How Far Are We from Real Synonym Substitution Attacks?

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Abstract

In this paper, we explore the following question: how far are we from real synonym substitution attacks (SSAs). We approach this question by examining how SSAs replace words in the original sentence and show that there are still unresolved obstacles that make current SSAs generate invalid adversarial samples. We reveal that four widely used word substitution methods generate a large fraction of invalid substitution words that are ungrammatical or do not preserve the original sentence’s semantics. Next, we show that the semantic and grammatical constraints used in SSAs for detecting invalid word replacements are highly insufficient in detecting invalid adversarial samples. Our work is an important stepping stone to constructing better SSAs in the future.

1 Introduction

Deep learning-based natural language processing models have been extensively used in different tasks in many domains and have shown strong performance in different realms. However, these models seem to be astonishingly vulnerable in that their predictions can be misled by some small perturbations in the original input (Gao et al., 2018; Tan et al., 2020). These imperceptible perturbations, while not changing humans’ predictions, can make a well-trained model behave worse than random.

One important type of adversarial attack in natural language processing (NLP) is the synonym substitution attack (SSA). In SSAs, an adversarial sample is constructed by substituting some words in the original sentence with their synonyms (Alzantot et al., 2018; Ren et al., 2019; Garg and Ramakrishnan, 2020; Jin et al., 2020; Li et al., 2020; Maheshwary et al., 2021). This ensures that the adversarial sample is semantically similar to the original sentence, thus fulfilling the imperceptibility requirement of a valid adversarial sample. While substituting words with their semantic-related counterparts can retain the semantics of the original sentence, these attacks often utilize constraints to further guarantee that the generated adversarial samples are grammatical and semantically similar to the original sentence. These SSAs have all shown to successfully bring down a well-trained text classifiers’ performance.

However, some recent works observe, by human evaluations, that the quality of the generated adversarial samples of those SSAs is fairly low and is highly perceptible by human (Morris et al., 2020a; Hauser et al., 2021). The adversarial samples generated by these SSAs are often filled with grammar errors and mostly do not preserve the semantics of the original samples, making them hard to understand by humans. The above traits of those adversarial samples violate the fundamental criterion of a real adversarial sample: semantics preserving and imperceptibility to humans. The above phenomenon motivates us to investigate what causes those SSAs to generate invalid adversarial samples. Only by answering this question can we move on to design more realistic SSAs in the future.

In this paper, we are determined to answer the following question: How far are we from real SSAs? We explore the answer to this question by scrutinizing the key components in several important SSAs and why they fail to generate valid adversarial samples. Specifically, we conduct a detailed analysis of how the word substitution sets are obtained in SSAs, and we look into the semantic and grammatical constraints used to filter invalid adversarial samples. We have the following astonishing observations:

- When substituting words by WordNet synonym sets, current methods neglect the word sense differences within the substitution set. (Section 3.1)
- When using counter-fitted GloVe embedding space or BERT to generate the substitution set,
the substitution set only contains a teeny-tiny fraction of synonyms. (Section 3.2)

- Using word embedding cosine similarity or sentence embedding cosine similarity to filter words in the substitution set does not necessarily exclude semantically invalid word substitutions. (Section 4.1 and Section 4.2)

- The grammar checker used for filtering un-grammatical adversarial samples fails to detect most erroneous verb inflectional forms in a sentence. (Section 4.3)

2 Backgrounds

In this section, we provide an overview of SSAs and introduce some related notations that will be used throughout the paper.

2.1 Synonym Substitution Attacks (SSAs)

Given a victim text classifier trained on a dataset \( D_{train} \) and a clean testing data \( x_{ori} \) sampled from the same distribution of \( D_{train} \); \( x_{ori} = \{x_1, \cdots, x_T\} \) is a sequence with \( T \) tokens. An SSA attacks the victim model by constructing an adversarial sample \( x_{adv} = \{x_1, \cdots, x_T\} \) by swapping the words in \( x_{ori} \) with their semantic-related counterparts. For \( x_{adv} \) to be considered as a valid adversarial sample of \( x_{ori} \), a few requirements must be met (Morris et al., 2020a): (1) \( x_{adv} \) should be semantically similar with \( x_{ori} \). (2) \( x_{adv} \) should be grammatical. (3) The word-level overlap between \( x_{adv} \) and \( x_{ori} \) should be high enough. (4) The modification made in \( x_{adv} \) should be natural and non-suspicious. In our paper, we will refer to the adversarial samples that fail to meet the above criteria as invalid adversarial samples.

SSAs rely on heuristic procedures to ensure that \( x_{adv} \) satisfies the preceding specifications. Here, we describe a canonical pipeline of generating \( x_{adv} \) from \( x_{ori} \) (Morris et al., 2020b). Given a clean testing sample \( x_{ori} \) that the text classifier correctly predicts, an SSA will first generate a candidate word substitution set \( S_{x_i} \) for each word \( x_i \). The process of generating the candidate set \( S_{x_i} \) is called transformation. Next, the SSA will determine which word in \( x_{ori} \) should be substituted first, and which word should be the next to swap, etc. After the word substitution order is decided, the SSA will iteratively substitute each word \( x_i \) in \( x_{ori} \) using the candidate words in \( S_{x_i} \) according to the pre-determined order. In each substitution step, an \( x_i \) is replaced by a word in \( S_{x_i} \), and a new \( x_{swap} \) is obtained. When an \( x_{swap} \) is obtained, some constraints are checked to verify the validity of \( x_{swap} \). The iterative word substitution process will end if the model’s prediction is successfully corrupted by a substituted sentence that sticks to the constraints, yielding the desired \( x_{adv} \) eventually.

Clearly, the transformations and the constraints are critical to the quality of the final \( x_{adv} \). In the remaining part of the paper, we will look deeper into the transformations and constraints used in SSAs and their role in creating adversarial samples. Next, we briefly introduce the transformations and constraints that have been used in SSAs.

2.2 Transformations

Transformation is the process of generating the substitution set \( S_{x_i} \) for a word \( x_i \) in \( x_{ori} \). There are four representative transformations in the literature.

WordNet Synonym Transformation constructs \( S_{x_i} \) by querying a word’s synonym using WordNet, a lexical database containing the word sense definition, synonyms, and antonyms of the words in English. This transformation is used in PWWS (Ren et al., 2019) and LexicalAT (Xu et al., 2019).

Word Embedding Space Nearest Neighbor Transformation constructs \( S_{x_i} \) by looking up the word embedding of \( x_i \) in a word embedding space, and finding its \( k \) nearest neighbors (\( k \) nearest neighbors) in the word embedding space. Using \( k \) nearest neighbors for word substitution is based on the assumption that semantically related words are closer in the word embedding space. Counter-fitted GloVe embedding space (Mrkšić et al., 2016) is the embedding space obtained from post-processing the GloVe embedding space (Pennington et al., 2014). Counter-fitting refers to the process of pulling away antonyms and narrowing the distance between synonyms. This transformation is adopted in TextFooler (Jin et al., 2020), Genetic algorithm attack (Alzantot et al., 2018), and TextFooler-Adj (Morris et al., 2020a).

Masked Language Model (MLM) Mask-Infilling Transformation constructs \( S_{x_i} \) by masking \( x_i \) in \( x_{ori} \) and asking an MLM to predict the masked token; MLM’s top-\( k \) prediction of the masked token forms the word substitution set of \( x_i \). Widely adopted MLMs includes BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019).
Using MLM mask-infilling to generate candidate set relies on the belief that MLMs can generate fluent and semantic-consistent substitutions for $x_{ori}$. This method is used in BERT-ATTACK (Li et al., 2020) and CLARE (Li et al., 2021).

**MLM Reconstruction Transformation** also uses MLMs. When using MLM reconstruction transformation to generate the candidate set, one just feeds the MLM with the original sentence $x_{ori}$ without masking any tokens in the sentence. Here, the MLM is not performing mask-infilling but reconstructs the input tokens from the unmasked inputs. For each word $x_i$, one can take its top-$k$ token reconstruction prediction as the candidates. This transformation relies on the intuition that reconstruction can generate more semantically similar words than using mask-infilling. This method is used in BAE (Garg and Ramakrishnan, 2020).

### 2.3 Constraints
When an $x_{ori}$ is perturbed by swapping some words in it, we need to use some constraints to check whether the perturbed sentence, $x_{swap}$, is semantically or grammatically valid or not. We use $x_{swap}$ instead of $x_{adv}$ here as $x_{swap}$ does not necessarily flip the model’s prediction and thus not necessarily an adversarial sample.

**Word Embedding Cosine Similarity** requires a word $x_i$ and its perturbed counterpart $x_i'$ to be close enough in the counter-fitted GloVe embedding space, in terms of cosine similarity. A substitution is valid if its word embedding’s cosine similarity with the original word’s embedding is higher than a pre-defined threshold. This is used in Genetic Algorithm Attack (Alzantot et al., 2018) and TextFooler (Jin et al., 2020).

