the probability of the case in which $H_0$ is reject while $H_0$ is true (a.k.a. Type I error), $\beta$ is the probability of the case in which $H_1$ is reject while $H_1$ is true (a.k.a. Type II error). $\rho$ is the confidence threshold described before and $\sigma$ is the indifference interval used to relax the threshold. We then test hypotheses $H_0(c_i) : P(f(x) = c_i) \geq p_0$ and $H_1(c_i) : P(f(x) = c_i) < p_1$ where $p_0 = \rho + \sigma$ and $p_1 = \rho - \sigma$. At line 6, we compute the likelihood ratio of SPRT which is defined as follows [58].

$$\text{Pr}(z, k, p_0, p_1) = \frac{p_1^z(1-p_1)^{k-z}}{p_0^z(1-p_0)^{k-z}}$$ (6)

At line 7, we check whether the ratio is no larger than $\frac{\beta}{\alpha}$. If it is the case, the hypothesis $H_0(c_i) \geq p_0$ is accepted and report the label $c_i$ as the true label with error bounded by $\beta$. If the ratio is no less than $\frac{1-\beta}{\alpha}$, we then accept $H_1(c_i) \leq p_1$ at line 11 and report the label $c_i$ as not the true label with error bounded by $\alpha$. Otherwise, it is inconclusive (i.e., more samples are required).

3.4 Overall Algorithm

The overall algorithm is shown in Alg. 4. The inputs include an input text $x$, a pair of NNs $f_1$ and $f_2$, a threshold $\epsilon$, the parameters required for hypothesis testing, and a threshold $\rho$. We first check whether $x$ is adversarial or not at line 1 using Algorithm 1. If it is the case, the hypothesis $H_0(c_i) \geq p_0$ is tested at line 16. If the conclusion is to accept $H_0(c_i)$, we identify a text in $X^*$ which is determined to be normal if $y$ has a label which is never seen before, we add the label to $C$ which is a set of potentially correct labels for $x$. Afterwards, for each potential label $c_i$ in $C$, we conduct hypothesis testing using Algorithm 3 at line 16. If the conclusion is to reject $H_0(c_i)$, we identify a text in $X^*$ which has the label $c_i$ as a repair of $x$ and return it. If the conclusion is to reject $H_0(c_i)$, the label $c_i$ is added into $D$ (so that it is never tested again) and we continue with the next iteration. Otherwise, if it is inclusive, we continue with the next iteration. Note that to reduce the computational overhead, we conduct hypothesis testing in a lazy way. That is, we maintain a set of witnessed labels $C$ (which is initially empty) and only test those in $C$. Furthermore, we maintain a set of rejected labels $D$ so that as soon as a label is rejected, it is never tested again.
Algorithm 4 always terminates. Given any label \( c_i \), Algorithm 3 always terminates since SPRT is guaranteed to terminate with probability 1 [58]. As there are finitely many labels, and each label is tested by Algorithm 3 once, it follows Algorithm 4 always terminates.

**Example 3.** We show how our algorithm works using an example. We are given two models, i.e., a TextCNN \( f_3 \) and an LSTM \( f_2 \), for topic labeling trained on the News Aggregator Dataset [51]. Given the original text “US city moves to stop Monkey Parking” in the dataset, an adversarial text “States city turns to stop Monkey Parking” is generated using TEXTBUGGER. Note that the original correct label is “business” while the adversarial text is classified as “Sci&Tec”. We feed the adversarial text into Algorithm 3 and adopt the SEAs perturbation method to generate perturbed texts. The parameters \( \alpha, \beta, \sigma \) and \( \rho \) in Algorithm 3 are 0.001, 0.001, 0.15, 0.8 respectively. The acceptance bound and rejection bound are consequently \(-6.9068\) and \(6.9068\) respectively. Our approach works as follows. The text is identified to be adversarial at line 1 in Algorithm 3. Then, SEAs is applied to generate perturbed texts for hypothesis testing to vote for the correct label. At the 31-th attempt, the algorithm starts a hypothesis testing procedure for label “business”. The testing procedures for label “health” and “entertainment” are started at 51-th and 73-th attempts respectively. Label “health” and “entertainment” are rejected at the 275-th and 278-th attempts when the SPRT ratio is 8.0155 and 7.7132 respectively. The algorithm immediately rejected “Sci&Tec” when the label first appeared since there are already many perturbed texts with label “business”. Label “business” is finally accepted at the 627-th attempt when its SPRT ratio is -6.9525. Figure 3 shows how the confidence of each label changes with an increasing number of perturbed texts.

![Fig. 3: Example of hypothesis testing](image)

**4 Experiments**

We have implemented our approach as a prototype targeting LSTM and TextCNN models trained for NLP classification tasks. The implementation is in PyTorch [1] with about 5000 lines of code. In the following paragraphs, we conduct multiple experiments to answer the following research questions (RQ).

