Towards Evaluating the Robustness of Chinese BERT Classifiers

Boxin Wang  
University of Illinois at Urbana-Champaign  
boxinw2@illinois.edu

Xin Li  
Tencent  
alfonsoli@tencent.com

Boyuan Pan  
Zhejiang University  
panby@zju.edu.cn

Bo Li  
University of Illinois at Urbana-Champaign  
lbo@illinois.edu

ABSTRACT
Recent advances in large-scale language representation models such as BERT have improved the state-of-the-art performances in many NLP tasks. Meanwhile, character-level Chinese NLP models, including BERT for Chinese, have also demonstrated that they can outperform the existing models. In this paper, we show that, however, such BERT-based models are vulnerable under character-level adversarial attacks. We propose a novel Chinese char-level attack method against BERT-based classifiers. Essentially, we generate "small" perturbation on the character level in the embedding space and guide the character substitution procedure. Extensive experiments show that the classification accuracy on a Chinese news dataset drops from 91.8% to 0% by manipulating less than 2 characters on average based on the proposed attack. Human evaluations also confirm that our generated Chinese adversarial examples barely affect human performance on these NLP tasks.

CCS CONCEPTS
- Information systems → Evaluation of retrieval results.

KEYWORDS
adversarial attack, Chinese BERT, human evaluation

1 INTRODUCTION
Recently, the impressive performance of BERT [4] has inspired many pre-trained large-scale language models [11, 22, 25], which have obtained state-of-the-art results over many downstream NLP tasks. Besides its dominant performance in English datasets, Tenney et al. [19] point out that BERT is also effective in ambiguous languages such as Chinese, whose granularity of words is less well defined than English [5], because BERT models can disambiguate information from high-level representation. Moreover, Li et al. [13] find that in the Chinese environment, using character-based models (e.g., BERT) is more suitable than word-based models, as the latter often suffer from data sparsity and out-of-vocabulary problems.

However, are Chinese char-based models such as BERT robust under adversarial settings? To the best of our knowledge, we are the first to study this problem in the Chinese domain. While a large number of studies focus on generating adversarial examples in the continuous data domain (e.g. image and audio), generating adversarial text examples in the discrete domain is much more challenging. Current adversarial text generation work [1, 8, 9, 12] is mainly heuristic and not scalable to Chinese in that Chinese characters are intrinsically polysemous. Some char-level adversarial attacks in the English context [6] are shown ineffective for Chinese char-level attacks, as the sizes of candidate characters increase by two orders of magnitude and the computational costs surge, especially for BERT-based classifiers.

In this paper, we propose an efficient Chinese character-level adversarial attack method that helps users to simulate and analyze the investment of funds. It uses interactive visual methods to display the fund market in China.

Adversarial Chinese Text: 5 youngsters were arrested for robbing the convenience store and killing the female owner.

Translation: Wangfubao is an on-line platform that helps users to simulate and analyze the investment of funds. It uses interactive visual methods to display the fund market in China.

Adversarial Chinese Text: 5 youngsters were arrested for robbing the convenience store and killing the owner. Yu.

Topic Prediction: Society News → Entertainment News

Table 1: Two adversarial examples generated by AdvChar for Chinese BERT classifiers on the THUCDC and WeChat Finance datasets. Simply replacing one character with another can lead the correct prediction to a wrong one.

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Table 1: Two adversarial examples generated by AdvChar for Chinese BERT classifiers on the THUCDC and WeChat Finance datasets. Simply replacing one character with another can lead the correct prediction to a wrong one.
Both quantitative and human evaluations demonstrate the effectiveness and validity of our attacks over BERT-based models on several large-scale Chinese datasets.

2 RELATED WORKS

In contrast to a large amount of adversarial attacks in the continuous data domain [3, 7, 23], there are a few studies focusing on the discrete text domain. Jia and Liang [8] use handcrafted rule-based heuristic methods along with crowd-sourcing to generate valid adversarial sentences and fool the question answering models. Similarly, Niven and Kao [14], Thorne and Vlachos [20] use rule-based heuristics to attack specific tasks such as fact verification and argument reasoning comprehension. However, these methods cannot be applied to other NLP tasks [15, 16] and need human-crafted rules to guide the search. To automatically find the valid adversarial examples, Ebrahimi et al. [6] propose a whitebox gradient-based attack method to find character-level substitution. However, this method is not efficient when it comes to the Chinese language, where there are thousands of common characters compared with 26 English characters. Additionally, the following studies [1, 9, 17, 24] consider different strategies to perform word-level replacement while maintaining grammatical correctness and semantic similarity.