**Sentence Embedding Cosine Similarity** demands that the sentence embedding cosine similarity between $x_{swap}$ and $x_{ori}$ are higher than a pre-defined threshold. Most previous works (Jin et al., 2020; Li et al., 2020; Garg and Ramakrishnan, 2020; Morris et al., 2020a) use Universal Sentence Encoder (USE) (Cer et al., 2018) as the sentence encoder; A2T (Yoo and Qi, 2021) use a DistilBERT (Sanh et al., 2019) fine-tuned on STS-B (Cer et al., 2017) as the sentence encoder.

In some previous work (Li et al., 2020), the sentence embedding is computed using the whole sentence $x_{ori}$ and $x_{swap}$. But most previous works (Jin et al., 2020; Garg and Ramakrishnan, 2020) only extract a context around the currently swapped word in $x_{ori}$ and $x_{swap}$ to compute the sentence embedding. For example, if $x_i$ is substituted in the current substitution step, one will compute the sentence embedding between $x_{ori}[i−w:i+w+1]$ and $x_{adv}[i−w:i+w+1]$, where $w$ determines the window size. $w$ is set to 7 in Jin et al. (2020) and Garg and Ramakrishnan (2020).

**LanguageTool** is an open-source grammar tool that can detect spelling errors and grammar mistakes in an input sentence. It is used in TextFooler-Adj (Morris et al., 2020a) to evaluate the grammaticality of the adversarial samples.

### 3 Problems with the Transformations in SSAs
In this section, we show that the transformations introduced in Section 2.2 are largely to blame for the invalid adversarial samples in SSAs. This is because the substitution set $S_{x_i}$ for $x_i$ is mostly invalid, either semantically or grammatically.

#### 3.1 WordNet Synonym Substitution Set Ignores Word Senses
In WordNet, each word is associated with one or more word senses, and each word sense has its corresponding synonym sets. Thus, the substitution set $S_{x_i}$ proposed by WordNet is the union of the synonym sets of different senses of $x_i$. When swapping $x_i$ with its synonym using WordNet, it is more sensible to first identify the word sense of $x_i$ in $x_{ori}$, and use the synonym set of the very sense as the substitution set. However, current attacks using WordNet synonym substitution neglect the sense differences within the substitution set (Ren et al., 2019), which may result in adversarial samples that semantically deviate from the original input.

As a working example, consider a movie review that reads "I highly recommend it". The word "recommend" here corresponds to the word sense of "express a good opinion of" according to WordNet and has the synonym set {recommend, commend}. Aside from the above word sense, "recommend" also have another word sense: "push for something", as in "The travel agent recommends not to travel amid the pandemic". This second word sense has the synonym set {recommend, urge, advocate}.

1The word senses and synonyms are from WordNet.
the original movie review. While "urge" is the synonym of "recommend", it obviously does not fit in the context and should not be considered as a possible substitution. We call substituting \(x_i\) with a synonym that matches the word sense of \(x_i\) in \(x_{ori}\) a matched sense substitution, and we use mismatched sense substitution to refer to swapping words with the synonym which belongs to the synonym set of a different word sense.

### 3.1.1 Experiments

To illustrate that mismatched sense substitution is a problem existing in practical attack algorithms, we conduct the following analysis. We examine the adversarial samples generated by PWWS, which substitutes words using WordNet synonym set. We use a benchmark dataset (Yoo et al., 2022) that contains the adversarial samples generated by PWWS against a BERT-based classifier fine-tuned on AG-News (Zhang et al., 2015), a news title classification dataset. The attack success rate on the testing set composed of 7.6K samples is 57.25%. More details about the datasets can be found in Appendix B.

We categorize the words replaced by PWWS into three disjoint categories: matched sense substitution, mismatched sense substitution, and morphological substitution. The last category, morphological substitution, refers to substituting words with a word that only differs in inflectional morphemes or derivational morphemes with the original word. We specifically isolate morphological substitution since it is hard to categorize it into either matched or mismatched sense substitution.

The detailed procedure of categorizing a replaced word’s substitution type is as follows: Given a pair of \((x_{ori}, x_{adv})\), we first use NLTK to perform word sense disambiguation on each word \(x_i\) in \(x_{ori}\). We use LemmInflect and NLTK, to generate the morphological substitution set \(ML_x\) of \(x_i\). The matched sense substitution set \(ML_x\) is constructed using the WordNet synonym set of the word sense of \(x_i\) in \(x_{ori}\); since this synonym set includes the original word \(x_i\) and may also include some words in the \(ML_x\), we remove \(x_i\) and words that are already included in the \(ML_x\) from the synonym set, forming the final matched sense substitution set, \(ML_x\). The mismatched sense substitution set \(MML_x\)

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1. Inflectional morphemes are the suffixes that change the grammatical property of a word, such as a verb’s tense or a noun’s number. For example, recommends → recommendation.

2. Derivational morphemes are affixes or suffixes that change the form of a word, such as changing a verb into a noun form. For example, recommend → recommendation.

is constructed by first collecting all synonyms of \(x_i\) that belong to the different word sense(s) of \(x_i\) in \(x_{ori}\) using WordNet, and then removing all words that have been included in \(ML_x\) and \(MML_x\).

After inspecting 4140 adversarial samples produced by PWWS, we find that among 26600 words that are swapped by PWWS, only 5398 (20.2%) words fall in the category of matched sense substitution. A majority of 20055 (75.4%) word substitutions are mismatched sense substitutions, which should be considered invalid substitutions since using mismatched sense substitution cannot preserve the semantics of \(x_{ori}\) and makes \(x_{adv}\) incomprehensible. Last, about 3.8% of words are substituted with their morphological related words, such as converting the part of speech (POS) from verb to noun or changing the verb tense. These substitutions, while maintaining the semantics of the original sentence and perhaps human readable, are mostly ungrammatical and lead to unnatural adversarial samples. The aforementioned statistics illustrate that only about 20% word substitutions produced by PWWS are real synonym substitutions, and thus the high attack success rate of 57.25% should not be surprising since most word replacements are highly questionable.

### 3.2 Counter-fitted Embedding kNN and MLM Masked-Infilling/Reconstruction

**Contains Few Matched Sense Synonym**

As shown in Section 3.1.1, even when using WordNet synonyms as the candidate sets, the proportion of the valid substitutions is unthinkably low. This makes us more concerned about the word substitution quality of the other three heuristic transformations introduced in Section 2.2. These three word substitution methods mostly rely on the assumptions about the quality of the embedding space or the ability of the MLM and require setting a hyperparameter \(k\) for the size of the substitution set. To the best of our knowledge, no previous work has systematically studied what the candidate sets proposed by the three transformations are like; still they have been widely used in SSAs.

#### 3.2.1 Experiments

To understand what those substitution sets are like, we conduct the following experiment. We use the benchmark dataset generated by Yoo et al. (2022) that attacks 7.6K samples in the AG-News testing data using TextFooler. For each word \(x_i\) in \(x_{ori}\) that is perturbed into another \(x_i\) in \(x_{adv}\), we use
Figure 1: The average words of different substitution types in the candidate word set of 30 words. If the average number of words of a substitution type is less than 1, we do not show the average number in the bar.

The vast majority of the substitution set comprises of words that do not fall in the previous four categories. We provide examples of how the substitution sets proposed by different transformations are like in Table 4, showing that the candidate words in the others substitution types are mostly unrelated words that should not be used for word replacement. It is understandable that words falling to the other substitution types are invalid candidates; this is because the core of SSAs is to replace words with their semantically close counterparts to preserve the semantics of the original sentence. If a substitution word does not belong to the synonym set proposed by WordNet, it is unlikely that swapping the original word with this word can preserve the semantics of the original sentence. Hauser et al. (2021) uses human evaluation to show that the adversarial samples generated from TextFooler, BERT-Attack, and BAE do not preserve the meaning of $x_{ori}$, which also backs up our statement. In practical attacks, whether these words in the candidate sets can be considered valid depends on the constraints. But can those constraints really filter invalid substitutions? We show in the next section that, sadly, the answer is no.

### Problems with the Constraints in SSAs

In this section, we show that the constraints in SSAs cannot filter invalid word substitutions.
We then query the counter-fitted GloVe embedding word is a high-frequency one or a low-frequency word embedding of words and calculate their cosine similarity with the TextFooler used in Section 3.2, and we gather all different types of substitution sets.