- **RQ1:** Is KL divergence useful in detecting adversarial texts?
- **RQ2:** Is our hypothesis for voting justified?
- **RQ3:** Is our approach effective at fixing adversarial texts?
- **RQ4:** What is the time overhead of our approach?

RQ1 is important as detecting adversarial texts is a prerequisite for our approach. Only with an effective adversarial sample detection approach, our repairing procedure can be triggered effectively. RQ2 asks whether our hypothesis that most of the texts generated through perturbing an adversarial text are normal is valid or not. Note that this would justify our approach for repairing. RQ3 then checks whether the overall approach would effectively repair adversarial texts. Lastly, we evaluate the time efficiency of our approach in order to see whether it is applicable in a time-constrained setting like online repairing. All experiments are carried out on a workstation with 1 Intel Xeon 3.50GHz CPU, 64GB system memory and 1 NVIDIA GTX 1080Ti GPU.

**4.1 Experiment Settings**

We conduct our experiments on the following three popular real-world datasets which include the two used by TEXTBUGGER [17].

- **News Aggregator (NA) Dataset** [51] This dataset contains 422419 news stories in four categories: business, science and technology, entertainment, and health. For the sake of efficiency, we randomly take 10% of the dataset for our experiment. The task is multi-topic labeling.
- **Rotten Tomatoes Movie Review** This dataset is another movie review dataset collected from Rotten Tomatoes pages [52] for sentiment analysis, which contains 5331 positive and 5331 negative sentences.
- **IMDB** This dataset is a widely used dataset for sentiment analysis classification and contains 50,000 movie reviews from IMDB [53] which are equally split into a training set and a test set. In total, there are 25k positive reviews and 25k negative reviews. Following [17], we randomly select 20% of the training data for training the NNs.

In the following paragraphs, unless stated otherwise, we follow the standard splitting to have 80% of the dataset for training and 20% for testing.

We adopt two heterogeneous NNs widely used for text classification as the target models: LSTM [44] and TextCNN [44]. LSTM is a classical recurrent neural network model used to deal with sequential data in natural language processing. In our case, LSTM is a vanilla one as used in [9]. TextCNN is a convolutional neural network for text classification. TextCNN has four different types based on the strategy of using word vectors: CNN-rand, CNN-static, CNN-non-static and CNN-multichannel. We choose CNN-static since we do not need to modify the pre-trained word vectors. We follow the configuration of TextCNN in [44]. To train both models for each of the three datasets, we first transform each word into a 300-dimensions numerical vector using the pre-trained word vectors GloVe [59]. The performance of our trained models is presented in Table 5, which is comparable to the state-of-the-art.

We adopt two state-of-the-art approaches to generate adversarial texts, i.e., TEXTBUGGER with Sub-W and SEAs. For each model, we randomly select 300 texts from the dataset and apply both attacks to generate adversarial texts. The 3rd column and 4th column in Table 5 summarize the number of adversarial texts generated using each method. Note that the number is smaller than 300 since the attack is not always successful. In total, we
have 3642 adversarial texts generated using two different attacking methods on six models.

To generate perturbations using random perturbations and Algorithm\(^2\)\ we limit the maximum number of words to be replaced to be 4 so that the resultant text is likely semantic-preserving. To obtain the synonyms of a chosen word, we use gensim\(^3\) which is an open-source library to find the most similar words in the word embedding space. To perform SEAs perturbation, we utilize the NMTs from an online Translation API service\(^2\).

### 4.2 Research Questions

**RQ1:** *Is KL divergence useful in detecting adversarial samples?*

To answer the question, we measure the accuracy of detecting adversarial texts using Algorithm\(^1\) and compare that to the alternative approach. Note that to apply Algorithm\(^1\)\ we must first select the threshold \(\epsilon\). Ideally, the threshold \(\epsilon\) should be chosen such that \(D_{KL}\) of normal texts are smaller than \(\epsilon\) and \(D_{KL}\) of adversarial texts are larger than \(\epsilon\) (in which case the accuracy of the detection is 1).

In our implementation, we adopt golden-section search\(^6\),\(^7\)\ which is commonly used to find the extremum of a function (i.e., accuracy of adversarial text detection) to identify \(\epsilon\). The search procedure consists of four steps: 1) given a search interval of \(D_{KL}\), e.g., \([a, b]\), we first split the interval \([a, b]\)

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**TABLE 5:** The number of generated adversarial texts and Threshold (\(\epsilon\)) in Algorithm\(^1\) where TextB is short for TEXTBUGGER and TextF is short for TEXTFOOLER. Without mentioning in the follow-up table, the same short form denotes the same thing.

| Dataset | Model | Attack | Threshold (\(\epsilon\)) |
|---------|-------|--------|--------------------------|
| NA      | TextCNN | SEAs   | 149                      | 0.0288 |
|         |        | TextB  | 159                      | 0.0266 |
|         |        | TextF  | 222                      | 0.0655 |
| RTMR    | TextCNN | SEAs   | 210                      | 0.111  |
|         |        | TextB  | 210                      | 0.111  |
|         |        | TextF  | 168                      | 0.1593 |
| IMDB    | TextCNN | SEAs   | 166                      | 0.1806 |
|         |        | TextB  | 166                      | 0.1806 |

