A Differentiable Language Model Adversarial Attack on Text Classifiers
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Abstract
Robustness of huge Transformer-based models for natural language processing is an important issue due to their capabilities and wide adoption. One way to understand and improve robustness of these models is an exploration of an adversarial attack scenario: check if a small perturbation of an input can fool a model.

Due to the discrete nature of textual data, gradient-based adversarial methods, widely used in computer vision, are not applicable per se. The standard strategy to overcome this issue is to develop token-level transformations, which do not take the whole sentence into account.

In this paper, we propose a new black-box sentence-level attack. Our method fine-tunes a pre-trained language model to generate adversarial examples. A proposed differentiable loss function depends on a substitute classifier score and an approximate edit distance computed via a deep learning model.

We show that the proposed attack outperforms competitors on a diverse set of NLP problems for both computed metrics and human evaluation. Moreover, due to the usage of the fine-tuned language model, the generated adversarial examples are hard to detect, thus current models are not robust. Hence, it is difficult to defend from the proposed attack, which is not the case for other attacks.

1 Introduction

Adversarial attacks (Yuan et al., 2019) in all application areas including computer vision (Akhtar and Mian, 2018; Khrulkov and Oseledets, 2018), natural language processing (Zhang et al., 2019b; Wang et al., 2019; Morris et al., 2020), and graphs (Sun et al., 2018) seek to reveal non-robustness of deep learning models. An adversarial attack on a text classification model perturbs the input sentence in such a way that the deep learning model is fooled, while the perturbations adhere to certain constraints, utilising morphology or grammar patterns or semantic similarity. The deep learning model then misclassifies the generated sentence, whilst for a human it is evident that the sentence’s class remains the same (Kurakin et al., 2017). Unlike for images and pixels, for textual data it is not possible to estimate the derivatives of class probabilities with respect to input tokens due to the discrete nature of the language and its vocabulary. Although a sentence or a word representation can lie in a continuous space, the token itself cannot be altered slightly to get to the neighbouring point. This turns partial derivatives useless. Many approaches that accept the initial space of tokens as input attempt to modify these sequences using operations like addition, replacement, or switching of tokens (Samanta and Mehta, 2017; Liang et al., 2017; Ebrahimi et al., 2018). Searching for the best modification can be stated as a discrete optimisation problem, which often appears to be computationally hard and is solved by random or greedy search heuristics in practice. (Ebrahimi et al., 2018). Otherwise gradient optimisation techniques can be leveraged in the embedding space (Sato et al., 2018; Ren et al., 2020). This approach has a bottleneck: all information contained in a sentence has to be squeezed into a single sentence embedding.

To alleviate these problems we propose a new differentiable adversarial attack model, which benefits from leveraging pre-trained language models, DILMA (Differentiable Language Model Attack). The proposed model for an adversarial attack has two regimes. The first regime is a random sampling that produces adversarial examples by chance. The second regime is a targeted attack that modifies the language model by optimizing the loss with two terms related to misclassification by the target model and a discrepancy between an initial sequence and its adversarial counterpart. Thus, we expect that the generated adversarial examples will fool a deep learning model, but will...
remain semantically close to the initial sequence. We use a trained differentiable version of the Levenshtein distance (Moon et al., 2018) and the Gumbel-Softmax heuristic to pass the derivatives through our sequence generation layers. As our loss is differentiable, we can adopt any gradient-based adversarial attack. The number of hyperparameters in our method is small, as we want our attack to be easily adopted to new datasets and problems. The training and inference procedure is summarised in Fig. 1. Examples of sentences generated via our attack DILMA are presented in Table 1.

To summarise, the main contributions of this work are the following.

• We propose a new black-box adversarial attack based on a masked language model (MLM) and a differentiable loss function to optimise during an attack. Our DILMA attack relies on fine-tuning parameters of an MLM by optimising the weighted sum of two differentiable terms: one is based on a surrogate distance between the source text and its adversarial version, and another is a substitute classifier model score (Sec. 3). Hence, we adopt a generative model framework for the task of the generation of adversarial examples.

• We apply DILMA to various NLP sentence classification tasks and receive superior results in comparison to other methods (Sec. 4).

• We show that a particular advantage of DILMA, when compared to other approaches, lies in the resistance to common defense strategies. The vast majority of existing approaches fail to fool models after they defend themselves (Sec. 5.2).

• We provide a framework to extensively evaluate adversarial attacks for sentence classification and conduct a thorough evaluation of DILMA and related attacks. Adversarial training and adversarial detection must be an essential part of the adversarial attack evaluation on textual data in support to human evaluation (Sec. 5.4).