### 4.1 Word Embedding Cosine Similarity Cannot Distinguish Valid/Invalid Swaps

Setting a threshold on word embedding cosine similarity to filter invalid word substitutions relies on the hypothesis that valid word swaps indeed have higher cosine similarity with the word to be substituted, compared with invalid word replacements. We investigate whether the hypothesis holds with the following experiment. We reuse the 7.6K AG-News testing samples attacked by TextFooler used in Section 3.2, and we gather all pairs of \((x_{ori}, x_{adv})\). For each word \(x_i\) in \(x_{ori}\) that is perturbed in \(x_{adv}\), we follow the same procedure in Section 3.2 to obtain the morphological substitution set, matched sense substitution set, mismatched sense substitution set, and the antonym set. We then query the counter-fitted GloVe embedding space to obtain the word embeddings of all those words and calculate their cosine similarity with the word embedding of \(x_i\). As a random baseline, we also randomly sample high-frequency words and low-frequency words in the training dataset of AG-News, and compute the cosine similarity between those words and \(x_i\). How these high-frequency and low-frequency words are sampled is detailed in Appendix D.2.

We plot the distribution of the cosine similarity between \(x_i\) and different substitution types in Figure 2. When analyzing the results in Figure 2, it is useful to keep in mind that the word embedding cosine similarity threshold used in TextFooler is 0.5. First, we can see that no matter whether the random word is a high-frequency one or a low-frequency one, its word embedding and the embedding of \(x_i\) have low cosine similarity, which centers around 0. Thus, the word embedding cosine similarity constraint can filter out random words if they are proposed by a transformation. On the other hand, synonym substitutions, both the matched and mismatched ones, have similar cosine similarity distribution, which indicates that word embedding’s cosine similarity is not helpful for filtering out mismatched sense substitutions. This should not be surprising, since the counter-fitted GloVe embedding space is a static embedding space, meaning that different word senses of a word share the same static word embedding. Also, a large proportion of the matched sense substitutions have low word embedding cosine similarity with the word to be swapped, implying that most valid word substitutions can actually be filtered out by the word embedding cosine similarity constraint. Next, we can see that the cosine similarity distribution for antonyms is highly overlapped with the distribution of synonyms, showing that using the word embedding similarity as a constraint cannot even separate antonyms in the substitution set. Among all substitution types, the most left-skewed one is the morphological substitutions, meaning that setting a high cosine similarity threshold will prefer morphological substitutions. However, as we previously argued, morphological swaps are mostly ungrammatical. In summary, setting a threshold on the word embedding cosine similarity does not really help to filter invalid substitutions and preserve the valid swaps.

### 4.2 Sentence Encoder Is Insensitive to Invalid Word Substitutions

To test if sentence encoders really can filter invalid word substitutions in SSA, we conduct the following experiment. We use the same attacked AG-News samples that were used in Section 3.2.1. For each pair of \((x_{ori}, x_{adv})\) in that dataset, we first collect the swapped indices set \(I = \{ i | x_i \neq x_i' \}\) that represents the positions of the swapped words in \(x_{adv}\). We shuffle the elements in \(I\) to form an ordered list \(\hat{I}\). Using \(x_{ori}\) and \(\hat{I}\), we construct a sentence \(x_{swap}^n\) by swapping \(n\) words in \(x_{ori}\). The \(n\) positions where the substitutions are made in \(x_{swap}^n\) are the first \(n\) elements in the ordered list \(\hat{I}\); at each substitution position, the word is replaced by a word randomly selected from a type of candidate word set. All the \(n\) replaced words in \(x_{swap}^n\) are the same type of word substitution. We conduct experiments with six types of candidate word substitution sets: matched sense, mismatched sense, morphological, antonym, random high frequency,
and random low-frequency word substitutions. After obtaining $x_{\text{swap}}^n$, we compute the cosine similarity between the sentence embedding between $x_{\text{swap}}^n$ with $x_{\text{ori}}$ using USE and set the window size $w$ to 7, following Jin et al. (2020) and Garg and Ramakrishnan (2020). We vary the number of replaced words from 1 to 10.\(^5\) This experiment helps us know how the cosine similarity changes when the words are swapped using different types of candidate word sets. More details on this experiment are in Appendix D.3 and Figure 4.

The results are shown in Figure 3. While replacing more words in $x_{\text{ori}}$ does decrease its cosine similarity with $x_{\text{ori}}$, the cosine similarity when substituting random high-frequency words is still roughly higher than 0.80. Considering that practical SSAs often set the cosine similarity threshold to around 0.85 or even lower\(^6\), depending on the SSAs and datasets, it is suspicious whether the constraint and threshold can really filter invalid word substitution. We can also observe that when substituting words with antonyms, the sentence embedding cosine similarity with the original sentence closely follows the trend of substituting words using a synonym, regardless of whether the synonym substitution matches the word sense or not. Recalling that we have revealed that the candidate set proposed by BERT can contain antonyms in Figure 1, the results here indicate that sentence embedding similarity constraint cannot filter this type of faulty word substitution. For the two different types of synonym substitutions, only matched sense substitutions are valid replacement that follows the semantics of the original sentence. However, the sentence embedding of $x_{\text{ori}}$ and the sentence embedding of the two types of different synonym substitutions are equally similar. The highest cosine similarity is obtained when the words in $x_{\text{ori}}$ are swapped using their morphological substitutions, and this is expected since morphological substitutions merely change the semantics.

In Figure 3, we only show the average cosine similarity and do not show the variance of the cosine similarity of each substitution type. In Figure 5, we show the distribution of the cosine similarity of different substitution types. The main observation from Figure 5 is that the cosine similarity distributions of different substitution types (for the same $n$) are highly overlapped, and it is impossible to distinguish valid word swaps from the invalid ones simply by using a threshold on the sentence embedding cosine similarity.

Overall, the results in Figure 3 demonstrate that USE tends to generate similar sentence embeddings when two sentences only differ in a few tokens, no matter whether the replacements change the sentence meaning or not. While we only show the result of USE, we show in Appendix E that different sentence encoders have similar behavior. Moreover, when we use the whole sentence instead of a windowed subsentence to calculate the sentence embedding, the cosine similarity is even higher than that shown in Figure 3, as shown in Appendix E. Again, these sentence encoders fail to separate invalid word substitutions from valid ones. While frustrating, this result should not be surprising, since most sentence encoders are not trained to distinguish sentences with high word overlapping.

### 4.3 LanguageTool Cannot Detect False Verb Inflectional Form

LanguageTool is used in TextFooler-Adj (TF-Adj) (Morris et al., 2020a) to prevent the attack to induce grammar errors. TF-Adj also uses stricter word embedding and sentence embedding cosine similarity constraints to ensure the semantics in $x_{\text{ori}}$ are preserved in $x_{\text{adv}}$. However, when browsing through the adversarial samples generated by TF-Adj, we observe that the word substitutions made by TF-Adj are often ungrammatical morphological swaps that convert a verb’s inflectional form. This indicates that LanguageTool may not be capable of detecting a verb’s inflectional form error.

To verify this hypothesis, we conduct the follow-
ing experiment. For each sample in the test set of AG-News that LanguageTool reports no grammatical errors, we convert the inflectional form of the verbs in the sample by a hand-craft rule that will always make a grammatical sentence ungrammatical; this rule is listed in Appendix D.4. We then use LanguageTool to detect how many grammar errors are there in the verb-converted sentences.

We summarize the experiment results as follows. For the 1039 grammatical sentences in AG-News, the previous procedure perturbed 4.37 verbs on average. However, the average number of grammar errors identified by LanguageTool is 0.97, meaning that LanguageTool cannot detect all incorrect verb forms. By this simple experiment and the results from Figure 2, 3, we can understand why the attack results of TF-Adj are often ungrammatical morphological substitutions: higher cosine similarity constraints prefer morphological substitutions, but those often ungrammatical substitutions cannot be detected by LanguageTool. Thus, aside from showing that the text classifier trained on AG-News is susceptible to inflectional perturbations, TF-Adj actually exposes that LanguageTool itself is vulnerable to inflectional perturbations.

5 Discussion and Conclusion

This paper discusses how the essential elements in SSAs lead to invalid adversarial samples. We highlight that the candidate word sets generated by all four different word substitution methods contain only a small fraction of semantically matched and grammatically correct word replacements. While these transformations produce inappropriate candidate words, this alone will not contribute to the invalid adversarial samples. The inferiority of those adversarial samples should be largely attributed to the deficiency of the constraints that ought to guarantee the quality of the perturbed sentences: word embedding cosine similarity is not always larger for valid word substitutions, sentence encoder is insensitive to invalid word swaps, and LanguageTool fails to detect grammar mistakes. These altogether bring about the adversarial samples that are human distinguishable, unreasonable, and mostly inexplicable. These adversarial samples are not suitable for evaluating the vulnerability of NLP models because they are not reasonable inputs. Unlike previous works that observe this phenomenon (Morris et al., 2020a; Hauser et al., 2021), we take a significant step further to understand the cause behind those observations, which is crucial for designing new SSAs.

