Universal Adversarial Perturbation for Text Classification

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Abstract
Given a state-of-the-art deep neural network text classifier, we show the existence of a universal and very small perturbation vector (in the embedding space) that causes natural text to be misclassified with high probability. Unlike images on which a single fixed-size adversarial perturbation can be found, text is of variable length, so we define the “universality” as “token-agnostic”, where a single perturbation is applied to each token, resulting in different perturbations of flexible sizes at the sequence level. We propose an algorithm to compute universal adversarial perturbations, and show that the state-of-the-art deep neural networks are highly vulnerable to them, even though they keep the neighborhood of tokens mostly preserved. We also show how to use these adversarial perturbations to generate adversarial text samples. The surprising existence of universal “token-agnostic” adversarial perturbations may reveal important properties of a text classifier.

1 Introduction
Deep neural networks (DNNs) are vulnerable to adversarial samples, i.e., carefully crafted samples with imperceptible perturbations designed to mislead a pre-trained model (Szegedy et al., 2013), raising security concerns.

Two types of adversarial perturbations can be considered: universal or sample-dependent. Sample-dependent perturbations can vary for different samples in a dataset, while universal ones remain fixed for all samples. Adversarial samples were first studied for image DNNs with various methods proposed to generate and defend both sample-dependent perturbations (Szegedy et al., 2016; Carlini and Wagner, 2017; Goodfellow et al., 2014; Moosavi-Dezfooli et al., 2016; Kurakin et al., 2016a,b; Cisse et al., 2017) and universal perturbations (Moosavi-Dezfooli et al., 2017a; Mopuri et al., 2017; Moosavi-Dezfooli et al., 2017b). Later, research on attacking DNNs for text applications emerged (Liang et al., 2017; Ebrahimi et al., 2017; Samanta and Mehta, 2018; Jia and Liang, 2017; Li et al., 2018; Ribeiro et al., 2018), where the definition of an “imperceptible perturbation” can differ from image-based perturbations.

Although most existing adversarial attack methods on textual deep learning models are sample-dependent, recently, Behjati et al. (2019) proposed universal adversarial attacks on text classifiers by generating a universal sequence of words that can be added to any input to fool a classifier with high probability. Their method is effective, but is unlikely to preserve the syntax or semantic of the original input text. In this paper, we instead seek to generate universal adversarial perturbations and samples for text classifiers, by explicitly limiting the norm of changes.

Our main contributions can be summarized as follows:

- We show that a textual deep model can be vulnerable to some small token-agnostic perturbation in the token embedding space.
- We propose an algorithm to compute such universal adversarial perturbations.
- We provide a way to generate adversarial samples in textual form, given the universal perturbations.

2 Related Work
In general, attack methods on textual deep learning models can be categorized based on the following five criteria (Zhang et al., 2019): (1) model access; (2) application; (3) target; (4) granularity and (5) the attacked DNNs.
2.1 White-Box Attack

Considering model access, white-box attacks require access to a model’s full information.

FGSM (Goodfellow et al., 2014) was the first attack on image-based models. TextFool (Liang et al., 2017) designed three perturbation strategies: insertion, modification, and removal to generate adversarial samples, based on the concept of FGSM. Samanta and Mehta (2018), adopting the same idea as TextFool, proposed to craft adversarial text samples by deleting or replacing the important or salient words in the text or by introducing new words to the text sample. Papernot et al. (2016) used the forward derivative such as JSMA (Papernot et al., 2015) to find the sequence that contributes the most towards the adversary direction. Grosse et al. (2016), on the other hand, crafted adversarial samples on input features by computing the gradient of the model Jacobian to estimate the perturbation direction. Sun et al. (2018) adopted the C&W method (Carlini and Wagner, 2017) for attacking predictive models of medical records. Other kinds of methods are summarized in (Zhang et al., 2019).

