Is BERT Really Robust? Natural Language Attack on Text Classification and Entailment

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Abstract

Machine learning algorithms are often vulnerable to adversarial examples that have imperceptible alterations from the original counterparts but can fool the state-of-the-art models. It is helpful to evaluate or even improve the robustness of these models by exposing the maliciously crafted adversarial examples. In this paper, we present the TextFooler, a general attack framework, to generate natural adversarial texts. By successfully applying it to two fundamental natural language tasks, text classification and textual entailment, against various target models, convolutional and recurrent neural networks as well as the most powerful pre-trained BERT, we demonstrate the advantages of this framework in three ways: (i) effective—it outperforms state-of-the-art attacks in terms of success rate and perturbation rate; (ii) utility-preserving—it preserves semantic content and grammaticality, and remains correctly classified by humans; and (iii) efficient—it generates adversarial text with computational complexity linear in the text length.

1 Introduction

In the last decade, machine learning (ML) models have achieved remarkable success in various tasks such as classification, regression and decision making. However, recently they have been found to be vulnerable to adversarial examples that are legitimate inputs altered by small and often imperceptible perturbations (Kurakin et al., 2016a,b; Papernot et al., 2017; Zhao et al., 2017). These carefully curated examples remain correctly classified by a human observer but can fool a targeted model. This has raised serious concerns regarding the security and integrity of existing ML algorithms. On the other hand, it has been demonstrated that robustness and generalization of ML models can be improved by crafting high-quality adversaries and including them in the training data (Goodfellow et al., 2015).

While existing works on adversarial examples have obtained great success in the image and speech domains (Szegedy et al., 2013; Carlini and Wagner, 2018), it is still challenging to deal with text data due to its discrete nature. Formally, besides the ability to fool the target models, outputs of such an attacking system in the text domain should also meet three key utility-preserving properties: 1) Human prediction consistency: prediction by humans should remain unchanged; 2) Semantic similarity: the crafted example should bear the same meaning as the source, as judged by humans; and 3) Language fluency: generated examples should look natural and be correct in grammar. Previous works have barely conformed to all three requirements (Li et al., 2016; Papernot et al., 2016). Especially, some works proposed to attack the targeted classifiers by replacing words in text with deliberately crafted misspelled words (Li et al., 2016; Liang et al., 2017; Gao et al., 2018; Li et al., 2018), which results in ungrammatical sentences.

In this work, we present a general framework, TextFooler, to generate adversarial examples in the context of natural language and a black-box setting, where no architecture or parameters of models are accessible. We aim to create both semantically and syntactically similar adversarial examples that meet the above-mentioned three desiderata. Basically, we first identify the most important words for the target model and then prioritize to replace them with the most semantically similar and grammatically correct words until the prediction is altered. We successfully applied this framework to attack three state-of-the-art models in five text classification datasets and two textual entailment datasets, respectively. We can always reduce the accuracy of target models to be under 10%
with less than 20% word perturbations. In addition, we validate that the generated examples are correctly classified by human evaluators, and that they are similar to the original text and grammatically acceptable via a human study.

Overall, our main contributions are summarized as follows:

- We propose a novel approach, TextFooler, to quickly generate high-profile utility-preserving adversarial examples to force the target models to make wrong predictions under the black-box setting.

- We evaluate TextFooler on a group of state-of-the-art deep learning models over five popularly used text classification datasets and two textual entailment datasets to demonstrate that it has achieved the state-of-the-art attack success rate and perturbation rate.

- We propose a comprehensive four-way automatic and three-way human evaluation of language adversarial attacks to evaluate the effectiveness, efficiency, and utility-preserving properties of our system.

- We open-source the code as well as the pre-trained target models and test samples for the convenience of future benchmarking.

2 Method

2.1 Problem Formulation

Given a pre-trained model \( \mathcal{F} : \mathcal{X} \rightarrow \mathcal{Y} \), which maps the input text space \( \mathcal{X} \) to the set of labels \( \mathcal{Y} \). A valid adversarial example \( x_{adv} \) is generated by altering the original data example \( x \in \mathcal{X} \) and should conform to the following requirements:

\[ \mathcal{F}(x_{adv}) \neq \mathcal{F}(x) \text{ and } S(x_{adv}, x) \geq \epsilon, \]

where \( S : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}^+ \) is a similarity function and \( \epsilon \in \mathbb{R}^+ \) is a threshold to preserve the utility of adversaries. In the natural language domain, \( S \) could be a semantic and syntactic similarity function.