2 Related work

There exist adversarial attacks for different types of data: the most mainstream being image data (Szegedy et al., 2014; Goodfellow et al., 2014), graph data (Zügner et al., 2018), and sequences (Papernot et al., 2016). The latter work is one of the first publications on generation of adversarial attacks for discrete sequences, such as texts. It identifies two main challenges for the task: a discrete space of possible objects and a complex definition of a semantically coherent sequence.

There is a well-established categorisation of textual attacks according to the perturbation level. Character-level attacks include replacing some of the characters with visually similar ones (Eger et al., 2019). HotFlip uses gradient-based decisions to swap, remove, or insert characters (Ebrahimi et al., 2018). (Tan et al., 2020) creates sub-word perturbations to craft non-standard English adversaries and mitigates the cultural biases of machine translation models. Token-level attacks replace a token (mostly word) in a given sentence, based on a salience score and following a specific synonym replacement strategy. Meng and Wattenhofer (2020) choose the best synonym replacement from WordNet to generate a sentence, close to the classifier’s decision boundary. Li et al. (2020) and Garg and Ramakrishnan (2020) utilise BERT’s masked model to generate the substitution to the target
| Dataset | Original                                | PWWS                                      | DILMA (ours)                            |
|---------|-----------------------------------------|-------------------------------------------|-----------------------------------------|
| rotten tomatoes | flat, misguided comedy                 | unconditional, misadvise comedy         | witty and misguide good comedy           |
|         | more likely to have you sc | more potential to have you sc | more likely to have you sc          |
|         | ratching your head than hidd | ing under your seat               | ing under your seat                |
|         | more a rehash of every gangster | movie from the past decade      | more a rehash of every good film of the past decade |
|         | rotten tomatoes                      | more likely to have you sc | more likely to have you sc          |
|         | more potential to have you sc | scraping your forefront than hiding under your seat | scraping your forefront than hiding under your seat |
|         | a rehash of every gangster movie from the past decade | more potential to have you sc | more likely to have you sc          |
|         | this is a story of two misfits who do not stand a chance alone but together they are magnificent | this is a | floor of two misfits who do not stand a chance alone but unitedly they are magnificent |
|         | this is a story of two misfits who do not stand a chance alone but together they are magnificent | this is a floor of two misfits who do not stand a chance alone but unitedly they are magnificent | this is a story of two misfits who do not stand a chance alone but together they are united |
|         | this is a story of two misfits who do not stand a chance alone but together they are magnificent | this is a | floor of two misfits who do not stand a chance alone but unitedly they are magnificent |
|         | a grippi | a genre | a genre |
|         | ng movie played with performances that are all understated and touching | a gripping movie played with performances that are all understated and touching | a horror movie with lyrics that are all understated and demanding |
|         | i wan | i wanna play the movie | i wanna play the movie |
|         | na play the movie | i wanna | i wanna play the movie |
|         | could you help me call a cab to the airport? | could you help me visit a cab | could you help me find a taxi to the airport? |
|         | i would like to book a room at a nearby hotel. | i would like to book | i would like to book a room at a nearby hotel. |

Table 1: Attack samples for the PWWS attack (top performing according to our evaluation) and our attack DILMA. DILMA can provide more diverse adversarial sequences with meanings similar to that of the initial sentence.

A word in multiple ways. The Metropolis-Hastings algorithm improves sampling from a constrained distribution, allowing to substitute a word in a sentence which belongs to a desired class (Zhang et al., 2019a). **Sentence-level** attacks aim to generate a new adversarial instance from scratch with the help of paraphrasing models (Gan and Ng, 2019), back translation (Zhang et al., 2019c) or competitive dialogue agents (Cheng et al., 2019a).

Another way to categorize textual adversarial attacks accounts for the amount of information received from the victim target model. **White box** attacks have full access to the victim model and its gradients. Generating adversarial examples guided by the training loss is intractable due to the discrete nature of textual data. Instead greedy methods (Cheng et al., 2019b) or the Gumbel trick (Yang et al., 2020) are used to make computations tractable. **Black box** attacks have access only to the model outputs. Victim’s scores may help to estimate word saliency (Jin et al., 2020). Black box attacks can emulate white box attacks. For example, DistFlip (Gil et al., 2019) is a faster version of HotFlip with a similar accuracy.

**Blind** attacks do not have access to the target model at all and can be seen as a form of text augmentation. Such attacks include stop word removal, dictionary-based word replacement, and rule-based insertion of negation (Niu and Bansal, 2018).

Methods to defend against attacks exploit adversarial stability training (Liu et al., 2020) and robust word and character representations (Jones et al., 2020). Back-off strategies to recognize intentionally replaced and corrupted words can detect perturbed inputs before actually passing them through a classifier (Pruthi et al., 2019).