2.2 Universal Adversarial Perturbation

Universal adversarial perturbation was first studied for image-based deep models by (Moosavi-Dezfooli et al., 2017a). They showed the existence of universal image-agnostic perturbations with remarkable generalization properties. Later on, Poursaeed et al. (2017) proposed to generate universal perturbations with neural networks. Shafahi et al. (2018), on the other hand, introduced an algorithm for universal adversarial training. For natural language processing, Behjati et al. (2019) proposed to generate universal adversarial samples by finding a universal sequence of words that can be added to any input to fool a classifier.

3 Proposed Methods

Given a set of samples \( X = \{x_i, i = 1, \ldots, N\} \), and a network \( f(w, \cdot) \) with frozen parameter \( w \) that maps each sequence of text \( x_i \) onto labels, we define a universal adversarial perturbation \( \delta \) to optimize the following objective:

\[
\max_{\delta} \frac{1}{N} \sum_{i=1}^{N} l(w, x_i + \delta) \quad \text{s.t.} \quad \|\delta\|_p \leq \epsilon \tag{1}
\]

Input : Training samples X, perturbation maximum norm \( \epsilon \), learning rate \( \lambda \)

Output: Universal adversarial perturbation \( \delta \)

Initialize \( \delta \leftarrow 0; \)

for epoch = 1, ..., \( N_{ep} \) do

for minibatch \( B \subset X \) do

if normalize gradients then

\[
g = \nabla_d l(w, x + \delta); \quad ng = -\epsilon \frac{g}{|g|}; \quad \delta \leftarrow \delta + \lambda ng;
\]

else

\[
g = \nabla_d l(w, x + \delta); \quad \delta \leftarrow \delta + \lambda g;
\]

end

Project \( \delta \) to \( l_p \) ball;

end

end

Algorithm 1: The proposed algorithm to generate a universal perturbation.

where \( l(w, \cdot) \) represents the loss used for training DNNs. We use cross-entropy as the training loss in this paper. \( \epsilon \) denotes the maximum \( p \)-norm of \( \delta \).

Given a sequence of text sample \( x_i = x_{i,1}, \ldots, x_{i,m} \) of length \( m \), with \( e_{i,1}, \ldots, e_{i,m} \) as the embeddings for each token, the corresponding perturbed sample \( x_i + \delta \) is generated by adding \( \delta \) to each embedding, i.e. \( e_{i,1} + \delta, \ldots, e_{i,m} + \delta \). The perturbation is “universal” as “token-agnostic”, i.e. it remains the same regardless of the token to which it is applied. We present the algorithm to generate universal adversarial perturbations in Algorithm 1.

While our definition of adversarial perturbations is similar to the one for images, the “imperceptibleness” is different as token embeddings, unlike images, usually have no direct semantic meaning for human beings. In this paper, we define “imperceptibleness” as the normalized intersection of the neighborhoods of a token \( t \) before and after perturbation \( (N_b^{(t)} \) and \( N_a^{(t)} \)), i.e.

\[
NI(t) = \frac{|N_b^{(t)} \cap N_a^{(t)}|}{\min(|N_b^{(t)}|, |N_a^{(t)}|)} \tag{2}
\]

and the “imperceptibleness” score for a vocabulary \( V \) is then defined as,

\[
NI(V) = \frac{1}{|V|} \sum_{t \in V} NI(t) \tag{3}
\]
### Table 1: The statistics of the datasets used for the experiments.

| Corpus | Train | Dev | Test | Task          | Metrics       | Domain          |
|--------|-------|-----|------|---------------|---------------|-----------------|
| MRPC   | 3.7k  | 0.4k| 1.7k | paraphrase    | acc./F1        | news            |
| CoLA   | 8.5k  | 1k  | 1k   | acceptability | Matthews corr. | misc.           |
| SST-2  | 67k   | 0.8k| 1.8k | sentiment     | acc.          | movie reviews   |
| QNLI   | 105k  | 5.5k| 5.4k | QA/NLI        | acc.          | Wikipedia       |

## 4 Experiment

### 4.1 Baseline

Although we are interested in a single universal perturbation applicable to all tokens, we establish a strong baseline where a unique adversarial perturbation is obtained for each token in a vocabulary. The “universality” is then considered as “sample-agnostic” as perturbations are now token-sensitive, but remain unchanged for the same token in different samples. These perturbations can be generated in a similar way as the one presented in Algorithm 1.