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**TABLE 6:** Effectiveness of adversarial detection over different adversarial texts. “BL” denotes the baseline detection method, i.e., vanilla differential testing, while “KL-D” denotes our KL-divergence based approach. “dr” and “fp” denotes the detection rate (%) and false positive rate (%). “TextB” and “TextF” is short for TEXTBUGGER and TEXTFOOLER respectively.

| Attack | Dataset | TextCNN | LSTM |
|--------|---------|--------|------|
|        | NA      | BL     | KL-D |
|        | RTMR    | BL     | KL-D |
|        | IMDB    | BL     | KL-D |
|        | SEAs    | Avg    | 52   |
|        | TextB   | Avg    | 60   |
|        | TextF   | Avg    | 60   |

---

**TABLE 7:** Effectiveness of detection and repair when the adversarial texts are from a third model. The “source model” in the first column refers to the model the adversarial texts generated for. The adversarial texts are generated from NA dataset with TEXTBUGGER.

| Source model | Models of detector | Detection results | Repair accuracy (%) |
|--------------|--------------------|-------------------|--------------------|
|              | BiLSTM             | BL, LSTM          | 89, 21             | 60, 64              |
|              | LSTM               | TextCNN, BiLSTM   | 92, 23             | 61, 64              |
|              | TextCNN            | LSTM, BiLSTM      | 87, 25             | 46, 53              |
|              |                    | Avg               | 89                | 55, 83              |

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2. https://radimrehurek.com/gensim/
3. http://api.fanyi.baidu.com/api/trans/product/index
the results of our approach. Furthermore, column ‘dr’, i.e., the detection rate, denotes the percentage of adversarial texts which are detected; and column ‘fp’, i.e., the false positive rate, denotes that out of all the text identified as adversarial, how many percent are actually normal texts. Note that all numbers are percentile. It can be observed that our approach detects most of the adversarial texts. Our algorithm significantly outperforms the baseline for all datasets and models, i.e., on average 76.5% of the adversarial texts generated by SEAs are detected, 87% of TEXTBUGGER and 84% of TEXTFOOLER are detected, which are 23.5%, 15% and 21.5% higher than that of the baseline respectively. In particular, the detection rate is 41% higher for the TextCNN model with SEAs as the attacking method on the NA dataset. This shows that our adversarial detection algorithm effectively addresses the problem due to the transferability of adversarial texts.

We also observe that Algorithm \(1\) achieves a higher detection rate in detecting adversarial texts generated by TEXTBUGGER than detecting those generated by SEAs, i.e., 10.5% higher on average. One possible explanation is that the adversarial texts generated by TEXTBUGGER are likely to have a relatively small ‘distance’ from the original text. In comparison, adversarial texts generated by SEAs may have different structures (after two translations) and thus a relatively large distance to the original text. We also notice that the detection rate of adversarial texts generated by TEXTBUGGER is close to that of adversarial texts generated by TEXTFOOLER, i.e., only about 3% gap. This is not surprising since the two methods in crafting adversarial text are pretty similar as depicted in Section \(2\). Furthermore, since the adversarial texts generated by TEXTFOOLER are more natural (it not only checks the semantic similarity but also takes the part-of-speech into account when replacing words.), these adversarial texts thus are more difficult to detect.

On average, our method has false positive rate of 26% for the adversarial texts generated by attacking the TextCNN model and 21% for those generated by attacking the LSTM model, which is higher than the baseline approach. Consider that the baseline approach overlooks many adversarial texts (e.g., almost half of those generated by SEAs), we believe this is acceptable. In addition, our framework aims to automatically repair the “alarms” and thus some false positives can be eliminated by the subsequent repair. Later, we will show the effectiveness of our approach on handling the false positive samples in RQ3.

**Effectiveness on a Third Model.** In the above experiments, we assume that the adversarial samples are from one of the two models used in detection. A natural question is that if our approach can deal with the adversarial texts from a model which is different from the two models used in detection. To answer this question, we introduce a third model, i.e., BiLSTM \(63\) which consists of two LSTMs: one taking the input in a forward direction, and the other in a backwards direction. Then, we apply our approach to detect the adversarial texts generated from one model and use the other two for the detection. For every third model, we take 1000 adversarial texts (generated by TEXTBUGGER) and 1000 normal texts for the experiments. The results are summarized in Table 7. We can observe that the average detection rate is 89%, which suggests our approach can effectively identify the adversarial texts from an unseen model.