Common tasks requiring defense from adversarial attacks by adversarial training, include classification, sentence pair problems, such as natural language inference (NLI) (Jin et al., 2020), and machine translation (Cheng et al., 2020; Huang et al., 2020).

From a technical point of view, two open source frameworks for textual adversarial attacks, adversarial training, and text augmentation, namely, OpenAttack (Zeng et al., 2020) and
TextAttack (Morris et al., 2020), facilitate the research in the area and help to conduct fast and correct comparison.

From the current state of the art, we see a lack of effective ways to generate adversarial categorical sequences and defend from such attacks. Existing approaches use previous generations of LMs based on recurrent architectures, stay at a token level, or use VAEs, despite known limitations of these models for modelling NLP data (Yang et al., 2017; Vaswani et al., 2017).

3 Methods

3.1 General description of the approach

We generate adversarial examples using two consecutive components: a masked language model (MLM) with parameters \( \theta \) that provides for an input sequence \( x \), conditional distribution \( p_\theta(x'|x) \), and a sampler from this distribution such that \( x' \sim p_\theta(x'|x) \). Thus, we can generate sequences \( x' \) by a consecutive application of the MLM and the sampler.

For this sequence to be adversarial, we optimise a proposed differentiable loss function that forces the MLM to generate semantically similar but adversarial examples by modifying the MLM parameters \( \theta \). The loss function consists of two terms: the first term corresponds to a substitute classifier \( C(x') \) that outputs a probability of belonging to a target class, and the second term corresponds to a Deep Levenshtein distance \( DL(x, x') \) that approximates the edit distance between sequences.

The general scheme of our approach is given in Fig. 1. We start with the description of the LM and the sampler in Subsection 3.2. We continue with the description of the loss function in Subsection 3.3. The formal description of our algorithm is given in Subsection 3.4. In later subsections 3.5 and 3.6, we provide more details on the use of the target and substitute classifiers and the Deep Levenshtein model correspondingly.

3.2 Masked Language model

The MLM is a model that takes a sequence of tokens (e.g. words) as input \( x = \{x_1, \ldots, x_t\} \) and outputs logits for tokens \( \mathbf{P} = \{p_1, \ldots, p_t\} \in \mathbb{R}^{d \times t} \) for each index \( 1, \ldots, t \), where \( d \) is a size of the dictionary of tokens. In this work we use a transformer architecture as the LM (Vaswani et al., 2017). We pre-train a transformer encoder (Vaswani et al., 2017) in a BERT (Devlin et al., 2018) manner from scratch using the available data.

The sampler is defined as follows: the MLM learns a probability distribution over sequences, so we can sample a new sequence \( x' = \{x'_1, \ldots, x'_t\} \) based on the vectors of token logits \( \mathbf{P} \). In this work we use Straight-Through Gumbel Estimator \( ST(P) : \mathbf{P} \rightarrow x' \) for sampling (Jang et al., 2017). To get the actual probabilities \( q_{ij} \) from logits \( p_{ij} \), we use a softmax with temperature \( \tau \) (Hinton et al., 2015), where \( \tau > 1 \) produces a softer probability distribution over classes. As \( \tau \rightarrow \infty \), the original distribution approaches a uniform distribution. If \( \tau \rightarrow 0 \), then sampling from it reduces to arg max sampling.

Our first method SamplingFool samples sequences from the categorical distribution with \( q_{ij} \) probabilities. The method is similar to the random search algorithm and serves as a baseline.

3.3 Loss function

The Straight-Through Gumbel sampling allows a propagation of the derivatives through the softmax layer. Hence, we optimise parameters \( \theta \) of our MLM to improve the quality of generated adversarial examples.

Let \( C_y(x) \) be the probability of the target classifier to predict the considered class \( y \). A loss function takes two terms into account: the first term estimates the probability score drop \( (1 - C_y(x')) \) of the target classifier, the second term represents the edit distance \( DL(x, x') \) between the initial sequence \( x \) and the generated sequence \( x' \). We should maximise the probability drop and minimise the edit distance, so it is as close to 1 as possible.

In the black-box scenario we do not have access to the true classifier score, so we use a substitute classifier score \( C_y(x') \approx C_y'(x') \). As a differentiable alternative to edit distance, we use the Deep Levenshtein model proposed in (Moon et al., 2018) — a deep learning model that approximates the edit distance: \( DL(x, x') \approx D(x, x') \).

This way, the loss function becomes:

\[
L(x', x, y) = \beta(1 - DL(x', x))^2 - \log(1 - C_y(x')) \tag{1}
\]

where \( C_y(x') \) is the probability of the true class \( y \) for sequence \( x' \) and \( \beta \) is a weighting coefficient. Thus, we penalise cases when a modification in more than one token is needed in order to get \( x' \) from \( x \). Since we focus on non-target attacks, the \( C_y(x') \) component is included in the loss. The
smaller the probability of an attacked class, the smaller the loss.