We build another set of baselines by randomizing all perturbations, and then normalizing them to the maximum $p$-norm limit $\epsilon$.

### 4.2 Classifier and Dataset

In this paper, we focus on generating universal adversarial perturbations for text classifiers. We adopt BERT (Devlin et al., 2018) as the classifier model for its promising performance on the task of text classification. We fine tune the BERT base model with its uncased tokenizer on four GLUE datasets (Wang et al., 2018): MRPC, CoLA, SST-2 and QNLI. The details of these datasets are shown in Table 1. For each task, we explore hyper-parameters with the following ranges, and pick the classifier with the best performance on the evaluation data.

- **Batch size**: 16, 32
- **Learning rate**: 5e-5, 3e-5 and 2e-5
- **Number of epochs**: 3, 4

We then split the training data of each task into train/dev sets and train our universal adversarial perturbation and samples on the train set with hyper-parameters picked on the dev set. We test the performance of these perturbation and samples on the original evaluation data of each task, which is never used for parameter-tuning or hyper-parameter selection for those perturbation and samples.

### 4.3 Result

| Task  | Maximum p-Norm $\epsilon$ |
|-------|-----------------------------|
| MRPC  | 0.05 0.1 0.15 0.2           |
| BaselineVR | 0.882 0.876 0.876 0.876 |
| BaselineSR | 0.884 0.884 0.882 0.884 |
| BaselineV  | 0.863 0.858 0.831 0.820   |
| Ours        | **0.860 0.811 0.770 0.748** |
| CoLA       | 0.05 0.1 0.15 0.2           |
| BaselineVR | 0.593 0.591 0.588 0.588   |
| BaselineSR | 0.586 0.588 0.583 0.578   |
| BaselineV  | 0.580 0.575 0.557 0.346    |
| Ours        | **0.580 0.566 0.278 0.168** |
| SST-2       | 0.05 0.1 0.15 0.2           |
| BaselineVR | 0.928 0.925 0.924 0.924    |
| BaselineSR | 0.928 0.929 0.930 0.931    |
| BaselineV  | 0.925 0.876 0.750 0.608    |
| Ours        | **0.892 0.823 0.704 0.585** |
| QNLI        | 0.05 0.1 0.15 0.2           |
| BaselineVR | 0.918 0.917 0.917 0.917    |
| BaselineSR | 0.917 0.917 0.916 0.915    |
| BaselineV  | 0.916 0.917 0.915 0.908    |
| Ours        | **0.916 0.897 0.844 0.499** |

We use Adam (Kingma and Ba, 2014) as the optimization algorithm and normalized gradient for the perturbation computation. For each task, we split the training data into train/eval sets with a 0.9/0.1 ratio, train the perturbation on the train set and early stop on the eval set. The train batch size is set to 32 and the eval batch size is set to 8. $p$ is set to 2 and the learning rate $\lambda$ is set to 0.05.

We range the maximum $p$-norm of perturbation $\epsilon$ from 0.05 to 0.2 and present the perturbed classifier’s performance on the evaluation data of each task.
task in Table 2. The choice of $\epsilon$ is determined so that the norm of the perturbation is significantly smaller than the average norm of token embeddings. For each task, we compare the proposed approach with three different baselines: Baseline$_{VR}$ - vocabulary based perturbations that are randomly initialized with $p$-norm scaled to $\epsilon$; Baseline$_{SR}$ - a single perturbation that is randomly initialized with $p$-norm scaled to $\epsilon$ and Baseline$_{V}$ - vocabulary based adversarial perturbations trained similarly as Algorithm 1.

The results in Table 2 indicate that (1) randomly initialized perturbations can hardly fool the classifier in spite of potentially larger $p$-norm than the trained ones; (2) our proposed single universal adversarial perturbation outperforms all the baselines on all the tasks.