In addition, while pretrained language models such as BERT [4] and XLMNet [22] have achieved state-of-the-art results in various NLP tasks, the robustness of these language models are challenged. Niven and Kao [14] point out that BERT is only learning the statistical cues, which can be broken by simply putting negation ahead. Jin et al. [9] also finds BERT is vulnerable under adversarial attacks.

3 METHODOLOGY

3.1 Problem Formulation

Given the input $x = [x_0, x_1, ..., x_n]$, where $x_0$ is a special token [CLS] prepended to every input and $x_1$ is a Chinese character, the BERT-based classification model $f$ maps the input to the final logits $z = f(x) \in \mathbb{R}^C$, where $C$ is the number of class, and outputs a label $y = \text{arg max} \ f(x)$. Formally, the BERT-based classifier $f$ first encodes the input

$$[h_0, h_1, ..., h_n] = \text{BERT}(x_0, x_1, ..., x_n),$$

and outputs the logits $z$ via a fully connected layer based on the hidden state $h_0$ of [CLS], which represents the sentence embedding for classification tasks [4].

During the adversarial evaluation, we investigate our attack algorithm efficiency by calculating the targeted attack success rate (TSR):

$$\text{TSR} = \frac{1}{|D_{\text{adv}}|} \sum_{x' \in D_{\text{adv}}} \mathbb{1}[\text{arg max} \ f(x') \equiv y^*]$$

and untargeted attack success rate (USR):

$$\text{USR} = \frac{1}{|D_{\text{adv}}|} \sum_{x' \in D_{\text{adv}}} \mathbb{1}[\text{arg max} \ f(x') \neq y]$$

where $D_{\text{adv}}$ is the adversarial dataset, $y^*$ is the targeted false class, $y$ is the ground truth label, and $\mathbb{1}(\cdot)$ is the indicator function.

3.2 Algorithm

The whole pipeline is shown in Algorithm 1.

**Character Substitution Procedure.** Due to the discrete nature of text, it is hard to directly utilize the gradient to guide character substitution in the character space. However, in BERT each discrete character $x_i \in \mathbb{R}^{1|V|}$ (one-hot vector, where $V$ is the Chinese character set) is mapped into a high-dimensional embedding space of dimension $d_v$ via the BERT embedding matrix $M_e \in \mathbb{R}^{d_v \times |V|}$:

$$[e_1, e_2, ..., e_n] = M_e [x_0, x_1, ..., x_n].$$

Therefore, we can search the perturbation in the embedding space and map the perturbed character embedding back to characters. Suppose we already have an optimal perturbation $e^*$ in the embedding space that can achieve the attack goal and is the minimal perturbation. We can choose the perturbed character $x'_i$ as the semantically closest character to the perturbed embedding $e'_i$

$$e'_i = e_i + e^*,$$

$$x'_i = \text{arg min} [e'_i; e'_i; ..., e'_i] - M_e).$$

If we control the perturbation $e^*$ to be small enough, most characters will remain the same and a very few characters is perturbed to its semantic close neighbors. In this way, the adversarial examples look still valid to the human but can fool the machines.

**Optimization-based Search.** We use the neural network to search for the optimal perturbation variable $e^*$. We freeze all the parameters of the BERT-based classifier $f$ and optimize the only variable $e^*$. Following Carlini and Wagner [2], we define the loss function as

$$\mathcal{L}(e^*) = ||e^*||_p + c \cdot g(x'),$$

where the first term controls the magnitude of perturbation, while $g(\cdot)$ is the attack objective function depending on the attack scenario. $c$ weighs the attack goal against the attack cost.
We first perform the adversarial evaluation in the whitebox setting. We conduct experiments on two Chinese classification datasets. A larger confidence encourages the classifier output targeted false class with higher confidence.

In the targeted attack scenario, we define $g(\cdot)$ as

$$g(x') = \max \{ \max \{ f(x')_i : i \neq t \} - f(x')_t, -\kappa \},$$

where $t$ is the targeted false class and $f(x')_i$ is the $i$-th class logit. A larger $\kappa$ encourages the classifier output targeted false class with higher confidence.