We estimate derivatives of $L(x', x, y)$ in a way similar to (Jang et al., 2016). Using these derivatives, a backward pass updates the weights $\theta$ of the MLM. We find that updating the whole set of parameters $\theta$ is not the best strategy, and a better alternative is to update only the last linear layer and the last layer of the generator.

We consider two DILMA options: initial DILMA that minimises only the classifier score (the second term) during the attack and DILMA with DL that takes into account the approximate Deep Levenshtein edit distance.

### 3.4 DILMA algorithm

Now we are ready to group the introduced components into a formal algorithm with the architecture depicted in Fig. 1.

Given a sequence $x$, the DILMA attack performs the following steps at iterations $i = 1, 2, \ldots, k$ starting from the parameters of a pre-trained MLM $\theta_0 = \theta$ and running for $k$ iterations.

**Step 1.** Pass the sequence $x$ through the pre-trained MLM. Obtain logits $P = LM_{\theta_{i-1}}(x)$.

**Step 2.** Sample an adversarial sequence $x'$ from the logits using the Gumbel-Softmax Estimator.

**Step 3.** Calculate the probability $C_y(x')$ and the Deep Levenshtein distance $DL(x', x)$. Calculate the loss value $L(x', x, y)$ (1).

**Step 4.** Do a backward pass to update the LM’s weights $\theta_{i-1}$ using gradient descent and get the new weights $\theta_i$.

**Step 5.** Obtain an adversarial sequence $x_i'$ by sampling based on the softmax with a selected temperature.

The algorithm chooses which tokens should be replaced. The classification component changes the sequence in a direction where the probability score $C_y(x')$ is low, and the Deep Levenshtein distance keeps the generated sequence close to the original one.

We obtain a set of $m$ sampled adversarial sequences on each iteration of the algorithm. The last sequence in this set is not always the best one. Therefore among generated sequences that are adversarial w.r.t. the substitute classifier $C_y(x')$ we choose $x_{\text{opt}}'$ with the lowest Word Error Rate (WER), estimated with respect to the initial sequence $x$. If all examples don’t change the model prediction w.r.t. $C_y(x')$, then we select $x_{\text{opt}}'$ with the smallest target class score, estimated by the substitute classifier.

We choose the hyperparameter set achieving the best NAD score with the Optuna framework (Akiba et al., 2019).

### 3.5 Classification model

In all experiments we use two classifiers: a target classifier $C^t(x)$ that we attack and a substitute classifier $C(x)$ that provides differentiable substitute classifier scores.

The target classifier is RoBerta (Liu et al., 2019). The substitute classifier is the LSTM model. The hidden size is 150, the dropout rate is 0.3.

The substitute classifier has access only to 50% of the data, whilst the target classifier uses the entire dataset. We split the dataset into two parts keeping the class balance similar for each part.

### 3.6 The Deep Levenshtein Model

The differentiable version of the edit distance allows gradient-based updates of parameters. Following the Deep Levenshtein approach (Moon et al., 2018), we train a deep learning model $DL(x, x')$ to estimate the Word Error Rate (WER) between two sequences $x$ and $x'$. We treat WER as the word-level Levenshtein distance.

Following (Dai et al., 2020), the Deep Levenshtein model receives two sequences $(x, y)$. It encodes them into dense representations $z_x = E(x)$ and $z_y = E(y)$ of fixed length $l$ using the shared encoder. Then it concatenates the representations and the absolute difference between them in a vector $(z_y, z_y - z_x, z_y - z_x)$ of length $4l$. At the end the model uses a fully-connected layer to predict WER. To estimate the parameters of the encoder and the fully connected layer we use the $L_2$ loss between the true and the predicted WER values. We form a training sample of size of about two million data points by sampling pairs of sequences and their modifications from the training data.

