An Attention Score Based Attacker for Black-box NLP Classifier

Yueyang Liu, Hunmin Lee, and Zhipeng Cai
Georgia State University, Atlanta, GA, 30303, USA
{yliu114, hlee185, zcai}@gsu.edu

Abstract. Deep neural networks have a wide range of applications in solving various real-world tasks and have achieved satisfactory results, in domains such as computer vision, image classification, and natural language processing. Meanwhile, the security and robustness of neural networks have become imperative, as diverse researches have shown the vulnerable aspects of neural networks. Case in point, in Natural language processing tasks, the neural network may be fooled by an attentively modified text, which has a high similarity to the original one. As per previous research, most of the studies are focused on the image domain; Different from image adversarial attacks, the text represents in a discrete sequence, traditional image attack methods are not applicable in the NLP field. In this paper, we propose a word-level NLP sentiment classifier attack model, which includes a self-attention mechanism-based word selection method and a greedy search algorithm for word substitution.

We experiment with our attack model by attacking GRU and 1D-CNN victim models on IMDB datasets. Experimental results demonstrate that our model achieves a higher attack success rate and more efficient than previous methods due to the efficient word selection algorithms are employed and minimized the word substitute number. Also, our model is transferable, which can be used in the image domain with several modifications.

Keywords: Attention Mechanism · Black-box NLP attack · Greedy search

1 Introduction

In recent years, the research and application of deep neural networks have become a prevalent domain within the academic field and a wide range of deep neural networks applications in solving real-world tasks have achieved good results, such as image classification and natural language processing as well as other fields. However, due to frequent and covert hacking activities, security and privacy of neural networks has gained attentions. Mainly, neural networks are vulnerable to attacks from input adversarial examples. NLP solutions for example, it is easily being fooled by a carefully modified text, and since
this altered text has a high similarity to the original text, attackers can pass through the spam detection by masquerading as a benign email [8]. This implies that the neural network classifier is likely to make prediction errors based on those modified texts, where we call these adversarial examples. Diverse studies have been conducted regarding generating the adversarial examples: Liang et al [15] suggest that using some negative words will change the meaning of the sentences. Huang et al [14] proposed a FGSM method by adding unreadable characters among the training sample sentences in order to create the adversarial examples. Although those methodologies succeeded in perturbing the classifier to misjudge, but they also alter the structure of the sentences obviously dissimilar to the original text which is not desirable. For instance, the change of emotional words within the analogous context (in terms of its semantic meanings) may fool the sentiment classifier leading to a contrasting result but the classification based on human’s decision will not be much different. The main reason for such difference in those two entities’ perception is essentially the text is a discrete sequence, and alternation of target words in given texts with terminology that has similar meanings would fool the neural networks. In this case, human can easily perceive that there was a perturbations, but eventual sentiment classification result would be similar [7]. In case of image manifestation, it data structure is continuous, and when minute perturbation is being introduced into the image and such variation is invisible to humans but can fool the neural networks.

In this paper, we propose a word-level attack model, based on the attention score word substitution method with a greedy search algorithm and cosine similarity penalty. We test our designed methodology through experiments using the IMDB dataset, which includes 25000 samples of training data and 25000 testing data, specially selected for sentiment analysis. Experimental results show that our generated adversarial samples are able to fool the GRU and 1D-CNN victim models and lead to a 20% of miss judging. We also conduct sentence similarity analyses to ensure our model adversarial example quality.

This paper is organized as follows. In section II, we explicate the backgrounds of major attention methods and three levels of NLP adversarial attacks, as well as related works on word substitution mechanisms. In section III, we introduce our self attention-based word ranking algorithm and a greedy-based word substitution algorithm. In section IV, describe the attack experiment on two victim models with our methodology. Finally, Section V presents our conclusions and future work.

2 Background

2.1 Attention Mechanism

Likewise, the attention method was devised based on the human ability to quickly filter out valuable information with limited resources [24], while the human eye can focus on a target area and then puts more attention on the area to obtain more detailed information and suppress other information. With the
development of deep neural networks, attention mechanism has been widely used in diverse application domains.