2.2 Threat Model

Under the black-box setting, the attacker is not aware of the model architecture, parameters, or training data, and is only capable of querying the target model with supplied inputs and obtaining the output predictions and their confidence scores.

The proposed framework for adversarial text generation is shown in Algorithm 1. Basically it is composed of the following two steps:

**Step 1: Word Importance Ranking (line 1-6)**
We prioritize to manipulate those words that most significantly influence the final prediction results so as to minimize the alterations and thus maintain the semantic similarity as much as possible. Due to the black-box constraint, gradients of the model are not directly available, which are widely used to select important words for alterations in the white-box scenario. Instead we define the classification influence score termed \( C_{w_j} \), to measure the prediction scores change before and after deleting a word \( w_j \), which is formally defined as follows,

\[
C_{w_j} = \begin{cases} 
F_y(s) - F_y(s'), & \text{if } F(s) = F(s') = y \\
F_y(s) - F_y(s') + F_{y'}(s') - F_{y'}(s), & \text{if } F(s) = y, F(s') = y' 
\end{cases}
\]

![Algorithm 1 Adversarial Attacking](image)

**Input:** text example \( x = (w_1, w_2, ..., w_n) \) and its ground truth \( y \), target model \( \mathcal{F} \), similarity function \( S \), threshold \( \epsilon \), word embeddings \( E \)

**Output:** adversarial example \( x_{adv} \)

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1Will be made public in the camera-ready version
where \( s = (w_1, ..., w_j, ..., w_n) \), \( s' = (w_1, ..., w_{j-1}, w_{j+1}, ..., w_n) \), and \( F_y(\cdot) \) represents the prediction score for the \( y \) label.

After ranking the words by their importance, we filter out stop words derived from NLTK\(^2\) and spaCy\(^3\) libraries such as “the”, “in”, and “none” to make sure that they will not be replaced. This simple step of filtering is quite important to avoid grammar destruction.

**Step 2: Token Transformer (line 7-32)** In this step, for a given word in text, we select a suitable replacement word that has similar semantic meaning, fits within the surrounding context, and can force the target model to make wrong predictions. In order to select the best replacement word for the selected word \( w \), we propose the following steps:

- We extract the \( N \) nearest synonyms of the selected word by computing the cosine similarity between words using a set of word embedding vectors specially curated for synonym extraction (Mrkšić et al., 2016). By applying counter-fitting to the Paragram-SL999 word vectors provided by Wieting et al. (2015), this embedding vectors achieved state-of-the-art performance on SimLex-999, a dataset designed to measure how well different models judge semantic similarity between words (Hill et al., 2015). Using this set of embedding vectors, we identify words with cosine similarity scores with respect to \( w \) greater than \( \delta \) and obtain the \( N \) largest ones. This corresponds to line 8 in Algorithm 1.

- Among the \( N \) candidates, we only select those that have the same part-of-speech (POS) as \( w \) to assure that the grammar of the text is not destroyed (line 9 in Algorithm 1).

- For the remaining candidates, each word is inserted in place of \( w \) and the corresponding prediction scores of target model and semantic similarity between the source and adversarial counterpart are computed. Specifically, we used the Universal Sentence Encoder (USE) (Cer et al., 2018) to encode the two sentences into high dimensional vectors and used the cosine similarity score of these two vectors as the semantic similarity. Those words whose similarity scores are above a preset threshold \( \epsilon \) are filtered into the final candidates pool (lines 10-18 in Algorithm 1).

- In the final candidate pool, if there exist any candidates that can already alter the prediction of the target model, then we select the one with the highest semantic similarity score among these winning candidates as the best replacement word and output the adversary example. But if not, then we select the word with the least confidence score of label \( y \) as the best replacement word and repeat step 2 to transform the next selected word (line 19-31 in Algorithm 1).