### 4 Experiments

The datasets and the source code are published online.\(^1\)

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\(^1\)The code is available at [https://anonymous.4open.science/r/4cf31d59-9fe9-4854-ba53-7be1f9f6be7d/](https://anonymous.4open.science/r/4cf31d59-9fe9-4854-ba53-7be1f9f6be7d/)
| Classes | Avg. length | Max length | Train size | Test size | Targeted RoBERTa accuracy | Substitute LSTM accuracy |
|---------|-------------|------------|------------|-----------|---------------------------|-------------------------|
| AG      | 4           | 6.61       | 19         | 115000    | 5000                      | 0.87                    | 0.86                   |
| DSTC    | 6           | 8.82       | 33         | 5452      | 500                       | 0.85                    | 0.85                   |
| SST-2   | 2           | 8.62       | 48         | 62349     | 5000                      | 0.82                    | 0.80                   |
| RT      | 2           | 18.44      | 51         | 8530      | 1066                      | 0.76                    | 0.70                   |

Table 2: Description of the datasets

|                | AG       | DSTC     | SST-2    | RT       |
|----------------|----------|----------|----------|----------|
| DeepWordBug    | 0.017 / 0.012 | 0.156 / 0.034 | 0.12 / 0.077 | 0.071 / 0.054 |
| HotFlip        | 0.015 / 0.009 | 0.09 / 0.084 | 0.023 / 0.001 | 0.034 / 0.011 |
| PWWS           | 0.018 / 0.011 | 0.142 / 0.025 | 0.156 / 0.068 | **0.102 / 0.072** |
| TextBugger     | 0.015 / 0.009 | 0.098 / 0.023 | 0.066 / 0.041 | 0.066 / 0.059 |
| **SamplingFool (ours)** | 0.015 / 0.004 | 0.218 / 0.113 | 0.137 / 0.126 | 0.04 / 0.022 |
| **DILMA (ours)** | **0.023 / 0.003** | **0.237 / 0.111** | **0.19 / 0.154** | 0.045 / 0.016 |
| **DILMA with DL (ours)** | **0.022 / 0.004** | **0.241 / 0.131** | **0.208 / 0.172** | **0.052 / 0.02** |

Table 3: NAD metric (↑) before/after adversarial training on 5,000 examples. The best values are in bold, the second best values are underscored. DILMA is resistant to adversarial training as well as Sampling Fool.

4.1 Competing approaches

We compared our approach to other popular approaches described below.

**HotFlip** (Ebrahimi et al., 2018) selects the best token to change, given an approximation of partial derivatives for all tokens and all elements of the dictionary. To change multiple tokens HotFlip selects the sequence of changes via a beam search.

**Textbugger** (Li et al., 2019) works at a symbol level and tries to replace symbols in words to generate new adversarial sequences using derivative values for possible replacements.

**DeepWordBug** (Gao et al., 2018) is a greedy replace-one-word heuristic scoring based on an estimate of importance of a word to a RNN model with each replacement being a character-swap attack. DeepWordBug is a black box attack.

**PWWS** (Ren et al., 2019) is a greedy synonym-swap method, which takes into account the saliences of the words and the effectiveness of their replacement. Replacements of the words are made with the help of the WordNet dictionary.

4.2 Datasets

We have conducted experiments on four open NLP datasets for different tasks such as text classification, intent prediction, and sentiment analysis. The characteristics of these datasets are presented in Table 2.

The AG News corpus (AG) (Zhang et al., 2015) consists of news articles on the web from the AG corpus. There are four classes: World, Sports, Business, and Sci/Tech. Both training and test sets are perfectly balanced. The Dialogue State Tracking Challenge dataset (DSTC) is a special processed dataset related to dialogue system tasks. The standard DSTC8 dataset (Abhinav et al., 2020) was adopted to the intent prediction task by extracting most intent-interpreted sentences from dialogues. The Stanford Sentiment Treebank (SST-2) (Socher et al., 2013) contains phrases with fine-grained sentiment labels in the parse trees of 11,855 sentences from movie reviews. The Rotten Tomatoes dataset (RT) (Pang and Lee, 2005) is a film-review dataset of sentences with positive or negative sentiment labels.

4.3 NAD metric

To create an adversarial attack, changes must be applied to the initial sequence. A change can be done either by inserting, deleting, or replacing a token in some position in the original sequence. In the WER calculation, any change to the sequence made by insertion, deletion, or replacement costs 1. Therefore, we consider the adversarial sequence to be perfect if $WER = 1$, and the target classifier output has changed. For the classification task, Normalised Accuracy Drop (NAD) is calculated in
We provide two additional metrics to judge the quality of our attacks. These metrics are indicative to estimate the diversity. A table for infrequent k-grams divided can be found in the Appendix. As we can see, presented methods preserve the lexical diversity.

5.4 Human evaluation
We conducted a human evaluation to understand how comprehensive DILMA adversarial perturbations are and to compare DILMA to other approaches. We used a sample from the SST-2 dataset of size 200, perturbed with five different attacks.

We recruited crowd workers from a crowdsourcing platform to estimate the accuracies of the methods we compare. Given a sentence and the list of classes, the workers were asked to define a class label. We used original sentences to control workers’ bias. We used the Stanza toolkit (Qi et al., 2020) for POS-tagging and dependency parsing. The detailed report about morphological and syntactic similarities can be found in the Appendix.