In the untargeted attack scenario, $g(\cdot)$ becomes

$$g(x') = \max \{ f(x')_i - \max \{ f(x')_j : i \neq t \}, -\kappa \},$$

where $t$ is the ground truth class.

## 4 EXPERIMENTAL RESULTS

We conduct experiments on two Chinese classification datasets. We first perform the adversarial evaluation in the whitebox settings and validate the effectiveness of our proposed attack. We also explore the transferability of these adversarial examples. The following human evaluation confirms that our generated adversarial examples barely affect human performances.

### 4.1 Datasets

**THUCTC** [18] is a public Chinese news classification dataset. It consists of more than 740k news articles between 2005 and 2011 extracted from Sina News. These articles are classified into 14 categories, including education, technology, society and politics. To speed up the evaluation process, we use the news titles for the classification. We evenly sampled articles from all classes. We use 585,390 articles as the training set, 250,682 articles as the development set, and another 1,000 articles as the testing set to perform the adversarial evaluation.

**Wechat Finance Dataset.** This dataset is a private dataset from the Wechat team, who collect 13,051 subscription accounts in the finance domain. Based on the account description, they use crowd-sourcing to classify the account into 11 sub-classes, including insurance, banks, credit cards and funds. Each account description has 94,18 Chinese characters on average. We split the dataset into the training set (10,000 descriptions), the validation set (1,163 descriptions) and the rest as the testing set (1,888 descriptions).

### 4.2 Adversarial Evaluation

**Baseline.** As there are no existing efficient Chinese character-level adversarial approaches, we propose a simple attack strategy as our baseline. We first cluster the character embedding by K-means and generate 1,000 embedding clusters. During attack, we randomly choose two or three characters and replace each of them with a random character belong to another random cluster.

### 4.3 Results

We perform our char-level adversarial attack on BERT-based classifiers for two datasets in both targeted and untargeted attack scenarios. The attack results are shown in Table 2.

We can see the untargeted attack can always achieve 100% attack success rate on both datasets, making the model performance drop to 0% by manipulating merely less than two tokens on average on the Chinese News Dataset. In the targeted attack scenario, we can always make BERT output our expected false class on the Wechat dataset, and achieve around 95% targeted attack success rate on the THUCTC dataset.

Surprised by the fragility of Chinese BERT, we conduct several case studies on the generated adversarial text. We conjecture that Chinese BERT classifiers tend to make predictions based on a certain set of characters (statistical cues) without understanding the sentences. Therefore, the adversarial attack can easily succeed by replacing such critical characters. For the topic prediction example in Table 1, “Yu” is a Chinese celebrity name and only appears in the Entertainment News in the training set. Therefore, the BERT classifier takes “Yu” as a strong signal to classify the news as the Entertainment News. Similarly, another wrong account prediction in Table 1 is because term “qi” is a frequent financial products (petroleum and gas) used in other financial management accounts.

We also find that increasing the constants $c$ and $\kappa$ can improve the attack success rate at the cost of more perturbed characters. Additionally, because the Wechat dataset has longer text than the...
We find the adversarial text can substantially affect the accuracy of blackbox models, in which we cannot access model parameters. In this setting, we can attack a blackbox BERT classifier of different parameters by using the adversarial text generated from a whitebox BERT trained by ourselves.

The transferability-based attack results are shown in Table 3. We find the adversarial text can still substantially affect the accuracy of blackbox models. In addition, the targeted attack success rate turns out to be stronger than the untargeted attack. Particularly, the targeted adversarial examples on the Wechat dataset can make the blackbox BERT classifier performance drop from 88.2% to 14.3%.

### 4.3 Human Evaluation
To confirm that our generated adversarial examples are valid to human, we conduct the following human evaluation. We randomly sample 50 clean sentences and 50 adversarial sentences generated by AdvChar (untargeted c/k = 5/5) on the Wechat dataset. We give volunteers two labels: a ground truth label and a fake label. For the clean sentence, the fake label is a random label different from the ground truth. As for the adversarial data, the fake label is the model’s wrong prediction. Both clean text and adversarial text are mixed together. Ten native Chinese student volunteers are asked to choose the correct label. These native Chinese students are not required to be equipped with professional finance knowledge, so their evaluation results could contain errors and may be not as accurate as the financial annotators employed by the Wechat team.