We first execute Step 1 to obtain the words in the text ranked by their importance to the final prediction to form the candidates pool. Then Step 2 repeatedly prioritizes to transform each word in this candidate pool until the prediction of the target model is altered.

### 3 Experiments

#### 3.1 Tasks

We study the effectiveness of our adversarial examples on two important NLP tasks, text classification, and textual entailment, whose dataset statistics are summarized in Table 1. For large test sets with more than 1,000 instances, we evaluate our algorithm on a set of 1,000 examples randomly selected from the test set.

| Task     | Dataset | Train | Test | Avg Len |
|----------|---------|-------|------|---------|
| Classification | AG’s News | 30K   | 1.9K | 43      |
|           | Fake News | 18.8K | 2K   | 885     |
|           | MR       | 9K    | 1K   | 20      |
|           | IMDB     | 25K   | 25K  | 215     |
|           | Yelp     | 560K  | 38K  | 152     |
| Entailment| SNLI     | 570K  | 3K   | 8       |
|           | MultiNLI | 433K  | 10K  | 11      |

Table 1: Overview of the datasets.

#### 3.1.1 Text Classification

To study the robustness of our model, we use text classification datasets with various properties, including news topic classification, fake news detection, and sentence- and document-level sentiment analysis, with average text length ranging from tens to hundreds of words.

- **AG’s News (AG):** Sentence-level classification with regard to four news topics: World, Sports, Business, and Science/Technology.
Following the practice of Zhang et al. (2015), we concatenate the title and description fields for each news article.

- **Fake News Detection (Fake):** Document-level classification on whether a news article is fake or not. The dataset comes from the Kaggle Fake News Challenge.

- **MR:** Sentence-level sentiment classification on positive and negative movie reviews (Pang and Lee, 2005). We use 90% of the data as the training set and 10% as the test set, following the practice in (Li et al., 2018).

- **IMDB:** Document-level sentiment classification on positive and negative movie reviews.

- **Yelp Polarity (Yelp):** Document-level sentiment classification on positive and negative reviews (Zhang et al., 2015). Reviews with a rating of 1 and 2 are labeled negative and 4 and 5 positive.

### 3.1.2 Textual Entailment

- **SNLI:** A dataset of 570K sentence pairs derived from image captions. The task is to judge the relationship between two sentences: whether the second sentence can be derived from entailment, contradiction, or neutral relationship with the first sentence (Bowman et al., 2015).

- **MultiNLI:** A multi-genre entailment classification dataset with a coverage of transcribed speech, popular fiction, and government reports (Williams et al., 2017). Compared to SNLI, the MultiNLI dataset contains a larger variety of written and spoken English, thus capturing more linguistic complexity.

### 3.2 Attacking Target Models

For each dataset, we train several state-of-the-art models on the original training set. Each model achieves an accuracy score on the original test set close to what is reported in the literature, which is shown in Table 2. We then generate adversarial examples which are semantically similar to the test set to attack the trained models and make them generate different results.

|               | WordCNN | WordLSTM | BERT |
|---------------|---------|----------|------|
| Fake          | 92.5    | 93.1     | 94.6 |
| MR            | 99.9    | 99.9     | 99.9 |
| IMDB          | 79.9    | 82.2     | 85.8 |
| Yelp          | 89.7    | 91.2     | 92.2 |
| AG            | 95.2    | 96.6     | 96.1 |

Table 2: Accuracy (%) of target models on the standard test sets.

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On the sentence classification task, we target three models: word-based convolutional neural network (WordCNN) (Kim, 2014), word-based long-short term memory (WordLSTM) (Hochreiter and Schmidhuber, 1997), and the state-of-the-art Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018).

For the WordCNN model, we used three window sizes of 3, 4, and 5, and 100 filters for each window size with dropout of 0.3. For the WordLSTM, we used a 1-layer bidirectional LSTM with 150 hidden units and a dropout of 0.3. For both models, we used the 200 dimensional Glove word embeddings pre-trained on 6B tokens from Wikipedia and Gigawords (Pennington et al., 2014). We used the 12-layer BERT model with 768 hidden units and 12 heads, with 110M parameters, which is called the base-uncased version.