**Effectiveness on Defending against White-box Attacks.** Another concern is that if the attacker is aware of our detection method, then he or she may devise an approach to generate adversarial texts evading the detection, i.e., generate adversarial texts which are claimed normal by Algorithm \(1\) which can be regarded as the white-box attack. To answer this question, we conduct the following experiment. We first modify TEXTBUGGER so that it aims to evade the detection by Algorithm \(1\), i.e., by changing the importance score of sentences and words so as to generate adversarial texts which keep lowering \(D_{KL}\). Then, we apply it to generate adversarial texts based on 1000 benign samples of each dataset and report the success rate (i.e., how often it evades the detection). The results are shown in Table 8. For comparison, the row ‘one’ shows the success rates of attack without detection and the row ‘two’ shows that with detection using two models. The last row ‘three’ is the success rate of the attack if we adopt three models for detection, i.e., a text is adversarial if the \(D_{KL}\) of any of the two models is more than the threshold. It can be observed that the success rate drops significantly with detection using two models, and drops even further if three models are used. In particular, for dataset NA and IMDB, almost none of the attack is successful. We thus conclude that our adversarial text detection approach is resilient to white-box attacks. Note that in the above two experiments, the training accuracy and test accuracy of the BiLSTM are 91.46%/86.93% for NA, 80.99%/78.30% for RTMR and 87.72%/87.28% for IMDB.

**Effect of \(\epsilon\).** As shown in Algorithm \(1\), the threshold \(\epsilon\) is a key parameter of our detection approach which also has impact on the follow-up repair. We thus conduct an experiment to exploit the impact of the threshold on our approach (note that in practice the value of \(\epsilon\) is automatically identified by golden-section search described before). We adopt TextCNN as the target model and take 1000 adversarial texts generated by TEXTBUGGER and 1000 normal texts from NA. We vary the threshold from 0.005 to 0.05 with a step size of 0.005, and record the detection results with each of the threshold value. The detection results are shown in Fig 5. We can observe detection rate gradually decreases (as the number of true positive decreases) when increasing the threshold and when the threshold is beyond 0.025, the overall performance of our detection tends to remain stable. It is as expected that a larger threshold will lead to fewer false alarms but a higher false negative rate. Our recommendation is to choose a smaller threshold while keeping the overall performance since the false positive samples can be mostly mitigated by the following repair.

**TABLE 8: Success rate (%) of white-box attack for our detection approach.** "#models" denotes the number of models to attack simultaneously.

| Source model | Models of detector | Detection results | Repair accuracy (%) |
|--------------|--------------------|-------------------|---------------------|
| BiLSTM       | BiLSTM, FastText   | 95                | 57.8                |
| FastText     |                     | 98                | 74                  |

**TABLE 9: The impact of the architecture on our detection approach and repair approach.**

| #models | Model(s) | Detection results | Repair accuracy (%) |
|---------|----------|-------------------|---------------------|
| One     | TextCNN  | 57.6              | 74.3                | 66.30              |
|         | LSTM     | 66.3              | 78.3                | 96.60              |
|         | BiLSTM   | 69                | 79.78               | 97.1               |
|         | Avg      | 64.3              | 77.46               | 86.16              |
| Two     | TextCNN+LSTM | 1.6              | 28.36               | 6.5                |
|         | TextCNN+BiLSTM | 0.8              | 24.4                | 10.7               |
|         | LSTM+BiLSTM | 2.8              | 24.27               | 43.8               |
|         | Avg      | 1.73              | 25.68               | 20.35              |
| Three   | TextCNN+LSTM+BiLSTM | 0.2              | 12.4                | 0                  |
which we will show later in RQ3.

Effect of Model Architecture. To exploit the impact of the architecture of the models used on the proposed algorithm, we introduced another two popular text classification models which have different architectures: BiLSTM and FastText \cite{bojanowski2017enriching}. The FastText is based on a neural network which incorporates the idea of n-gram for word embedding. To evaluate the performance of our approach on the two models, for either of them, we first generate 1000 adversarial texts by TEXTBUGGER from NA dataset, and then apply our approach for detection. The results are shown in the “Detection results” column of Table \ref{table:results} We can observe that our approach still can effectively identify the adversarial samples, i.e. 95% and 98% detection rate for BiLSTM and FastText respectively.

![Detection results of our approach with different thresholds](image)

Table 5: Detection results of our approach with different thresholds. The “TP”, “TN”, “FP” and “FN” denote that out of 2000 input texts the number of true positive texts, true negative texts, false positive texts and false negative texts respectively.

Answer to RQ1: Algo. \ref{algo:repair} is effective in detecting adversarial texts with a relatively low false positive rate.

RQ2: Is our hypothesis for voting justified? To answer this question, we measure whether the majority of the perturbed texts generated from an adversarial text have the correct label. We take all the adversarial texts and apply semantic-preserving perturbations to generate 100 perturbed texts (using SEAs and TEXTFOOLER) for each of them and measure the percentage of the perturbed texts that are labeled correctly. The results are shown in the “Detection results” column of Table \ref{table:results} We can observe that our approach still can effectively identify the adversarial samples, i.e. 95% and 98% detection rate for BiLSTM and FastText respectively.