By the analyses in the paper, we show that we may still be far away from real SSAs, and how to construct valid synonym substitution adversarial samples remains an unresolved problem in NLP. While there is still a long way to go, it is essential to recognize that the prior works have contributed significantly to constructing valid SSAs. Although prior SSAs may not always produce reasonable adversarial samples, they are still valuable since they pave the way for designing better SSAs and help us uncover the inadequacy of the transformations and constraints for constructing real synonym substitution adversarial samples. Only by identifying the causes of the failures in prior SSAs can we construct better SSAs. As an initiative to stimulate future research, we provide some possible directions and guidelines for constructing better SSAs, based on the observation in our paper. (1) Consider the word senses when making a replacement with WordNet. (2) Use better sentence encoders that are sensitive to token replacements that change the semantics of the original sentence. For example, DifCSE (Chuang et al., 2022) is shown to be able to distinguish the tiny differences between sentences. (3) When designing transformations, one should always verify the validity of the proposed method through well-controlled experiments. These experiments include recruiting human evaluators to check the quality of the transformations or using experiments as in Section 3 to check what the candidate sets proposed by the transformations are like. It is perilous to solely rely on heuristics or black-box models such as sentence encoders to guarantee the quality of the transformation. (4) Since the sentences crafted by SSAs may largely deviate from normal sentences, one should test how those constraint models, such as grammar error checker or sentence encoder model, can perform as we expected when faced with those abnormal sentences. For example, one can perform stress tests, as introduced in Ribeiro et al. (2020), to test the behaviour of the constraint models. The tests need to be tailored to contain all kinds of inputs that might be generated during an SSA. This can prevent us from exploiting the vulnerability of the constraint model when attacking the target text classifier.

Our work is at a turning point in the research of SSAs, and we envision our work drawing more attention and provoking more discussion on this
topic. We believe that our paper can serve as a good starting point for constructing reasonable adversarial attacks to assess the vulnerability of NLP models and make them more robust.
Limitations

In this paper, we only discuss the SSAs in English, as this has been the most predominantly studied in adversarial attacks in NLP. The authors are not sure whether SSAs in a different language will suffer from the shortcomings discussed in this paper. However, if an SSA in a non-English language uses the transformations or constraints discussed in this paper, there is a high chance that this attack will produce low-quality results for the same reason shown in this paper. Still, the above claim needs to be verified by extensive human evaluation and further linguistic-specific analyses.

Another limitation is that we only include the result of one dataset (AG-News) and one model type (text classifier fine-tuned from BERT) in the main content. To mitigate the above issue, we include supplementary analyses in Appendix F for different model types and datasets, which supports all the claims and observations in the main contents.

The last limitation of our paper is that we do not conduct human evaluations on what the other substitution types in Figure 1 are. As stated in Section 3.2.1, while we do not perform human evaluations on this, the readers can browse through Table 4 to see what the others substitutions are. It will be interesting to see what human evaluators will think about the other substitutions in the future.

Ethics Statement and Broader Impacts

The goal of our paper is to highlight the overlooked details in SSAs that cause their failures. By mitigating the problems pointed out in our paper, there are two possible consequences:

1. One may find that there exist no real synonym substitution adversarial samples, and the NLP models currently used are robust. This will cause no ethical concerns since this indicates that no harm will be caused by our work. Previous observations on the vulnerability are just the product of low-quality adversarial samples.

2. There exists real synonym substitution adversarial samples, and excluding the issues mentioned in this paper will help malicious users easier to find those adversarial samples. This will become a potential risk in the future. The best way to mitigate the above issue is to construct new defenses for real SSAs. We discuss this in Section 5.

While our goal is to raise the attention on how far we are away from valid SSAs, we are not advocating malicious users to attack text classifiers using better SSAs. Instead, we would like to highlight that there is still an unknown risk, the real SSAs, against text classifiers, and we researchers should devote more to studying this topic and develop defenses against such attacks before they are adopted by adversarial users.

Another major ethical consideration in our paper is that we challenge prior works on the quality of the SSAs. While we reveal the shortcomings of previously proposed methods, we still highly acknowledge their contributions. As emphasized in Section 5, we do not and try not to devalue those works in the past. We scientifically and objectively discuss the possible risks of those transformations and constraints, and our ultimate goal is to push the research in adversarial attacks in NLP a step forward; from this perspective, we believe that we are in common with prior works.

We believe that our work has a broad impact on NLP. We pinpoint the problems in current SSAs in Section 3 and Section 4, and we have stated clearly in Section 5 that our study serves as the first step toward designing better SSAs, making our work very constructive.

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A Related Works

We discuss three important related works in this section, and highlight out contributions over theirs. Part of the discussions in this section will be added to the ninth page in the camera-ready version upon acceptance.

First, we highlight the difference between Morris (2020) and ours. In Morris (2020), they also question the suitability of sentence encoders as semantic constraints. They attack the sentence encoders by swapping words in a sentence with their antonyms and the attack goal is to maximally preserve the swapped sentence’s sentence embedding cosine similarity with the original sentence. This is slightly related to our experiments in Section 4.2. However, we point out major differences between our experiments and theirs.

• When swapping words, we only swap the words that are really swapped by TextFooler; on the contrary, the words swapped in Morris (2020) are not necessarily words that are actually substituted in an SSA. The words swapped when attacking a sentence encoder and attacking a text classifier can be significantly different. This is because SSAs usually use specially designed methods to select which words to be substituted that change the model’s prediction; on the contrary, when attacking the sentence encoder in Morris (2020), the goal of word substitution is to preserve the model’s prediction. Since our goal is to verify how sentence encoders behave when used in the context of SSAs, it makes more sense to only swap the words that are really replaced by an SSA. Thus, our word substitution method is closer to SSAs, compared to theirs.

• We swap words of different types and compare the sentence embedding similarity of different substitution types. This is because we find that those different substitution types exist in the substitution set proposed by different transformations, shown in Section 3, and it is thus important to know whether those different substitution types can be distinguished by USE. On the contrary, Morris (2020) only uses antonyms for word substitution.

Next, our work differs with Morris et al. (2020a) in that they only reveal that SSAs sometimes produce low-quality adversarial samples using human evaluation. They attribute this to the insufficiency of the constraints and use stricter constraints and LanguageTool to generate better adversarial samples. Our work further point out the problem is not only in the constraints; we show that the transformations are the fundamental problems in SSAs. We further show that the grammar checker they use cannot detect ungrammatical verb inflectional forms, and reveal that the adversarial samples generated by their proposed method exploit the weakness of LanguageTool and are often made up of ungrammatical morphological substitutions.

Last, our work is fundamentally different with Hauser et al. (2021). Hauser et al. (2021) use human evaluations and probabilistic statements to show that SSAs are low quality and do not preserve original semantics. Our work reveals the fundamental cause of their observed phenomenon through well-controlled experiments and analyses. While they have also shown some results about the word embedding similarity, those results are quite different from ours. This is because we compare the cosine similarity of valid and invalid word substitutions, and thus the reader can have a better idea of why this word embedding cosine similarity constraints fail to work in SSAs. On the contrary, Hauser et al. (2021) only shows the cosine similarity between the original word \(x_i\) and the word \(x_i'\) swapped by an SSA.

In summary, our contribution is unique and ample.

B Dataset

In our paper, we use benchmark adversarial datasets generated by Yoo et al. (2022). Yoo et al. (2022) generates adversarial samples using the TextAttack (Morris et al., 2020b) module. Yoo and Qi (2021) release the dataset with a view to facilitating the detection of adversarial samples in NLP and reducing the redundant computation resources to re-generate adversarial samples. They thus generate adversarial samples using PWWS (Ren et al., 2019), TextAttack (Jin et al., 2020), BAE (Garg and Ramakrishnan, 2020) and TextFooler-Adj (Morris et al., 2020a) on LSTM, CNN, BERT, and RoBERTa trained/fine-tuned on SST-2 (Socher et al., 2013), IMDB (Maas et al., 2011), and AG-News (Zhang et al., 2015).

In the main content of our paper, we only use two datasets: the adversarial samples obtained using PWWS to attack BERT fine-tuned on AG-News,
and the adversarial samples obtained by attacking TextFooler on BERT fine-tuned on AG-News. The testing set of AG-News contains 7.6K samples; the adversarial samples obtained by attacking these datasets will be less than 7.6K since the attack success rates of the two SSAs are not 100%. We summarize the detail of these two datasets in Table 1.