We also implemented three target models on the textual entailment task: standard InferSent (Conneau et al., 2017), ESIM (Chen et al., 2016), and fine-tuned BERT.

### 3.3 Automatic Evaluation

We first report the accuracy of the target models on the original test samples before attacking as the original accuracy. Then we test the target models against the adversarial samples crafted from the test samples, denoted as the attack accuracy. By comparing these two accuracy values, we can evaluate how successful the attack is. We then report the perturbed word percentage as the ratio of the number of perturbed words to the text length. Besides, we used the USE tool to mea-

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4https://www.kaggle.com/c/fake-news/data
5https://datasets.imdbws.com/
6https://github.com/huggingface/pytorch-pretrained-BERT
7https://github.com/facebookresearch/InferSent
8https://github.com/coetaur0/ESIM
9https://tfhub.dev/google/universal-sentence-encoder
Table 3: Automatic evaluation results of the attack system on text classification datasets. “Orig. Acc.” means “Original Accuracy”, “Pert.” means “Perturbed”, and “Avg. Text Len.” means “Average Text Length.”

| WordCNN | | WordLSTM | | BERT |
|---------|----|---------|----|------|
| MR      | IMDB| Yelp    | AT | Fake | MR      | IMDB| Yelp | AT | Fake | IMDB| Yelp | AT | Fake |
| Orig. Acc. (%) | 78.0 | 99.2 | 91.5 | 96.7 | 80.7 | 98.5 | 91.3 | 94.9 | 84.0 | 90.9 | 95.6 | 94.2 | 97.8 |
| Attack Acc. (%) | 2.8 | 0.0 | 1.5 | 15.9 | 0.3 | 2.1 | 3.8 | 16.4 | 11.5 | 13.6 | 6.8 | 12.5 | 19.3 |
| Pert. Word (%) | 14.3 | 3.5 | 8.3 | 15.2 | 11.0 | 14.9 | 5.1 | 10.6 | 18.6 | 10.1 | 16.7 | 6.1 | 12.8 | 22.0 |
| Semantic Similarity | 0.68 | 0.89 | 0.76 | 0.82 | 0.67 | 0.87 | 0.79 | 0.63 | 0.80 | 0.65 | 0.86 | 0.74 | 0.57 | 0.76 |
| Query Number | 123 | 524 | 487 | 228 | 3367 | 126 | 666 | 629 | 273 | 3343 | 166 | 1134 | 743 | 357 | 4403 |
| Avg. Text Len. | 20 | 215 | 152 | 43 | 885 | 20 | 215 | 152 | 43 | 885 | 20 | 215 | 152 | 43 | 885 |

sure the semantic similarity between the original and adversarial texts. These two metrics, the perturbed words percentage and the semantic similarity score, together evaluate how semantically similar the original and adversarial texts are. We finally report the number of queries to count how many times the attack system sends input samples to the target model and fetches the output probability scores. This metric can reveal the efficiency of the attack model.

3.4 Human Evaluation

We also asked human judges to rate the adversarial examples on three aspects: semantic similarity, grammaticality, and classification accuracy. We randomly selected 100 samples of each task to generate adversarial examples, one targeting the WordLSTM model on MR dataset and another targeting BERT on SNLI. We first shuffled all model-generated adversarial examples and asked human judges to give a grammaticality score of the generated sentence on a Likert scale of 1−5, similar to the practice of Gagnon-Marchand et al. (2018). Next, we evaluated the semantic similarity of the original and adversarial sentences by asking humans to judge whether the generated adversarial sentence is similar, ambiguous, or dissimilar to the source sentence. Lastly, we evaluate the classification consistency by shuffling both the original and adversarial sentences together, ask humans to rate all of them and then calculate the consistency rate of both classification results. Each task is completed by two human judges.