To evaluate the “imperceptibleness” of the perturbation, we show the “imperceptibleness” score defined in Equation (3) in Table 3. The number of neighbors for each token is set to 5 and we use cosine similarity as the distance measure between any two tokens. Single perturbation based methods are better at preserving the neighborhood of each token than vocabulary based ones. And our proposed method is comparable with Baseline$_{SR}$ with slightly lower performance.

We further evaluate how much data is required to generate the universal adversarial perturbation and present the result in Table 4. The performance is reported as Accuracy on the SST-2 dataset with various ratios (from 10% to 90%) of training data used to generate the perturbation. The maximum $p$-norm is set to 0.15 and we adopt SGD as the optimization algorithm with momentum set to 0.9 and gradients unnormalized. The result indicates that 10% of training data is enough to generate perturbations with comparable performance, suggesting the scalability of our method on large-scale real-world corpora.

### 4.4 Adversarial Samples

We generate adversarial samples in textual form by (1) for each token in the vocabulary, find its closest neighbor after perturbation; (2) for each input sample, replace the token with its found neighbor such that the distance (cosine) between the two is the largest among all tokens and their corresponding neighbors in the input sample. We list a few examples.

| Text (top: original, bottom: adversarial) | Prediction |
|------------------------------------------|------------|
| the bears sniffed                        | 1          |
| a bears sniffed                         | 0          |
| i walk and dana runs .                   | 1          |
| i walk , dana runs .                     | 0          |
| sue gave to bill a book .                | 1          |
| sue gave to bill the book .              | 0          |
| terry delighted .                       | 0          |
| terry delighted ;                       | 1          |
| dana walking and leslie running .        | 0          |
| dana walking , leslie running .          | 1          |

Table 5: A few adversarial samples generated on CoLA evaluation data. $\epsilon$ is set to 0.2.

| Task               | Maximum $p$-Norm $\epsilon$ | Data Ratio |
|--------------------|------------------------------|-------------|
| MRPC               | 0.05 0.1 0.15 0.2            |             |
| Baseline$_{VR}$    | 0.907 0.830 0.762 0.697      |             |
| Baseline$_{SR}$    | 0.974 0.949 0.919 0.885      |             |
| Baseline$_{V}$     | 0.897 0.811 0.731 0.658      |             |
| Ours               | 0.968 0.935 0.904 0.863      |             |
| CoLA               | 0.05 0.1 0.15 0.2            |             |
| Baseline$_{VR}$    | 0.920 0.853 0.789 0.726      |             |
| Baseline$_{SR}$    | 0.972 0.944 0.913 0.879      |             |
| Baseline$_{V}$     | 0.906 0.815 0.740 0.690      |             |
| Ours               | 0.963 0.931 0.905 0.863      |             |
| SST-2              | 0.05 0.1 0.15 0.2            |             |
| Baseline$_{VR}$    | 0.916 0.840 0.776 0.719      |             |
| Baseline$_{SR}$    | 0.975 0.949 0.920 0.888      |             |
| Baseline$_{V}$     | 0.895 0.804 0.717 0.654      |             |
| Ours               | 0.954 0.913 0.871 0.835      |             |
| QNLI               | 0.05 0.1 0.15 0.2            |             |
| Baseline$_{VR}$    | 0.886 0.793 0.716 0.649      |             |
| Baseline$_{SR}$    | 0.975 0.950 0.922 0.891      |             |
| Baseline$_{V}$     | 0.866 0.761 0.678 0.608      |             |
| Ours               | 0.959 0.943 0.916 0.877      |             |

Table 4: The evaluation result (Accuracy) on SST-2 with the universal adversarial perturbation trained on different ratios of training data. 10% of training data is enough to generate perturbation with good performance.
some examples on CoLA in Table 5. One may argue that the low evaluation score on CoLA is be expected as the generated adversarial samples are unlikely to be linguistically acceptable. However, these results suggest that the classifier may be confused easily.