**Global Attention** Mnih et al [21] proposed an algorithm with attention mechanism for the image classification in 2014. Instead of processing an entire image or even bounding box at once, at each step, the model selects the next location to attend to based on past information and the demands of the task, while it can reduce time complexity, and their result indicate that it can achieve remarkable results in image classification tasks. Bahdanau et al [2] utilized the attention mechanism to the Neural Network Machine Translation (NMT) domain for the initial attempt. Their model can find a best position where the most information is concentrated. Then, the model predicts the target word based on the context vector associated with these source positions and all the previous generated target words. Their study solve the word alignment problems and improves the translation quality of encoder–decoder model and those approach is known as the global attention [17]. In Bahdanau et al [2] work, a Bidirectional LSTM encoder is used to gain a hidden state \( h_1, h_2, \ldots h_t \) from input sequence, while to the decoder of hidden state can be represent as \( (h_1, h_2, \ldots h_j) \). At each time step \( t \), a alignment weight vector can be calculate based on source states \( h_s \) and target states \( h_t \):

\[
a_t(s) = \frac{\exp(score(h_t, h_s))}{\sum_{s' = 1}^{T} \exp(score(h_t, h_s'))}
\]

the context vector:

\[
c_t = \sum_{j=1}^{T} \alpha_t h_j
\]

However, the computational cost of global attention mechanism is relatively large, while the length of the source text will decrease, increasing the overall performance of the attention model.

**Local Attention** Since the global attention model has the drawback of having an expensive computation amount, Luong et al [17] proposed a local attention mechanism that selectively focuses on a small subset of the source positions per target word. In their paper they suggest the context vector \( c_t \) of aligned position \( p_t \) is derived as a weighted average over the set of source hidden states within the window \([p_t - D, p_t + D]\), the context vector:

\[
c_t = \sum_{j=p_t-D}^{p_t+D} \alpha_t h_j
\]

And in the alignment weights calculation step a standard normal distribution product term was added, which gives more weight to when the alignment is close to \( P_t \). In their experiment, the local attention is higher than the global attention in the BLEU index, which proves that the local attention obtains a more accurate translation with a smaller computational.
Self-Attention Different from the general attention process, the self-attention mechanism’s Query, Key, and Value are originated from the identical input, which can be used to compute the attention distributions among the source, searching the dependency between each lexical item [16].

\[
\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right)V
\]

The model based on intra-attention gains a better perplexity score than LSTM or RNN model, and it has empirically shown to have an outstanding performance in sentiment analysis and Natural Language Inference (NLI) tasks [6]. In the Transformer model, Vaswani et al [26], implemented a stacked self-attention and point-wise fully connected layers for both encoder and decoder cells rather than LSTM or CNN architectures. In the translation tasks, the Transformer can be trained significantly faster than architectures based on recurrent or convolutional layers.

A number of previous works have confirmed the effectiveness of the attention mechanism in sentiment analysis tasks [20], the attention mechanism can assign weights to features so that the classifier can use feature information in a focused manner.

2.2 Word-level Textual Adversarial Attack

According to whether they have the access to the model parameters, the attack method can be divided into two types: white-box attacks and black-box attacks. The white box attacker is able to access all the parameters and knows the structure of the model, while the black box attacks lack that information. Commonly, black box attacks are more challenging, which use constant query and observation of the output of the target model to generate the optimal disturbance of the victim model. In this paper, we mainly discuss the black box attack. According to the perturbations units, textual adversarial attacks can be divided into three levels according to the generated adversarial examples: character-level attacks, word-level attacks, and sentence-level. A character-level attack is to disturb several characters in a word, which can be deletion, insertion, or swapping of two characters, however, misspellings can be easily detected [13]. A word-level attack is to manipulate the whole word in the text. The most common word-level attacks are insertion and swapping, the modifications are mainly based on synonym substitution. Hence, after a careful design, humans are more imperceptible to those word-level modifications than char-level attacks. Meanwhile, according to the way of selecting manipulated words, the word-level adversarial attack can be classified into gradient-based, importance-based [10]. In the sentence-level attack, The modified sentence is to add a paragraph of irrelevant sentence at the beginning or end of the text. In this case, the original text will remain logical and grammar correct, but it will fool the classifier.