Diversity across the generated sentences was evaluated by two measures. The first measure, Dist-\(k\), is the total number of distinct \(k\)-grams divided by the total number of produced tokens in all the generated sentences (Li et al., 2016). The second measure, Ent-\(k\) (Zhang et al., 2018) considers that infrequent \(k\)-grams contribute more to diversity than frequent ones. Table 5 presents the results for \(k = 2\). We choose this value as being more indicative to estimate the diversity. A table for other values of \(k\) can be found in the Appendix.

### 5.3 Linguistic evaluation
To measure the linguistic features of the generated adversarial examples, we compared the quality metrics in supplementary materials. For most of the datasets, we provide reasonable results, whilst our methods perform significantly better before and after retraining the initial target classifier, but also after its re-training with additional adversarial samples added to the training set. After re-training the initial target classifier, competitor attacks cannot provide reasonable results, whilst our methods perform significantly better before and after retraining for most of the datasets. We provide additional attack quality metrics in supplementary materials.

5.2 Additional metrics for evaluation
We provide two additional metrics to evaluate the quality of our and competitors’ attacks: accuracy of target models changing after attacks; probability difference is a difference between true model scores before and after an attack. Higher values for probability differences mean that an attack is more successful in affecting the target model decision.

Discriminator training (Xu et al., 2019) is another defence strategy we followed. We trained an additional discriminator on 10,000 samples of the original sequences and adversarial examples. The discriminator detects whether an example is normal or adversarial. The discriminator has an LSTM architecture with fine-tuning of GloVe embeddings and was trained for 50 epochs using the negative log-likelihood loss with early stopping based on validation scores.

We provide all these scores in Table 4. As we can see our methods are top performer with respect to the obtained accuracy scores and probability differences. Due to smaller and more careful changes, HotFlip is harder to detect by a discriminator. However, ROC AUC scores are close to a ROC AUC score of a random classifier for two of four datasets for our attacks.

\[ NAD(A) = \frac{1}{N} \sum_{i=1}^{N} \frac{1\{C'(x_i) \neq C'(x'_i)\}}{WER(x_i, x'_i)} \]

where \(x'_i = A(x)\) is the output of an adversarial generation algorithm for the input sequence \(x\), \(C'(x)\) is the label assigned by the target classification model, and \(WER(x', x)\) is the Word Error Rate. The highest value of NAD is achieved when \(WER(x'_i, x_i) = 1\) and \(C(x_i) \neq C(x'_i)\) for all \(i\). Here we assume that adversaries produce distinct sequences and \(WER(x_i, x'_i) \geq 1\).

5 Evaluation and comparison
5.1 Adversarial attack evaluation
Results for the considered methods are presented in Table 3. We demonstrate not only the quality of attacks on the initial target classifier, but also after re-training with additional adversarial samples added to the training set. After re-training the initial target classifier, competitor attacks cannot provide reasonable results, whilst our methods perform significantly better before and after retraining for most of the datasets. We provide additional attack quality metrics in supplementary materials.
### 6 Conclusion

Constructing adversarial attacks for natural language processing is a challenging problem due to the discrete nature of input data and non-differentiability of the loss function. Our idea is to combine sampling from a masked language model (MLM) with tuning of its parameters to produce truly adversarial examples. To tune parameters of the MLM we use a loss function based on two differentiable surrogates – for a distance between sequences and for an attacked classifier. This results in the proposed DILMA approach. If we only sample from the MLM, we obtain a simple baseline SamplingFool.

In order to estimate the efficiency of adversarial attacks on categorical sequences we have proposed a metric combining WER and the accuracy of the target classifier. For considered diverse NLP datasets, our approaches demonstrate a good performance. Moreover, in contrast to competing methods, our approaches win over common strategies used to defend from adversarial attacks. Human and linguistic evaluation also show the adequacy of the proposed attacks.

### References

Rastogi Abhinav, Zang Xiaoxue, Sunkara Srinivas, Gupta Raghav, and Khaitan Pranav. 2020. Schema-guided dialogue state tracking task at dstc8. arXiv:2002.01359v1.

Naveed Akhtar and Ajmal Mian. 2018. Threat of adversarial attacks on deep learning in computer vision: A survey. IEEE Access, 6:14410–14430.

Takuya Akiba, Shotaro Sano, Toshihiko Yanase, Takeru Ohta, and Masanori Koyama. 2019. Optuna: A next-generation hyperparameter optimization framework. In Proceedings of the 25rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
Minhao Cheng, Wei Wei, and Cho-Jui Hsieh. 2019a. Evaluating and enhancing the robustness of dialogue systems: A case study on a negotiation agent. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 3325–3335.