C Synonym Substitution Attacks

We list the transformations and constraints of the SSAs that are discussed or mentioned in our paper in Table 2. We only include the semantic and grammaticality constraints in Table 2 and omit other constraints such as the word-level overlap constraints. The "window" in the sentence encoder cosine similarity constraint indicates whether use a window around the current substitution word or use the whole sentence. The "compare with x_{ori}" indicates that x_{swap} will be compared against the sentence embedding of x_{ori}, and "compared with x_{n-1}", means that x_{swap} will be compared against the sentence embedding of x_{n-1}, that is, the sentence before the current substitution step.

C.1 Random Adversarial Samples

To illustrate that the adversarial samples generated by SSAs are largely made up of invalid word replacements, we randomly sample two adversarial samples generated by PWWS (Ren et al., 2019), TextFooler (Jin et al., 2020), BAE (Garg and Ramakrishnan, 2020), and TextFooler-Adj (Morris et al., 2020a). To avoid the suspicion of cherry-picking the adversarial samples to support our claims, we simply select the first and the last successfully attacked samples in AG-News using the four SSAs in the dataset generated by Yoo et al. (2022). Since the dataset is not generated by us, we cannot control which sample is the first one and which sample is the last one in the dataset, meaning that we will not be able to cherry-pick the adversarial samples that support our claims.

The adversarial samples are listed in Table 3. The blue words in x_{ori} are the words that will be perturbed in x_{adv}. The red words are the swapped words. The readers can verify the claims in our paper using those adversarial samples. We recap some of our claims as follows:

- PWWS uses mismatched sense substitution: This can be observed in all the word substitutions of PWWS in Table 3. For example, the word "world" in the second example of PWWS have the word sense "the 3rd planet from the sun; the planet we live on". But it is swapped with the word "cosmos", which is the synonym of the word sense "everything that exists anywhere".
- Counter-fitted embedding substitution set contains a large proportion of others substitution types, which are mostly invalid: This can be observed in literally all word substitutions in TextFooler.
- BERT reconstruction substitution set contains a large proportion of others substitution types, which are mostly invalid: This can be observed in literally all word substitutions in BAE.
- Morphological substitutions are mostly ungrammatical: This can be observed in the first adversarial sample of TextFooler-Adj.
- TextFooler-Adj prefers morphological swap due to its strict constraints: This can be observe in almost all substitutions in TextFooler-Adj, excluding goods→wares.

C.1.1 Example of the Word Substitution Sets of Different Transformations

In this section, we show the substitution sets using different transformations. We only show one example here, and this example is the second successful attack example in the adversarial sample datasets (Yoo et al., 2022) that attacks a BERT fine-tuned classifier trained on AG-News using TextFooler. We do not use the first sample in Table 3 because we would like to show the readers a different adversarial sample in the datasets.

x_{ori}: The Race is On: Second Private Team Sets Launch Date for Human Spaceflight (SPACE.com) - TORONTO, Canada – A second team of rocketeers competing for the $10 million Ansari X Prize, a contest for privately funded suborbital space flight, has officially announced the first launch date for its manned rocket.

x_{adv}: The Race is Around: Second Privy Reemt Set Lanza Timeline for Humanitarian Spaceflight (SEPARATION.com) - CANADIENS, Countries – para second squad of rocketeers suitors for the #36;10 billion Ansari X
|                          | PWWS | TextFooler |
|--------------------------|------|------------|
| Success attacks          | 4140 | 5885       |
| Attack success rate      | 57.25% | 81.39% |
| Average words per sample | 38.57 | 38.57 |
| Average perturbed words percentage | 17.63% | 23.38% |

Table 1: Details of the adversarial sample datasets obtained by attacking a BERT fine-tuned on AG-News using PWWS and TextFooler.

Nobel, a contestant for convertly championed suborbital spaceship plane, had solemnly proclaim the first began timeline for its desolate bomb.

We show the substitution set for the first four words that are substituted by TextFooler in Table 4. We do not show that substitution set for all the attacked words simply because it will occupy too much space, and our claim in the main content that "others substitution sets of counterfitted embedding substitution and BERT mask-infilling/reconstruction mostly consist of invalid swaps" can already be observed in Table 4.

D Implementation Details

D.1 Experiment Details of Section 3

In this section, we give details on how we obtain different word substitution types for a \( x_{\text{ori}} \). The whole process is summarized in Algorithm 1. In Algorithm 1, the reader can also find how the perturbed indices list \( I \) used in Section 4.2 is obtained.

An important detail that is not mentioned in the main content is that when computing how many synonyms are in the substitution set of BERT MLM substitution, we actually perform lemmatization on the top-30 predictions of BERT. This is because, for example, if BERT proposes to use the word "defines" to replace the original word "sets" (the third person present tense of the verb "set") in the original sentence, and the word "define" happens to be a synonym according to WordNet; in this case, the word "defines" will not be considered as a synonym substitution. But "defines" should be considered as a synonym substitution since it is the third person present tense of "define". Lemmatizing the prediction of BERT can partially solve the problem. However, if the lemmatized word is already in the top-30 prediction of BERT, we do not perform lemmatization. This process is detailed on Line 6 of Algorithm 2. This can ensure that words can be considered as synonyms while words that should be considered as morphological swaps are mostly not affected.

D.2 Experiment Details of Section 4.1

Here, we explain how the random high/low-frequency words are sampled in Section 4.1. First, we use the tokenzier of BERT-base-uncased to tokenize all the samples in the training dataset of AG-News. Next, we count the occurrence of each token in the vocabulary of the BERT-base-uncased, and sort the tokens based on their occurrence in the training set in descending order. The vocabulary size of BERT-base-uncased is 30522, including five special tokens, some subword tokens, and some unused tokens. We define the high-frequency words as the top-50 to top-550 words in the training dataset. The reason that we omit the top 50 words as the high-frequency token is that these words are often stop words, and they are seldom used as word substitutions in SSAs. The low-frequency words are the top-10K to top-10.5K occurring words in AG-News’ training set.

D.3 Experiment Details of Section 4.2

Here, we give more details on the sentence embedding similarity experiment in Section 4.2. The readers can refer to Algorithm 1 to see how we obtain the different types of word substitution sets, the substituted indices set \( I \) and the ordered list \( O \) from a pair of \( (x_{\text{ori}}, x_{\text{adv}}) \).

We also use a figurative illustration to show how we obtain \( x_{\text{swap}}^n \) in Figure 4. In Figure 4, we show how to use the same sense substitution set to replace the words in \( x_{\text{ori}} \) based on the ordered list \( O \). As can be seen in the figure, we swap the words in \( x_{\text{ori}} \) according to the order determined by \( O \); since the first element in \( O \) is 5, we will first replace \( x_5 \) in \( x_{\text{ori}} \) with one of the same sense synonyms of \( x_5 \). We thus obtain the \( x_{\text{swap}}^n \). In order to compute the sentence embedding similarity between \( x_{\text{swap}}^1 \) and \( x_{\text{ori}} \), we extract a context around the word just replaced; in this case, we will extract the context around the fifth word in \( x_{\text{ori}} \); this is because...
| Attack                        | Transformation                                           | Constraints                                                                                                                                 |
|------------------------------|----------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Genetic Algorithm Attack     | Counter-fitted GloVe embedding kNN substitution with $k = 8$ | Word embedding mean square error distance with threshold 0.5; language model perplexity (as a grammaticality constraint)                      |
| PWWS                        | WordNet synonym set substitution                         | None                                                                                                                                         |
| TextFooler (Jin et al., 2020)| Counter-fitted GloVe embedding kNN substitution with $k = 50$ | USE sentence embedding cosine similarity with threshold 0.878, window size $w = 7$, compare with $x_{ori}$; word embedding cosine similarity with threshold 0.5; disallow swapping words with different POS but allow swapping verbs with nouns or the reverse |
| BERT-Attack (Li et al., 2020)| BERT mask-infilling substitution with $k = 48$          | Sentence embedding cosine similarity with different thresholds for different dataset, and the highest threshold is 0.7, no window, compare with $x_{ori}$ |
| BAE (Garg and Ramakrishnan, 2020)| BERT reconstruction substitution                        | USE sentence embedding cosine similarity with threshold 0.936, window size $w = 7$, compare with $x_{n-1 swap}$                                  |
| TextFooler-Adj (Morris et al., 2020a) | Counter-fitted GloVe embedding kNN substitution with $k = 50$ | USE sentence embedding cosine similarity with threshold 0.98, window size $w = 7$, compare with $x_{ori}$; word embedding cosine similarity with threshold 0.9; disallow swapping words with different POS but allow swapping verbs with nouns or the reverse; adversarial sample should not introduce new grammar errors, checked by LanguageTool |
| A2T (Yoo and Qi, 2021)       | Counter-fitted GloVe embedding kNN substitution with $k = 20$ or BERT reconstruction with $k = 20$ | Word embedding cosine similarity with threshold 0.8; DistilBERT fine-tuned on STS-B sentence embedding cosine similarity with threshold 0.9, window size $w = 7$, compare with $x_{ori}$; disallow swapping words with different POS |
| CLARE (Li et al., 2021)      | DistilRoBERTa mask-infilling substitution, instead of using top-$k$, they select the predictions whose probability is larger than $5 \times 10^{-3}$; this set contains 42 tokens on average | USE sentence embedding cosine similarity with threshold 0.7, window size $w = 7$, compare with $x_{ori}$                                      |