5 Future Work

In the future, we plan to look into theoretical explanations for the existence of token-agnostic universal adversarial perturbations. We also seek to find a better way to utilize these universal perturbations, e.g., adversary training.

References

Melika Behjati, Seyed-Mohsen Moosavi-Dezfooli, Mahdieh Soleymani Baghsah, and Pascal Frossard. 2019. Universal adversarial attacks on text classifiers. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 7345–7349. IEEE.

Nicholas Carlini and David Wagner. 2017. Towards evaluating the robustness of neural networks. In 2017 IEEE Symposium on Security and Privacy (SP), pages 39–57. IEEE.

Moustapha Cisse, Yossi Adi, Natalia Neverova, and Joseph Keshet. 2017. Houdini: Fooling deep structured prediction models. arXiv preprint arXiv:1707.05373.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. 2017. Hotflip: White-box adversarial examples for text classification. arXiv preprint arXiv:1706.06751.

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

Kathrin Grosse, Nicolas Papernot, Praveen Manoharan, Michael Backes, and Patrick D. McDaniel. 2016. Adversarial perturbations against deep neural networks for hardware classification. CoRR, abs/1606.04435.

Robin Jia and Percy Liang. 2017. Adversarial examples for evaluating reading comprehension systems. arXiv preprint arXiv:1707.07328.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Alexey Kurakin, Ian Goodfellow, and Samy Bengio. 2016a. Adversarial examples in the physical world. arXiv preprint arXiv:1607.02533.

Alexey Kurakin, Ian Goodfellow, and Samy Bengio. 2016b. Adversarial machine learning at scale. arXiv preprint arXiv:1611.01236.

Jinfeng Li, Shouling Ji, Tianyu Du, Bo Li, and Ting Wang. 2018. Textbugger: Generating adversarial text against real-world applications. arXiv preprint arXiv:1812.05271.

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.

Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, Omar Fawzi, and Pascal Frossard. 2017a. Universal adversarial perturbations. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1765–1773.

Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, Omar Fawzi, Pascal Frossard, and Stefano Soatto. 2017b. Analysis of universal adversarial perturbations. arXiv preprint arXiv:1705.09554.

Seyed-Mohsen Moosavi-Dezfooli, Alhussein Fawzi, and Pascal Frossard. 2016. Deepfool: a simple and accurate method to fool deep neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2574–2582.

Konda Reddy Mopuri, Utsav Garg, and R. Venkatesh Babu. 2017. Fast feature fool: A data independent approach to universal adversarial CoRR, abs/1707.05572.

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.

Nicolas Papernot, Patrick D. McDaniel, Somesh Jha, Matt Fredrikson, Z. Berkay Celik, and Ananthram Swami. 2015. The limitations of deep learning in adversarial settings. CoRR, abs/1511.07528.

Omid Poursaeed, Isay Katsman, Bicheng Gao, and Serge J. Belongie. 2017. Generative adversarial perturbations. CoRR, abs/1712.02328.

Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2018. Semantically equivalent adversarial rules for debugging nlp models. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 856–865.
Suranjana Samanta and Sameep Mehta. 2018. Generating adversarial text samples. In Advances in Information Retrieval, pages 744–749, Cham. Springer International Publishing.

Ali Shafahi, Mahyar Najibi, Zheng Xu, John Dickerson, Larry S Davis, and Tom Goldstein. 2018. Universal adversarial training. arXiv preprint arXiv:1811.11304.

Mengying Sun, Fengyi Tang, Jinfeng Yi, Fei Wang, and Jiayu Zhou. 2018. Identify susceptible locations in medical records via adversarial attacks on deep predictive models. CoRR, abs/1802.04822.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2818–2826.

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. 2013. Intriguing properties of neural networks. arXiv preprint arXiv:1312.6199.

Alex Wang, Amapreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. arXiv preprint arXiv:1804.07461.

Wei Emma Zhang, Quan Z. Sheng, and Ahoud Abdulrahmn F. Alhazmi. 2019. Generating textual adversarial examples for deep learning models: A survey. CoRR, abs/1901.06796.