Minhao Cheng, Jinfeng Yi, Pin-Yu Chen, Huan Zhang, and Cho-Jui Hsieh. 2020. Seq2sick: Evaluating the robustness of sequence-to-sequence models with adversarial examples. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 3601–3608.

Yong Cheng, Lu Jiang, and Wolfgang Macherey. 2019b. Robust neural machine translation with doubly adversarial inputs. arXiv preprint arXiv:1906.02443.

Xinyan Dai, Xiao Yan, Kaiwen Zhou, Yuxuan Wang, Han Yang, and James Cheng. 2020. Convolutional embedding for edit distance.

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. 2018. Hotflip: White-box adversarial examples for text classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 31–36.

Steffen Eger, Gözde Gül Şahin, Andreas Rücklé, Ji-Ung Lee, Claudia Schulz, Mohsen Mesgar, Krishnkant Swarnkar, Edwin Simpson, and Iryna Gurevych. 2019. Text processing like humans do: Visually attacking and shielding nlp systems. In Proceedings of NAACL-HLT, pages 1634–1647.

Wee Chung Gan and Hwee Tou Ng. 2019. Improving the robustness of question answering systems to question paraphrasing. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6065–6075.

Ji Gao, Jack Lanchantin, Mary Lou Soffa, and Yanjun Qi. 2018. Black-box generation of adversarial text sequences to evade deep learning classifiers. In IEEE Security and Privacy Workshops, pages 50–56. IEEE.

Siddhant Garg and Goutham Ramakrishnan. 2020. Bae: Bert-based adversarial examples for text classification. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6174–6181.

Yotam Gil, Yoav Chai, Or Gorodisky, and Jonathan Berant. 2019. White-to-black: Efficient distillation of black-box adversarial attacks. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1373–1379.

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network.

Shujian Huang, Jun Xie, Xinyu Dai, CHEN Jiajun, et al. 2020. A reinforced generation of adversarial examples for neural machine translation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 3486–3497.

Eric Jang, Shixiang Gu, and Ben Poole. 2016. Categorical reparameterization with gumble-softmax.

Eric Jang, Shixiang Gu, and Ben Poole. 2017. Categorical reparameterization with gumble-softmax. In International Conference on Learning Representations (ICLR 2017). OpenReview.net.

Di Jin, Zhijing Jin, Joey Tianyi Zhou, and Peter Szolovits. 2020. Is bert really robust? A strong baseline for natural language attack on text classification and entailment. In Proceedings of the AAAI conference on artificial intelligence, volume 34, pages 8018–8025.

Erik Jones, Robin Jia, Aditi Raghunathan, and Percy Liang. 2020. Robust encodings: A framework for combating adversarial typos. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2752–2765.

Valentin Khrulkov and Ivan Oseledets. 2018. Art of singular vectors and universal adversarial perturbations. In IEEE CVPR, pages 8562–8570.

Alexey Kurakin, Ian J. Goodfellow, and Samy Bengio. 2017. Adversarial machine learning at scale. https://arxiv.org/abs/1611.01236.

J Li, S Ji, T Du, B Li, and T Wang. 2019. Textbugger: Generating adversarial text against real-world applications. In 26th Annual Network and Distributed System Security Symposium.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 110–119, San Diego, California. Association for Computational Linguistics.

Linyang Li, Ruotian Ma, Qipeng Guo, Xiangyang Xue, and Xipeng Qiu. 2020. Bert-attack: Adversarial attack against bert using bert. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6193–6202.
Bin Liang, Hongcheng Li, Miaoqiang Su, Pan Bian, Xirong Li, and Wenchang Shi. 2017. Deep text classification can be fooled. arXiv preprint arXiv:1704.08006.

Hui Liu, Yongzheng Zhang, Yipeng Wang, Zheng Lin, and Yige Chen. 2020. Joint character-level word embedding and adversarial stability training to defend adversarial text. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 8384–8391.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach.

Zhao Meng and Roger Wattenhofer. 2020. A geometry-inspired attack for generating natural language adversarial examples. In Proceedings of the 28th International Conference on Computational Linguistics, pages 6679–6689.

Seungwhan Moon, Leonardo Neves, and Vitor Carvalho. 2018. Multimodal named entity recognition for short social media posts. In Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 852–860.

John Morris, Eli Lifland, Jin Yong Yoo, Jake Grigsby, Di Jin, and Yanjun Qi. 2020. Textattack: A framework for adversarial attacks, data augmentation, and adversarial training in nlp. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 119–126.

Tong Niu and Mohit Bansal. 2018. Adversarial oversensitivity and over-stability strategies for dialogue models. In Proceedings of the 22nd Conference on Computational Natural Language Learning, pages 486–496.