Word substitute based on salience Samanta and Mehta [23] proposed a word-level black-box attack based on word salience, This method first is to uses
FGSM to approximate the contribution of a word to the classification result. Then the adverb words that have a great contribution to the classifier will be substituted by a candidate. The candidate pool consists of synonyms, typos, and genre-specific keywords whose term frequencies are high in the corpus. Ren et al [22] improved Samanta and Mehta’s method and gave out a greedy algorithm called probability-weighted word saliency (PWWS). The synonym set is built with WordNet, the candidate is selected if the substitute causes the most significant change in the classification probability.

**Word substitute based on Swarm Intelligence Optimization Algorithms**

Alzantot et al [1] proposed a black-box attack algorithm based on a genetic algorithm, first they design a subroutine called Perturb, in the subroutine, it randomly selects a word, first, it uses GloVE word space and Google 1 billion words language model create a candidate pool with $k$ words. Last, choose one word in the $k$ words to maximize the target label prediction probability. By calling the Perturb subroutine many times they create an initial generation set. In the GA computed the target label prediction probability, once the predicted label is equal to the target label, finish the optimization. Otherwise, samples from the current generation to create child generations applied the Perturb subroutine again until the target label prediction changed.

### 3 Methodology

We conduct our black-box attack, which setting will be more close to the real application environment. Assuming the attacker has no access to the model architecture, parameters, or training progress, and is only capable of querying the target model with supplied inputs and the output predictions. In our word-level adversarial attack model, it incorporates two parts: namely, the attention score-based word substitution method and greedy-based synonyms search algorithm. Different from previous approaches like [1][23][22], our model generates the word attention score and ranks those words which have greater contributions to the current task first, then conducts a word substitution task. Our model limits the word substitute number to reduce the computational resource, also while making word substitutions, we conduct a greedy method to select the most similar words in order to avoid introducing grammatical mistakes.

**Attention score based word rank algorithm** In previous attempts [24][3] and [26] to render self-attention able to learn the dependencies between words in sentence and capture the inner structure information within sentence have seen. Inspired by Yang et al [28], we designed an attention score-based word rank algorithm, which contains a word sequence encoder and a word-level attention layer. To the word sequence encoder part, we use a two-layer Bidirectional LSTM [11] to obtain the hidden layer. In the self-attention layer, it provides a set of summation weight vectors for the LSTM hidden states. Weight vectors are dotted
with the LSTM hidden states. Given a sentence with \( n \) length and each word \( x_t \) while the \( t \in n \) is embed with

![Figure 1. attention score based word rank model](image)

the ‘GloVE.6B.100d’ vector; In the forward LSTM, we get the forward hidden state

\[
h_{t1} = f_{lstm}(w_t, h_{t1-1})
\]

To the backward LSTM with the same step, we have the backward hidden state:

\[
h_{t2} = f_{lstm}(w_t, h_{t2-1})
\]

And we concatenate the two direction hidden state, then the hidden output for the word vector \( x_t \) will be

\[
h_{t12} = [h_{t1}, h_{t2}]
\]

To calculate the words’ attention scores, we achieve that by feed the concatenated hidden output \( h_{t12} \) through a single-layer perception:

\[
u_t = \tanh(W_w h_{t12} + b_w)
\]

then we measure the attention score of each word as the similarity of \( u_t \) with a word level context vector \( u_{\text{similar}} \) and get a normalized importance weight \( \alpha_t \) through a softmax function.

\[
\alpha_t = \frac{\exp(u_t^\top u_{\text{similar}})}{\sum \exp(u_i^\top u_{\text{similar}})}
\]

**The greedy based synonyms search algorithm** We designed a greedy-based synonyms search algorithm to select the candidate that will cause the most classifier confidence decrease from the candidate pool. For each word \( w \) need to be substituted, we maintain a max word-loss score pair \((w', \sigma)\), by selecting the nearest neighbors in GloVE word embedding space as our candidate pool \( w' \) with \( k \) candidates \( w'_i \in \{w'_1, \ldots, w'_k\} \), thus will ensure semantic similarity afterword
substitute, while going through the candidate pool, substitutes the original word \( w \) with candidate \( w' \) and create an intermediate adversarial example \( s' \) then feed the sample into the victim classifier \( f \), update the word-loss score pair while having a higher loss. Here we use a Cross-Entropy Loss as our loss function:

\[
\arg \max_{w' \in W} -(f(w_i) \cdot \log(f(w'_i)) + (1 - f(w_i)) \cdot \log(1 - f(w'_i)))
\]

After iteration is finished the word-loss score pair \((w', \sigma)\) will have the final election word which chosen used in the final adversarial example. By selecting the nearest neighbors in GloVE word embedding space as our candidate pool, thus will ensure semantic similarity afterword substitute, by picking nearest neighbors in GloVE vectors, the generated adversarial example will only fool the victim classifier, and keep the grammar correct.