The evaluation results are shown in Table 4. We find that our adversarial text barely impacts the human perception, since the human performance on adversarial data is only 4% lower than the clean data, in contrast to the huge performance drop of BERT classifiers from 82% to 0%.

### 5 CONCLUSION
In this paper, we propose a novel character-level adversarial attack method to probe the robustness of BERT-based Chinese classifiers. Our experiments show that existing character-level BERT-based models are not robust in both whitebox and blackbox settings. While we observe the impressive improvements using the pretrained language models, we expect our study can encourage further research into the robustness problems of current pretrained language understanding models.

| Dataset         | Clean | Adversarial |
|-----------------|-------|-------------|
| Human           | 0.84 ±0.04 | 0.80 ±0.06 |
| BERT            | 0.82  | 0.00        |

Table 4: Human performances compared with BERT classifiers in original dataset and adversarial dataset.

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5 CONCLUSION
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A APPENDICES

A.1 Model Settings

Classifier. We use BERT [4] as the classifier for both datasets. BERT is a transformer [21] based model, which is unsupervisedly pretrained on large Chinese corpuses and is effective for downstream Chinese NLP tasks. We use the 12-layer BERT-base model with 768 hidden units, 12 self-attention heads and 110M parameters. We fine-tune BERT on each dataset independently with a batch size of 64, learning rate of 2e-5 and early stopping.

A.2 Analysis

In this section, we will evaluate the possible factors that will affect the attack success rate.

Norm selection. In the main experiment, we use $l_2$ norm for our attack loss function (equation 7). However, because $l_1$ norm is known for good at feature selection and generating sparse features, we conduct the following experiments by set $l_p$ to $l_1$ and make an comparison with $l_2$ norm. The experimental results are shown in Table 5 and 6. We find the overall attack success rates decrease when switching to $l_1$ norm. However, given the same set of constants $c$ and $\kappa$, we find the $l_1$ attack does change less words.

Table 5: Untargeted attack success rates on Chinese BERT-based classifier for THUCTC dataset. “target” and “untarget” calculate the targeted attack success rate (equation 2) and the untargeted attack success rate (equation 3). “#/chars” counts the number charcters are modified in average.

| Dataset | Original | AdvChar ($l_2$ untargeted) | AdvChar ($l_1$ untargeted) | Baseline |
|---------|----------|-----------------------------|----------------------------|----------|
|         | Acc      | $c/k$ 5/5 10/5 10/10       | 10/10 10/100 20/20        | (untargeted) |
| THUCTC  | 0.918    | target - - -              | 1.000 1.000 0.983 0.983 0.995 | 0.040 |
|         |          | untarget - - -            | 1.583 1.690 1.718 1.577 1.614 1.884 | 2.000 |

Table 6: Targeted attack success rates on Chinese BERT-based classifier for THUCTC dataset. “target” and “untarget” calculate the targeted attack success rate (equation 2) and the untargeted attack success rate (equation 3). “#/chars” counts the number charcters are modified in average.

| Dataset | Original | AdvChar ($l_1$ targeted) | AdvChar ($l_2$ targeted) | Baseline |
|---------|----------|--------------------------|--------------------------|----------|
|         | Acc      | $c/k$ 10/10 10/20 30/30 | 5/5 10/5 10/10           | (untargeted) |
| THUCTC  | 0.918    | target 0.797 0.797 0.898 | 0.941 0.915 0.945        | -        |
|         |          | untarget 0.828 0.828 0.920 | 0.953 0.958 0.958        | 0.040    |
|         |          | #/chars 2.000 1.956 3.280 | 2.924 3.186 3.045        | 2.000    |

Attack Strategy. As we have achieved 100% attack success rate in the untargeted attack scenario, we now focus on the targeted attack scenario and see which factor contributes to the targeted attack success rate. It is straightforward to think different targeted attack strategy will impact the targeted attack success rate, because maybe some classes look “farther” than semantic closer classes. So we tried two strategies on THUCTC dataset: 1) as used in the main paper, we set the targeted false class as “entertainment news”. 2) we enumerate all the classes and set the target class to be the next class. The targeted attack success rate is shown in Table 7. We do find choosing different attack strategy will impact the attack success rate.