Bo Pang and Lillian Lee. 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In Proceedings of the ACL.

Nicolas Papernot, Patrick McDaniel, Ananthram Swami, and Richard Harang. 2016. Crafting adversarial input sequences for recurrent neural networks. In MILCOM 2016-2016 IEEE Military Communications Conference, pages 49–54. IEEE.

Danish Pruthi, Bhuwan Dhingra, and Zachary C Lip ton. 2019. Combating adversarial misspellings with robust word recognition. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5582–5591.

Peng Qi, Yuhao Zhang, Yuhui Zhang, Jason Bolton, and Christopher D. Manning. 2020. Stanza: A Python natural language processing toolkit for many human languages. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations.

Shuhuai Ren, Yihe Deng, Kun He, and Wanxiang Che. 2019. Generating natural language adversarial examples through probability weighted word saliency. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1085–1097, Florence, Italy. Association for Computational Linguistics.

Yankun Ren, Jianbin Lin, Siliang Tang, Jun Zhou, Shuang Yang, Yuan Qi, and Xiang Ren. 2020. Generating natural language adversarial examples on a large scale with generative models. arXiv preprint arXiv:2003.10388.

Suranjana Samanta and Sameep Mehta. 2017. Towards crafting text adversarial samples. arXiv preprint arXiv:1707.02812.

Motoki Sato, Jun Suzuki, Hiroyuki Shindo, and Yuji Matsumoto. 2018. Interpretable adversarial perturbation in input embedding space for text. In IJCAI.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1631–1642, Seattle, Washington, USA. Association for Computational Linguistics.

Lichao Sun, Ji Wang, Philip S Yu, and Bo Li. 2018. Adversarial attack and defense on graph data: A survey. arXiv preprint arXiv:1812.10528.

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna Estrach, Dumitru Erhan, Ian Goodfellow, and Robert Fergus. 2014. Intriguing properties of neural networks. In ICLR.

Samson Tan, Shaqi Joty, Min-Yen Kan, and Richard Socher. 2020. It’s morphin’ time! combating linguistic discrimination with inflectional perturbations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2920–2935.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In NeurIPS, pages 5998–6008.

Wenqi Wang, Benxiao Tang, Run Wang, Lina Wang, and Aoshuang Ye. 2019. A survey on adversarial attacks and defenses in text. arXiv preprint arXiv:1902.07285.

Han Xu, Yao Ma, Haochen Liu, Debayan Deb, Hui Liu, Jiliang Tang, and Anil Jain. 2019. Adversarial attacks and defenses in images, graphs and text: A review. arXiv preprint arXiv:1909.08072.
Puyudi Yang, Jianbo Chen, Cho-Jui Hsieh, Jane-Ling Wang, and Michael I Jordan. 2020. Greedy attack and gumbel attack: Generating adversarial examples for discrete data. *Journal of Machine Learning Research*, 21(43):1–36.

Zichao Yang, Zhiting Hu, Ruslan Salakhutdinov, and Taylor Berg-Kirkpatrick. 2017. Improved variational autoencoders for text modeling using dilated convolutions. In *ICML*, pages 3881–3890. JMLR.org.

Xiaoyong Yuan, Pan He, Qile Zhu, and Xiaolin Li. 2019. Adversarial examples: Attacks and defenses for deep learning. *IEEE transactions on neural networks and learning systems*, 30(9):2805–2824.

Guoyang Zeng, Fanchao Qi, Qianrui Zhou, Tingji Zhang, Bairu Hou, Yuan Zang, Zhiyuan Liu, and Maosong Sun. 2020. Openattack: An open-source textual adversarial attack toolkit. *arXiv preprint arXiv:2009.09191*.

Huangzhao Zhang, Hao Zhou, Ning Miao, and Lei Li. 2019a. Generating fluent adversarial examples for natural languages. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5564–5569.

Wei Emma Zhang, Quan Z Sheng, Ahoud Alhazmi, and CHENLIANG LI. 2019b. Adversarial attacks on deep learning models in natural language processing: A survey. *arXiv preprint arXiv:1901.06796*.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. *Character-level convolutional networks for text classification*.

Yizhe Zhang, Michel Galley, Jianfeng Gao, Zhe Gan, Xiujun Li, Chris Brockett, and Bill Dolan. 2018. Generating informative and diverse conversational responses via adversarial information maximization. *Advances in Neural Information Processing Systems*, pages 1815–1825.

Yuan Zhang, Jason Baldridge, and Luheng He. 2019c. Paws: Paraphrase adversaries from word scrambling. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1298–1308.

Daniel Zügner, Amir Akbarnejad, and Stephan Günnemann. 2018. Adversarial attacks on neural networks for graph data. In *24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2847–2856.