![Detection results](image)

To answer this question, we systematically apply Algorithm \ref{algo:repair} to all the adversarial texts, and measure its overall repair accuracy. Formally, the overall repair accuracy is defined as follows:

\[
\text{overall repair accuracy} = \frac{\#\text{correctly repaired texts}}{\#\text{adversarial texts}}
\]

where \#adversarial texts denotes the total number of adversarial texts to repair, and \#correctly repaired texts denotes the number of texts which can be correctly predicted after repair. We set the parameters for SPRT as follows: the error bounds \( \alpha \) and \( \beta \) are both 0.1, the confidence threshold \( \rho \) is 0.8, and the indifference region \( \sigma \) is to be 0.2 \( \times \rho \). We remark that a higher confidence can be achieved by setting a larger threshold and smaller error bounds. The price to pay is that it would typically require more perturbed texts (and thus time overhead). Note that when we apply ParaPer to generate perturbed texts, we use 25 different target languages for generating 25 semantic-preserving perturbations through two translations. If more is required, we use two target languages each time (and three translations), which provides us additionally 25 \( \times \) 25 perturbed texts. To be consistent with ParaPer, we set the perturbation budget (maximum number of perturbations) for RP and SubW as 650 as well.

We compare our approach with two baselines \cite{shafahi2018adversarial, binkert2018对抗}. Both baselines can automatically detect and correct adversarial texts generated by SEAs and TEXTFOOLER. This is reasonable as the adversarial texts generated by SEAs and TEXTFOOLER are more semantically similar to the original texts compared with these texts generated by TEXTBUGGER.

Answer to RQ2: Our hypothesis for voting is justified.

RQ3: Is our approach effective in repairing adversarial texts? To answer this question, we systematically apply Algorithm \ref{algo:repair} to all the adversarial texts, and measure its overall repair accuracy. Formally, the overall repair accuracy is defined as follows:

\[
\text{overall repair accuracy} = \frac{\#\text{correctly repaired texts}}{\#\text{adversarial texts}}
\]

where \#adversarial texts denotes the total number of adversarial texts to repair, and \#correctly repaired texts denotes the number of texts which can be correctly predicted after repair. We set the parameters for SPRT as follows: the error bounds \( \alpha \) and \( \beta \) are both 0.1, the confidence threshold \( \rho \) is 0.8, and the indifference region \( \sigma \) is to be 0.2 \( \times \rho \). We remark that a higher confidence can be achieved by setting a larger threshold and smaller error bounds. The price to pay is that it would typically require more perturbed texts (and thus time overhead). Note that when we apply ParaPer to generate perturbed texts, we use 25 different target languages for generating 25 semantic-preserving perturbations through two translations. If more is required, we use two target languages each time (and three translations), which provides us additionally 25 \( \times \) 25 perturbed texts. To be consistent with ParaPer, we set the perturbation budget (maximum number of perturbations) for RP and SubW as 650 as well.

We compare our approach with two baselines \cite{shafahi2018adversarial, binkert2018对抗}. Both baselines can automatically detect and correct adversarial texts generated by SEAs and TEXTFOOLER. This is reasonable as the adversarial texts generated by SEAs and TEXTFOOLER are more semantically similar to the original texts compared with these texts generated by TEXTBUGGER.

![Detection results](image)

Table 10: Results of justifying voting, where “RP”, “SubW” and “ParaPer” refers to the three semantic-preserving perturbation methods: random perturbation, TEXTBUGGER based method and paraphrase based perturbation.
TABLE 11: Overall repair accuracy (%) comparison between our approach and two baselines.

| Attack | Dataset | Model     | Our Approach | Baselines |
|--------|---------|-----------|--------------|-----------|
|        |         |           | RP | SubW | PARA | Autocorrect | scRNN |
| SEAs   | NA      | TextCNN   | 23.66 | 42.75 | 70.23 | 4.70 | 27.52 |
|        |         | LSTM      | 26.71 | 49.32 | 67.81 | 5.66 | 28.93 |
|        | MR      | TextCNN   | 50.00 | 60.00 | 76.00 | 6.76 | 30.18 |
|        |         | LSTM      | 50.38 | 51.13 | 78.20 | 5.71 | 19.05 |
|        | IMDB    | TextCNN   | 60.94 | 53.13 | 79.69 | 4.82 | 38.69 |
|        |         | LSTM      | 55.25 | 54.42 | 75.81 | 10.12 | 34.34 |
|        |         | Avg       | 41.16 | 48.46 | 74.56 | 6.30 | 29.79 |
| TEXTBUGGER | NA      | TextCNN   | 64.94 | 67.53 | 79.74 | 18.79 | 29.09 |
|        |         | LSTM      | 52.35 | 58.82 | 82.84 | 18.79 | 36.81 |
|        | MR      | TextCNN   | 72.57 | 67.43 | 80.01 | 19.24 | 29.26 |
|        |         | LSTM      | 69.40 | 59.02 | 79.23 | 23.81 | 25.97 |
|        | IMDB    | TextCNN   | 87.62 | 73.27 | 93.56 | 27.19 | 68.86 |
|        |         | LSTM      | 62.15 | 56.52 | 90.44 | 29.63 | 58.31 |
|        |         | Avg       | 68.17 | 63.77 | 84.30 | 22.90 | 42.47 |
| TEXTFOOLER | NA      | TextCNN   | 37.37 | 52.00 | 70.71 | 12.00 | 22.60 |
|        |         | LSTM      | 38.21 | 46.21 | 75.51 | 12.90 | 21.60 |
|        | MR      | TextCNN   | 40.39 | 48.21 | 54.95 | 20.30 | 23.30 |
|        |         | LSTM      | 59.35 | 41.49 | 56.99 | 22.10 | 23.50 |
|        | IMDB    | TextCNN   | 82.25 | 71.57 | 90.09 | 29.30 | 57.21 |
|        |         | LSTM      | 23.97 | 45.63 | 87.30 | 36.07 | 57.19 |
|        |         | Avg       | 48.61 | 50.85 | 72.69 | 23.81 | 34.23 |
|        |         | **Avg**   | 52.65 | 54.36 | 77.18 | 17.67 | 35.49 |