Table 2: Detailed transformations and constraints of different SSAs mentioned in our paper.
| Attack | $x_{ori}$ | $x_{adv}$ |
|--------|-----------|-----------|
| PWWS   | Ky. Company **Wins Grant to Study Peptides** (AP) - A company founded by a chemistry researcher at the University of Louisville won a grant to develop a method of producing better peptides, which are short chains of amino acids, the building blocks of proteins. | Ky. Company **profits yield to bailiwick Peptides** (AP) - amp company founded by a chemistry researcher at the University of Louisville won a grant to develop a method of producing better peptides, which are short chains of amino acids, the building blocks of proteins. |
| PWWS   | Around the **world** Ukrainian presidential candidate Viktor Yushchenko was poisoned with the most harmful known dioxin, which is contained in Agent Orange, a scientist who analyzed his blood said Friday. | Around the **cosmos** Ukrainian presidential candidate Viktor Yushchenko was poisoned with the most harmful known dioxin, which is contained in Agent Orange, a scientist who analyzed his lineages said Friday. |
| Text-Fooler | Fears for T N pension after talks **Unions representing workers** at Turner Newall say they are ‘disappointed’ after talks with stricken parent firm Federal Mogul. | Fears for T percent pension after debate Syndicates portrayal worker at Turner Newall say they are ’disappointed’ after chatter with bereaved parenting corporations Canada Mogul. |
| Text-Fooler | 5 of arthritis patients in Singapore take Bextra or Celebrex &lt;...&lt;/b&gt; SINGAPORE : Doctors in the United States have warned that painkillers Bextra and Celebrex may be linked to major cardiovascular problems and should not be prescribed. | 5 of bursitis patients in Malaysia taken Bextra or Celebrex &lt;seconds&gt;...&lt;/lieutenants;/iii&gt; SINGAPORE : Medecine in the United Nations get reminding that sedatives Bextra and Celebrex may pose link to enormous cardiovascular woes and planned not be planned. |
| BAE    | Fears for T N pension after talks **Unions representing workers** at Turner Newall say they are ‘disappointed’ after talks with stricken parent firm Federal Mogul. | Fears for T pl pension after talks **Unions representing workers** at Turner network say they are ’disappointed’ after talks with stricken parent firm Federal Mogul. |
| BAE    | 5 of arthritis patients in Singapore take Bextra or Celebrex &lt;...&lt;/b&gt; SINGAPORE : Doctors in the United States have warned that painkillers Bextra and Celebrex may be linked to major cardiovascular problems and should not be prescribed. | 5 of arthritis patients in Singapore take cd or i &amp;x&gt;...&lt;/b&gt; SINGAPORE : doctors in the United state have warned that painkillers used and Celebrex may be linked to major cardiovascular harm and should not be prescribed. |
| Text-Fooler -Adj | Venezuela Prepares for Chavez Recall Vote Supporters and rivals warn of possible fraud; government says Chavez’s defeat could produce turmoil in world oil market. | Venezuela Prepares for Chavez Recall Voted Supporters and rivals warn of possible fraud; government says Chavez’s defeat could produce turmoil in world oil marketed. |
| Text-Fooler -Adj | EU to Lift U.S. Sanctions Jan. 1 BRUSSELS (Reuters) - The European Commission is sticking with its plan to lift sanctions on $4 billion worth of U.S. goods on Jan. 1 following Washington’s repeal of export tax subsidies in October, a spokeswoman said on Thursday. | EU to Lift U.S. Sanctions Jan. 1 BRUSSELS (Reuters) - The European Commission is sticking with its plan to lift sanctions on $4 billion worth of U.S. wares on Jan. 1 following Washington’s repeal of export taxation subsidies in October, a spokeswoman said on Thursday. |

Table 3: Adversarial samples from the benchmark dataset generated by Yoo and Qi (2021).
| $x_i$ | Counter-fitter GloVe embedding | BERT MLM | BERT reconstruction |
|-------|--------------------------------|----------|---------------------|
| On    | Orn, Pertaining, Per, Toward, Dated, Towards, Circa, Dates, Relating, Pour, Relative, Sur, Into, Date, Concerning, Onto, Around, About, In, To, Sobre, Relate, During, Respecting, For, Regarding, At, Days, Throughout, Relation | following, completed, ongoing, over, in, included, contested, followed, this, now, below, announced, after, split, for, therefore, concluded, titled, currently, follows, planned, listed, thus, held, on, to, that, scheduled, called, where | around, round, a, here, ongoing, over, in, the, involved, pending, at, next, now, under, for, ahead, set, off, currently, onto, given, considered, about, held, on, of, to, by, time, with |
| Private | Confidentiality, Camera, Personal, Clandestine, Privately, Hoc, Undercover, Confidential, Secretive, Secrets, Dedicated, Secret, Surreptitiously, Confidentially, Belonged, Peculiar, Personally, Specialty, Fenced, Owned, Covert, Particular, Especial, Covertly, Own, Deprived, Secretly, Privy, Soldier, Special | google, my, o, a, from, hs, the, 1, chapter, 1st, in, this, mv, md, ukrainian, le, facebook, baltimore, hr, of, th, to, that, donald, and, by, gma, where, with | personal, vr, 2012, my, a, from, own, official, local, the, vc, small, for, national, billionaire, social, private, 2014, 2010, pv, facebook, public, independent, of, privately, to, new, family, and, by |
| Team  | Panels, Grouping, Machine, Equipments, Tasks, Task, Devices, Pc, Group, Appliance, Cluster, Computers, Groups, Teams, Tooling, Accoutrements, Remit, Pcs, Appliances, Grupo, Teamwork, Chore, Apparatus, Squad, Computer, Device, Machines, Panel, Squads, Equipment | fund, label, launch, google, team, sponsor, investor, project, citizen, investigator, sector, plane, foundation, company, helicopter, website, line, platform, rocket, and, group, blog, planet, computer, charity, to, jet, pilot, party, fan | firm, one, weekend, partnership, round, team, committee, teams, number, couple, country, site, button, company, line, side, crew, ballot, group, nation, winner, division, club, boat, of, to, family, party, time |
| Sets   | Defines, Stake, Matches, Provides, Prescribes, Determine, Set, Betting, Establishes, Stipulates, Jeu, Gambling, Staking, Stipulated, Toys, Determines, Defined, Game, Defining, Playing, Gaming, Games, Determining, Define, Jeux, Gamble, Identifies, Stipulate, Plays, Play | google, a, from, estimated, first, larsen, the, 1, 1st, 3, at, next, announced, top, named, def, or, possible, predicted, 3rd, facebook, 000, online, about, on, of, to, and, no, with | reaches, established, announce, places, records, official, announcing, begins, forms, indicates, announced, declares, sets, starts, estimates, determines, set, details, draws, lays, lists, specifies, calls, setting, stages, of, gives, establishes, announces, names |

Table 4: Candidate substitutions proposed by different transformations. We use green to denote matched sense substitution, orange to denote mismatched sense substitution, brown to denote morpheme substitution, and purple to denote antonyms. The other type substitution is denoted using the default black.
Algorithm 1 Process of obtaining the substitution set