4 Results

4.1 Automatic Evaluation

The main results of black-box attacks in terms of automatic evaluation on the text classification and textual entailment tasks are summarized in Table 3 and 4, respectively. Overall, as can be seen from our results, we are able to achieve a high success rate when attacking with a limited number of modifications on both tasks. No matter how long the text is, and no matter how accurate the target model is, TextFooler can always reduce the accuracy from the state-of-art values to under 15% (except on the Fake dataset) with less than 20% word perturbation ratio (except the AG dataset under the BERT target model). For instance, it only perturbs 5.1% of the words of one sample on average when reducing the accuracy from 89.8% to only 0.3% on the IMDB dataset against the WordLSTM model. Notably, our attack system makes the WordCNN model on the IMDB dataset totally wrong (accuracy of 0%) with only 3.5% word change rate. As the IMDB dataset has an average length of 215 words, the system only perturbed 10 words or fewer per sample to conduct successful attacks. This means that our attack system can successfully mislead the classifiers into assigning wrong predictions via subtle manipulation.

Comparing the semantic similarity scores in both Tables 3 and 4 against the perturbed word ratios, we find that they have a high positive correlation. Empirically, when the text length is longer than 10 words, the semantic similarity measurement becomes more stable. Since the average text lengths of text classification datasets are all above 20 words and those of textual entailment datasets are around or below 10 words, we need to treat the semantic similarity scores of these two tasks individually. Therefore we performed a linear regression analysis between the perturbation ratio and semantic similarity for each task and obtained r-squared values of 0.94 and 0.97 for text classification and textual entailment tasks, respectively. Such high values of r-squared reveal that our proposed semantic similarity has high correlation (negative) with the perturbed words ratio, which can both be good automatic measurements to evaluate the degree of alterations of the original texts.

We include the average text length of each dataset in the last row of Tables 3 and 4 so that
| Model | SNLI | MultiNLI (m/mm) | SNLI | MultiNLI (m/mm) | SNLI | MultiNLI (m/mm) |
|-------|------|----------------|------|----------------|------|----------------|
| Original Accuracy (%) | 84.3 | 70.9/69.6 | 86.5 | 77.6/75.8 | 89.4 | 85.1/82.1 |
| Attack Accuracy (%) | 3.5 | 6.7/6.9 | 5.1 | 7.7/7.3 | 4.0 | 9.6/8.3 |
| Perturbed Word (%) | 18.0 | 13.8/14.6 | 18.1 | 14.5/14.6 | 18.5 | 15.2/14.6 |
| Semantic Similarity | 0.50 | 0.61/0.59 | 0.47 | 0.59/0.59 | 0.45 | 0.57/0.58 |
| Query Number | 57 | 70/83 | 58 | 72/87 | 60 | 78/86 |
| Average Text Length | 8 | 11/12 | 8 | 11/12 | 8 | 11/12 |

Table 4: Automatic evaluation results of the attack system on textual entailment datasets.

it can be conveniently compared against the query number. The query number is linear to the text length and overall the ratio of query number to the average text length is between 2 and 8. Notably, the longer the text is, the smaller this ratio, which validates the efficiency of TextFooler.

Although there are no open-source pre-trained target models for directly benchmarking our model against the published systems, we can still perform an indirect comparison under the same target model architecture and dataset, which is summarized in Table 5. From this table, we can clearly see that our system beats the state-of-the-art models in terms of both the attack success rate (calculated by dividing the number of wrong predictions by the total number of adversarial examples) and perturbed word ratio.

| Dataset | Model | Success Rate | Perturbed Word |
|---------|-------|--------------|----------------|
| IMDB    | BUGGER | 86.7 | 6.9 |
|         | NAE    | 97.0 | 14.7 |
|         | Ours   | 99.7 | 5.1 |
| SNLI    | NAE    | 70.0 | 23.0 |
|         | Ours   | 95.8 | 18.0 |
| Yelp    | AE     | 74.8 | -   |
|         | Ours   | 97.8 | 10.6 |

Table 5: Comparison of our attack system against published systems in terms of attack success rate (%) and perturbed word ratio (%). NAE is from Alzantot et al. (2018), BUGGER is from Li et al. (2018), and AE is from Kuleshov et al. (2018). The target model for IMDB and Yelp is LSTM and SNLI is InferSent.