TABLE 12: Example of adversarial text repaired with our approaches.

| Ori | Adv | SubW | PARA |
|-----|-----|------|------|
| a silly, self-indulgent film about a silly, self-indulgent filmmaker | a silly, indulgent film about a silly, indulgent director | a silly, decadent film about a silly, indulgent director | a silly, sumptuous movie about a silly, indulgent director |

examples with misspellings. The first baseline [31] used the Python autocorrect package [4] to detect and automatically correct the adversarial texts with misspellings. In the following, we refer this baseline to Autocorrect. The second baseline [65] proposed a word recognition model scRNN for the same task. We first attempt to repair adversarial texts using each baseline and then test the accuracy of the target model on the repaired texts.

We summarize the results of different models and datasets in Table 12. On average, we are able to correctly repair 54.66%, 56.12% and 79.43% of the adversarial texts using RP, SubW and PARA respectively, while the two baselines achieve 14.60% and 36.91%. That is, all the three sort of methods in our approach outperform the two baselines and PARA achieves the best overall performance among the three. Comparing adversarial texts generated using different methods, we observe that adversarial texts generated by SEAs are harder to repair than those generated by TEXTBUGGER. This is expected as adversarial texts generated by SEAs (with two translation) are often structurally different from the original normal texts, whereas adversarial texts generated by TEXTBUGGER are very similar to the original normal texts. Comparing different repairing methods on different adversarial texts, we see that PARA performs significantly better than the other methods. This is expected to be due to the same reason above, i.e., other methods are ineffective in repairing adversarial texts which are structurally different from the original normal texts. The performance of the two baselines are significantly worse than our approaches, i.e., at least 17.75% gap (between the best performance of baselines and the worst performance of our approach), which is as expected since the two baselines are to detect the misspellings and thus are not able to handle semantic-preserved adversarial texts. Surprisingly, the performance of RP is close to that of SubW on adversarial texts generated TEXTBUGGER. The possible explanation is that these adversarial texts are near to the classification boundary and thus a random perturbation is sufficient for the repair. Table 12 shows a concrete example of repaired text using different perturbation methods. The first row shows an original text from RTMR, the label of which is negative. The adversarial text, at the second row, is generated by TEXTBUGGER with the LSTM model. The subsequent rows then show successful repairs which are generated using different methods. Note that by suggesting a simple edit (of one word), the text is no long considered adversarial and would be labeled correctly using the trained model.

We also compare our approach with the adversarial training method. We retrained the target model by adding 10% of adversarial texts (half of them are generated by TEXTBUGGER and half by TEXTFOOLER) into the training set. The retraining procedure is stopped once its accuracy on test set reaches the original level and at least 90% of adversarial texts in the training set can be correctly predicted. We compare the performance of the two methods from the following two aspects. Firstly, we compare the robustness of the models obtained through the two approaches. The results are shown in Table 13. We can observe that, respectively, 78.5% and 51.92% of adversarial texts can be predicted correctly by our approach and models from adversarial training. Secondly, we conducted experiments to evaluate if the model obtained through adversarial training is robust against different attacks. The results are shown in Table 14. We can observe that the success rate of attacking indeed decreases, but not significantly, i.e. a 3.3% drop on average. This is consistent with the well-known result that adversarial training easily overfits and has limited effectiveness in defending against unknown attacks [66], which is also evidenced in [45] where adversarial training only decreases the attack success rate by 7.2% on MR dataset. On the other hand, our approach is resilient under different kinds of attacks with a totally different defense paradigm, i.e. decreasing the attack success rate by 59.4%.

4. https://pypi.org/project/autocorrect/
on average.