Require: $x_{ori}, x_{adv}$

1. $I \leftarrow []$  \hspace{1cm} $\triangleright$ Initialize the perturbed indices list
2. for $x_i \in x_{ori}$ do
3. \hspace{1cm} if $x_i = x_i'$ then
4. \hspace{2cm} continue
5. \hspace{1cm} end if
6. \hspace{1cm} $x_i \leftarrow x_i.lower()$  \hspace{1cm} $\triangleright$ Get the lower case of $x_i$
7. \hspace{1cm} $x_i' \leftarrow x_i'.lower()$ \hspace{1cm} $\triangleright$ Get the lower case of $x_i'$
8. \hspace{1cm} $S_{ml} \leftarrow \text{GetMorph}(x_i, x_{ori})$ \hspace{1cm} $\triangleright$ Get morphological substitutions
9. \hspace{1cm} $S_{ms} \leftarrow \text{GetMatchedSense}(x_i, x_{ori})$ \hspace{1cm} $\triangleright$ Get matched sense synonym by first using word sense disambiguation then WordNet synonym sets
10. \hspace{1cm} $S_{mms} \leftarrow \text{GetMismatchedSense}(x_i, x_{ori})$ \hspace{1cm} $\triangleright$ Get mismatched sense synonym by first using word sense disambiguation then WordNet synonym sets
11. \hspace{1cm} $A \leftarrow \text{GetAntonym}(x_i)$ \hspace{1cm} $\triangleright$ Get antonyms by WordNet
12. \hspace{1cm} $S_{ml} \leftarrow S_{ml} \setminus \{x_i\}$
13. \hspace{1cm} $S_{ms} \leftarrow S_{ms} \setminus S_{ml} \setminus \{x_i\}$
14. \hspace{1cm} $S_{mms} \leftarrow S_{mms} \setminus S_{ms} \setminus S_{ml} \setminus \{x_i\}$ \hspace{1cm} $\triangleright$ Remove overlapping elements to make $S_{ml}, S_{ms}, S_{mms}$ disjoint
15. \hspace{1cm} $S_{emb} \leftarrow \text{GetEmbeddingSwaps}(x_i)$
16. \hspace{1cm} $S_{MLM} \leftarrow \text{GetMLMSwaps}(x_i, x_{ori})$
17. \hspace{1cm} $S_{recons} \leftarrow \text{GetReconsSwaps}(x_i, x_{ori})$
18. \hspace{1cm} if $x_i' \in S_{ml}$ then
19. \hspace{2cm} The substitution is a morphological substitution
20. \hspace{1cm} else if $x_i' \in S_{ms}$ then
21. \hspace{2cm} The substitution is a matched sense substitution
22. \hspace{1cm} else if $x_i' \in S_{mms}$ then
23. \hspace{2cm} The substitution is a mismatched sense substitution
24. \hspace{1cm} else if $x_i' \in A$ then
25. \hspace{2cm} The substitution is an antonym substitution
26. \hspace{1cm} else
27. \hspace{2cm} This substitution is a other type
28. \hspace{1cm} end if
29. \hspace{1cm} Check the substitution types of each word in $S_{emb}$ by comparing with $S_{ml}, S_{ms}, S_{mms}, A$
30. \hspace{1cm} Check the substitution types of each word in $S_{MLM}$ by comparing with $S_{ml}, S_{ms}, S_{mms}, A$
31. \hspace{1cm} Check the substitution types of each word in $S_{recons}$ by comparing with $S_{ml}, S_{ms}, S_{mms}, A$
32. \hspace{1cm} if $S_{ml}, S_{ms}, S_{mms}, A \neq \emptyset$ then
33. \hspace{2cm} $I$.append(i) \hspace{1cm} $\triangleright$ We only include the words whose have morphological substitutions, matched sense substitutions, mismatched sense substitutions
34. \hspace{1cm} end if
35. \hspace{1cm} end for
36. $\forall \leftarrow \text{shuffle}(.I)$
Algorithm 2 GetMLMSwaps $x_i, x_{ori}$

Require: $x_i, x_{ori}$, BERT, Lemmatizer

1: $x_mask \leftarrow \{x_1, \ldots, x_i-1, [\text{MASK}], x_{i+1}, \ldots, x_n\}$ $\triangleright$ Get masked input
2: Candidates $\leftarrow \text{Top-k prediction of } x_{mask} \text{ using BERT}$
3: New_Candidates $\leftarrow []$
4: for $w \in \text{Candidates}$ do
5: $w_{\text{lemmatized}} \leftarrow \text{Lemmatizer}(w)$
6: if $w_{\text{lemmatized}} \notin \text{Candidates}$ and $w_{\text{lemmatized}} \notin \text{New_Candidates}$ then
7: New_Candidates.append($w_{\text{lemmatized}}$)
8: else
9: New_Candidates.append($w$)
10: end if
11: end for
12: return New_Candidates

using $w = 7$ is too large for this example. Thus, we should extract $x_1^{\text{swap}}[4:7]$ and $x_{ori}[4:7]$; however, since the sentences only have 5 words, the context to be extracted will exceed the length of the sentences. In this case, we simply extract the context until the end of both sentences. The parts that will be used for computing the sentence embeddings in each sentence are outlined with a dark blue box in Figure 4. Next, we follow a similar process to obtain $x_2^{\text{swap}}$ and $x_3^{\text{swap}}$ and compare their sentence embedding cosine similarity with $x_{ori}$.

D.4 Experiment Details of Section 4.3

In this experiment, we use the POS tagger in NLTK to identify the verb form of the verbs. The inflectional form of the verbs are obtained using LemmInflect. Here, we list the verb inflectional form conversion rules:

- For each third-person singular present verb, it is converted to the verb’s base form.

- For each third past tense verb, it is converted to the verb’s gerund or present participle form (V+ing).

- For all verbs whose form is not third-person singular present and is not past tense verb, we convert them into the third-person singular present. We provide three random examples from the test set in AG-News that are ungrammatical. Interestingly, LanguageTool detects no grammar errors in all the six samples in Table 5.

E Supplementary Materials for Experiments of Sentence Encoders

E.1 Distribution of the Sentence Embedding Cosine Similarity of Different Substitution Types

In Figure 5, we show the distribution of the USE sentence embedding cosine similarity of different word replacement types using different numbers of word replacements $n$. The left subfigure shows the distribution of the cosine similarity between $x_{ori}$ and $x_1^{\text{swap}}$ and the right subfigure is the similarity distribution between $x_{ori}$ and $x_8^{\text{swap}}$. While in Figure 3, we can see that the sentence embedding cosine similarity of different word substitution types is sometimes separable on average, we still cannot separate valid and invalid word substitution simply using one threshold. This is because the word embedding cosine similarity scores of different word substitution types is sometimes separable on average, we still cannot separate valid and invalid word substitution simply using one threshold. This is because the word embedding cosine similarity scores of different word substitution types are highly overlapped, which is evident from Figure 5. This is true for different $n$ of $x_n^{\text{swap}}$, and we only show $n = 1$ and $n = 8$ for simplicity.

E.2 Different Methods For Computing Sentence Embedding Similarity

In this section, we show some supplementary figures of the experiments in Section 4.2. Recall that in the main content, we only show the sentence embedding cosine similarity results when we compare $x_n^{\text{swap}}$ with $x_{ori}$ around a 15-word window around the $n$-th substituted word. But we have mentioned
In Section 2.3 that this is not what is always done. In Figure 6, we show the result when we compare \(x_{swap}^n\) with \(x_{ori}\) using the whole sentence. It can be easily observed that it is still difficult to separate valid swaps from the invalid ones using a threshold on the cosine similarity. One can also observe that the similarity in Figure 6 is a lot higher than that in Figure 3.

Another important implementation detail about sentence encoder similarity constraint is that some previous work does not calculate the similarity of the current \(x_{swap}\) with \(x_{ori}\). Instead, they calculate the similarity between the current \(x_{swap}\) and the \(x_{swap}\) in the previous substitution step (Garg and Ramakrishnan, 2020). That is, if in the previous substitution step, 6 words in \(x_{ori}\) are swapped, and in this substitution step, we are going to make the 7th substitution. Then the sentence embedding similarity is computed between the 6-word substituted sentence and the 7-word substituted sentence.

In Figure 7, we show the result when we compare \(x_{swap}^n\) with \(x_{ori}\) around a 15-word window around the \(n\)-th substituted word using DistilBERT fine-tuned on STS-B, which is the sentence encoder used in Yoo and Qi (2021). Figure 9 shows that DistilBERT fine-tuned model better distinguishes between antonyms and synonym swaps, compared with the USE in Figure 3. However, it still cannot distinguish between the matched and mismatched synonym substitutions very well. Interestingly, this model is flagged as deprecated on huggingface for it produces sentence embeddings of low quality. We also show the result when we use a DistilRoBERTa fine-tuned on STS-B in Figure 10. Interestingly, this sentence encoder can also better distinguish antonym substitutions and synonym substitutions on average. This might indicate that the models only fine-tuned on STS-B can have the ability to distinguish valid and invalid swaps.

In Figure 11, we show the result when we compare \(x_{swap}\) with \(x_{ori}\) around a 15-word window around the \(n-th\) substituted word using sentence-
IBM to hire even more new workers By the end of the year, the computing giant plans to have its biggest headcount since 1991.

Giddy Phelps Touches Gold for First Time Michael Phelps won the gold medal in the 400 individual medley and set a world record in a time of 4 minutes 8.26 seconds.

Table 5: Examples of the verb-perturbed sentences. The perturbed verbs are highlighted in red, and their unperturbed counterparts are highlighted in blue.

F.2 Statistics of Different Datasets

In this section, we show the statistics of types of word substitution of another two datasets in Yoo et al. (2022). The result is in Table 10. Clearly, our observation that valid word substitutions are scarce can also be observed in both SST-2 and IMDB.

G FAQ

Q1 In Table 2, most candidate set sizes are larger than 30 that is used in this paper. Why is this so, and will different k change the observation of this paper?