4.2 Human Evaluation

We sampled 100 adversarial examples on the MR dataset with the WordLSTM model and 100 examples on SNLI with the BERT model. We verified the quality of our examples via three experiments. First, we ask human evaluators to give a grammaticality score of a shuffled mix of original and adversarial examples. As shown in Table 6, the grammaticality score of the adversarial sentences are quite close to the original sentences on both datasets. By sensibly substituting synonyms, our model generates smooth outputs such as “the big metaphorical wave” in Table 7.

| Input | MR (WordLSTM) | SNLI (BERT) |
|-------|---------------|-------------|
| Original Grammar | 4.22 | 4.50 |
| Attack Grammar | 4.01 | 4.27 |

Table 6: Grammaticality of original and adversarial examples for MR (WordLSTM) and SNLI (BERT) models on a 1 – 5 scale.

We then asked the human raters to assign labels to both original and adversarial samples from both MR and SNLI datasets. The overall agreement between the labels of the original sentence and the adversarial sentence is relatively high, with 92% on MR and 85% on SNLI. Though our adversarial examples are not perfect in every case, this shows that majorities of adversarial sentences have the same attribute as the original sentences from humans’ perspective. Table 7 demonstrates typical examples of sentences with almost the same meanings that result in contradictory classifications by the attacked target model.

Lastly, we asked human judges to decide whether each adversarial sample retains the meaning of the original sentence. They need to decide whether the synthesized adversarial example is similar, ambiguous, or dissimilar to the provided original sentence. We regard similar as 1, ambiguous as 0.5, and dissimilar as 0, and obtained sentence similarity scores of 0.91 and 0.86 on MR and SNLI respectively, which shows the perceived difference between original and adversarial examples is small.

5 Discussion

5.1 Ablation Study

Word Importance Ranking To validate the effectiveness of step 1 in Algorithm 1, i.e., the word importance ranking part, we remove this step and instead randomly select the words in text to perturb. We keep the perturbed word ratio and step
Movie Review (Positive ↔ Negative)

| Original [Label: NEG]  | Attack [Label: POS]                          |
|------------------------|---------------------------------------------|
| The characters, cast in impossibly contrived situations, are totally estranged from reality. | The characters, cast in impossibly engineered circumstances, are fully estranged from reality. |

| Original [Label: POS]  | Attack [Label: NEG]                          |
|------------------------|---------------------------------------------|
| It cuts to the knot of what it actually means to face your scares, and to ride the overwhelming metaphorical wave that life wherever it takes you. | It cuts to the core of what it actually means to face your fears, and to ride the big metaphorical wave that life wherever it takes you. |

SNLI (Entailment, Neutral, Contradiction)

| Premise | Original [Label: CON]  | Adversary [Label: ENT] |
|---------|------------------------|------------------------|
| Two small boys in blue soccer uniforms use a wooden set of steps to wash their hands. | The boys are in band uniforms. |

| Premise | Original [Label: NEU]  | Adversary [Label: ENT] |
|---------|------------------------|------------------------|
| A child with wet hair is holding a butterfly decorated beach ball. | The youngster is at the shore. |

Table 7: Examples of original and adversarial sentences from MR (WordLSTM) and SNLI (BERT) datasets.

We examined whether adversarial texts transfer between different models, focusing on the IMDB and SNLI datasets. We collected the test adversarial examples that are wrongly predicted by one target model and then measured the prediction accuracy of them against the other two target models, whose results are summarized in Table 8. As we can see, there is a moderate degree of transferability between models and the transferability is higher in the textual entailment task than the text classification task. Moreover, the model with higher prediction accuracy generally has higher transferability.

5.2 Transferability

We examined whether adversarial texts transfer between different models, focusing on the IMDB and SNLI datasets. We collected the test adversarial examples that are wrongly predicted by one target model and then measured the prediction accuracy of them against the other two target models, whose results are summarized in Table 10. As we can see, there is a moderate degree of transferability between models and the transferability is higher in the textual entailment task than the text classification task. Moreover, the model with higher prediction accuracy generally has higher transferability.
|                   | WordCNN | WordLSTM | BERT |
|-------------------|---------|----------|------|
| IMDB              | 0.0     | 0.0      | 84.9 |
|                   | 74.9    | 8.0      | 87.9 |
|                   | 84.1    | 85.1     | 0.0  |
| InterSent         | 0.0     | 62.7     | 67.7 |
| SNLI              | 49.4    | 0.0      | 59.3 |
|                   | 58.2    | 54.6     | 0.0  |

Table 10: Transferability of adversarial examples on the IMDB and SNLI dataset. Row i and column j show the accuracy of adversarial samples generated for model i evaluated on model j.