Effectiveness on False Positive Samples. Considering that our detection approach may report false positive samples, one question is whether our repair is effective on these samples. To address this concern, we conduct a simple experiment on NA dataset with TextCNN and LSTM. Concretely, we apply our approach to repair randomly selected 1000 samples which are wrongly detected as adversarial. The results show that 81.4% (for TextCNN) and 85.2% (for LSTM) of samples can be correctly classified after repair. This suggests that our approach can correctly handle most of the false positive samples. It is reasonable that our approach can repair the false positive samples effectively as these false positive samples are mostly wrongly identified because of the large KL divergence (though their final predicted labels could be the same). As a result, we only need to generate repaired candidates with a KL divergence smaller than the threshold, which could be achieved effectively with Alg.

Effectiveness on a Third Model. We also exploit the effectiveness of our approach in the case where the adversarial texts from a model which is different from the two models used in detection. The results are shown in the column “Repair accuracy” of Table 7. We can observe that our approach achieves 57.8% and 74% overall repair accuracy for BiLSTM and FastText respectively, which, again, shows the robustness of our approach’s performance on different architectures. We notice that the average repair accuracy is even higher compared with TextCNN and LSTM. This is reasonable as an adversarial text is repaired by our approach using adversarial perturbation methods. As a result, a more easily attacked model is likely to be more easily repaired. In our experiments, the attack success rate of TextCNN on NA is 55% while that of FastText is 78.34%, and correspondingly the repair accuracy of TextCNN is lower than that of FastText, i.e., 67.53% and 74% respectively. We also notice that the repair accuracy of BiLSTM and LSTM are close (i.e., 74.7% and 75.3% respectively) as the attack success rate of the two models are comparable (i.e., 62.9% and 60.67% respectively).

Answer to RQ3: Our approach can repair about 80% of the adversarial texts. ParaPer performs the best.
TABLE 15: Time overhead

| Attack   | Dataset | Model  | Detect (ms) | Repair (s) |
|----------|---------|--------|-------------|------------|
|          |         |        | RP | SubW | ParaPer |
| SEAs     | NA      | TextCNN | 7.6 | 35.1 | 1.2 | 181.6 |
|          | LSTM    | TextCNN | 8.2 | 48.8 | 1.0 | 223.2 |
|          | LSTM    | TextCNN | 3.2 | 46.3 | 1.4 | 171.6 |
|          | TextCNN | LSTM    | 3.3 | 36.5 | 1.1 | 144.0 |
|          | LSTM    | TextCNN | 13.4| 61.5 | 1.0 | 134.8 |
|          | LSTM    | LSTM    | 13.3| 92.7 | 1.1 | 167.3 |
|         | Avg     |         | **8.2** | **56.8** | **1.1** | **170.5** |
| TEXTBUGGER | NA      | TextCNN | 6.6 | 35.0 | 0.7 | 157.8 |
|          | LSTM    | TextCNN | 6.4 | 31.2 | 0.8 | 171.5 |
|          | LSTM    | TextCNN | 3.6 | 39.6 | 1.4 | 81.1 |
|          | TextCNN | LSTM    | 3.4 | 40.0 | 1.2 | 67.7 |
|          | LSTM    | TextCNN | 15.2| 51.7 | 0.8 | 47.0 |
|          | LSTM    | LSTM    | 17.3| 101.0| 1.0 | 76.3 |
|          | Avg     |         | **8.8** | **49.7** | **1.0** | **102.8** |
| TEXTFOOLER | NA      | TextCNN | 6.7 | 47.4 | 0.7 | 109.0 |
|          | LSTM    | TextCNN | 8.6 | 54.5 | 0.7 | 98.0 |
|          | LSTM    | TextCNN | 4.9 | 34.2 | 0.8 | 85.7 |
|          | TextCNN | LSTM    | 4.8 | 46.9 | 1.1 | 90.3 |
|          | LSTM    | TextCNN | 28.9| 141.4| 1.5 | 79.4 |
|          | LSTM    | LSTM    | 32.8| 102.6| 1.1 | 99.6 |
|          | Avg     |         | **14.5** | **71.2** | **1.0** | **95.7** |
|          |         |         | **10.5** | **59.2** | **1.0** | **122.4** |

RQ5: What is the time overhead of our approach? The time overhead of our approach mainly consists of two parts: detection and repairing. For detection, measuring the time spent is straightforward. For repairing, precisely measuring the time is a bit complicated. For RP and SubW, the time taken to obtain the synonymy might be different depending on the configuration of gensim. For ParaPer, our implementation uses an online NMT service which often suffers from network delay and as a result, the time measure is inaccurate. To discount the effect of the network delay, we thus count the average number of perturbed texts required for voting, which is then multiplied with the average time needed to obtain a perturbed text using the respective methods. According to our empirical study on 1000 trials, the average time taken for generating one perturbed text is 0.55 seconds for RP, 0.09 seconds using SubW, and 1.44 seconds for ParaPer.