A1 We select k = 30 to better balance the k = 8 in Alzantot et al. (2018) and k = 48 in Li et al. (2020) and k = 50 in Jin et al. (2020). BERT-Attack (Li et al., 2020) discuss the effect of the candidate size k and claims that larger k will "result in less semantic similarity", and thus using k = 30 should contain more valid more substitutions compared to k = 48. We show the proportion of different substitution types when we set k to 50 in Figure 13, which leads to the same observation as in the main content of our paper.

Q2 Should we normalize the sentence embedding vector before we calculate their cosine similarity?

A2 No, one should not do so. This is because, during the training of those sentence encoders, they do not normalize those sentence embedding vectors. If we normalize those embeddings during inference, this will cause a sig-
Figure 5: The USE sentence embedding cosine similarity distribution between x_{ori} and the series of sentences obtained by replacing words in x_{ori} with one type of word substitution. The window size is the same as Figure 3. The left subfigure shows the distribution of the cosine similarity between x_{ori} and x^{1}_{swap} and the right subfigure is the similarity distribution between x_{ori} and x^{8}_{swap}.

Table 6: Attack statistics of other models on AG-News. The SSA use to attack the models is PWWS.

| Model   | Matched sense | Mismatched sense | Morphological | Antonym | Others     |
|---------|---------------|------------------|---------------|---------|------------|
| CNN     | 5449 (16.8%)  | 23727 (73.2%)    | 788 (2.43%)   | 0 (0.0%)| 2434 (7.51%)|
| LSTM    | 5185 (15.7%)  | 24621 (74.5%)    | 788 (2.38%)   | 0 (0.0%)| 2467 (7.46%)|
| BERT    | 4319 (16.2%)  | 19467 (73.2%)    | 1026 (3.86%)  | 0 (0.0%)| 1788 (6.72%)|
| RoBERTa | 5057 (16.3%)  | 21741 (70.2%)    | 1253 (4.05%)  | 0 (0.0%)| 2905 (9.38%)|

Q3 If using word sense disambiguation can resolve the mismatched sense substitution, why didn’t previous works use sentence disambiguation when constructing adversarial samples?

A3 We cannot infer why they did not do so, but our guess is that using matched sense substitution will significantly reduce the attack success rate.

Q4 This paper seems to be critical and does not provide constructive suggestions on this topic, and the contribution of this paper is thus unclear.

A4 We believe that our paper contributes a lot. We pinpoint the problems in current SSAs in Section 3 and Section 4, and we have stated clearly in Section 5 that our study serves as the first step toward designing better SSAs, making our work very constructive.

Q5 Why cannot an adversarial sample be ungrammatical?

A5 Whether allowing adversarial samples to be grammatical is subject to the task of interest. If the datasets to be attacked already contain a lot of grammar errors, it may be fine for an SSA to induce more grammar errors. However, for those datasets that contain few grammar errors, an SSA that generates ungrammatical perturbations will make the adversarial samples seem suspicious. Thus, an SSA should not rely on inducing grammar errors for creating perturbations.

Q6 On Line 496, the authors say that "GLoVe embedding cannot distinguish word sense", why is this the case?

A6 For example, "recommend" and "advocate"
Table 7: Attack statistics of other models on AG-News. The SSA use to attack the models is TextFooler.

| Model   | Matched sense | Mismatched sense | Morphological | Antonym | Others         |
|---------|---------------|------------------|---------------|---------|----------------|
| CNN     | 319 (0.891%)  | 897 (2.5%)       | 1464 (4.09%)  | 0 (0.0%)| 33138 (92.5%)  |
| LSTM    | 304 (0.752%)  | 1125 (2.78%)     | 1662 (4.11%)  | 0 (0.0%)| 37350 (92.4%)  |
| BERT    | 399 (0.806%)  | 1632 (3.3%)      | 2471 (4.99%)  | 0 (0.0%)| 45008 (90.9%)  |
| RoBERTa | 391 (0.783%)  | 1613 (3.23%)     | 2276 (4.56%)  | 2 (0.004%)| 45656 (91.4%)  |

Table 8: Attack statistics of other models on AG-News. The SSA use to attack the models is BAE.

| Model   | Matched sense | Mismatched sense | Morphological | Antonym | Others         |
|---------|---------------|------------------|---------------|---------|----------------|
| CNN     | 34 (1.21%)    | 73 (2.6%)        | 232 (8.25%)   | 5 (0.178%)| 2468 (87.8%)   |
| LSTM    | 30 (0.998%)   | 62 (2.06%)       | 234 (7.78%)   | 7 (0.233%)| 2674 (88.9%)   |
| BERT    | 21 (0.88%)    | 39 (1.6%)        | 184 (7.7%)    | 8 (0.34%) | 2128 (89.4%)   |
| RoBERTa | 25 (0.755%)   | 61 (1.84%)       | 304 (9.18%)   | 6 (0.181%)| 2914 (88.0%)   |

Figure 6: The USE sentence embedding cosine similarity between $x_{ori}$ and the series of sentences obtained by replacing words in $x_{ori}$ with one type of word substitution. Different from Figure 3, we use the whole sentence (without using window) to compute the sentence embedding of $x_{ori}$ and $x_{swap}$.

shares a word sense, and their word embedding will be close in the embedding space. However, when we want to look up the $k$NN of "recommend" that has the word sense of "express a good opinion of", "advocate" is not a valid word. But since "recommend" and "advocate" share a word sense, their embedding will be close in the embedding space, and "advocate" will be used as a candidate word. This shows that GLoVe embedding space cannot deal with word sense differences.

Figure 7: The USE sentence embedding cosine similarity between $x_{ori}$ and the series of sentences obtained by replacing words in $x_{ori}$ with one type of word substitution. Different from Figure 3, we compare $x_{swap}^n$ with $x_{swap}^{n-1}$ for $n \geq 2$. The sentence embedding is calculated using a 15-word window around the $n$-th substituted word, as in Figure 3.

Figure 8: The USE sentence embedding cosine similarity between $x_{ori}$ and the series of sentences obtained by replacing words in $x_{ori}$ with one type of word substitution. The sentence embedding similarity shown in this figure is calculated by the whole sentence without windowing and the cosine similarity is calculated between $x_{swap}^n$ and $x_{swap}^{n-1}$.
Table 9: Attack statistics of other models on AG-News. The SSA used to attack the models is TextFooler-Adj.

| Model  | Matched sense | Mismatched sense | Morphological | Antonym | Others |
|--------|---------------|------------------|---------------|---------|--------|
| CNN    | 65 (3.86%)    | 176 (10.5%)      | 706 (42.0%)   | 0 (0.0%)| 735 (43.7%) |
| LSTM   | 70 (3.9%)     | 208 (11.6%)      | 698 (38.9%)   | 0 (0.0%)| 820 (45.7%) |
| BERT   | 53 (4.32%)    | 118 (9.62%)      | 530 (43.2%)   | 0 (0.0%)| 526 (42.9%) |
| RoBERTa| 59 (4.21%)    | 137 (9.79%)      | 581 (41.5%)   | 0 (0.0%)| 623 (44.5%) |

Table 10: Attack statistics of other BERT fine-tuned on other datasets. The SSA used to attack the models is TextFooler.

| Model | Matched sense | Mismatched sense | Morphological | Antonym | Others |
|-------|---------------|------------------|---------------|---------|--------|
| SST-2 | 34 (0.945%)   | 118 (3.28%)      | 206 (5.72%)   | 0 (0.0%)| 3241 (90.1%) |
| IMDB  | 1881 (1.43%)  | 4825 (3.66%)     | 8708 (6.6%)   | 21 (0.0159%)| 116479 (88.3%) |

Figure 9: Using the DistilBERT fine-tuned on STS-B as the sentence encoder. Sentence embedding cosine similarity between $x_{ori}$ and the series of sentences obtained by replacing words in $x_{ori}$ with one type of word substitution.

Figure 10: Using the DistilRoBERTa fine-tuned on STS-B as the sentence encoder. Sentence embedding cosine similarity between $x_{ori}$ and the series of sentences obtained by replacing words in $x_{ori}$ with one type of word substitution.

Figure 11: The sentence-transformers/all-MiniLM-L12-v2 as the sentence encoder. Sentence embedding cosine similarity between $x_{ori}$ and the series of sentences obtained by replacing words in $x_{ori}$ with one type of word substitution.

Figure 12: The sentence-transformers/all-mpnet-base-v2 as the sentence encoder. Sentence embedding cosine similarity between $x_{ori}$ and the series of sentences obtained by replacing words in $x_{ori}$ with one type of word substitution.
Figure 13: The average words of different substitution types in the candidate word set with 50 words for each transformation. If the average number of words of a substitution type is less than 1.7, we do not show the average number in the bar.