**Attention Score Based Attacker Model** The attack model can be seen in the Algorithm 1. The model starts by creating the initial generation of a list of size \( k \) by calling the Attention score-based word rank algorithm to create a pair of words attention score to the original sentences. Then, the member having the highest attention score of each population member in the current generation is substituted by one of the nearest neighbors of the GloVE model, and the loss value computed as the target label prediction probability, found by querying the victim model function \( f \). If the loss value is higher than the previous, use the nearest neighbor to substitute the word in the original sentences, otherwise, drop the candidate. Once the predicted label is equal to the target label, the optimization is complete.

**Algorithm 1 Attention Score Based Attacker**

**Input:** original sample \( s \), word attention score list \( \nu \), victim classifier \( f \)

\[
\sigma_0 \leftarrow \text{Loss}(f(s))
\]

for each \( w \) in \( s \) with max \( \nu_i \)

find \( k \) candidates \( w' \leftarrow (w'_1, \ldots, w'_k) \) of \( w \)

for each \( w'_i \) in \( w' \)

\( s' \leftarrow \text{substitute } w \text{ with } w'_i \)

if \( \sigma(f(s')) > \sigma_0 \)

\( \sigma_0 \leftarrow \sigma(f(s')) \)

\( w \leftarrow w'_i \)

\( \nu_w \leftarrow -\nu_w \) \quad \triangleright \text{substitute with the candidate}

end if

end for

if \( d(s') \neq d(s) \) \quad \triangleright \text{stop iterate when success fool the victim}

return \( s' \)

end if

end for

return \( s \) \quad \triangleright \text{failed fool the victim, return original}
4 Experiments

Data Set We trained our model and the victim models using the IMDB dataset of movie reviews\[19\]. The IMDB dataset consists of 25,000 training examples and 25,000 test examples.

Victim Models We trained a CNN model and a GRU model as our victim model, we limit the word dictionary length to 30000, the CNN model consists of an embedding layer that performs 100-dimensional word embedding on 2500-dimensional input vectors, two 1D-convolutional layers, a 1D-max-pooling layer, and two fully connected layers. In the GRU model, it includes a 2 layer of recurrent layer and embedding dimensions set to 100. In both models, we use Adam as our optimizer. In the test dataset, the GRU model achieved an 87.13% accurate rate with a 0.315 loss, and the 1D-CNN model achieved an 80.74% with a 0.467 loss in binary classification.

Attack Model In the attack model, we use drawn out each word’s attention score in each sample with the Attention score-based word rank algorithm. Then we run our Greedy-based synonyms search algorithm\[1\] 15 times, and in each iterate, we select the word with the max score in each sample and substituted it with a candidate chosen from the $k$ nearest neighbor.

Evaluation In this section we evaluate our method on the valid dataset driven from the test dataset, after the use of the attack model generates adversarial examples, thus we create a valid dataset with different percentages of words are been substituted. We evaluate the performance of attack models including the attack success rates and the quality of generated adversarial examples.

Success Rate Since the more effective the attacking method is, the more the classification accuracy of the model drops. Table 1 illustrates the classification accuracy of different models on the original samples and the adversarial samples generated by the different numbers of words been substituted. Results indicate that our two victim models achieved 80.74% and 87.12% of accuracy and 0.467 and 0.331 loss on the initial dataset, after 15 words are been substituted from the initial dataset, our attack model reduces the classification accuracy to 65.01% and 75.53% respectively. From the figure 2 and figure 3, the convex function indicates that our attack model achieves such effects after a very few word substitute, our Attention score based word rank algorithm is able to figure out the words have a larger contribution to the classification prediction, the adversarial examples can be created with the least number of word substitution.