Table 7: Attack success rates on Chinese BERT-based classifier for two datasets. “target” and “untarget” calculate the targeted attack success rate (equation 2) and the untargeted attack success rate (equation 3). “#/chars” counts the number characters are modified in average.

| Dataset | Original | AdvChar ($c/\kappa = 10/10$) | Baseline |
|---------|----------|-----------------------------|----------|
|         | Acc      | strategy 1 strategy 2       | (untargeted) |
| THUCTC  | 0.918    | target 0.945 0.903          | -        |
|         |          | untarget 0.958 0.915        | 0.040    |
|         |          | #/chars 3.045 4.545         | 2.000    |
A.3 Chinese Adversarial Examples
| Table 8: Chinese Adversarial Examples generated by AdvChar for BERT-based classifier. |  |
|---|---|
| **Input** (red = Modified character, bold = original character.) |  |
| **Original Chinese Text:** 乌鲁木齐中考答案超出答题边框视为无效 | **Translation:** Wu Lu Mu Qi’s Middle School Examination does not take into consideration answers exceeds the border box. |
| **Adversarial Chinese Text:** 乌鲁木齐中考答案超出答题边框视为无效 | **Translation:** Wu Lu Mu Qi’s Middle School Examination does not take into consideration answers exceeds the border body. |
| **Model Prediction:** Education News (教育新闻) → Society News (社会新闻) |  |
| **Original Chinese Text:** 教授称出租车特许经营无法可依提出审查被驳 | **Translation:** A professor said that there was no official laws for the cab drivers to legally run business and proposed to review the laws but refuted. |
| **Adversarial Chinese Text:** 教授称出租车特许经营无法可依提出审查被驳 | **Translation:** An American professor said that there was no official laws for the cab drivers to legally run business and proposed to review the laws but refuted. |
| **Model Prediction:** Society News (社会新闻) → Stock News (股票新闻) |  |
| **Original Chinese Text:** 15 比 7！专家一边倒支持热火球迷却挺小牛 | **Translation:** 15 to 7! Sports Professors all support Miami Heat but American fans vote for Dallas Mavericks |
| **Adversarial Chinese Text:** 1568 7！专家一边倒支持热火球迷却挺小牛 | **Translation:** 1568 7! Sports Professors all support Miami Heat but American fans vote for Dallas Mavericks |
| **Model Prediction:** Sports News (体育新闻) → Lottery News (彩票新闻) |  |
| **Original Chinese Text:** 教师要求表现差学生交 2000 元入学保证金 | **Translation:** The teacher asked the students who showed poor performance to pay 2,000 yuan for the enrollment certificate. |
| **Adversarial Chinese Text:** 教师要求表现差学生交 2000 元入学保证金 | **Translation:** The teacher Wei asked the students who showed poor performance to pay 2,000 yuan for the enrollment certificate. |
| **Model Prediction:** Society News (社会新闻) → Education News (教育新闻) |  |
| **Original Chinese Text:** 贝卢斯科尼达成离婚协议每月付 35 万欧元赡养费 | **Translation:** Berlusconi reaches a divorce agreement to pay 350,000 Euros a Month for Maintenance. |
| **Adversarial Chinese Text:** 贝卢斯科尼达成离婚协议每月付 35 万欧元赡养费 | **Translation:** Berlusconi reaches a divorce agreement to pay 350,000 Euros a Month for Maintenance. |
| **Model Prediction:** Politics News (时政新闻) → Society News (社会新闻) |  |
| **Original Chinese Text:** 《快乐星球》2 月 11 日登陆央视将参与网络春晚 | **Translation:** 《Happy Planet》will land on CCTV on February 11 to participate in the Internet Spring Evening. |
| **Adversarial Chinese Text:** 《快乐星球》2 月 11 日登陆央视将参与网络春晚 | **Translation:** 《Final Happy Planet》will land on CCTV on February 11 to participate in the Internet Spring Evening. |
| **Model Prediction:** Entertainment News (娱乐新闻) → Technology News (科技新闻) |  |
| **Original Chinese Text:** 债券已处牛市前夜 市翻身 6 年来最惨一跌结束 | **Translation:** Bonds have been in the bull market since yesterday when the bond market goes up and ends the worst drop in six years. |
| **Adversarial Chinese Text:** 债券已处牛市前夜 市翻身 6 年来最惨一跌结束 | **Translation:** Bonds have been in the bull market since yesterday when the Hong Kong market goes up and ends the worst drop in six years. |
| **Model Prediction:** Financial and economic news (财经新闻) → Stock news (股票新闻) |  |
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