5.3 Adversarial Training

We performed a preliminary experiment to see if adversarial training can be used to lower the attack success rate. We collected the test adversarial examples that are wrongly predicted and appended them to the original training set. We then used the updated dataset to adversarially train a model from scratch and attacked this adversarially-trained model. We conducted this experiment on the MR and SNLI datasets against the BERT model, and the results are shown in Table 11. From this table, we see that after adversarial training, the attack accuracy and perturbed words ratio both increase, indicating that the attack difficulty increases after exposing the model to adversaries. This reveals one of the potency of our attack system that we can enhance the robustness of a model to future attacks by retraining it with original training data plus the generated adversarial examples.

|                   | MR      | SNLI    |
|-------------------|---------|---------|
|                   | Attack Acc. | Pert. Word | Attack Acc. | Pert. Word |
|                   | w/o Adv.  | 11.5    | 16.7    | 4.0     | 18.5    |
|                   | w/ Adv.   | 18.7    | 21.0    | 8.3     | 20.1    |

Table 11: Results of adversarial training on MR and SNLI dataset against the BERT model (all numbers are in percent). “w/ Adv.” and “w/o Adv.” mean that we use or not adversarial training, respectively.

5.4 Error Analysis

Our adversarial samples are susceptible to three types of errors: word sense ambiguity, grammatical error, and task-sensitive content shift. Although large thesauri are available, a word usually has many meanings, with a set of synonyms for each word sense. One example can be the transfer from an original sentence “One man shows the ransom money to the other” to the synthesized “One man testify the ransom money to the other”, where “testify” in this case is not the appropriate synonym of “show”.

Grammatical errors are also frequent in text generation. For example, the sentence “A man with headphones is biking” and “A man with headphones is motorcycle” differ by the word “biking”, which can be both a noun and a verb, as well as a fairly similar word to “motorcycle”. As future work, some carefully designed heuristics can be applied to filter out grammatical errors.

Content shift can be seen in a task-specific situation. In the sentiment classification task, a change of words might not affect the overall sentiment, whereas in the task of textual entailment, the substitution of words might result in a fundamental difference. For example, if the premise is “a kid with red hat is running”, and the original hypothesis is “a kid is running (ENTAILMENT)”, then if the adversarial example becomes “a girl is running”, the sensible result turns into NEUTRAL instead.

6 Related Work

Adversarial attack has been extensively studied in computer vision (Goodfellow et al., 2014; Kurakin et al., 2016a; Madry et al., 2017; Moosavi-Dezfooli et al., 2017; Rosca et al., 2017). Most works have been done in the context of continuous input spaces (Szegedy et al., 2013; Goodfellow et al., 2014), where adversarial attacking was achieved by gradient-based perturbation to the original input.

Adversarial attack on discrete data such as text is more challenging. Inspired by the approaches in computer vision, previous works in language adversarial attack have focused on variations of gradient-based methods. For example, Zhao et al. (2017) transformed input data into a latent representation using generative adversarial networks (GANs), and then retrieved adversaries close to the original instance in the latent space.

Other works observed the intractability of GAN-based models on text and the shift in semantics in the latent representations, so heuristic methods such as scrambling, misspelling, or removing words were proposed (Ebrahimi et al., 2017; Alzantot et al., 2018; Li et al., 2016, 2018).

7 Conclusions

Overall, we study adversarial attacks against state-of-the-art text classification and textual entailment models under the black-box setting. Extensive ex-
Experimental results demonstrate that our proposed system, TextFooler, is effective and efficient for generating targeted adversarial texts. And our human study validated that the generated adversarial inputs are legible, grammatical, and similar in meaning to the original input.

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