Sentence Similarity To evaluate the adversarial example quality\[9\], we designed an algorithm to calculate the Pearson Correlation Coefficient between the initial sample and the generated adversarial examples after each iterator. After iterating
Table 1. Test accuracy and loss of victim model

| Cases       | Accuracy (%) | Loss  |
|-------------|--------------|-------|
| CNN-initial | 80.74        | 0.467 |
| CNN-5 times | 71.75        | 0.563 |
| CNN-10 times| 67.55        | 0.605 |
| CNN-15 times| 65.01        | 0.628 |
| GRU-initial | 87.12        | 0.331 |
| GRU-5 times | 81.86        | 0.430 |
| GRU-10 times| 78.26        | 0.502 |
| GRU-15 times| 75.53        | 0.566 |

Fig. 2. The accuracy and loss of CNN classifier

Fig. 3. The accuracy and loss of GRU classifier

time $k$, we have original sample matrix $m_0$ and adversarial examples $m_n$ each matrix has a size $n$, to simplify, we have the equation below:

$$\rho_k = \sum |1 - \frac{6\sum(m_0 - m_n)^2}{n^3 - n}|$$

Figure 4 illustrates the Pearson Correlation Coefficient after each iterate. The minimum coefficient of generated examples after each iterator remains over 0.5. Nevertheless, we drove out some samples used for human evaluation, in Table 2, the heat map indicates the word attention score in a sample, the deeper the color the higher value the word got, in the two samples after we substituted the top 7 words and 9 words, and successfully make the victim model make the wrong prediction: 0.139(negative) to 0.723(positive) and 0.852(positive) to 0.379(negative) separately.
Fig. 4. Sentence Similarity (Pearson Correlation Coefficient)

Table 2. Adversarial example in the IMDB dataset with GRU model

| Text example                                                                 | Original | Adversarial |
|-------------------------------------------------------------------------------|----------|-------------|
| If only to avoid making this type of film in the future. This film is interesting fascinating as an experiment analysis but tells no cogent story. One might feel virtuous honest for sitting thru it because it touches on so many IMPORTANT issues but it does so extremely without any discernable motive. The viewer comes away with no new perspectives (unless one comes up with one while one’s mind wanders amble, as it will invariably do during this pointless, perfect, film). One might better spend one’s time staring open out a window at a tree growing. | 0.139(Neg) 0.723(Pos) | 0.852(Pos) 0.379(Neg) |
| Originally I was a Tenacious D fan of their first album and naturally listened to a few tracks off The P.O.D. and was rather disappointed. After watching the movie, my view was changed. The movie is pretty very amusing from beginning to the end and found my self engaged in it even though it was really was a stupid dull storyline because of the attitudes that KG and Jaybles portray in the movie. Much more extra entertaining affecting and enjoyable affecting than movies I have seen in the theaters lately, ex. Saw III (bored and dragging), Casino Royale (way to homo-erotic) which in prior installments I have really certainly enjoyed. If you enjoyed Borat, you will enjoy the tale of The Greatest Band on Earth. | 0.139(Neg) 0.723(Pos) | 0.852(Pos) 0.379(Neg) |

5 Conclusions and Future Work

Based on those evaluation result, our method are able to generate suitable adversarial example, compared with Alzantot et al. Ren et al. it has the advantage of cost less, it only goes through searching the nearest neighbor of words.
that have a higher score. Experiments also show that our method can greatly reduce the text classification accuracy with a low substitution rate. Also, the attention mechanism makes the model more explainable. Our model not only can be used to verify the robustness of a pre-trained NLP model but also can use to generate adversarial examples in Generative Adversarial Network training. In the future, we would like to apply the method to more NLP domains like multi-class classify, textual entailment. However, due to the limitation, we only verified a few generated adversarial examples manually and the Pearson Correlation Coefficient still indicates that the semantics of some synonyms are not as accurate as of the original words. Nevertheless, the synonyms or search area is limited by the GloVE model, some high-ranking words may not have enough synonyms or are not included in the model, we current policy is to skip those words. And when we test the adversarial examples generated by our method on the GRU classifier, the attacking effect is slightly inferior to the CNN model. In the future, we may give out a more precise evaluation matrix and provide more experiments in various domains like textual entailment.

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