The results are summarized in Table 15 where column ‘Detect’ is the average detection time and column ‘Repair’ is the average repair time. The results show that detection is very efficient, i.e., the maximum time used is 17.3 ms and the average time across all datasets are 8.2 ms, 8.8 ms and 14.5 ms for SEAs, TEXTBUGGER and TEXTFOOLER generated adversarial texts respectively. This is expected as Algorithm 1 only requires to obtain the probability vectors of two neural network models and compare their difference to a threshold. Note that the more complex a model is, the more time is required. For example, detecting adversarial texts from IMDB requires more time than those from RTMR as the IMDB models are more complex.

For repairing, RP needs 59.2 seconds on average (maximum 141 seconds); SubW needs 1 seconds on average (maximum 1.5 seconds); ParaPer needs 122.4 seconds on average (maximum 223.2 seconds). Repairing using SubW takes much less time as SubW is designed to generate perturbed texts under the guidance of $D_{KL}$ and the resulting texts thus have a much higher probability to be detected as normal. Besides, we observe that repairing adversarial texts generated by SEAs and TEXTFOOLER are more difficult (consistent with the above). On average, the time needed for repairing adversarial texts generated by the three methods are 76.13 seconds, 51.16 seconds and 55.3 seconds respectively. The results show that adversarial texts generated by TEXTFOOLER are relatively time-consuming to be repaired compared with that of TEXTBUGGER. This is reasonable since the adversarial texts generated by TEXTFOOLER is more nature compared with that of TEXTBUGGER. If our approach is to be used in an online setting, we thus would recommend repairing with SubW which repairs 77% of the adversarial texts with a total time overhead of 1.1 seconds. We remark that we can easily parallelize the generation of perturbed texts to reduce the time overhead for all three methods.

Answer to RQ4: Our approach has the potential to detect and repair adversarial texts at runtime.

4.3 Threats to Validity

Quality of NMTs Our SEAs perturbation method requires the availability of multiple NMTs. In this work, we utilize the online industrial NMTs. The quality of NMTs will influence the performance of our repair algorithm, i.e., we might need more perturbations for a successful repair with worse NMTs.

Word substitution Both random perturbation and Algorithm 2 work by replacing selected words with their synonyms. Currently, we look for synonyms by searching the neighborhood of a given text in the embedding space. However, this may not always find the ideal synonyms, i.e., words which cause syntactical or grammar errors may be returned. Besides, finding better synonyms usually takes more time, which can be time-consuming.

Limited datasets and adversarial texts Our experiments results are subject to the selected datasets and generated adversarial texts, which have a limited number of labels. In general, it is difficult to vote for the correct label if there are many candidate labels, i.e., more perturbations are needed. Besides, we evaluate our approach on two existing attacks, it is not clear if our algorithm repairs adversarial texts from future attacks.
5 RELATED WORKS

This work is related to work on adversarial attacks in the text domain, which can be roughly divided into the following categories. One category is adversarial misspelling, which tries to evade the classifier by some “human-imperceptible” misspelling on certain selected characters [14], [17], [67]. The core idea is to design a strategy to identify the important positions and afterwards some standard character-level operations like insertion, deletion, substitution and swap can be applied. Another category is adversarial paraphrasing. Compared to misspelling, paraphrasing aims to generate semantics-preserving adversarial samples either by replacing certain words with their synonyms [17] or paraphrasing the whole sentence [18], [68]. For instance, the work in [18] uses NMTs to paraphrase the input; in work [68], the authors proposed Syntactically Controlled Paraphrase (SCPNs) to generate adversarial texts with the desired syntax. Our work uses paraphrasing as a way of generating repairs instead.

This work is related to detect adversarial perturbation. Existing detection methods for adversarial perturbation mainly focuses on the image domain [27], [28], [29], [30]. Recently, Rosenberg et al. devised a method to detect adversarial texts for Recurrent Neural Networks [34]. The idea is to compare the confidence scores of the original input and its squeezed variant. An input is regarded as adversarial if the two confidence scores are significantly different.

This work is related to work on defending adversarial perturbation, which mainly focus on the image domain, e.g., adversarial training [11], [69] and robust optimization [19]. Rosenberg et al. [34] presented several defense methods for adversarial texts, like adversarial training in the text domain or training ensemble models. Pruthi et al. [65] proposed to place an auxiliary model before the classifier. The auxiliary model is separately trained to recognize and correct the adversarial spelling mistakes. In [70], Wang et al. proposed Synonyms Encoding Method to defend adversarial texts in the word level, which maps all the semantically similar words into a single word randomly selected from the synonyms. The approach is shown to be effective to resist attacks generated by word-substitution.

To the best of our knowledge, our approach is the first to repair the adversarial texts without modifying/retraining the model and thus is complementary to existing approaches.

6 CONCLUSION

In this work, we propose an approach to automatically detect and repair adversarial texts for neural network models. Given an input text to a pair of neural network models, we first identify whether the input is adversarial or normal. Afterwards, we automatically repair the adversarial inputs by generating semantic-preserving perturbations which collectively vote for the correct label until a consensus is reached (with certain error bounds). Our experiments on multiple real-world datasets show the effectiveness of our approach.

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